Police Strategies for Fugitive Interception

A case study in the metro network of Rotterdam

Delft University of Technology

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A case study in the metro network of Rotterdam

by

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Preface

Dear reader,

With this thesis, I mark the completion of my master's degree in Engineering & Policy Analysis at the Delft University of Technology.

I would like to thank my committee for helping me realise this thesis. First of all, many thanks to Irene van Droffelaar, for your advice, guidance, and confidence. Without your help I would not have been able to write this thesis. I enjoyed our meetings and always walked away with a smile. Second, I would like to thank Kateřina Staňková and Alexander Verbraeck for your enthusiasm and invaluable feedback anytime I needed it. You gave me a lot of freedom during the project and supported me in whichever way I went.

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Additionally, I would like to thank the experts from the police and RET team for inviting me to the control rooms. I am grateful for the time you took to participate in my interviews and the interesting conversations that arose from them.

Enjoy the reading!

Cécile van Heukelom
Rotterdam, February 2024

Summary

When a crime is committed, catching the offender in the act has several benefits. Among others, it provides evidence of the offender's involvement in the crime, which simplifies the conviction process. However, to capture an offender in the act, the collaboration of multiple police officers is required. When a crime is being reported through the emergency line, it is the responsibility of the police officers in the control room to answer the call. They gather information on the type of crime, the location, a description of the offender, etc. Subsequently, they dispatch police units to the crime scene. The first unit prioritizes reaching the crime scene to ensure the safety of citizens, while the other units are tasked with locating and apprehending the offender.

To adequately respond to reported crimes, police officers in the control room and units on the street rely on intuition, experience, and habit. This leads to the development of individual-specific strategies for handling interception scenarios. Reducing the dependency on these individualized approaches by identifying proven and robust strategies could increase the likelihood of successfully capturing a suspect. However, how the police currently save data on fugitive interception scenarios, does not allow for such identification. Hence, alternative approaches to overcome this limitation must be found. Therefore, this paper explores whether simulation and game theoretic analysis are suitable methods for determining robust interception strategies for the police, aiming to increase the catch rate in fugitive interception scenarios.

Classical game theory is the mathematical theory of interactions among rational decision-makers with opposing interests. It offers valuable insights into the decision-making processes, compromises, and strategies the police and offenders may employ in real-world situations. To analyze the fugitive interception scenario with game theory, it is first simulated with an agent-based model. In this simulation model, the police and offender are individual agents with opposing interests and individual decision-making processes. Before modeling, research is conducted to find the current strategies that the police and offenders can potentially adopt.

Given the limited availability of data on fugitive interception scenarios, literature and expert interviews serve as sources for data collection. They provide insights into the behavior and strategies of both agents. Both sources emphasize the nature of the crime as a primary indicator of the offender's escape behavior. Large crimes, such as assassinations or armed robberies, are typically well-planned, and characterized by predefined escape routes and rational behavior. During their escape offenders of large crimes are found to be less susceptible to external factors such as crowd flows or police sightings. On the other hand, smaller crimes are more frequently committed spontaneously and associated with bounded rational behavior. This is depicted by their chaotic and unpredictable escape routes while taking many turns.

For the game theoretic analysis, the results of the simulation model are analyzed. The fugitive interception project is regarded as a non-cooperative zero-sum game. The results are presented in a payoff table, in which

Nash equilibria are calculated. Nash equilibria are the points at which no player can single-handedly improve their outcome, when the other player does not change strategy.

The pure-strategy Nash equilibrium resulted from the offender strategy where they started at a central metro station and aimed to transfer to a train network. These routes were frequently identified as the shortest compared to other end goals. Conversely, strategies that focused on getting as far away as possible, as quickly as possible, were found to be the least successful.

In determining the success of the police strategy, two factors were found to be crucial. Firstly, strategies where the police conducted surveillance on the metro platforms, as opposed to the station exits, proved significantly more effective. This highlights the importance for the police to strategically position themselves where the offender is most likely to pass, irrespective of assuming it to be the offender's final destination. Secondly, the police's response time served as an indicator for capture success. The quicker the crime is reported, the faster the police can take action to capture the offender, which increases capture chances.

Additionally to the game theoretic analysis, the relationship between the model's output and its sensitivity to changes in input variables is tested. Results showed that variations in input did not lead to significant changes in output. This can be attributed to the deep uncertainty of this model. To address this challenge, the model must be refined, and done with more iterations.

In conclusion, by combining simulation and game theory new insights can be found beyond what either method can provide individually. By modeling the dynamic nature of a fugitive interception scenario, the success of the offender and police behaviour can be found. This can help the police during decision-making to adopt more robust strategies while considering the dynamic nature of the environment and strategic interactions with the offender.

The study addresses the knowledge gap by simulating offender and police behavior, and analyzing the result with classical game theory. This study has created a simulation model with an intuitively driven agent in a complex dynamic problem. Potential improvements in offender capture chances, with findings informing effective and unbiased police interception strategies. The study aims to contribute to crime reduction and foster increased trust in the Dutch national police. However, before generalizing the results future research must be done to overcome limitations resulting from the simplifications of this simulation model.

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1 Introduction

1.1 Societal problem

Though the registered crime rate in the Netherlands has been decreasing, the country remains subject to large-profile criminals (Openbaar Ministerie, 2022). For example, a high-profile offender like Ridouan Taghi has been able to remain under the radar of the police for a long time, building large criminal networks throughout the entire country (Adér et al., 2021). This has led the Netherlands to become a significant player in the influx of drugs into Europe (Yeşilgöz-Zegerius, 2022). Taghi, along with other famous Dutch criminals, such as Willem Holleeder, Joran van der Sloot, and Cor van Hout, create a lingering sense of fear throughout the Dutch population (Sooknanan and Seemungal, 2023). To combat organized crime, the Dutch government allocated an extra 524 million euros to the National police in 2022, aimed at improving societal and economic resilience against criminal influences. However, the police indicate that approximately 600 million euros is needed to effectively do so (Politie, 2021).

Despite the increased financial support the police received, the year 2022 showed an increase of 6% in unique offenders compared to the year 2021 (Openbaar Ministerie, 2022; Adér et al., 2021). Interviews with police confirmed this trend to continue in 2023, especially noticeable during the explosions in Rotterdam (Appendix B; Politie, 2022). In most instances, the offenders managed to escape and were untraceable. Police attribute this to the fact that most offenders were young individuals entering the criminal circuit for the first time. Therefore they were unknown to the police, making identification difficult (Appendix B).

In the Netherlands, the likelihood of identifying and locating the offender after the crime varies depending on the nature of the offense. On average, in approximately 32% of the crimes the perpetrator is identified, from which roughly 62% of them are unique offenders (Openbaar Ministerie, 2022). When a crime is committed by an individual with no prior record, the police lack personal information about them. This makes it considerably more challenging to trace and locate the offender (Appendix B).

To prevent the need for locating an offender after a crime has occurred, one effective strategy is capturing the offender red-handed. In Dutch law, catching an offender red-handed refers to a capture "when the offense is discovered while it is being committed or immediately after it is committed" (Wetboek van Strafvordering, 1926). Seizing an offender in the act offers three key advantages. Firstly, it enables the immediate apprehension of the wrongdoer, preventing further damage, harm, and potential future crimes. Secondly, it serves as a message signaling to other offenders that police actively monitor criminal activities, which can demotivate future offenders. Lastly, capturing an offender red-handed provides prosecutors with solid evidence for legal proceedings, enhancing the chances of conviction (Appendix B). If a red-handed capture fails, police will have to locate the offender. Once tracked, the conviction must undergo multiple procedures to get sufficient evidence to put the offender away.

According to Weisburd (2021), the success rate of catching offenders red-handed is closely linked to the time it takes for the police to reach the crime scene. Depending on the severity of the crime, there are specific time constraints within which the police must arrive. For instance, emergency calls categorized as 'prio-1 reports' involve life-threatening situations, which require a unit to be at the crime scene within 15 minutes (Politie, 2023). In 2022, the Dutch Police succeeded in arriving at the crime scene within this time frame 84% of the time.

Intercepting fleeing suspects can be a challenging task, mainly due to their uncertain route choices to the police. Currently, police often rely on individual-specific strategies based on their intuition and past experiences rather than employing data-driven or systematic approaches. This dependence on intuition and habit makes it challenging to identify and define effective strategies for intercepting fleeing suspects (Appendix B). By reducing this dependence and finding proven robust strategies, the chances of successfully apprehending a suspect can be increased. To find robust strategies, a comprehensive understanding and analysis of the decision-making process of the police is required. Additionally, to evaluate the success of police strategies, an analysis of offender behaviours is essential. Without understanding offender behaviour, assessing the effectiveness of various police strategies is challenging. Therefore, to increase the capture rate of an offender in the act of committing a crime, this study aims to identify robust police interception strategies by analyzing the capture values resulting from typical offender and police behaviours during a fugitive interception project.

Different methods can be used to analyse fugitive interception problems, of which one is through game theory. Game theory is a mathematical analysis of interaction. From a game theoretic perspective, situations with multiple interacting parties, referred to as players, are defined as a game. It can be used to explore strategic interactions among decision-makers, who seek to optimize their outcomes (Krebs et al., 2003). This is further elaborated on in in Section 2.2.

Simulation is another method which can be employed to analyze fugitive interception problems. Simulation involves creating models to mimic real-world scenarios and processes (Yonas et al., 2013 In a simulation, various factors and variables are defined to represent different aspects of the problem, such as the behaviours of the police and offenders, the terrain, and environmental conditions. By simulating the interactions and dynamics of these elements over time, it can observed how different strategies in specific scenarios perform (Escobar et al., 2023; Helbing et al., 2000). This method will be further discussed in Section 2.1.

1.2 Knowledge gap

This section explores the existing gaps in scientific and societal knowledge about the application of simulation and game theory the context of fugitive interception scenarios.

1.2.1 Scientific knowledge gap

Classical game theory is the study of strategic interactions among rational decision-makers (Gibbons, 1992). It is advantageous for analyzing a fugitive interception project as it allows the study of strategic behaviour between the police and offenders, considering them as players with conflicting objectives (Hespanha, 2017). By imitating reality, where players do not have complete information about the scenario or the other player's moves or desires, individuals operate in uncertain scenarios (Bonau, 2017; Eichberger et al., 1993). Particularly valuable in situations such as fugitive interception problems where players have conflicting interests, game theory provides insights into decision-making, competition, and compromises in real-world scenarios

(Ross, 2021; Gibbons, 1992). Based on those findings, robust strategies for output maximization can be determined (Peters, Vissers, et al., 1998).

In the context of interception, one application of game theory is pursuit-evasion games. These games feature at least two players – a pursuing player (typically the police) aiming to catch or intercept an evading player (typically the offender) attempting to escape (Hohzaki, 2016; Isaacs, 1999). In pursuit-evasion games, both pursuer and evader can adopt diverse strategies to outmaneuver each other, to achieve their desired outcomes. The complexity increases as players continuously adjust their strategies in response to one another player's actions, creating a dynamic and ever-changing game environment (Haas and Ferreira, 2017).

Despite the criminal application of a pursuit-evasion game, limited literature exists on the usage of such games on fugitive interception scenarios which analyze the robustness of police strategies based on real-life police and offender behaviour. The majority of literature applies pursuit-evasion games on moving robotic objects, thereby simplifying decision-making to certain pre-set processes. For example, in Vidal et al. (2002), objects were either moving randomly or based on evader-detection using a camera. And in Y. Wang et al.'s (2020) study evaders and pursuers move according to predetermined algorithms and reinforced learning. By basing strategies on mathematical equations, behaviour is excluded from significant factors in the decision-making process such as feelings of distress, fright, and hurry. This can lead to (unexpected) changes in strategies (Vidal et al., 2002).

Additionally, only limited literature proposes a pursuit-evasion game applied to a real-life traffic network. This reduces the complexity of the problem but simultaneously omits external factors in a police pursuit, such as time factors or the existence of other citizens. Incorporating factors such as real traffic networks into pursuit-evasion models can provide insight into the interaction between the police, civilian presence, and traffic conditions. Further discussion on game theory is done in Section 2.2.

In conclusion, while pursuit-evasion games offer insights into strategic interactions between police and offenders, they are mathematically complex. As a result, game theory will be used as an analytical framework to understand interaction between strategies of the police and offenders. To model these strategies simulation will be used. By simulating various scenarios and incorporating real-life behaviours, uncertainties, and external factors the stochastic nature of a fugitive interception can be captured. This is further discussed in Section 2.

1.2.2 Societal knowledge gap

In the Netherlands, governed by the rule of law, the police must consistently be able to justify their actions. Acting based on intuition is deemed as an insufficient defense in case of incidents. However, currently, police officers adopt interception strategies based on experience, instinct, and habit (Appendix B). This implies that police strategies are often subconsciously influenced by biases, for example, the ones based on ethnic profiling. To ensure the objectivity of the police, data-driven approaches can assist in defining robust strategies, thereby fostering transparency and accountability. In turn, contributing to fair and unbiased police practices. However, the data on fugitive interception scenarios is limited. Firstly, because police do not gather the data in a way that can be used to formalize optimal police strategies (Appendix B). Secondly, making the data meaningful for an interception project requires knowledge of which police strategies proved effective and ineffective against specific offender strategies. However, the police only possess information about scenarios where offenders were apprehended, lacking insights into strategies when offenders successfully evaded capture.

Instead, finding robust interception strategies for the police can be achieved through modeling (Escobar et al., 2023). Models are valuable tools to gain insights into behaviour and aid in identifying crucial relationships and factors within a system (Chan et al., 2010). Simulation can be used to model offender and police strategies, after which their success rates can be analyzed. In doing so, real factors in the system of a fugitive interception scenario can be included and their effects researched (Yonas et al., 2013; Mohler et al., 2011; Chastain et al., 2016).

1.3 Scope of research

This project aims to optimize the catch rate in a fugitive interception scenario through a game theoretic approach. Due to time constraints, the study will concentrate on the Rotterdam metro network as a case study. Despite being a complex system with multiple lines, stations, and junctions, the metro network's structure narrows down the scope to a specific set of possible routes for the offender. The layout and operations of the network offer a simplified environment for testing the success of offender and police strategies. The analysis will explore various strategies available to the police and recommend the most effective and robust course of action to increase the likelihood of capturing the fugitive.

It is important to note that in the vast majority of cases where the offender uses the metro network to escape a crime scene, the offender is identified by metro cameras. Every metro is equipped with cameras covering the entire space in Rotterdam's metros. Police interception strategies are based on information from these cameras, leading to successful captures in the vast majority of cases (Appendix B). Unfortunately, this information was discovered late in the project timeline, preventing a change in scope. Therefore, the scope is altered to exclude scenarios with cameras, allowing the fugitive interception game to be played without camera information. By excluding the influence of cameras, the model simulates a scenario of a fleeing suspect where no cameras are available, as this is most often the case in a fugitive interception scenario that is not in the metro. The robust strategies identified for this scenario are valuable, as cameras are not always present in reality. Additionally, the model focuses on police behaviour and offender behaviour, which is relevant for the police (Appendix B). The findings can be generalized and used in scenarios where the police have no prior knowledge of the offender and when no continuous camera footage is available. Such scenarios can occur in a fugitive interception scenario on the highway, or in a closed building. Further generalization is done in Section 10.5.

1.4 Research questions

This study aims to improve the catch rate in a fugitive interception scenario by finding robust interception strategies for the police. These are tested against multiple evasion strategies offenders can adopt. As pursuit-evasion games are found to be too complex as a modeling method, game theory is used as an analytical tool to analyze the results of the simulation model. This is further elaborated in Section 2. Based on interviews and literature this research formalizes a set of strategies and calculates the probabilities for a successful pursuit. The goal is to provide the Dutch National Police with valuable insights into the unpredictable and chaotic escape behaviours of offenders. This can be used to identity potential robust police strategies for use in fugitive interception operations.

The main research question, based upon the research goal and knowledge gap identified through literature and the Dutch National Police is presented below.

Main research question

How can game theory and simulation help in finding optimal interception strategies for the police to increase the catch rate in fugitive interception scenarios?

The research question will be applied to the metro network of Rotterdam, as defined in Section 1.3. When a crime occurs and the perpetrator uses the Rotterdam metro network to evade capture, the scenario for this project starts. The police can employ various strategies to apprehend the offender. Similarly, the offender can adopt multiple strategies to evade capture by the police. A more detailed explanation of the police's context is provided in Section 4, and a sample scenario is described and visualized in Section 7.5.

To address the main research question with its application on the metro network of Rotterdam, four sub-questions are formulated.

Sub-questions

1. What strategy can a fleeing fugitive adopt to minimize the probability of an interception by the police when escaping through the metro network of Rotterdam?
2. What strategy can the police adopt to maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam?
3. What is the effect of information on the probability of an interception with the offender?

SQ1: *What strategy can a fleeing fugitive adopt to minimize the probability of an interception by the police when escaping through the metro network of Rotterdam?*

This sub question will be answered through literature and expert interviews. Based on this information, the simulation model will contain several escape strategies, which will be analyzed based on its success rate.

A fugitive attempting to escape through the metro network of Rotterdam may employ various escape strategies, including switching metro lines, exiting at different stations to avoid detection, utilizing different entrances and exits at metro stations, or blending in with crowds by remaining in densely populated metro areas. Furthermore, the offender's behaviour can influence their strategy, with a panicked offender behaving differently from one who is not in a state of panic.

SQ2: *What strategy can the police adopt to maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam??*

The police can adopt several interception strategies when attempting to intercept a fleeing fugitive. Based on literature and expert interviews the simulation model will will analyze the effectiveness of multiple interception strategies in capturing an offender. Such behaviour involves agent allocation, surveillance at metro stations, the number of units or using undercover officers.

SQ3: *What is the effect of information on the probability of an interception with the offender?*

This sub-question builds upon the strategies conceptualized in sub-questions 1 and 2. How does information influence the interception game? In the simulation, both the offender and the police can modify their behaviour based on incoming information, thereby attempting to enhance the chances of reaching their desired goals. By addressing this aspect, the importance of information in a fugitive interception is analyzed, which can support the decision-making of the police in such scenarios.

In conclusion, the objective of this study is to identify robust courses of action for the police to ensure a successful capture. This is done by facilitating an understanding of potential strategies an offender may adopt during an escape. The aim is not to prescribe a definitive solution but to support decision-making in the face of deep uncertainties, such as the unpredictable behaviour of the offender.

It's important to note that this study refers to the offender or suspect indicating the same person, as suggested by the police (see Appendix B). However, in the simulation, they are referred to as the criminal, implying guilt. However, it's crucial to recognize that a suspect is not considered guilty until proven, which is not researched in the scope of this study. Therefore, the terms offender, suspect, and criminal are used interchangeably, but without any insinuation about their offender status.

1.5 Relevance

This section discusses the significance of this paper's research from both scientific and societal perspectives, highlighting its potential contributions and implications.

The scientific purpose of this question is to apply a systematic viewpoint to a chaotic problem, full of intuitively driven actions. Rationally exploring a pursuit-evasion game as a fugitive interception and comparing it to the strategies that follow from a game theoretic perspective can lead to new insights and therefore new improved methods.

Moreover, this research will expand pursuit-evasion games to a fugitive interception scenario by including behavioural and uncertain aspects. Behavioural factors add complexity to the analysis, which offers a more complete understanding of the dynamics involved in fugitive interception scenarios. This to formalizing strategies and thus contributing to the development of innovative police methods.

The societal objective of this research is to enhance the effectiveness of offender capture strategies by the Dutch National Police. A detailed simulation model will be constructed to analyze the dynamic interactions between police and offenders during pursuit scenarios. The insights gained from this model can contribute valuable information for the development of effective interception strategies by the police. Additionally, by creating strategies based on offender behaviour, it can contribute to the elimination of biases such as ethnic profiling in police work (Appendix B).

Furthermore, understanding which strategies are most effective in capturing an offender can also aid in optimizing resource allocation. Resource allocation includes financial considerations, the deployment of police vehicles during operations, and the duration until an interception. This multifaceted approach aims to address various aspects of operational efficiency and effectiveness. By increasing the catch rate through strategic decision-making, the research aims to contribute to the reduction of overall crime rates and increase trust in the capabilities of the Dutch National Police.

1.6 Research outline

To answer the research question of this paper, this study uses Greasley's (2008) steps to build a simulation model. These are:

1. Formulate the simulation project
2. Data collection
3. Process mapping
4. Modelling input data

5. Building the model
6. Validation and verification
7. Experimenting and analysis
8. Presentation of results
9. Implementation

Each step is characterized by its own goal within a simulation model design. Once all the steps have been completed, the research questions can be answered. The last step is left out in this research. Figure 1.1 gives a visual representation of the research design outline.

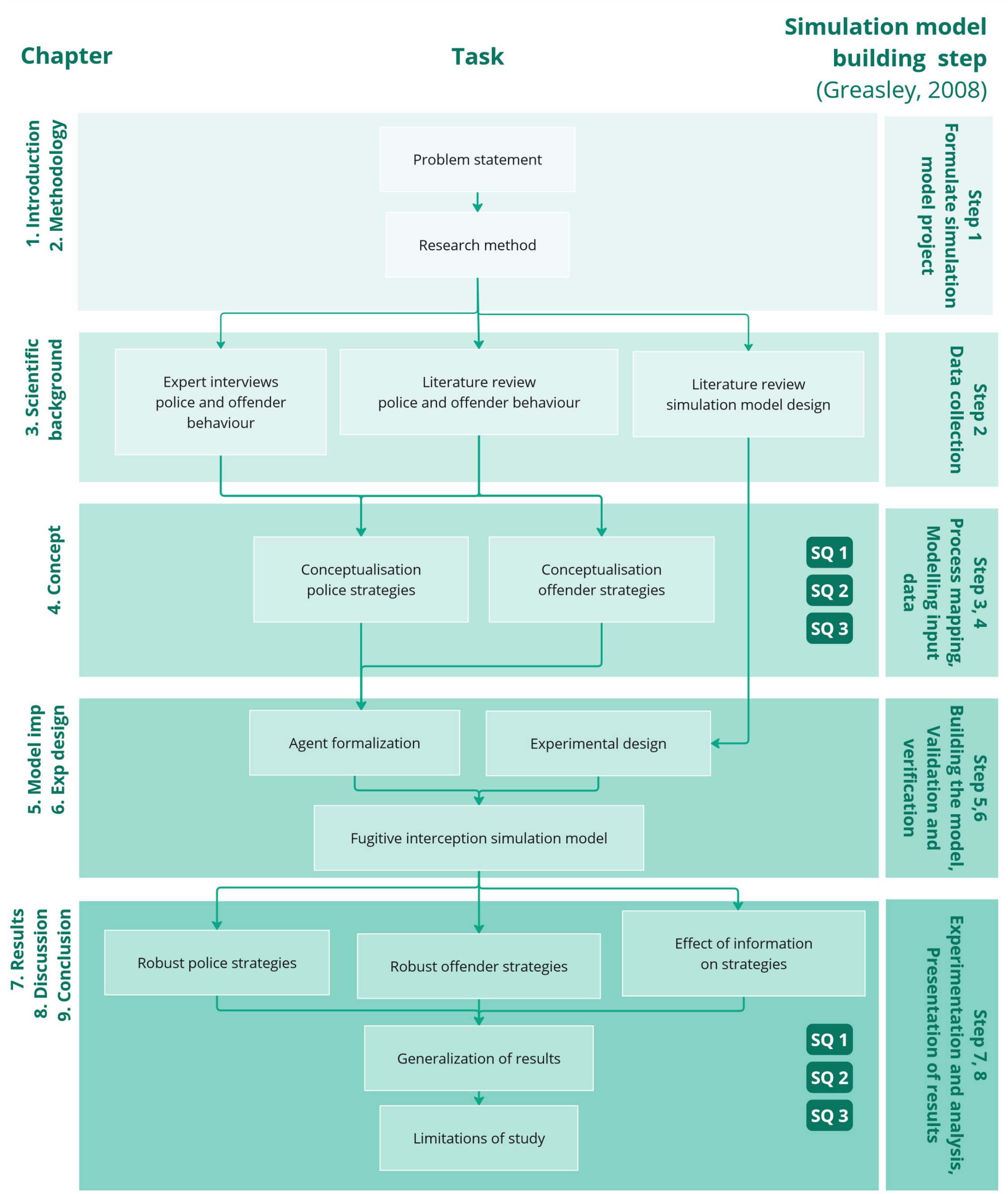


Figure 1.1: Research design diagram

Step 1: Formulate the simulation project

This step is intended to get familiar with the topic. The purpose of the simulation model is defined and its boundaries are established. For the fugitive interception project this has been done in the current chapter in Section 1.3.

Step 2: Data collection

This step aims to identify the relevant elements of the system and the relations within it by collecting data.

To achieve this, qualitative research is done to gather specific knowledge on evasion and pursuing strategies in fugitive interception. Besides literature, expert interviews will give insights into real strategies currently adopted in Rotterdam. Further information on the interview approach and findings of the literature will be discussed in Section 3. Summaries of expert interviews are found in Appendix B.

Step 3 & 4: Process mapping & modeling input data

The objective of this step is to translate the information about the system found in step 2, to model elements. The agents are conceptualized, answering the research questions' theoretical parts. Strategies for the agents, representing the real system, are identified in Section 5.

Step 5 & 6: Building the model & validation and verification

In the final step of the design process the concepts are implemented; creating the simulation model. Implementation is an iterative process between testing and modeling. The simulation model is an agent-based model that explores the police's strategies against a multitude of offender strategies. An important aspect of this step is model validation, which analyzes the suitability of the model to represent the system (PMBOK Guide, 2017), which is done through expert interviews (Appendix B). A detailed explanation of the game construction and validation process will be given in Section 6. Besides the formalization of the model, the experimental design is also defined in this step, which is done in Section 7.

Step 7 & 8: Experimentation and analysis & presentation of the results

The remaining sections of this paper discuss the results and analyze these using game theoretic concepts such as the Nash equilibrium (Nash, 1950). Conclusions are drawn, and the limitations of this study are discussed. Finally, the sub-questions are used to answer the main research question.

2 Related literature on methods

This section explores literature on Agent-Based Models (ABM) and game theory. Section 2.1 discusses ABM's application and relevance in simulating fugitive interception patterns. Next, Section 2.2 examines game theoretic models applied to such scenarios. Both subsections conclude by evaluating the adequacy of simulation as a modeling tool and game theory as an analytical tool for a fugitive interception scenario.

2.1 Literature on simulation

A fugitive interception problem can be seen as a stochastic model which involves multiple chaotic and unpredictable elements such as offender behaviour, dynamic environments with driving metros, and third parties such as traveling citizens. All these factors influence the decision-making of police agents and offender agents. While agent-based modeling (ABM) and discrete event modeling (DEM) are both able to capture the nature of a stochastic model, ABM seems to be a more appropriate method for this project for three important reasons (Maidstone, 2012). First, ABM is able to differentiate between a multitude of agents, which all have unique interests and motivations. Agents can initiate their own actions, and thus have an individual decision-making process, whereas DES relies on a central mechanism during decision-making (Chan et al., 2010; Maidstone, 2012). Second, ABM is able to capture interaction effects between agents and their environment (Chan et al., 2010). Interactions can create opportunities through which tipping-points of behaviour can be measured. This, thirdly, leads to agents in ABM being able to learn from interactions, and can thus adapt to their dynamic environment (Siebers et al., 2010). Therefore, changing circumstances in a fugitive interception scenario will be able to be featured in an ABM approach.

The capability of Agent-Based Models (ABM) to simulate offender patterns has been widely acknowledged and empirically supported in numerous studies (Escobar et al., 2023; Helbing et al., 2000; Groff et al., 2018). These models have demonstrated effectiveness in replicating the complex behaviors and interactions of individuals within a given environment. Gerritsen (2015) studied the adequacy of ABM in identifying criminal patterns. She concludes that the ABM effectively identifies hotspots of residential burglary. Overall, the study demonstrates the utility of agent-based modeling in understanding the complex dynamics of criminal behavior and informing practical interventions to enhance community safety. This is relevant because it shows the potential of ABM to provide insights into crime patterns and inform targeted crime prevention strategies, which this study will do.

Additionally, Yonas et al. (2013) found ABM to be an effective method to simulate intervention models. Similarly, the work of Malleson and Birkin (2012), showed that ABM is an efficient tool in refining crimes geographically, for example, based on wealth or household size. This is relevant because it demonstrates how ABM can be utilized to explore the effectiveness of intervention strategies by the police and understand the spatial distribution of crime based on socio-economic factors. This information can be used to adequately locate police officers at areas which are more prone to crime.

Furthermore, studies have underscored the importance of simulation models in testing and validating various crime theories (Chastain et al., 2016). Zhu and F. Wang (2021) searched major databases to find all publications using ABM to simulate urban crime patterns, to analyze the contributions of ABM in criminological research. She found that ABM can improve understanding of and inform practical interventions in crime by adequately simulating theories and policies. This is relevant because it highlights the role of ABM in testing and validating crime theories and policies in simulated environments.

Now that the choice for an ABM approach has been explained based on its ability to represent complex systems, the modeling tool must be chosen (Van Horn, 1971). Based on previous experience, and ability to visualize and capture complex dynamic systems, the Mesa package is chosen. Mesa is a Python library that allows building, analyzing, and visualizing agent-based models. Complex systems where agents interact with each other and their environment are simulated using built-in components such as agents and schedulers (Masad and Kazil, 2015).

In the simulation model players use strategies, based on behaviour, to achieve specific outcomes. To build a simulation model, the nine building steps to a simulation model of Greasley (2008) are used. The simulation model is designed to assist in identifying robust police and offender strategies during an interception scenario, as outlined in the research questions in Section 1.4. Literature on the affectiveness of ABM to simulate crime patters is discussed in Section 2.1.

2.2 Literature on game theory

Game theory is the study of mathematical models of strategic interactions between rational decision-makers. It analyzes how individuals or entities make choices, considering the impact of those decisions on the outcome of the problem (Gibbons, 1992). Based on incomplete or uncertain information, individuals strategies their moves to achieve a desired outcome (Bonau, 2017; Eichberger et al., 1993). In situations where multiple parties are interdependent, game theory can give insights on decision-making, competition, and compromises, making it valuable for understanding real-world scenarios (Ross, 2021; Gibbons, 1992). Game theory distinguishes between cooperative and non-cooperative games. The first focuses on how players can share outcomes (Hespanha, 2017), and the latter on individual outcome optimization (Hespanha, 2017). The upcoming section assesses the suitability of game theory for a fugitive interception project, followed by an exploration of its practical implementation.

The fugitive interception game involves two players: the offender and the police, further explained in Section 4. Due to their conflicting objectives (capture and escape), the simulation model is considered a non-cooperative game (Hespanha, 2017). Additionally, nine key characteristics classify this study's fugitive interception scenario as a game-theoretic problem (Ross, 2021). At the beginning of the game, both players share (1) common knowledge, such as the crime location and the metro network. Common knowledge is information universally known among all players, creating a foundation of (2) mutual awareness (Binmore and Brandeburger, 1988). As the offender initiates their escape, (3) private information is generated, resulting in (4) information asymmetry between the players, which can be strategically advantageous (Camerer and Ho, 2015; A. Kalai and E. Kalai, 2010). Next, (5) time delays, such as the reporting delay of a crime or the time taken by the police to realize the offender's departure from the metro, are integral to this non-cooperative game (Binmore and Brandeburger, 1988). Additionally, both players can make (6) simultaneous decisions throughout the game, which means that they do not have to wait for their turn to make a move (Binmore and Brandeburger, 1988). Even though the moves by both players are made (7) independently and (8) parallel, (9) strategic interdependence exists between the offender and police, meaning the choices of one player can impact the payoffs of the others (Binmore and Brandeburger, 1988). In this particular scenario, the winning player's gain is equivalent to the losing player's loss (as a win for the police means a loss for the offender), adding up to a net improvement of zero. Such games are referred to as zero-sum games, and are characterized by the impossibility of a shared common goal outcome (Isaacs, 1999).

As seen in the previous paragraph, game theory is a suitable tool to analyze a fugitive interception scenario. It offers insights into diverse strategies with associated trade-offs. It aids in understanding which information and/or strategies are crucial for winning the game, keeping in mind the incentives and actions of all players. Therefore, this project uses game theory as a method to find robust strategies in a fugitive interception problem. Next, literature offering different game theoretic approaches to this problem are discussed.

Pursuit- evasion game

A pursuit-evasion game involves a pursuer and evader, each pursuing different objectives. With conflicting goals (capture and evasion), this game falls into the category of a zero-sum game (Isaacs, 1999). These games can be solved using differential equations, which alter the state of players over time, in response to their own and others' previous states and actions.

In 1978, Parsons was the first to add a graphical illustration to pursuit-evasion games, visually representing it (Parsons, 1978). Here, both the evader and pursuer start on nodes of a graph. Alternating turns, the player can choose whether to move along an edge to a different node, or to remain stationary. Once the evader and pursuer are on the same node, the pursuer wins and the game is terminated. With his graph visualization, Parsons was able to find optimal conditions for capture.

One of the first real-life applications of a pursuit-evasion game was done by Isaacs (1999), where military scenarios such as missile, (sub)marine and aeroplane interceptions were analyzed. Slightly later, Vidal et al. (2002) applied a pursuit-evasion game to a scenario where unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV) pursued a ground vehicle. He found that the global max policy, which searches an entire map to compute a maximum probability of capturing an evader has the best performance. Later, the effect of multiple targets was added and applied to other domains such as wilderness searches, sea rescues (Bourgault et al., 2003; 2006) and clearing multiple environments of an evader (Gerkey et al., 2005).

In recent years pursuit-evasion games have become a popular field of study in three main research areas: behavioural biology, neurology and game theory fields (Al-Talabi, 2017). Within game theory, the most common application that has been studied is for military purposes. Pursuit-evasion games have, for example, been proven useful in interception scenarios, missile avoidance operations and rescue missions (Isaacs, 1999).

Pursuit- evasion game applied to police

Haas and Ferreira (2017) used the theory of pursuit-evasion games to provide the police with a tool to find more effective strategies for interdiction patrols and pursuits. Their case is applied to poachers entering wildlife reserves. The tool consists of an algorithm calculating multiple patrol routes, and estimating the probability of capture for each one. A potential patrolling route is based on previous poaching incidents and the roads that lead to this location. The demonstrated effectiveness of this tool in preventing wildlife crime and improving arrest rates underscores the significance of accounting for past behaviours in optimizing law enforcement efforts.

Furthermore, in 2017, Al-Talabi developed an optimizing algorithm for a group of pursuers aiming to capture a single evader. In their game, pursuers and evaders have the same speed, forcing them to seek out the most efficient routes. Their algorithm relies on two key principles. First, the pursuers must move following the parallel guidance law. Meaning, that the pursuer who can capture the evader will move towards it, if capture is not possible the pursuer will follow its course in parallel with the evader making sure the difference in their distance does not increase. Second, the pursuer who can reduce the difference in distance is positively rewarded. Thus, the algorithm continuously reevaluates one's position and aims to reduce its difference based on the evader's movements. This research proves valuable as it takes into consideration the spatial dynamics between pursuers and evaders.

Finally, Y. Wang et al. (2020) applied pursuit-evasion games on a 2D environment where multiple pursuers try to capture one evader (Y. Wang et al., 2020). All players are modeled as objects that can interact physically. The evader has better maneuverability than the pursuers, and can use random or pre-trained intelligent strategies to evade capture; an escape policy or a random escape policy. The pursuers have limited observation of the environment and play a cooperative game where they can communicate with each other through a network, and are aware that the evader can employ multiple strategies. Results showed that a "learning to communication" mechanism to improve information sharing leads to more efficient distributed cooperative interception control policies. This research highlights the critical importance of communication among players in pursuit-evasion games, ultimately positioning effective information exchange as a primary reason for increased capture rates.

Pursuit- evasion games with asymmetric information

A pursuit-evasion game with asymmetric information refers to a situation where not all players know the states or moves of the other players (Camerer and Ho, 2015). Makkapati et al. (2022) applied information asymmetry to a two-player zero-sum game. They found that players with an information disadvantage are the minimizing players, who developed conservative strategies. This implies that players with little information act conservatively, based on information they know.

Based on the findings from the literature, it is apparent that existing game theoretic models tend to be overly mathematical for this study and lack the incorporation of behavioral uncertainties. Agents are often depicted as robotic entities. Therefore, this paper will not use pursuit-evasion theories to create the simulation model. Instead, this paper uses game theory as an analytical tool for interpreting results. The Nash equilibrium will be used to identify robust strategies.

Nash equilibrium is a known concept in game theory named after mathematician John Nash (Nash, 1950). It represents a point where each player's strategy is optimal given the strategies of others. In simpler terms, it is a situation where no player has an incentive to unilaterally deviate from their current strategy, as doing so would not result in a better outcome for them. This equilibrium captures the notion of stability in strategic interactions, where each player's actions are rational responses to the actions of others, leading to an equilibrium state.

Nash equilibrium is its broad applicability across various types of games, such as from zero-sum games, games with perfect/ imperfect information, and games with multiple players Kreps, 1989. It is used for analyzing strategic interactions in economics, politics, and social sciences, offering insights into decision-making processes and predicting outcomes in competitive environments.

3 Data collection

This section outlines the methodology for Greasley, 2008's (Greasley, 2008) second simulation building step: data collection. The data for the simulation model is collected through interviews and a literature review. The findings of this section are used to build the simulation model. The literature is divided into research about the offender behaviour, and research about police behaviour in a fugitive interception scenario.

3.1 Primary data collection: interviews

This project uses expert interviews as an important means of data gathering. Where limited literature on actual fugitive interception cases in a metro network is available, interviews can give in-depth information on this topic. Interviews are done with Dutch national police officers and officers in control rooms, which will provide valuable insights regarding their experiences. Information and assumptions gathered from these interviews contributed to the development of the theoretical background and model conceptualization.

This project adopts a semi-structured interview approach, which means that the interviews are a combination of structured and unstructured questioning. By doing so, follow-up questions can be adapted to the answers of the interviewee (Kallio et al., 2016). Also, the form of questions can be altered based on the direction of the interview, and responses of the police.

Following the approach outlined by Kallio et al. (2016), the interview design will be done in five phases. (1) Initially, the semi-structured interview approach is selected, given the limited knowledge on the subject of fleeing fugitives in the metro network (Åstedt-Kurki and Heikkinen, 1994). (2) Next, available information on the topic is gathered to establish a comprehensive understanding of the problem. (3) The third phase involves formulating a preliminary interview, where main themes are identified, and potential follow-up questions are prepared. (4)(5), In the last two phases the interview is analysed, revised and conducted (Kallio et al., 2016).

Overall, interviews are an effective means of gathering data for research projects. They allow for in-depth exploration of a topic, offer flexibility in questioning, and can be tailored to the individual being interviewed. The advantage is that real-life experiences and situations from the streets of Rotterdam are discussed, which is information that cannot be found in literature or data.

Lastly, the interviews conducted for this project are highly confidential. The majority of interviewees hold positions within the Dutch National Police force, which is why sensitive information such as their names, age, and specific roles are omitted. Before conducting the interviews, the participants were asked to sign an informed consent form, indicating they understood and agreed to the project's objectives and how information from the interviews would be used. The informed consent form can be found in Appendix A

3.2 Secondary data collection: literature review

A systematic literature review is conducted and functions as a guide for transparently comparing publications, in search for answers to the research questions, following Snyder's (2019) guidelines. To find relevant literature, three sets of search terms were used, each for every sub-question. The search terms were inserted in 3 different databases: ScienceDirect, Scopus and JSTOR. If the search terms lead to more than 30 results, the results from that search engine were neglected, as the quantity was overwhelming. In combination with the search terms, inclusion and exclusion criteria were used to narrow the search. For the search results per database, along with its search term and search criteria see Appendix D. The last search date is the 21st of January 2024. The review was conducted in multiple consecutive steps. First, a selection was done based on the relevance of titles, then articles were selected on their abstract and conclusion, and lastly, the full texts were read (Snyder, 2019).

Besides literature found through the search engines mentioned above, data published by the Dutch national police and by the TU Delft are also used. In addition, forward and backward snowballing was applied to the resulting articles, to find more information regarding a specific subject. Snowballing refers to the process of using the reference list and 'cited by' of relevant literature, to find other articles (Wohlin, 2014).

3.2.1 Offender behaviour

This section reviews the literature found on offender behaviour in combination with the results from multiple interviews with the Dutch national police, grouped by characteristics which are finally incoorporated in the simulation model.

Location

Certain neighborhoods experience higher crime rates than others, as noted by Gladwell, 2006, a phenomenon evident in the city of Rotterdam as well (Gemeente Rotterdam, 2022). Research indicates that individuals frequently faced with criminal activities are more likely to engage in criminal behaviour themselves (Sooknanan and Seemungal, 2023). Individual behaviour is influenced by social norms, which, in turn, are shaped by the behaviour of others. Therefore, in social groups where criminal behaviour and dishonesty are prevalent, the threshold for individuals to adopt similar behaviour is low (Ino et al., 2009; Shepherd and Purcell, 2015). Kar et al. (2017) reemphasises this by stating that offenders have a regularity in committing crimes. Implying that once criminal behaviour has occurred, it frequently occurs again.

Moreover, the socio-geographical environment not only influences the initiation of criminal behaviour but also plays a role in the location of the crime (Boggs, 1965; Zhoa et al., 2021). As early as the 1960s, studies found that central business districts in urban areas were often targets of criminal activity, while offenders were more likely to reside in low-class, non-white neighbourhoods. Similar trends are found in Rotterdam (Gemeente Rotterdam, 2022).

Once the crime has been committed, offenders start their escape. In Rotterdam, offenders are frequently seen to hide in safe houses after having committed a crime, before heading to their actual final destination. By doing so, they disappear for a few days and attempt to escape the immediate search actions of the police (Appendix B).

Based on this information the offender in the simulation model will be given a limited set of locations to start and to escape to. This surpports the idea that offenders can come from the same neighbourhoods or hide in the same safe houses. Each potential end location of the offender is characterised by a unique characteristic. This is further explained in Section 5.2.

Behaviour

Offender escape strategies are influenced by a variety of behavioural factors that stem from the nature of the crime and the mental state of the offender (Tutuarima, 2023; Appendix B). Understanding these factors are valuable in identifying possible strategies for the offender in the simulation model.

During interviews with the police, the mental state of the offender was categorized as either 'rational' or 'bounded rational.' Rational offenders were perceived to commit planned crimes without reaching a panic state, whereas bounded rational offenders were thought to engage in spontaneous crimes and experience a state of panic. The remainder of this paper follows these definitions.

Rational behaviour

Rational behaviour is described as the act of deliberate reasoning, where individuals are not affected by changes in external features (Kahneman, 2003). In cases of larger crimes, such as assassinations or armed robberies, offenders tend to engage in detailed planning (Appendix B; Zhao et al., 2020). This planning includes the selection of a predefined escape route, indicating a rational and premeditated approach. The choice of escape route reflects the offenders' strategic thinking and calculated decision-making, as they aim to evade police effectively. Predefined routes where the offender is not in panic are characterized by a relatively straight route from start to end. In these scenarios, the offender often uses a vehicle to get out of the city as quickly as fast as possible. This is done through taking main roads and driving at high speed (Appendix B).

Bounded rational behaviour

Smaller crimes, on the other hand, often involve spontaneous and impulsive actions; in this study referred to as bounded rational actions. In such actions, offenders face cognitive limitations when attempting to escape (Jones, 1999). This happens when, for example, offenders do not have a predetermined escape plan and therefore behave more chaotically, resulting in erratic movements and unpredictable escape routes.(Carpio et al., 2022; Zhao et al., 2020).

The level of stress experienced by offenders is also a reason for bounded rational behaviour. Feelings of panic can influence decision-making, causing offenders to make impulsive and unpredictable choices when attempting to escape (Carpio et al., 2022; Kempenaar, 2022). These escape routes are characterized by taking many turns and mainly side roads, which leads to effectively, a longer escape route (Appendix B). This is supported by Bode et al. (2015), who found that people in panic are less likely to base their decision on time-based factors such as route length or speed. Instead, offenders who are bounded rational tend to show behaviour of habit, and fall back on what they know. Therefore, it is safe to assume that if offenders in Rotterdam are in panic and take they metro, they are familiar with the metro network (Appendix B; Escobar et al., 2023).

Based on the knowledge gathered regarding the mental state of an offender two variables will be included in the model. One which specifies the rationality of the agent, and one which deterimines its transition from rationality to bounded rationality during its escape, see Section 5.2.

Detection

Since 2000, the city of Rotterdam has installed surveillance cameras in public spaces to enhance safety (Rotterdam, 2020). The number of cameras has significantly risen over the years, extending to the inside of metros as well (Appendix B). Police regularly utilize the footage to locate offender activity and identify areas prone to potential risks. Nevertheless, offenders have also adapted to this technological shift, altering their behaviour accordingly (Jiabo et al., 2022). Two behaviours are possible. Offenders either tend to avoid open spaces and areas with high visibility to blend in and avoid detection (Zhao et al., 2020). This is a characteristic integrated into the simulation model. Or, another behaviour that is noticed is behaviour ignoring cameras; where offenders hide under their hood but allow themselves to be captured on camera. However, wearing plain black outfits, the offenders are still unidentifiable to the police (Appendix 3.1)

Besides the mentioned behavioural characteristic affecting the fugitive's escape plan, many other factors play a role. Tutuarima (2023) found that factors such as obstacle avoidance, risky behaviour, traffic avoidance, route distance and maximum speed, and preference for main or residential roads are all important when it comes to route choice. However, how these factors impact the route is complex and depends on external factors (Tutuarima, 2023).

3.2.2 Police behaviour

For the scientific background some literature was found, but most information was retrieved during interviews with the Dutch national police. Since the simulation model describes a specific scenario for a fugitive interception in the city of Rotterdam, the theories and best practices of the Dutch police serve as base for the police strategies in the model. Section 4 describe the current process from the initial report of a crime until the police officers on the street take action. The current section further discussed the actions police offers on the street can take, for a scenario where camera's don't exist.

In Rotterdam, police units are assigned specific areas for surveillance, called 'zorggebieden' (Appendix B). With rising crime rates, the effective allocation of police resources becomes increasingly crucial (Gemeente Rotterdam, 2022). Therefore, strategies that optimize the placement of units and yield robust outcomes are essential (X. Wang et al., 2018). As most police officers in Rotterdam use cars, bikes, or scooters for transportation when an offender uses the metro network as a means of escaping, a pursuit can become difficult due to the differences in means of transportation. Since the police cannot follow the offender directly, accurately estimating the potential whereabouts of an offender using the Rotterdam metro network to escape is difficult. Therefore, police must make precise predictions about the potential station which could offer an interception (Zhao et al., 2020).

4 Actor network

Prior to conceptualizing the simulation model, it is important to understand and define the context and actors (players) in the the fugitive interception problem (Greasley, 2008). This section conducts a system analysis, through which the problem and its context are analyzed (Peters and Westelaken, 2014). It helps in determining which elements should be incorporated into the simulation model, which agents should be included, and how these relate to one another (Greasley, 2008). Based on this information initial rules and player characteristics are formulated.

The context of a fugitive interception problem has been defined in Section 1.3. An actor analysis is conducted to examine the actors involved in a system or situation. An actor is an entity that can act on or influence decisions in a system (Enserink et al., 2010). Actors have personal understandings, roles, interests, and relationships in a system, which leads to unique behaviour. Table 4.1 identifies the actors in this model, their objectives, resources, and dependencies. Important to mention is that the table represents a real-life situation where cameras are used in a fugitive interception project. Appendix C gives a detailed description of this real-life scenario.

Table 4.1: Actor identification

Actor group	Specific actor	Interest and objective	Resources	Dependency (on others
Offender	Suspect	Getting away from crime scene and escaping police	Metro network	High - on police ability and metro network
Police	Police unit on street	Citizen safety and catching offenders	car	High - on police in CR
	Police in CR	Citizen safety, catching offender and guiding police on the street	Police cameras, RET cameras, police on streett	- Extremely high - on camera's, RET workers, police on street and call to inform crime.
	Regional police	Citizen safety	Authority approval	Moderate - Police in CR
	National police	Citizen safety	Authority approval	Moderate - Regional police
RET employees	RET workers in metro	Safety of citizens in metro	Metro	High - on information from workers in control room
	RET workers in metro CR	Safety of citizens in metro and helping police catch suspect	Camera's in metros	High - on cameras
Citizens in metro	Public transportation and safety	metro network		High - on offender and police
	Citizens in Rotterdam	Safety		High - on offender and police

The table illustrates numerous dependencies within a fugitive interception scenario. The initial dependence involves the police relying on a phone call to report a crime. Following this, the officer in the Control Room (CR) notifies both the RET and the police on the streets. If the offender is identified, the RET provides information about their location to the police officers in the CR, who can forward this information to the police on the street, explained in more detail in Appendix C.

In situations where the scale of the incident exceeds the capacity of the street-level and CR police officers, the regional police officers can be informed (Appendix B). These officers possess greater authority and are automatically granted approval for undertaking specific actions. Regional officers can directly assign tasks to the police units operating on the streets and do not need to pass police officers in the CR. Similarly, if an incident exceeds the capacity of the regional police, it is transferred to the national police, following the same procedure.

Now that the actors, with their objectives and resources, have been identified, a power-interest (PI) grid can be made, see Figure 4.1. The power interest grid can be divided into 4 quadrants with different actor characteristics identifying agents' interest and power in taking actions in the system (Enserink et al., 2010).

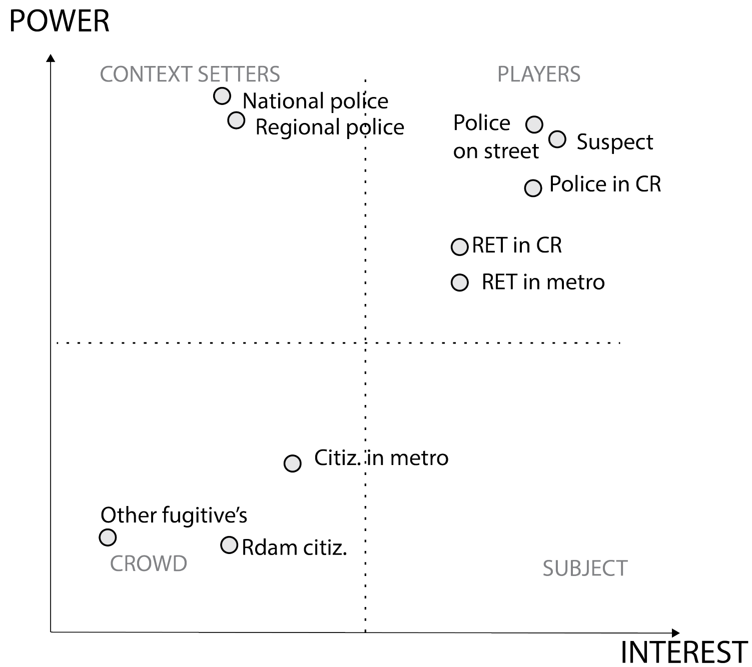


Figure 4.1: Power interest grid

The suspect has the most interest in the escape, as for them it is a matter of a personal future. The police on the street and the police in the CR have an equivalent amount of power, as they are interdependent and have the same interests. The RET workers in the metro and in the CR have slightly less interest, as their primary objective is safety. Although possessing somewhat less authority, their actions, such as halting the metro, can significantly impact the capture chance.

In the lower-left quadrant, other fugitives, citizens in metro, and Rotterdam citizens are positioned. This is explained by their relatively lower interest in the success of a capture, coupled with minimal power. Among the citizens, metro citizens in the metro hold slightly higher interest and power compared to citizens in Rotterdam.

Finally, the regional and national police have the highest power but slightly less interest. Typically, local police handle such interceptions, while regional and national police are engaged in larger projects. However, if it becomes apparent that the local police cannot manage the interception, the interest of the regional police would shift one quadrant to the right.

Based on the scope, context, and actor analysis presented in this section, the formulation of the simulation run will be determined. The actor analysis reveals that the interests of the national and regional police become relevant only when the local police exceed its capacity. However, for the simulation model's purposes, it is assumed that this situation does not occur, and therefore, the regional and national police will be excluded from the simulation model. Similarly, despite the citizens having an interest in the safety of the city and, by extension, in the capture of an offender, their ability to take action is very limited. Therefore, this player will also be omitted from the simulation run. However, the citizens in the metro will be included as a variable as they can affect the fugitive interception situation, as they can be in the same metro as the offender and therefore serve as an external factor or third party.

Moreover, interviews with the RET indicated that when an offender is detected on camera, the probability of capture increases to almost 99% (Appendix B). Therefore, police behaviour relies heavily on camera footage. Meaning, that the relevance of this study is relatively low, if success is almost guaranteed. As a result, this simulation excludes the presence of camera footage, solely focusing on the strategies and behaviours of the offender and the police, explained in Section 1.3. This narrows the role of the RET to that of metro drivers, which is why they can be excluded as players in the simulation model.

Finally, only two players remain in the simulation model: the escaping offender and the police on the street. The police on the street can receive information from the CR, which will be modeled as an input variable with occasional information updates. Therefore, the next section will analyze agent behaviour of the offender and the police, as these are the only players actively participating in the simulation model for this study.

5 Conceptualisation

Once the physical and system borders of the scope, and therefore model, have been set, the model can be conceptualized. This follows Greasley's (2008) third and fourth step: process mapping and modelling input data. In this phase the knowledge gathered in Section 3.2 and Appendix B are conceptualized to model elements. It begins with a detailed description of the idea or concept of a model, which is done in Section 5.1. Next, the agent behaviour and remaining system components are defined (Lukosch et al., 2018). The chapter offers explanations for each strategy where needed, thereby answering sub-questions 1, 2, and 3.

Sub-questions

1. What strategy can a fleeing fugitive adopt to minimize the probability of an interception by the police when escaping through the metro network of Rotterdam?
2. What strategy can the police adopt to maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam?
3. What form of information can lead to a change in the probability of an interception?

5.1 General rules of the simulation model

Prior to conceptualizing the agents in the simulation model, the model settings must be defined (Lukosch et al., 2018). The most relevant components from a real-life interception scenario are included in the model, which are then simplified (Peters and Westelaken, 2014). Certain contextual elements are assumed and treated as constant variables; as elaborated in Appendix H. Important definitions in the simulation model are explained in table 5.1. These rules establish a shared understanding, forming the foundation upon which the fugitive interception simulation model is conceptualized.

Table 5.1: General rules of the fugitive interception simulation model

Component	**Rule**
City	The simulation run takes place in the metro system of Rotterdam. Each metro stop that was used by the RET in March 2023 is incorporated.
Schedule	The metro schedule of a regular weekday in March 2023 is used. This means the duration between two metro stops is equal to the time it took the metros in March 2023.
Delays	Metros cannot be delayed or canceled.
Platforms	No differentiation is made between different platforms. This is done based on the assumption that the police will know in which direction the crime took place, and can therefore place itself on the metro coming from that direction.
Metro speed	All metros drive at the same speed.
Crime locations	Crimes have to happen in Rotterdam for the simulation run to be played.
Suspect starting position	Suspect starts at a metro station. The crime is not included in the simulation run.
Police agent starting position	The police start at police stations.
Police agent speed	Police drive 50 km/h.
Police arrival time	The time it takes for police agents to get from the burea to its desired metro stations depends on the distance between the two nodes, calculated by NetworkX.
Capture	Capture means a loss for the suspect and a win for the police. Capture can occur at two points in the simulation run. Either when the police and the suspect are on the same platform, or when the police guard the same station exit that the suspect takes. In both cases, the capture and detection probability must be true.
Escape	Escape means a loss for police, win for suspect. This occurs when suspect exits its desired metro station without any police being able to capture them. It is possible that police is present.
Suspect travel time	The suspect must travel at least 5 stops before they have a chance of safely exiting the metro.

The table establishes the model's boundaries, emphasizing that various components from real life have been simplified in the model's rules. The model's transparency is enhanced by eliminating stochastic elements, such as delays, and varying travel speeds. These simplifications allow for a focused examination of behavioural factors in the agents' interception strategies.

Using a game theoretic approach, this project aims to optimize fugitive interception strategies for the offender and the police. Game theory characterizes itself by analyzing interaction effects between strategic agents, and studies how decisions affect the outcome. Therefore, this simulation gives agents the option to choose their next move. To do so, it is important to include the decision-making process of agents in the simulation. The following sections conceptualize the behaviour, upon which the decision making is based, for both agents.

5.2 Offender behaviour

The scientific background and interviews about offender escape behaviour showed that behaviour profiles are difficult to distinguish. Behaviour is too complex to accurately simulate its randomness and uncertainty (Averill, 2011; Bonau, 2017; Kuligowski, 2011). However, two main components of escape behaviour were prominent in literature and expert interviews; the offender's social background and the offender's rationale. Therefore, this study proposes the simulated offender strategy to be divided into three components: the offender's starting position, their goal and their behaviour throughout the escape (influenced by their rationale). These are predefined at the start of a simulation run, visualised in 5.1. Table D.3 in Appendix D shows the literature used to conceptualize each strategic component.

Figure 5.1: Visualisation suspect strategy

Start positions & Station goal

Literature indicates that criminal behaviour varies across neighborhoods in cities. The social context of a neighborhood may make it more prone to criminal activity. However, while some neighborhoods may exhibit higher criminality, it's not guaranteed that the offenders themselves live there. City data shows that also in Rotterdam there is a difference in the safety of neighbourhoods. To simulate the diversity of neighborhoods in being prone to criminality and living areas of offenders, the offender's starting position and end goal can vary between three regions.

Given the focus of this study on the metro network of Rotterdam, a decision has been made not to differentiate between actual safety indexes between neighborhoods in Rotterdam. Instead, the simulation distinguishes between neighborhoods with different metro characteristics. Consequently, the offender's starting positions can vary between the 'center', representing a central metro station in the city. 'End' represents an end metro station, and 'one line' represents a station with only one metro line passing through it.

Similarly, its desired goal can vary between, 'furthest', 'to train' and 'random'. 'Furthest' signifies that the suspect aims to reach a metro station as far as possible from their starting location. 'To train' indicates the desire to reach a metro station where the offender can transfer to the train network. A 'random' represents an end goal in which the suspect does not strive for a specific type of end goal but will randomly choose one, regardless of its metro characteristics. This is done to simulate the uncertainties of criminal behaviour and the lack of knowledge about where offenders go after committing a crime.

Behaviour

In addition to the offender's starting location and desired end location, its strategy is influenced by its behaviour throughout the escape. The offender's behaviour depends on two factors: rationality (panic) and flexibility in changing desired end goals (loose goal). Firstly, the offender can be considered to behave either rationally (calm and predefined) or bounded rationally (in panic and chaotic). The criminal can start rationally, and transition to bounded rationally throughout the simulation run. The specific modeling of this distinction is explained in Section 6. Furthermore, literature and interviews showed that planned crimes often involve rational behaviour, while spontaneous crimes frequently exhibit bounded rational escape behaviour. Although this model does not differentiate between the nature of the crime, one could argue that the rational state of the offender serves as a proxy for the type of crime committed.

Secondly, the characteristic of a 'loose goal' refers to the offender's ability or willingness to change goals during the simulation run. This implies that, in moments of panic or when the offender perceives the presence of the police, they can alter their end goal. Essentially, they have the option to continue riding the metro to another station if their current desired station becomes less attractive. If the offender does not have this flexibility, the offender will try to exit the metro network at their desired end station regardless of its adequacy for an escape upon arrival.

To conclude, the first part of the first sub question can be answered:

Sub-question 1

What strategy can a fleeing fugitive adopt to minimize the probability of an interception by the police when escaping through the metro network of Rotterdam?

The strategy of the offender depends on their initial starting position, on their end goal, on their rationale, and on their flexibility in changing goals. The first two define the path the offender will take, and the latter two describe the behaviour the offender shows along the route. Each unique combination of these characteristics will be formulated into a strategy. Interviews indicated that police units in Rotterdam base their actions moslty on intuition, habit and instinct. This makes it difficult to summarize their behaviour into set strategies.

5.3 Police behaviour

Where the offender's main goal is to escape the police, the police's main objective is to capture the offender. Without knowing the initial strategy of the offender, the police will, blindly, adopt a strategy. The police can change their behaviour throughout a run, based on intuition or new information coming in. Whereas the offender's strategy is made up of three components, the police's strategy is conceptualized using two components: the end goal and its behaviour, presented in 5.2. The omitted component in the police's strategy, compared to the offender's strategy, is its starting goal. This omission is explained by the fact that the start location of the fugitive interception scenario is determined by the offender, as they commit the crime. Police agents are positioned throughout Rotterdam, and those located strategically for the potential interception of an offender are utilized in this simulation run (Appendix B). Table D.4 in Appendix D shows the literature used to conceptualize each strategic component.

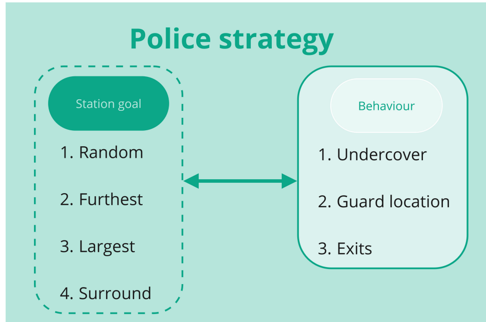


Figure 5.2: Visualisation police strategy

Station goal

Based on the assumption that the police do not know the destination of the offender, the strategy involves identifying potential capture locations at four different types of metro stations. Similar to the offender's location choices, these locations are not predefined; instead, characteristics of metro stations are defined, and the police choose relevant stations to surveil accordingly.

Firstly, the police can surveil random metro stations. In this scenario, multiple police units make independent decisions about where to surveil without any shared criteria. This strategy is only adopted in the base case to establish a reference point for comparison. Secondly, the police may choose to surveil the 'furthest' metro stations, assuming that the offender might aim to quickly reach the outskirts of Rotterdam in an attempt to leave the city. In this strategy, the police will wait at stations far from the crime scene, to prevent the offender from escaping to another city. In another approach, when surveilling the 'largest' metro stations, the police focus on stations where multiple metro lines come together. This increases the likelihood that the offender will pass these stations during their escape, increasing interception chances. Finally, the police can adopt the 'surrounding' approach, aiming to encircle the offender by surveilling the surrounding metro stations from where the offender entered the metro network.

Behaviour

Once the police have reached the station they intend to surveil, they can adopt several behaviours. Firstly, they can choose to surveil undercover or not. By surveilling undercover, the police reduce the chances of that the offender detects their presence, thereby limiting the offender's chances for escape.

Secondly, the police can differentiate between the locations to surveil at a metro station. They can either surveil at the metro platform or the station exits. Surveilling at the metro platform allows the police to also monitor incoming and outgoing metros, while guarding the station exits involves checking everyone entering and exiting the station.

Finally, if the police decide to guard the station exits or if the metro platforms of that specific station are already under surveillance, they can choose between guarding the main exits or the side exits. Some metro stations in Rotterdam have more than four exits, requiring the police to strategically position themselves.

To conlude, the first part of the second sub question can be answered:

Sub-question 2

What strategy can the police adopt to maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam?

The police strategy depends firstly on the type of metro station they choose to surveil: a far, large, surrounding, or random station. Once this decision is made, the police can choose to surveil undercover and decide whether to focus on the metro platforms, the main station exits, or the side station exits. The capture rates of these strategies will be analyzed in Section 8.

5.4 Interaction

Sub-question 3

What is the effect of information on the probability of an interception with the offender?

Following the analysis of the success rates of the strategies of the offender and police in Section 8, the study will investigate the impact of information on these strategies, addressing the third research question. As discussed in Section 2.2 on Pursuit-evasion games with asymmetric information, this interaction between agents can influence the simulation results. Due to the time limit and scope of this study, the shape in which information is offered to the agents is not simulated in detail. Information includes updates on the locations of other agents and the ability to make upcoming moves based on this information, as explained in more detail in Section 6.

6 Model implementation

In this chapter the simulation model is built and validated, as explained in Greasley's (2008) third and fourth simulation building steps. The conceptualized model is formalized, which is tested and revised until it sufficiently represents the system. First, the model is set up, based on the model boundaries and rules of the simulation run in Section 5.1. Next, the agent's behaviour is formalized accordingly.

The code for the simulation model can be found on GitHub using this link:https://github.com/Cvanheukelom/EPA$_{T}hesis_{2}$024

6.1 Model settings

Model settings are an important part of the in simulation, as they symbolize the environment and elements from the real-life system (Peters and Westelaken, 2014). In essence, model settings serve as the configuration framework for a simulation, influencing its overall dynamics and outcomes. Table 6.1 shows the model settings that are used to formalize the model.

Table 6.1: Model set up

Setting	Definition	Explanation
Time units	Seconds	-
Time tick	30 seconds	This allows the offender to transfer between metros that are one minute apart
Model step time	1 time tick	The model takes steps of 30 seconds
Model max run time	720 ticks = 360 minutes = 6 hours	Warm-up time + simulation run time
Warmp-up time	2 hours	All the metros start at both end stations of their respective metro lines, after two hours the metros will be spread out throughout the network and run as they do during the day in Rotterdam
Simulation run time	4 hours	If the offender is not found and has not reached its goal yet the simulation is game over. This is to prevent runs from being included in the data where the offender is stuck in a metro loop.
Simulation run initiation time	0-9 minutes	The starting time varies between 0 and 9 minutes to prevent the offender from always starting at the same point in time of the metro schedule. All metros start within 10 minutes when the model is initiated, meaning that a variance of 10 minutes for the simulation run initiation means that the offender will always start in a different metro cycle.
Network	Metro network from rotterdam using NetworkX	See Section 6.2

The model settings play a crucial role in shaping the simulation environment, providing a foundation for the dynamic interactions within the system's agents. The defined time units, time ticks, and model step time ensure a consistent and realistic representation of the scenario, with as less computational time as possible. The model's max run time, warm-up time, and simulation run time, establish the temporal boundaries for the simulation, where the warm-up period allows the system to reach a realistic state for the metro locations, while the four hours of simulation run time provide a window for the fugitive interception simulation model. The initiation time variation enhances the model's robustness by introducing variability in the offender's starting point within the metro schedule. Overall, these model settings are essential parameters that contribute to consistent simulation settings and outcomes.

The model is formalized in Python, using NetworkX and the Mesa environment. This will be discussed in the upcoming sections.

Lastly, the Key Performance Indicator (KPI) for the strategies is the mean capture value, representing the average capture across multiple runs for the same scenario. Another frequently considered output variable is time, given its significance in fugitive interception projects for the police. The duration of a fugitive interception scenario is crucial, as a long duration is found to diminish the chances of a successful capture in reality (Appendix B).

6.2 Network set-up

NetworkX is a Python library for creating, analyzing, and visualizing complex infrastructure networks. Points in the network are referred to as nodes, and paths between these points are edges (Hagberg et al., 2008). As the network of this study purely focuses on the metro network of Rotterdam, OpenStreetMaps (OSMnx) could not be used. The detailed information necessary for the simulation model was, at the time of formalization, not available in OSMnx. Therefore, the points of interest and their attributes were acquired by hand, mainly through Google Maps. The attributes that are needed per metro station:

- Coordinates (lat, lon)
- Number of exits
- Train station at that metro station
- Start, end, or connecting metro station

The points of interest for this study are the metro stations and police stations in Rotterdam. The list of police stations included in the model shown in Appendix E. Figure 6.1, gives a visual representation of the metro lines going through Rotterdam and the location of police stations. Where Figure 6.1a shows the geographical visualization through Google Maps, and Figure 6.1b shows the metro network with police stations visualized in NetworkX.

(a) Google Maps (b) NetworkX

Figure 6.1: Rotterdam metro network with police stations

It is evident that despite NetworkX using real coordinates for the metro, it visualizes the metro network differently from Google Maps. This difference can be explained by variations in algorithms or processing techniques for network representation between the two. While Google Maps focuses on visualizing the geographical world, NetworkX analyzes, constructs, and illustrates network structures to study their underlying structure and dynamics (Hagberg et al., 2008).

To ensure that the distances between nodes representing metro stations accurately reflect the real-life system, the metros adhere to the time schedule of a weekday in Rotterdam, which is further discussed in Section 6.3.2. The shortest path algorithm is used to calculate the most efficient route for the agents from the starting position to the goal. As for the police, the coordinates of points, coupled with the police's driving speed, are used to determine the duration of the ride.

During the model execution, a log file, also known as audit trails or transaction logs, is generated (Rozinat et al., 2009). A log file serves as a chronological record that captures events, activities, and outputs throughout the simulation. It is a valuable tool in the simulation process, providing a detailed account of the simulation's runtime, processes, agent's activities and states. The log file can be used to trace the model's behaviour and investigate unexpected outcomes. Throughout the model's implementation phase for this study, the log file has proven extremely useful, facilitating an iterative approach between modeling, testing, and revision (Lukosch et al., 2018).

6.3 Agent set-up

The simulation model is initiated with a sub-model that monitors time steps and interactions among agents. Initially, metro agents are prompted to start their journeys from their respective start locations. Metros can initiate their trips from both ends of a metro line, following to departure times set for a random weekday in Rotterdam. To ensure an even distribution of metros throughout the city, the model incorporates a 2-hour warm-up time during which only metro agents travel through the network. At the simulation run initiation time (Table 6.1), the offender is activated at their starting location. Finally, after the delay time of contacting the emergency line to inform the police about a crime, police units are initialized.

Once all metro-, offender-, and police-agents are initialized, each agent evaluates its state at every time tick to determine the necessary actions. The specific behaviours of each agent are discussed in more detail in the upcoming subsections. However, first the starting locations of the agents will be visualized.

6.3.1 Starting locations

Section 5 and Section 6.2 identified the starting locations for the offender and police, respectively. For the offender, a differentiation is made between the characteristic of metro stations. The offender can start at a metro station with one line, an end metro station, or a central metro stations. Per category, the offender can start at one out of two stations, shown in Table 6.2.

Table 6.2: Offender starting locations

Category	**Station 1**	**Station 2**
One line	Poortugaal	Slotlaan
End	De Akkers	Binnenhof
Centre	Schiedam	Beurs

Each category comprises two stations; this enhances the dynamics of the simulation results and increases the reliability of the results. The police start locations are the same as the location of police stations in Rotterdam, as specified in Appendix E. Figure 6.2 gives a visual representation of the start locations of all agents. The metro agents start at both outer stations of a metro line.

Figure 6.2: Agent start locations with RET metro map (2024)

6.3.2 Metro agent

The metro agent is triggered according to its departure time on a weekday in Rotterdam. The time it takes to arrive at the next station is determined by the departure time at the next station. Its arrival time is the departure time at that station - 1 time tick. This is done so that the metro agent arrives one time tick before departing, for the offender to have a chance to get on or off the metro. The metros do not consider potential delays or night schedules.

XLRM framework

The metro agent is configured using the XLRM framework developed by Lempert et al. (2003). Elements of the system can be categorized into four groups. The 'L' stands for levers, which are the strategic policies explored in the model. Secondly, the 'X' represents exogenous uncertainties, which are external factors that influence model outcomes. Thirdly, 'M' stands for performance metrics or the outcomes of interest in the model. Finally, the 'R' describes the relationships between all of the identified elements (Lempert et al., 2003; Kwakkel, 2017). Figure 6.3 illustrates the framework representing the metro agents in the fugitive interception simulation model.

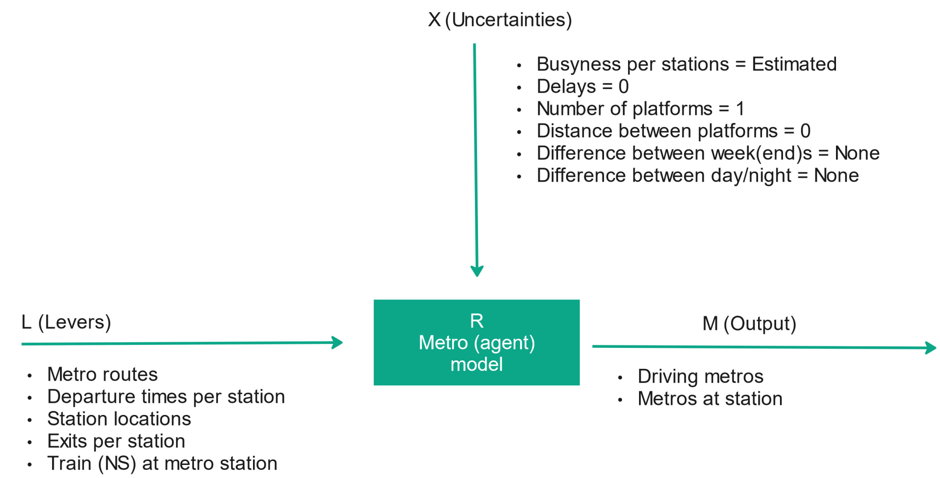


Figure 6.3: XLRM metro agent

In Figure 6.3, the levers represent input variables. Lempert et al. (2003) refers to levers as policies, but even in that context, it implies that the policies are input variables. The system's output consists of the states of the metro, indicating whether it is in motion or stationed. If a metro reaches its end station, it is removed from the simulation run. Metros do not reverse direction, meaning returning metros are treated as new agent instances. However, given the assumption that the offender always takes the most efficient route to its goal, it cannot travel to an end station and turn around within the same line. This makes the creation of new metro instances instead of turning agents not a limitation in this model.

External uncertainties are indicated by the vertical arrow entering the system agent. As the fugitive interception model involves uncertainties related to behaviour (explained in Section 8.7), the metro model is simplified to prevent further uncertainties. Consequently, the uncertain factors of the metro agents are assigned constant assumed values, shown in Figure 6.3.

6.3.3 Offender agent

The offender's behaviour is conceptualized in Section 5.2 upon which its implementation is built. First, the XLRM of the offender is discussed, after which its moves are identified and visualized in a flow diagram.

XLRM framework

Similarly to the metro agent, the offender agent is formalized using an XLRM framework, as depicted in Figure 6.4. The figure illustrates that the levers are equivalent to the variables constituting the offender strategy, as shown in Figure 5.1. The uncertainties will be discussed in Section 8.7. The most crucial output value is 'capture', with the other variables providing additional information for further analysis of specific outputs. Appendix G contains two tables specifying the model names for the variables presented in the XLRM diagram, along with their respective definitions.

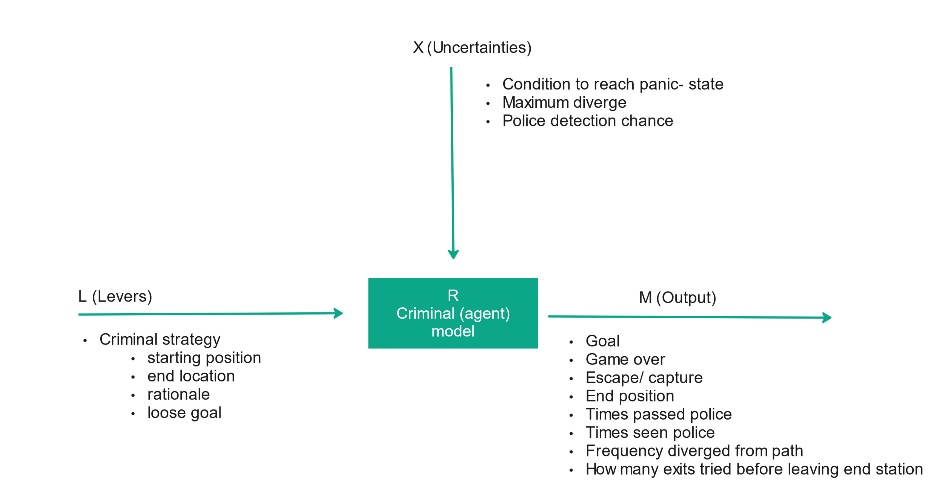


Figure 6.4: XLRM offender agent

The input variables of the offender are equal to the variables that make up their strategy. There are more output variables than 'capture', which is done if further analysis is needed on the results. The input uncertainty variables are defined, but not given a value. This is done in Section 7.2.

Moves

In this fugitive interception simulation model, designed to analyze interaction effects among strategic agents in motion, agents can choose their next moves. These moves are determined by their own state or the states of other agents. Table 6.3 illustrates the possible moves an offender can make during the simulation run. Information that can influence agents' actions and states is made accessible to them accordingly to its experiment, further elaborated in Section 7.

However, it is important to note that in this model, which analyzes the success of strategies, the strategies themselves cannot change throughout the simulation run. This means that, as indicated in Figure 5.1, the values for these strategic components are predefined and remain constant during a simulation run. The manner in which the offender interacts with information is determined by the combination of these components, representing a strategy. The only variable that can change throughout a simulation run is the offender's panic state, transitioning from a rational state at the start to a bounded rational state as the simulation run progresses if complying with certain requirements.

Table 6.3: Offender moves in simulation model

Move	**Description**	**Dependence (other than own)**
1. Wait for metro	The suspect is at a metro platform and waiting for a metro in the desired direction. If a metro arrives going in the opposite direction they will wait till next metro. They can also decide to wait if they find the upcoming metro too empty.	Metro, metro population
2. Get on metro	The suspect enters a metro which is at the same metro station as itself, going into the desired direction. This can also be done if the metro goes in the wrong direction but the suspect is either in panic or has detected a police agent and therefore wants to leave this station as they are afraid of capture.	Metro, police agents, metro population
3. Get off metro	If the metro has arrived at the suspect's desired station they can get off the metro. This can also be done if the suspect finds the metro too empty and is afraid of exposition, upon which they can decide to leave the metro regardless of the station.	Metro, police agent, metro population
4. Remain in metro	Stay in metro if the metro has not arrived at (correct) station. Also possible if the suspect finds the station too empty and is afraid of exposure.	Metro, station population
5. Leave metro network	Exit metro network if at the desired station.	Metro
6. Choose a new final goal	If in panic a new final destination can be chosen.	Metro, station population

Table 6.3 illustrates the various moves an offender can make throughout the simulation run. The timing of these moves depends on other agents and the offender's strategy. The decision-making process for these moves is describes below.

Offender decision making process

The decision-making process for these moves is visualozed in Figures 6.5 and 6.6. The first figure presents the flow diagram for when the offender is in the metro, while the second one is shows the behaviour when the offender is not in the metro. In both instances, the diagrams illustrate the behaviour in scenarios where the offender can act with information, identified by green dashed boxes. Refer to Appendix F for the flow diagrams without information.

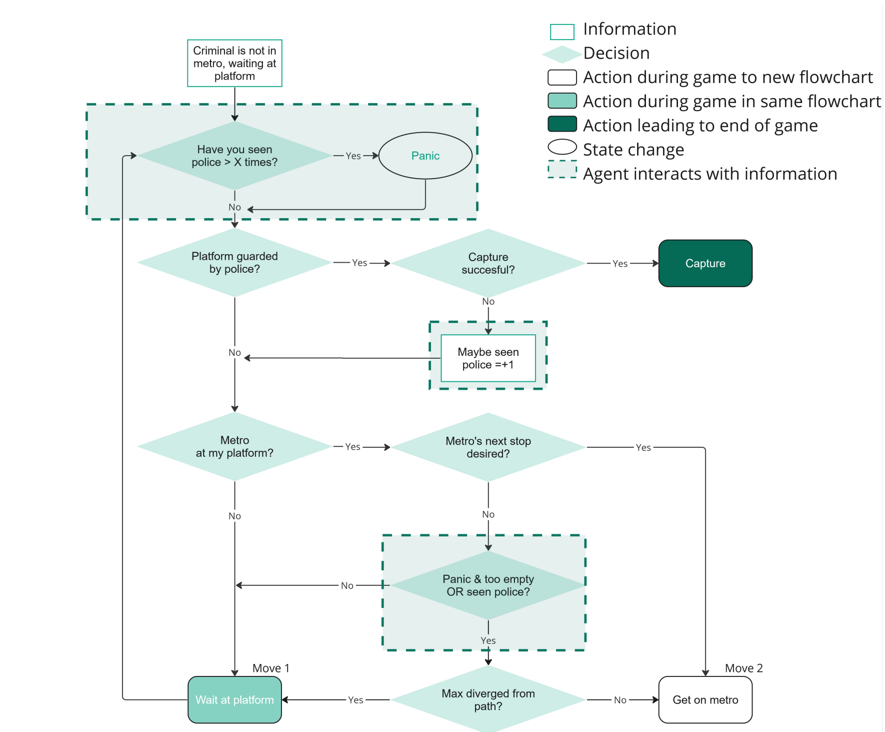


Figure 6.5: Flow diagram offender not in metro

When the offender is not on a metro or at their destination, they are waiting at a platform for a metro in the right direction (Figure 6.5). During this waiting period, there is a continuous risk of police arriving at the platform; searching the offender. In the event of such a situation, the offender faces a (predefined) probability of being caught. If they manage to evade the police, they will remain on the platform until the next subway arrives. Important to understand is that if the police enter the metro platform, the offender cannot leave or hide. Leaving the metro platform would mean exiting the simulation model. They can only get on a metro.

Once a metro arrives at the platform, the offender has two alternative courses of action. They can choose to board the metro for three reasons. First, if the train is headed toward their desired destination. Second, if they are in panic and therefore find the station is too empty and feel exposed. Or third, if they have become aware of the presence of police officers on the platform. If the offender does not decide to enter the metro, they will remain on the platform and wait for a metro heading in the desired direction.

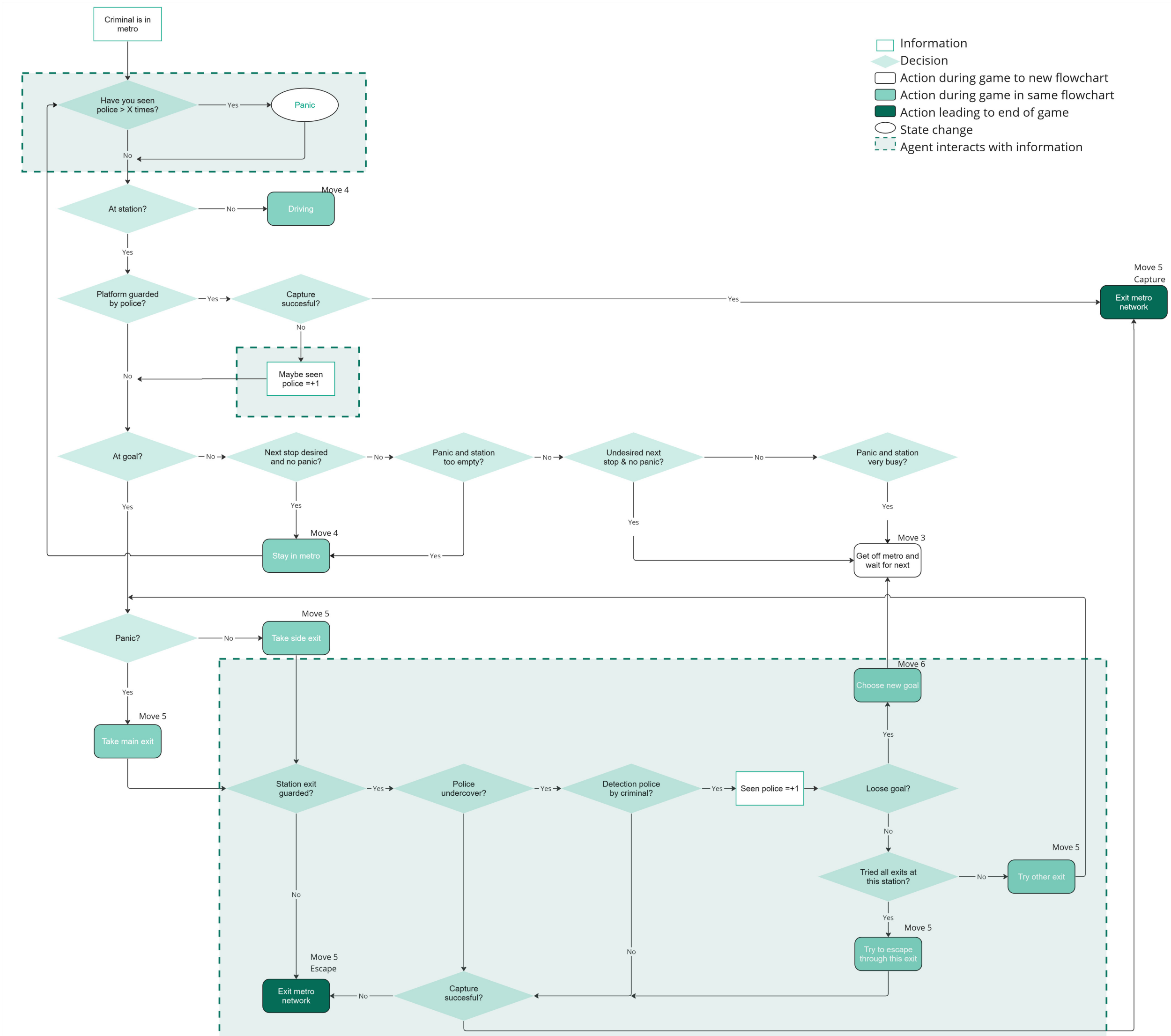


Figure 6.6: Flow diagram offender in metro

When an offender is in a metro (Figure 6.6), they first assess whether the metro they are currently in has reached a station. If it has not, this means that the metro is still in transit between stations, and consequently, the offender is unable to take any action and continues their journey to the upcoming metro station.

When the metro has arrived at a station, the offender faces two possibilities. Firstly, they evaluate the risk of being apprehended by police officers who may be surveilling the metro platform. However, even if the police is at the same platform, there exists the possibility that the offender is unnoticed by the police and can therefore proceed with their activities despite the police's presence on the platform.

If the offender evades capture or if the police are not present, they can take multiple actions. Initially, they will consider whether the current station is their final destination. If it is not, they must decide whether to remain aboard the metro. This decision hinges upon whether the metro is bound for their desired destination or if they are in panic and feel exposed in the empty station (and will therefore rather stay on the metro). They may also decide to exit the metro and await the arrival of another metro traveling in their desired direction.

If they have reached their final destination, the offender faces a choice regarding the use of the main or side exits of the station. This choice is influenced by their rationale state. If they are in panic, blending into the crowd and utilizing the main exits becomes the preferred course of action. Conversely, if they are not in panic, they opt for the side exits, aiming to leave the station unseen.

During the exit process, there is a chance that police officers are stationed at the exits. In such instances, the offender has a chance of detecting the police. This is a predefined percentage, unless when the police is operating undercover, then this chance diminishes to zero. If the offender detects the police, they either choose a new final destination and return to the metro or they can attempt to leave the simulation model through other station exits until finding one unguarded, or until they have exhausted all possibilities. If the offender selects an exit guarded by police, there is also a possibility that the police does not identify the offender, or that it does not capture the offender, leading to an escape.

6.3.4 Police agent

XLRM framework

Similarly to the offender agent, the input variables for the police agents correspond to the variables that make up the police strategy in Figure 5.2. Furthermore, the XLRM for the police agent in Figure 6.7 displays different uncertainties and output variables compared to the offender, as the police's strategies are influenced by distinct uncertainties and explained by different output variables. While the offender aims for a low capture value, the police aim for a high capture value. Appendix G contains two tables specifying the model names for the variables presented in the XLRM diagram, along with their respective definitions.

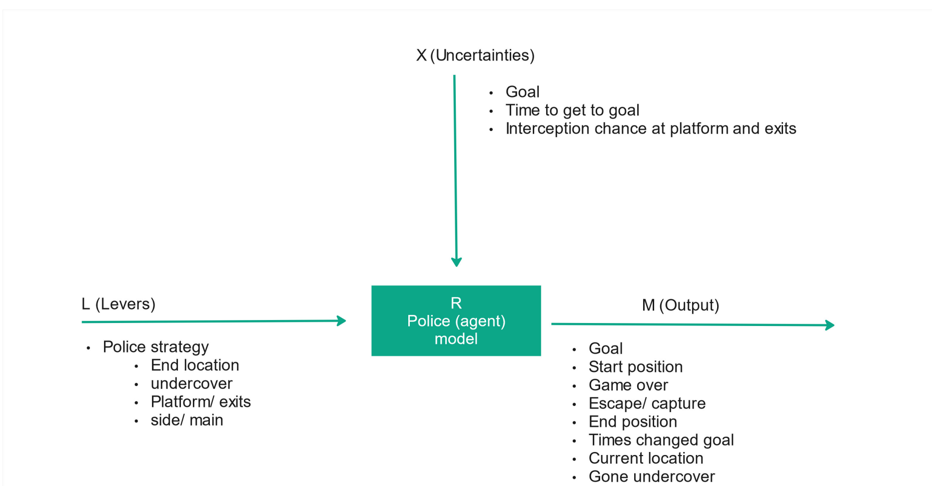


Figure 6.7: XLRM police agent

Similar to the offender, the input variables of the police are equal to the variables that make up their strategy. There are more output variables than 'capture', which is done if further analysis is needed on the results. The input uncertainty variables are defined, but not given a value. This is done in Section 7.2.

Moves

The police will be able to make a move simultaneously with the offender every round. Moves will be made according to their strategy in combination with incoming information (about the offender's behaviour). In reality, such information can include the offender's location, direction, the station where they were last seen, or specific metro lines they are using. In some cases, the police may also receive information about the physical features of the offender, which may help them identify and capture the fugitive. However, in this simulation model, the information the police can receive about the offender is its location, depending on the delay of information. Table 6.4 shows the moves the police can make.

Table 6.4: Police moves in simulation model

Move	**Description**	**Dependence (other than own)**
1. Driving	Police has not arrived at guarding destination	Time
2. Guarding metro platform or exit	Police is guarding at the predefined location	-
3. Guarding main or side exit	Police is guarding at the predefined location	-
4. Going undercover	If offender has been seen multiple times but has been able to escape, police can decide to go undercover to minimize the chance that the offender can detect them.	Offender
5. Choosing new guarding destination	Based on information about the offender the police can decide to guard at another destination	Offender

The moves of the police are, similar to the offender, dependent on its strategy, other agents, and incoming information. The decision-making process leading to these moves is discussed below.

Police decision making process

The decision-making process before the moves is visualized in the flow diagram in Figure 6.8. There are separate flow diagrams for the experiments where the police interact with information and when it does not, the one below shows the experiment in which the police can interact with information.

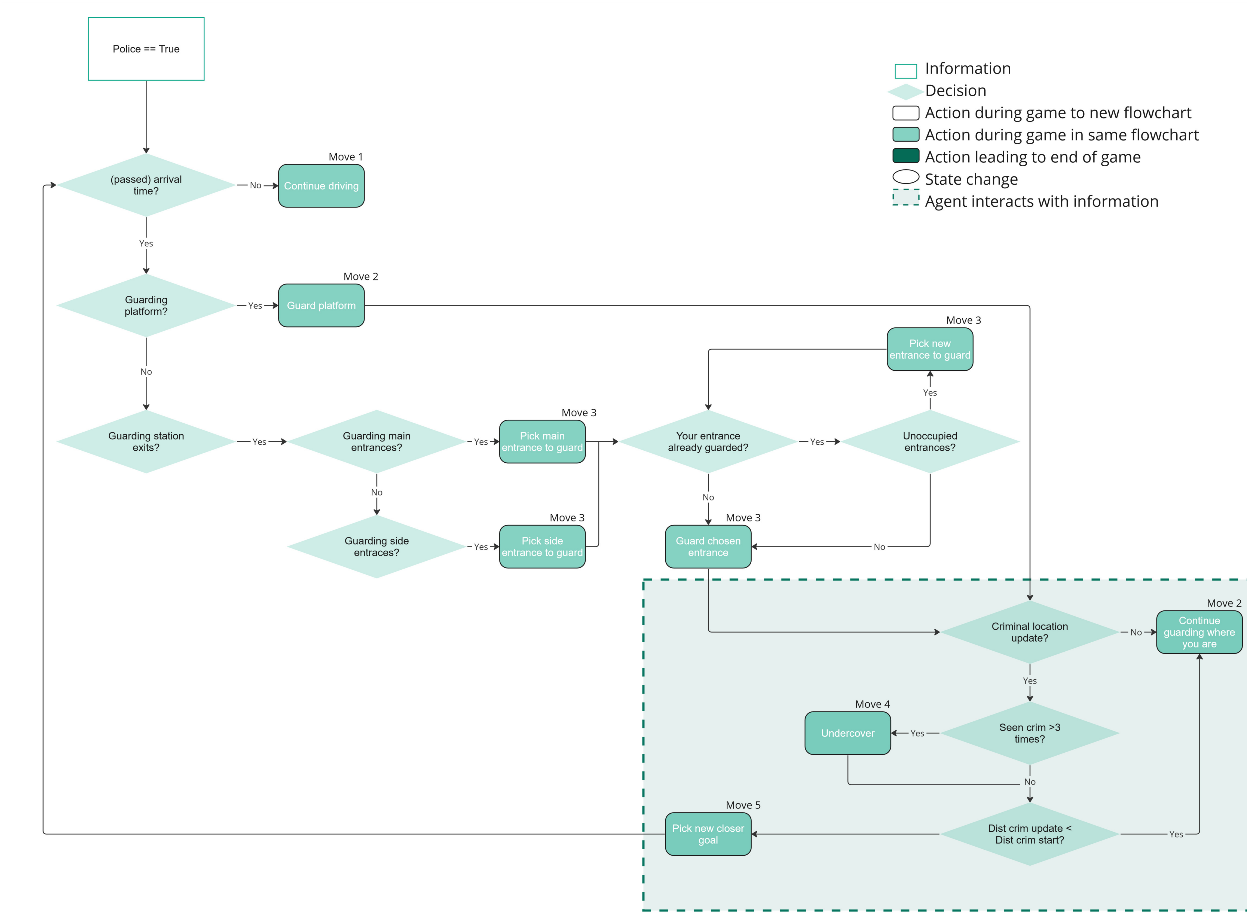


Figure 6.8: Flow diagram police

The police are provided with a surveil destination and select an initial starting position accordingly. The logic behind this initialization lies in the operational center's decision-making process. The officers in the CR determine which location must be surveilled by the police, and then send a nearby unit on the street. Subsequently, a nearby police officer is dispatched to the desired location.

Every time tick, the police officer assesses whether they have reached their destination. If they have not, they continue driving. If they have arrived, they will either guard the metro platform or the station exits, both of which are pre-defined in the model.

When assigned to guard the metro platform, no distinction is made between individual platforms. The underlying assumption is that since the police know where the offender started. They know from which direction the offender should be approaching, allowing them to guard the correct platforms.

In the scenarios where the police guard the station exits, they must choose between guarding the main exits and the side exits, as specified in the model. If the exit they intend to secure is already being guarded by other police officers, they will guard a different exit, irrespective of whether it is a main or side exit.

In experiments where the police interacts with information, they periodically receive updates on the offender's location. These updates can be obtained through various means such as phone calls, cameras, RET staff, etc, which is unspecified in the model. The information updates are subject to delays, which is equal to the initial call delay time for that scenario.

Updates about offender information contains two critical pieces of data. Firstly, the police are informed about the number of police officers the offender has bypassed during their journey (since the police know the offender's starting point and a recent location, they can deduce how many police officers were encountered en route). If the offender has encountered more than three officers, the police will go undercover to reduce their likelihood of detection and mislead the offender into thinking the police have lost their trail. Secondly, the police receive information regarding the offender's location. However, due to the inherent delay in this information, the location data for the offender is several minutes outdated (equal to the initial call delay which is predefined in every scenario). The police will assess whether the offender has moved closer or further away from their own position in comparison to the offender's initial location. If the offender has drawn nearer, it means the offender is moving in the direction of the police. In this case, the police will maintain their surveillance spot. If the offender has distanced themselves, indicating moving away from the police, police officers will abandon their surveillance position. They will then select a closer metro station to surveil. This is in line with Al-Talabi (2017).

6.4 Model validation

When constructing a model, it is crucial to validate both its structural design and outcomes. Peters, Vissers, et al. (1998) defines validity as the degree to which the reference system aligns with the simulated model of the system. Due to the limited availability of data on representative fugitive interception scenarios, the validation of the model and its outcomes relies on interviews (see Appendix B). Experts are consulted to assess whether the model outcomes accurately represent the real system (Carson, 2002).

First, the model setup will be discussed. Interviews revealed that the police accept the model's simplification of the network. Given that police units on the street drive through specified areas, police agents starting their interception at a police station is validated. However, the scenario in which no camera footage is available is highly unlikely and does not accurately represent the real system. Nevertheless, as the primary emphasis lies on analyzing police and offender strategies, the approach of this model is validated and deemed useful for the police.

Secondly, the offender strategies will be discussed. Certain neighborhoods in Rotterdam have varying levels of offender activity, justifying the division of the start location into six possible locations. Additionally, the differentiation between rational and bounded rational offenders, along with its behavioural consequences in the model, is recognized and validated by the police.

Finally, validating police behaviour proves challenging. Police actions are primarily driven by intuition and habit, leading to significant variations in strategies among police officers during an interception scenario. Moreover, in reality, the police heavily rely on camera footage, making it difficult to validate the strategies proposed in this paper. For instance, in practice, the police know the offender's location through camera footage most of the time and do not go to a metro platform unless certain of an interception. Whereas, this model introduces uncertainty for the police, allowing for the chance of guarding a metro platform without intercepting the offender.

7 Experimental design

This section explains how each scenario is created and which input variables are included. Next, it introduces the base scenario per experiment in Section 7.4. And finally, Section 7.5 uses the base scenario of the fourth experiment as a sample scenario to visualize a sample model run.

7.1 Constructing a scenario

To construct the experiment, the input values for each scenario must be defined. This is part of Greasley's (2008) fifth design phase: building the model. The experiments are structured to efficiently explore relationships between variables and draw reliable conclusions. By systematically varying the independent variables, and observing their effects on dependent variables, experimental design serves as a basis for the analysis of results (Janković et al., 2021).

The simulation model is divided into four experiments. Each scenario holds a unique combination of input variables, these are identified in Section 7.1.1. Once the experiment is defined, the scenarios are formalized. Each scenario forms a unique combination of variable values, elaborated in Section 7.1.2. Finally, each scenario will be iterated multiple runs. Each run with a unique combination of the model uncertainties, shown in Section 7.1.3.

7.1.1 Experimental design

To assess the effectiveness of strategies, it is essential for offenders and police to interact. However, to analyze the effectiveness of their strategies independently, the interaction is systematically varied in four distinct experiments.

In the first experiment neither agent interacts with information. The second experiment only allows the offender to interact with information. In the third experiment, the interaction is limited to the police accessing information. Finally, in the fourth experiment, both offender and police agents can interact with information. As elaborated in 6, the agent's ability to interact with information introduces new variables. Consequently, each experiment is characterized by distinct input variables and uncertainties, as illustrated in Figure 7.1.

	Experiment 1 No interaction	Experiment 2 Criminal interaction	Experiment 3 Police interaction	Experiment 4 Full interaction
Levers	Criminal start pos Criminal end goal Criminal panic state Criminal max path diverge Police end goal Police guarding location Police guarding entrances Police units Police units at same station	Criminal start pos Criminal end goal Criminal panic state Criminal max path diverse **Criminal loose end goal** **Criminal time till panic state** Police end goal Police guarding location Police guarding entrances Police units Police units at same station	Criminal start pos Criminal end goal Criminal panic state Criminal max path diverge Police end goal Police guarding location Police guarding entrances Police units Police units at same station **Police undercover**	Criminal start pos Criminal end goal Criminal panic state Criminal max path diverse **Criminal loose end goal** **Criminal time till panic state** Police end goal Police guarding location Police guarding entrances Police units Police units at same station **Police undercover**
Uncertainties	Police capture % at platform Police capture % at station exit Police initial call delay	**Criminal detection % police** Police capture % at platform Police capture % at station exit	Police capture % at platform Police capture % at station exit **Police initial call delay** **Police info update frequency**	**Criminal detection % police** Police capture % at platform Police capture % at station exit **Police initial call delay** **Police info update frequency**
Output	Capture	Capture **Criminal got panic** **Criminal tried exits**	Capture **Police gone undercover** **Police changed goal**	Capture **Criminal got panic** **Criminal tried exits** **Police gone undercover** **Police changed goal**

Figure 7.1: Variables per experiment

In Figure 7.1 the input variables, uncertainties and output variables of the model are identified. The highlighted variables are added in the respective scenario.

7.1.2 Scenario design

Once the experiment is defined, we know which variables are included in the scenarios. However, to form a scenario, the input variables must be specified. To do so, multiple methods exist, such as Latin hypercube sampling (LHS) or Monte Carlo sampling. Both create a subset of scenarios. However, as this study wants to analyze the effect of all strategies and the variables thereof, this study adopts a full factorial design (FFD) approach.

In a FFD, all variables are systematically varied to include all possible combinations of factors and their levels in an experiment (Janković et al., 2021). Each factor is tested at every level, allowing for the examination of main effects and interactions (Farooq et al., 2016). The total number of scenarios is found by multiplying the number of variable values. This design method is resource-intensive and therefore computationally heavy. However, it allows for understanding complex system behaviour as an effect of each variable.

As explained in Section 6, this study aims to analyze the existence of robust strategies in a fugitive interception scenario. This is achieved by creating strategies for all agents, incorporating multiple behavioural variables such as the offender's rationale and the police's unit count. If a sampling technique other than FFD were employed, only a subset of scenarios would be considered instead of the full range. This would result in the exclusion of certain strategies, and thus behaviours, from the analysis (Janković et al., 2021). Therefore, FFD is chosen to ensure a comprehensive exploration of the experimental space.

7.1.3 Iteration design

Once the input variables for the scenarios are defined, the number of iterations must be determined. In this study, the iterations per scenario are dependent on two factors: the number of uncertainties and the start location of the offender.

First, the number of uncertainties per experiment is outlined in Figure 7.1, with specific values provided in Table 7.2. Following the prior adopted approach of an FFD, the uncertainties are systematically tested through all possible combinations. Consequently, every unique combination of uncertainty values is used to execute the scenarios.

Second, the offenders are assigned predefined start locations: 'centre,' 'one line,' or 'end.' Each category includes two specific start locations, as outlined in Table 6.2. In every scenario, the simulation is executed twice, once for each start location within the category. Thus, each run, featuring a distinct combination of uncertainties, is duplicated. Once run for station 1 and once for station 2. The purpose is to subject each start location category to testing twice. By running the scenario a second time with an alternative metro station with identical characteristics, potential bias associated with a specific start location is limited. This approach aims to reduce coincidental outcomes and enhance the robustness of the results.

7.2 Model input uncertainties

Besides defining the input values for the police and offender strategies, the uncertainties associated with these inputs must also be specified. This ensures a comprehensive understanding of the model's behavior under varying conditions. In the XLRM diagrams for the offender and police in Section 6.3.4 and 6.3.3, distinct uncertainties influence the behaviours of each agent. The definitions of these uncertainties are found in Appendix G, Table G.1. Unlike the metro agent, where uncertainties are assigned constant values, uncertainties for the offender and police agents are dynamic and vary across scenarios. Moreover, depending on the experiment, either a selection or all all uncertainties are incorporated into the model, as elaborated in Section 7.

An exploratory run is conducted solely for the first scenario due to computational constraints to determine the values for these uncertainties. In this scenario, only three uncertainties are involved. The values of these uncertainties were tested using Boundary Value Testing (BVT) (Dobslaw et al., 2020). This technique assesses the boundaries of valid input ranges to ensure the robustness and reliability of a system, aiming to uncover errors or issues at the edges or boundaries of acceptable input values (Reid, 1997). The chosen boundaries for the uncertainties in Experiment 1 are outlined in Table 7.1.

Table 7.1: Uncertainty values for exploratory run

Uncertainty	**Value**
offender_detection_police	-
crim_Mguard_percent	25%, 50%, 75%, 100%
crim_Sguard_percent	25%, 50%, 75%, 100%
init_call_delay	1 min, 3 min, 6 min
info_update_freq	-

The results of the exploratory run are shown in Figure 7.2, where runs are grouped based on unique combinations of input uncertainties. The X-axis represents the time of the simulation run, while the Y-axis displays the cumulative number of captures, reflecting the cumulative captures over time. The highlighted lines represent three scenarios with distinct uncertainty combinations. It is evident that irrespective of the uncertainty combination, the output behaviour follows a consistent trend. The differences in output between the uncertainty combination lie in the size of total captures for each scenario, not in its structural behaviour.

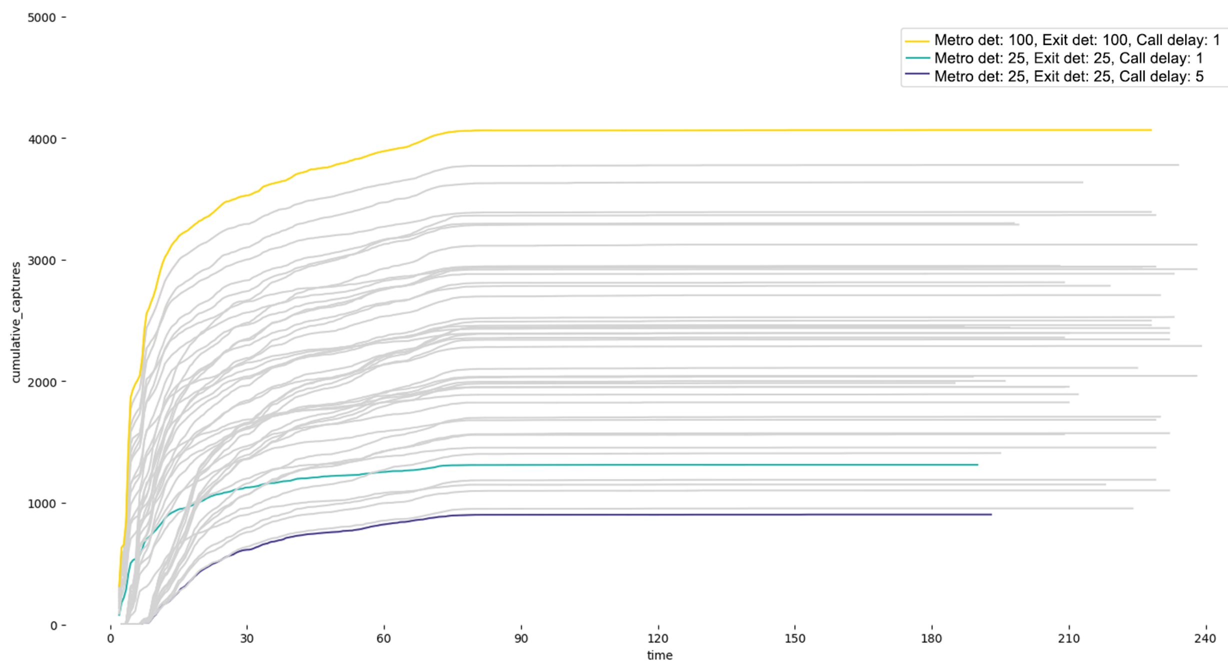


Figure 7.2: Exploratory run for model input uncertainties

The impact of one variable stands out; the *initial call delay*. The figure illustrates that the three unique values for this uncertainty show their effect in the initial minutes of the simulation run, which determines the output of the scenarios. Specifically, when the initial call delay is minimal, captures increase more rapidly compared to when it is at its maximum. Furthermore, following the lines corresponding to the respective call delay values, it becomes apparent that scenarios with larger call delays result in fewer cumulative captures than those with the smallest initial call delay.

Based on the insights gained from the exploratory run, the uncertainty values for the experiments are selected. The fact that none of the uncertainty values in the exploratory run led to unpredictable behaviour demonstrates the model's robustness to extreme input variables.

For the first uncertainty, the *initial call delay* is maintained at the same values as during the exploratory run. This decision is influenced by the realization that the initially chosen values were not particularly extreme. Reducing the range of *initial call delay* further might lead to unrealistic scenarios (Appendix B; van Justitie en Veiligheid, 2023). Additionally, the effects of changes in this variable are currently seen, and are interesting to analyze in the experimental runs.

Additionally, for the variables *crim_Sguard_percent* and *crim_Mguard_percent*, the behaviour displays a robust pattern, regardless of their value. However, setting the offender detection percentage for the police to range from 25% to 100% implies a high uncertainty in the police's ability to detect the offender; where the detection chance is sometimes equal to flipping a coin (50%). Therefore, to narrow the range of these uncertainties in the experiments for the simulation model, the detection percentages vary between 50%, 70%, and 90%. Table 7.2 presents the values for all uncertainties across all experiments.

Table 7.2: Final uncertainty values

Uncertainty	**Value**
offender_detection_police	50%, 70%, 90%
crim_Mguard_percent	50%, 70%, 90%
crim_Sguard_percent	50%, 70%, 90%
init_call_delay	1 min, 3 min, 6 min
info_update_freq	1 min, 3 min, 6 min, 10 min

The uncertainties in this study are assigned specific values instead of value ranges. This limits the number of scenarios and, consequently, computational time. Additionally, these values are assigned to represent chance, a challenging variable to estimate accurately in a fugitive interception scenario. Therefore, the fixed values exhibit considerable differences from one another, aiming to indicate whether significant changes in detection chance impact the output.

However, there is a potential drawback to using fixed numerical values as it may limit the exploration of the parameter space. This restriction could result in overlooking valuable insights that might arise from variations within a range of values. Nevertheless, the uncertainties are systematically tested with extreme values, revealing consistent behavioural patterns. Consequently, it can be concluded that setting the variables to limited range of values presented in Table 7.2 values would not neglect any substantial differences in behaviour.

7.3 Variable exclusion

During the exploratory run the effect of variance of input variables on the output was analyzed. The variance in the output values capture and time were tested based on changing input values per variable (excluding the input uncertainties). This provides insights into parameters that may not significantly influence the output (Saltelli et al., 2000; Geffray et al., 2019). Due to the time limit of the study and to reduce computational time, it can be useful to exclude variability in insignificant variables. However, excluding explanatory variables from the simulation model may lead to neglecting their cumulative impact, which could, nonetheless, contribute significantly. Therefore, fixing the values of non-influential parameters must be done carefully (Pourgol-Mohamad et al., 2009). Table 7.3 shows the frequency, in percentages, of scenarios where changes in input values lead to a maximum of 15% difference in output value.

Table 7.3: Frequency (%) that value change in input variable leads to max 15% difference in output value

Input variable	**Capture**	**Time**
Police_entrance	99.31%	12.52%
crim_max_diverge	97.84%	2.83%
P_multiple_at_station	97.84%	1.70%
crim_bounded_rat	97.15%	6.96%
crim_pos	77.01%	0.00%
units	73.10%	2.11%
crim_strat	66.31%	0.00%
pol_strat	52.26%	1.70%
pol_guarding	14.47%	0.31%

From the table it appears that for the output variable time, no change in input values leads to less than a maximum change in output of 15% a significant number of times. However, for the output capture 4 variables stand out:*police_entrance*, *crim_max_diverge*, *p_multiple_at_station*, *crim_bounded_rat*. For all variables, changes in its value lead to less than 15% difference in output value more than 95% of the time.

The first variable, *police_entrance*, refers to the exits that the police guard, either the main or site exits. Assigning a constant value to this variable would imply that in all scenarios where the offender uses the alternative exit, they have a 100% chance of escaping, as the police will consistently guard the other type of exit. Therefore, this variable is chosen to remain variable and not be fixed, even though its effect in output is minimal.

The second variable, *crim_max_diverge*, represents the number of times an offender can alter its route. In the exploratory run, this variable varied between 3, 6, and 10 times. Given that this variable exhibited no significant impact on the output variable capture, it is set to a fixed value of 10. Since having the ability to diverge more times does not result in increased computational time or incur any cost for the offender, the upper boundary of this input value is selected.

The next variable exhibiting low variability in output based on value changes is *p_multiple_at_station*. This variable refers to the number of units that can guard the same station, regardless of whether they guard the metro platform or the station exits. It varied between 2, 5, and 10 units. Fundamentally, the model spreads the police units as widely as possible, which makes the chance that all units are assigned small. Therefore, it is unlikely that the upper boundary is reached. Additionally, in reality the likelihood of 10 units guarding the same police station is also minimal. Therefore, the value of 10 is excluded from this variable. However, if many police units are disposable in the simulation model it could be that the model occasionally assigns more than three units to the same metro station. Consequently, this variable is fixed at the value 5.

The last variable to discuss is *crim_bounded_rat*. This variable indicates the rational state of the offender. If the value is True, the offender is considered to be in a state of panic and behaves accordingly. Conversely, if the value is False, the offender is regarded as behaving rationally, which influences its behaviour differently. Locking this variable would exclude a significant portion of offender behaviour from the study's analysis, as explained in Section 3.2.1. Since the study's goal is to analyze various offender strategies, it is not advisable to fix a variable on which many actions are based. Therefore, this variable is not locked.

In conclusion, based on the exploratory run the model locks two variables to become constant values. This decreases the number of scenarios and therefore the also computational time of the simulation model. The values for the locked variables are shown in Table 7.4.

Table 7.4: Values for locked variables

Input variable	Locked value
crim_max_diverge	10
P_multiple_at_station	5

7.4 Base scenario

To establish a reference point for comparison, this paper employs a base case for each scenario. This base case serves as a benchmark scenario with predefined input variables, providing a standard against which the effects of strategic variations can be assessed. It represents a controlled starting point for understanding the system's behaviour and responses. Not all analysis use the base case as a reference point.

In Table 7.5, the variable values for the base case are presented per scenario. A key aspect of the base case is the police's goal determination, random. This random goal selection is exclusive to the base case, as assessing the effectiveness of a strategy that includes random variables is challenging. Nonetheless, comparing the effectiveness of strategies to the (base) scenario where the police act randomly can be insightful. It can highlight noteworthy strategies that outperform this random approach. In contrast, the offender uses random goal selection in various experiments to account for the possibility that offenders may choose random locations as a hiding place after committing a crime (Ino et al., 2009; Shepherd and Purcell, 2015; Appendix B).

Table 7.5: Values for input variables for the base scenario across all experiments

Variable	Exp 1	Exp 2	Exp 3	Exp 4
Offender starting pos	Centre	Centre	Centre	Centre
Offender goal	Random	Random	Random	Random
Offender bounded rational	False	False	False	False
Offender time until bounded rational	-	1	-	1
Offender loose goal	-	False	-	False
Police goal	Random	Random	Random	Random
Police guarding	Metro platform	Metro platform	Metro platform	Metro platform
Police entrances guarding	Main	Main	Main	Main
units	3	3	3	3
Police undercover	-	-	False	False

7.5 Sample case

In this Section the base scenario of experiment 4 is explained and visualized, serving as a sample scenario. Figure 7.3 shows the start locations and the end goals for the agents in the simulation model.

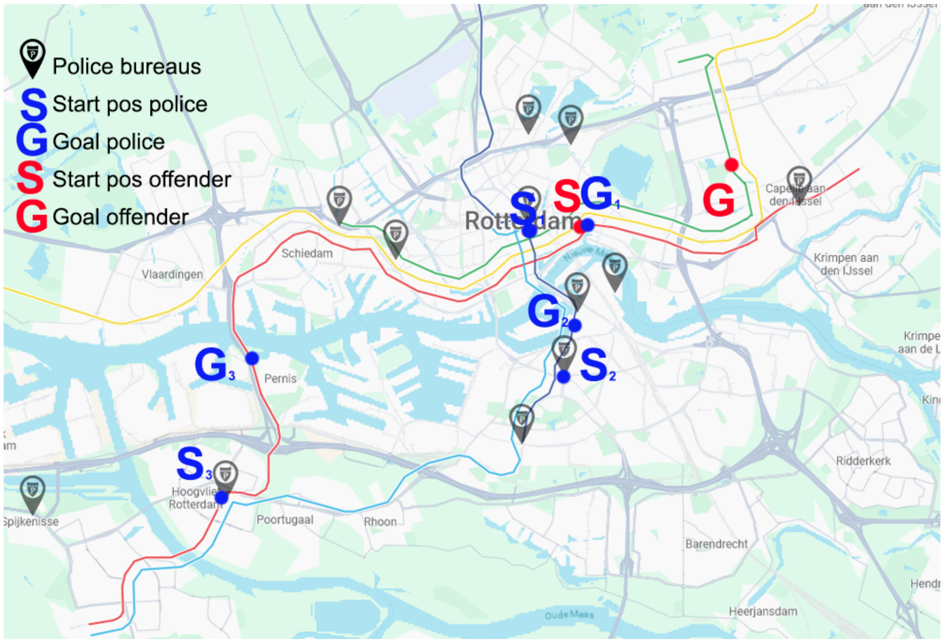


Figure 7.3: Start locations and goals for offender and police

Starting with the offender, the offender has committed a crime in the centre, and uses the metro station at Beurs to start its escape route. The final destination is randomly selected; in this sample case, it is Alexander. The offender starts the escape rationally, but the sight of one police officer triggers a state of panic, leading to the offender to behave bounded rationally for the remainder of the game. Additionally, the offender is unable to alter its end station, forcing its exit at Capelsebrug, regardless of police presence.

Moving to the police, the police are attributed with three units on the streets this interception game The first unit heads to the crime scene location, triggered by the offender's initiation at Beurs. The remaining two units randomly select their goals, as illustrated in the Figure. According to the model setup, once the police determine their end goal, they choose the police station closest to that goal to starts the interception. Throughout the game, the police units are positioned to guard metro platforms and main exits, without operating as undercover agents.

Examining the Figure, it is evident that police units 2 and 3 do not have an end goal which will facilitate an interception with the offender's path, given its starting point at Beurs and its destination at Alexander. However, in Experiment 4, which involves information interaction, the police agents are likely to adjust their final goals during the game. This adaptation occurs when they realize that the offender is moving farther away, indicating that interception will not occur unless the police reposition themselves.

8 Results

In this chapter the results from the experiments with unique interaction levels are discussed. The most important output variable is capture, which is mostly expressed in a 'mean capture value'. In the individual iterations, a capture by the policies is identified as 1, and an escape by the offender is identified as 0. As a result, the mean capture value combines this value for iterations of the same scenario. A mean capture value of 1 would indicate that all runs combined guarantee a 100% capture. Besides the mean capture value, a 'mean time value' is also evaluated.

First, the base scenarios for all experiments are presented, as those will be used as a threshold during some analyses. Next, in Section 8.2 the feature importance will be discussed, which indicates the dependence of the output variables capture and time on input variables. In Section 8.3, parallel plots explore the combined effectiveness of behaviour variables in achieving captures, followed by a sensitivity analysis, to assess the impact of varying input parameters on the simulation outcome. The chapter concludes with a payoff matrix visualizing interactions between offender and police strategies resulting in capture values, in Section 8.6.

The analyses discussed in the upcoming chapter are done using Exploratory Modeling and Analysis methodology from the EMA workbench (Kwakkel, 2017).

8.1 Base scenarios

In the simulation model a base scenario was run for each experiment. For some analysis, it serves as a reference point for which input is worthy of further analysis. By comparing the strategies with a base scenario, their relative impact and effectiveness are put into perspective. The input values for the base scenario are provided in Section 7.4.

As both the police and the offender randomly select their goal, comparing the experiments against the base scenarios can give us insight into which strategies work better than random actions. The mean capture and mean time of the base scenarios are presented in Table 8.1.

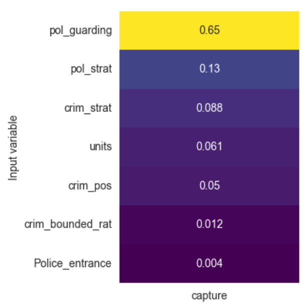
Experiment	μ capture	σ capture	μ time (min)	σtime
Exp 1	0.38	0.48	18.48	12.53
Exp 2	0.26	0.44	18.91	18.90
Exp 3	0.29	0.46	18.13	10.98
Exp 4	0.36	0.48	17.33	11.11

Table 8.1: Mean (μ) and standard deviation (σ) output for base scenarios

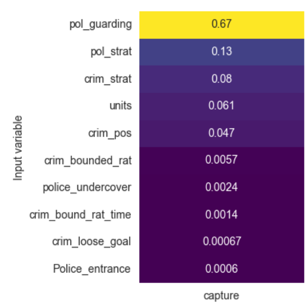
For the experiment where either both the offender and police interact with information (exp 4) or both do not (exp 1), the mean capture is highest. The mean time varies slightly across the experiments, but only a matter of seconds. Before these scores can be interpreted the full experiment results must be analyzed.

8.2 Feature importance

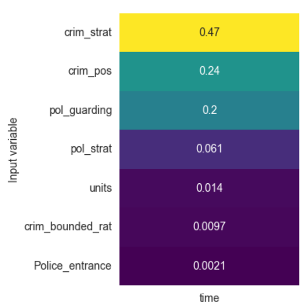
Feature scoring provides a means to gain insights into the comparative impact of diverse input varibales on model outcomes. It is used to analyse the most relevant feature(s) within the model (Kwakkel, 2017). Figure 8.1 shows the feature scores for the input variables in the model for both output variables capture and time. Both are done for experiments 1 and 4. The feature importances of all experiments are shown in Appendix I.



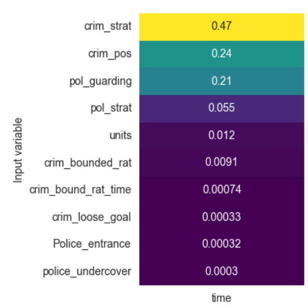
(a) Exp 1- Feature importance for output capture



(b) Exp 4- Feature importance for output capture



(c) Exp 1- Feature importance for output time



(d) Exp 4- Feature importance for output time

Figure 8.1: Feature importances for output variables capture and time

The figure shows that for both experiments and both output variables, there is one main determining variable. For output capture, this is *pol_guarding* and for output time this is *crim_strat*. For output capture, the next most important feature, with importance approximately five times smaller than *pol_guarding*, is *pol_strat*. The fact that the second most important feature is a police behavioural variable as well, indicates that the behaviour of the police significantly influences the model output. The following three important features, *crim_pos*, *crim_strat*, and *units*, vary in their significance order. However, important to note is that these three feature are roughly ten times smaller than the most important feature, *pol_guarding*. This implies that differences in the values of these features are most likely overshadowed by the variations in the *pol_guarding* variable.

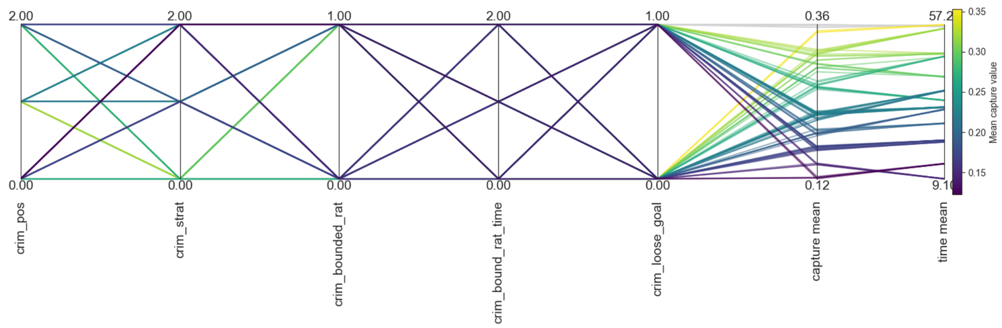
The differences between the feature importances between the experiments show that variables indicating interaction between the agents do not have a major effect on output. In experiment 4 the new variables, as shown in Figure 7.1 are *police_undercover*, *crim_bound_rat_time*, and *crim_loose_goal*. For both output capture and time, these variables are amongst the bottom four of least influencing variables. However, since the difference between the experiments mainly lies in the interaction between agents, these feature importances cannot be used to interpret the success of any strategies. This chapter further analyses which variations or combinations of features have a substantial impact on model output.

8.3 Parallel plot

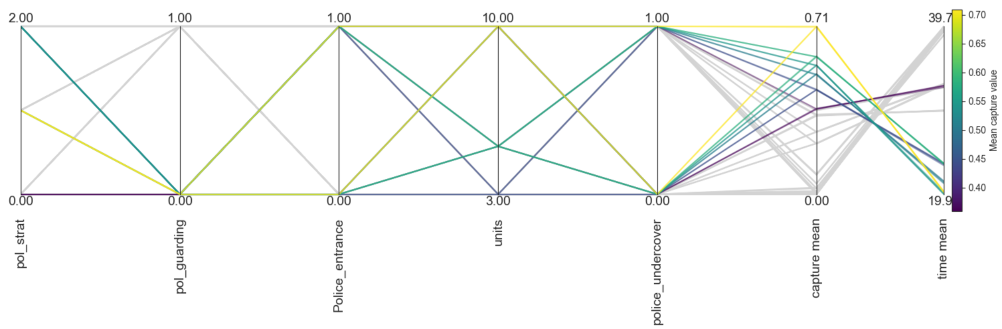
The parallel coordinate plot (PCP) visualize high-dimensional data, which can be used to detect patterns, clusters, correlations or outliers in data (Moustafa, 2011). In these plots, each variable is represented by a separate vertical axes, with its unique values on it. Lines connecting points across these axes show relationships and patterns within the dataset, representing a scenario iteration. As the simulation model has many input variables, which vary between two or three values, this visualization tool can help in giving a first glance at the patterns or trends within the output data.

In Figure 8.2, two PCP's are shown for the simulation model of experiment 4. Different plots are made for the input variables relating to offender behaviour (Figure 8.2a) and police behaviour (Figure 8.2b). The first vertical parallel axes represents the input variables, and the two on the right show its relation to the model outputs mean capture and mean time. In both Figures, the lines are compared to the base scenarios. For offender behaviour, the highlighted lines show the scenarios where the mean capture value is below the base scenario. For police behaviour the highlighted lines show the scenario where the mean capture value is above the base scenario. The reason behind this difference is that the offender desired a low capture chance, and the police a high capture chance. So for both players their desired results are highlighted in comparison to the base case. The behaviours which lead to undesired outcomes compared to the base case are represented in grey.

Figure 8.2 shows the parallel plots for experiment 4, for the parallel plots of all experiments see Appendix J.



(a) Offender behaviour



(b) Police behaviour

(c) Explanation table encoded variables

Variable	Value 0	Value 1	Value 2
crim_pos	Centre	End	One line
crim_strat	Furthest	Random	To train
crim_bounded_rat	False	True	-
crim_bound_rat_time	1	3	5
crim_loose_goal	False	True	-
pol_strat	Furthest	Largest	Surround
pol_guarding	Platform	Station exit	-
Police_entrance	Main	Side	-
units	3	5	10
Police_undercover	False	True	-

Figure 8.2: Parallel plots agent behaviour vs. model output (experiment 4)

First the PCP for offender behaviour is examined (Figure 8.2a). The yellow lines on the *mean_capture* axis represent the highest mean_capture. There does not seem to be a dominant strategy which leads to high capture. However, yellow lines can be seen at the values *crim_strat* = 0 and *crim_pos* = 1, indicating a potential correlation with higher capture rates. This could suggest that these variables predominantly contribute to higher captures. For other variables, each unique value appears to correspond to a darker line, which indicates lower capture values. However, if multiple values for a single variable show this pattern, it is difficult to determine that one value consistently leads to lower captures compared to another value for the same variable.

The PCP also shows that a high capture chance usually is paired with a relatively higher simulation time (the last vertical axis), and scenarios with lower capture values are generally combined with somewhat lower simulation times.

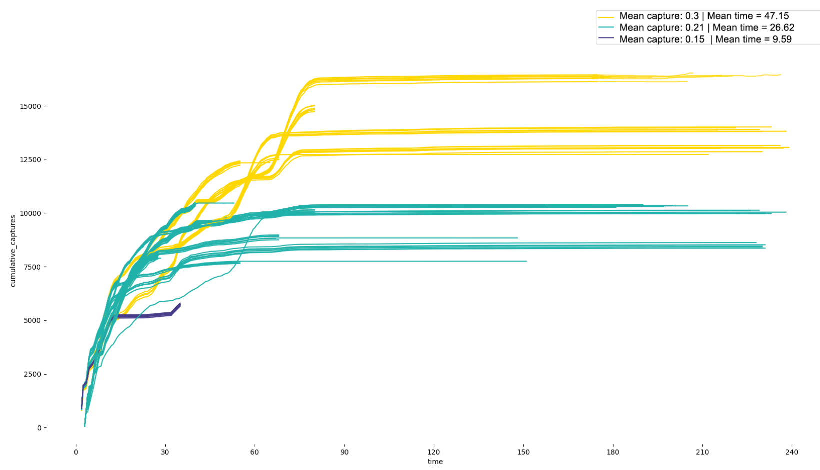
Now the PCP for the police behavioural variables are discussed (Figure 8.2b). Firstly, this plot has more grey lines than the PCP for offender behaviour. This suggests that, in proportion to the base case, the police have a greater variety of strategies that outperform the random actions of the offender. This indicates that the base case performs relatively well in apprehending the offender.

When following the yellow lines from the axis indication high capture values to the vertical left-hand axes representing the police behavioural input variables, a slight pattern emerges. Moving from left to right, the only yellow line originates from $pol\_strat = 1$. Similarly, for *pol_guarding*, all lines that outperform the base case correspond to the value $pol\_guarding = 0$. This is consistent with the feature importance results in Figures I.1a and I.1d, which indicated that the most importance feature in determining capture is pol_guarding. For variable *units*, all yellow lines stem from $units = 10$. However, for the remaining variables, *police_entrance* and *police_undercover*, the yellow lines do not align with a specific value, indicating no dominant value which leads to a high mean capture value.

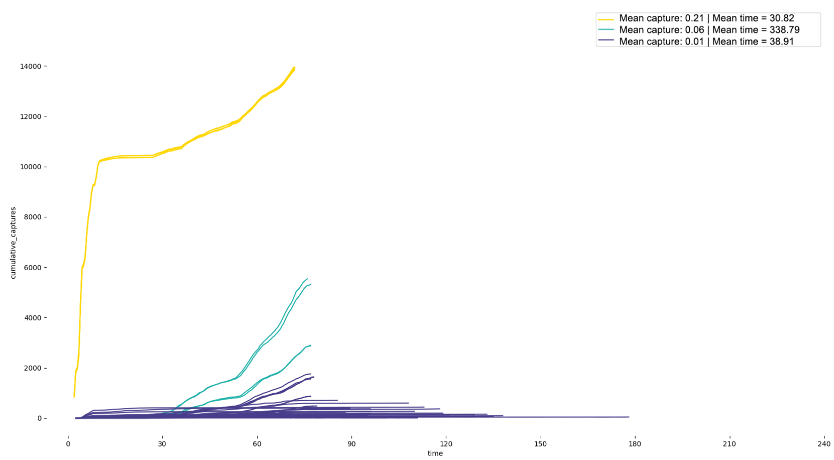
Furthermore, apparent is the relationship between *mean_capture* and *mean_time* in the police PCP. Unlike the offender PCP, the capture value appears to have a negative relation with time. When the mean capture value is high, the simulation time is low, when the mean capture value is low, the simulation time is high. To analyse this in further detail the next Section will zoom in on the relationship between the output variables time and capture.

8.4 Relation output variables

As seen in Section 8.3, there is a strong relationship between the output variables capture and time for police behaviour. To illustrate this relationship, Figure 8.3 plots the capture and time values for experiment 1, based on police and offender behaviours. See Appendix K for the Figures of all experiments.



(a) fig: Relation capture and time for offender behaviour



(b) fig: Relation capture and time for police behaviour

Figure 8.3: Relation output variables with offender and police behaviour (experiment 4)

This plot, shows that instances where police achieve a faster average capture of offenders are also characterized by a higher frequency of successful captures. Furthermore, it highlights the significance of the initial 30 minutes in an interception scenario. Failure to capture the offender within the first 30 minutes results in an approximate 50% reduction in the apprehension. Summarized, extreme capture probabilities are associated with extremely short capture times. This correlation could be attributed to the initial call delay of the crime being reported. However, in this model, the call delay is considered an uncertainty and is therefore further discussed 8.7.

Contrary to these findings, as found in the PCP for offender behaviour, no evident relation between capture and time is observed for offender behaviour. The operational speed of the offender does not serve as an indicator of capture likelihood.

8.5 Sensitivity analysis of input variables

Sensitivity analysis explores the relationship between the model's output and its sensitivity to changes in input values. It can help in identifying influential and (in)significant variables, examining variable interactions, and explaining model output variations through input changes (Saltelli, 2007).

There are three main ways to perform sensitivity analysis: One-at-a-Time (OAT), regional sensitivity, and global sensitivity analysis. One-at-a-Time (OAT) sensitivity analysis is a straightforward and commonly used method to assess the sensitivity of a model to variations in individual input parameters. In OAT, each input parameter is varied one at a time while keeping all other parameters constant, and the impact on the model's output is observed. In this simulation model, each experiment consisted of multiple scenarios, in which one variable was varied every time. In total, this resulted to 1000 - 8000 scenarios (depending on the experiment). Therefore, this paper does not use the OAT sensitivity as the dataset is too large for this purpose.

In a global sensitivity analysis the overall sensitivity of a model's output to simultaneous variations in multiple input parameters is assessed. Where the One-at-a-Time (OAT) method evaluates the individual impact of changes in input on output, global sensitivity analysis evaluates the collective impact of changes in several input variables on the model's output All-at-a-Time (AAT) (Pianosi et al., 2016). By doing so, this technique considers interactions among different parameters. As Figures I.1a and I.1d showed that there is one dominant variable in determining output, combining all variables might result in the sensitivity of the dominant variable overshadowing the effects of other variables.

This paper uses a regional sensitivity analysis to evaluate the effects of input variables on the output variables(Frey and Patil, 2002). Pianosi et al. (2016) considers regional sensitivity analysis a part of global analyses, where the focus is identifying specific regions in the input space that correspond to particular output values. As this simulation model has two sorts of players: the offender and the police, with contradicting interests (capture and escape respectively) and unique behaviours, the regional sensitivity analysis seems most appropriate for this model. The dataset is grouped by the unique values for each behavioural variable, for which the mean (μ), standard deviation (σ), and covariance (Cov) are calculated. This means that different scenarios are combined, based on the value of the variable which is tested. Meaning that as the relevant variable value varies, other variables also change. However, as this experiment is conducted through a full factorial design, and therefore all possible combinations of values for each input variable are tested, the changes in other variables balance out.

Tables 8.2 and 8.3 show the coefficients of variation for offender and police behavioural variables in experiment 4. For the sensitivity tables of all experiments see Appendix L.

Table 8.2: Mean (μ), standard deviation (σ), and covariance (Cov) for offender behavioural variables vs. output capture and time (experiment 4)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time (min)**	**σ time**	**Cov time**
crim_pos	Centre (0)	0.20	0.40	0.01	23.89	18.89	3.05
	End (1)	0.26	0.44		41.49	22.88	
	One line (2)	0.22	0.42		33.11	19.98	
crim_strat	Furthest (0)	0.30	0.46	-0.04	47.19	23.67	-8.63
	Random (1)	0.20	0.40		30.48	19.52	
	To train (2)	0.18	0.38		21.36	12.57	
crim_bounded_rat	False(0)	0.22	0.41	0.00	31.77	20.61	0.56
	True (1)	0.24	0.42		34.03	23.05	
crim_bound_rat_time	1	0.23	0.42	0.00	32.93	21.91	-0.03
	3	0.23	0.42		32.92	21.87	
	5	0.23	0.42		32.83	21.86	
crim_loose_goal	False(0)	0.23	0.42	0.00	32.91	21.90	-0.01
	True (1)	0.23	0.42		32.88	21.87	

The results of the sensitivity analysis for offender behaviour are consistent for with the patterns found in the PCP (Figure 8.2a). *Crim_pos* = end and *crin_strat* = furthest lead to the largest changes in μ capture and μ time for their variable. Variation in values for *crim_bound_rat_time* and *crim_loose_goal* lead to negligible changes in the capture and time output.

Table 8.3: Mean (μ), standard deviation (σ), and covariance (Cov) for police behavioural variables vs. output capture and time (experiment 4)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time (min)**	**σ time**	**Cov time**
pol_strat	Furthest (0)	0.16	0.36	0.03	36.11	22.21	-1.85
	Largest (1)	0.27	0.45		32.01	20.83	
	Surround (2)	0.25	0.43		30.56	22.21	
pol_guarding	metro platform(0)	0.44	0.50	-0.11	26.36	20.88	3.29
	station exit(1)	0.01	0.12		39.53	20.87	
Police_entrance	main(0)	0.23	0.42	0.0	32.90	21.89	-0.01
	side(1)	0.23	0.42		32.88	21.88	
units	3	0.17	0.37	0.13	34.15	22.06	-2.65
	5	0.23	0.42		32.72	21.84	
	10	0.28	0.45		31.80	21.69	
pol_undercover	False(0)	0.23	0.42	0.0	32.77	21.82	0.06
	True(1)	0.23	0.42		33.01	21.94	

The sensitivity analysis for police behaviour variables is also consequent with the results from Figure 8.2b. Differences in values for *pol_strat*, *pol_guarding* and *units* seem to have an effect on output, where Largest, metro platform, and 10, respectively, lead to a higher μ capture. For the remaining variables the effects on output capture and time and negligible.

For both tables it is crucial to emphasise that the standard deviation (σ) is considerably high compared to its mean. This implies that no meaningful conclusions can be drawn regarding the significance of differences in output. Furthermore, since the (σ) is negligible for all variables, no conclusions can be drawn from the covariances. Additionally, given that the behaviour of the other player varies throughout the sensitivity analysis for a value, it can be concluded that there are no robust strategies for either player to force its desired output. The output is dependent on the actions of both players.

Furthermore, a significant factor contributing to this high (σ) can be attributed to the deep uncertainty in this model. In modeling, deep uncertainty arises when essential elements of a system, its behaviour, or the external environment are complex, making it difficult to assign precise probabilities or parameter values to different variables. This type of uncertainty refers to areas where there may be fundamental gaps in knowledge. In this simulation model, numerous uncertainties and assumptions exist which are further elaborated on in Section 5.1 and Section 7.2 respectively.

8.6 Payoff matrix

The offender and police's strategies are made up out of multiple variables, which makes it is difficult to analyze these variables independently. This section analyzes the combined effects of behavioural variables, resulting in strategies, on the capture rate. Figure 8.4, shows the payoff matrix. Where the mean capture value (the payoff) is a result of an offender strategy (x-axis) and a police strategy (y-axis). The higher the mean capture value, the more yellow on the color scale.

This analysis is focused on the payoff matrix corresponding to experiment 1, chosen for its reduced number of strategies compared to the other experiments. However, the observed general trends and patterns within this matrix are found to be consistent with those observed in experiments 2, 3 and 4. This is not surprising as Figure 8.1, showed relatively low feature importances for interaction variables, indicative of their limited impact on the mean capture value. Furthermore, Tables 8.2 and 8.3 revealed that variations in interaction variables resulted in insignificant alterations to the mean capture value. Appendix M shows the capture matrices for all experiments.

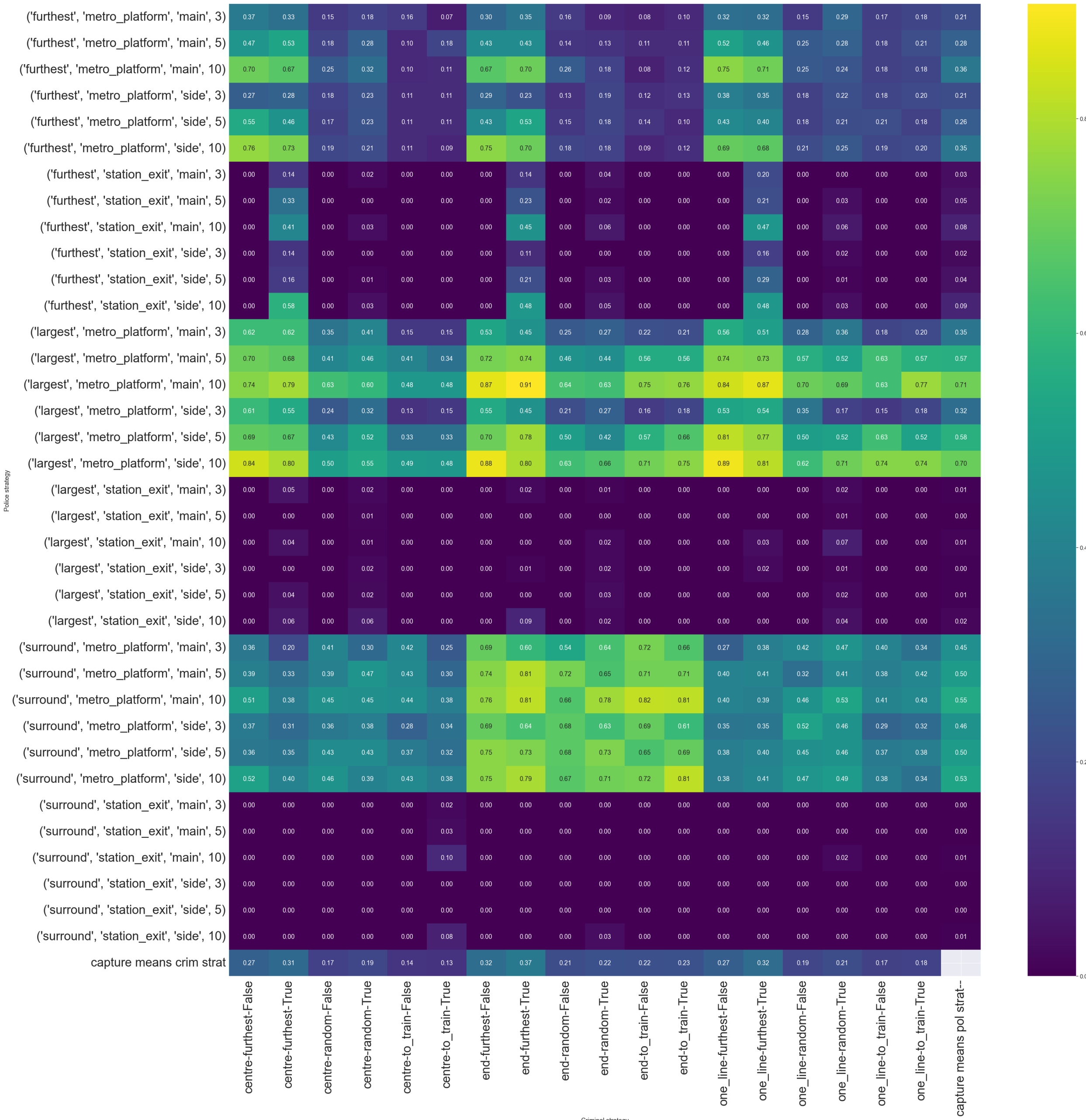


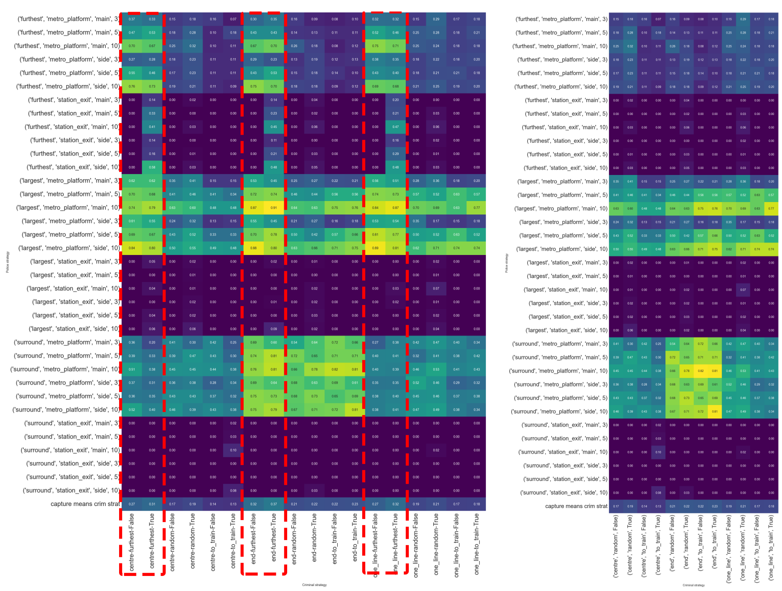
Figure 8.4: Payoff matrix offender vs. police strategies (experiment 1)

8.6.1 Offender strategies

Since the offender aims to escape the police, a successful strategy refers to strategies leading to low capture values, which are characterized by their dark-blue color in the payoff matrix presented above. The mean capture value per offender strategy, across all police strategies, is shown in the lowest row of the matrix.

Figure 8.4 shows that the success of the offender's stategy is dependent on the police's strategies, as the capture value for one offender strategy varies across differenrt rows. This is not surprising, as the feature importance table in Section 8.2 found that capture is mostly dependent on the police's behaviour variable *pol_guarding*. It can be assumed that the police will never adopt strategies where the capture chance is lowest, which is further discussed in Section 8.6.2. The current section will focus on which offender strategies optimize an escape. Section 8.6.2 does the same for the police strategies.

Figure 8.4 also reveals that some offender strategies are dominated by other strategies. Most likely, the offender would never employ the strategies that are always outperformed, and can therefore be excluded from the payoff matrix. The first strategy always outperformed is the strategy in which the offender aims to go to a far station, highlighted in Figure 8.5a. This is apparent from the strategies in upper rows, when the police go to a far metro station. In these rows, the outlined columns show higher capture rates than the same rows but different columns. This means that the strategies in which both the police and offender go to a far station consistently lead to higher capture rates. As the offender aims to achieve the lowest capture chance possible, it can be concluded that the offender will not prefer the strategies in which they go to a far goal. These can therefore be removed from the payoff matrix, shown in Figure 8.5b.

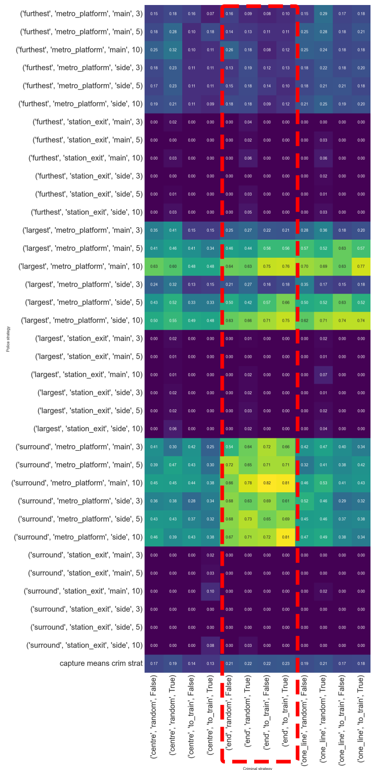


(a) Payoff matrix - offender strategies highlighting a 'furthest' end goal

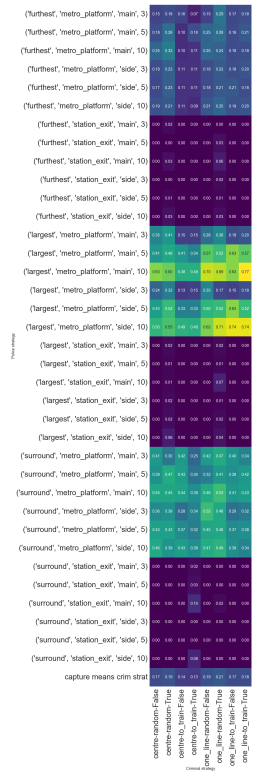
(b) Subset payoff matrix - offender strategies excluding a 'furthest' end goal

Figure 8.5: Payoff matrix highlighting offender behaviour: 'furthest' end goal (experiment 1)

Another strategy that frequently leads to a higher capture value is when the offender starts at an end station, highlighted in Figure 8.6a. Especially when the police adopt a surrounding surveillance strategy, the highlighted strategies perform poorly. This is also evident from the increased mean capture value for those strategies, as seen in the bottom row of the payoff matrix in the figure. Besides the surrounding strategies, the police can also surveil far and large stations, meaning that the chance that the police guard surrounding stations is 33% chance. With such a high risk of increased capture, the offender will most likely not choose strategies that start at an end metro station. Figure 8.6b excludes these and shows the remaining offender strategies.



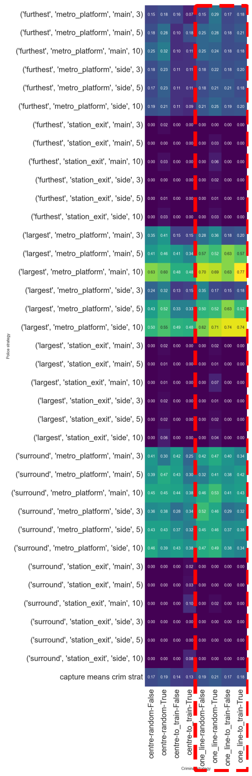
(a) Subset payoff matrix - offender strategies highlighting ‘end station’ as start position



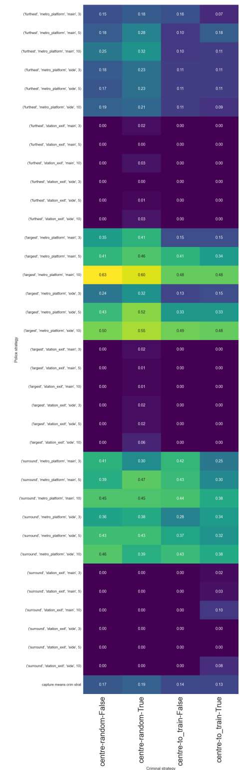
(b) Subset payoff matrix - offender strategies excluding ‘end station’ as start position

Figure 8.6: Payoff matrix highlighting offender behaviour: ‘end station’ as start position (experiment 1)

The payoff matrix in Figure 8.6b contains the remaining strategies, from which it appears that some strategies still generally perform worse than others. For example, the strategies that start at metro stations with only one line, are always outperformed by strategies that start at metro stations in the centre. This is shown in Figure 8.7a, where the outlined strategies generally show lighter cells, indicating higher capture rates. It can be assumed that the offender will therefore always choose to start their escape route at a center station, and thus the other strategy can be removed from the payoff matrix, as seen in Figure 8.7b



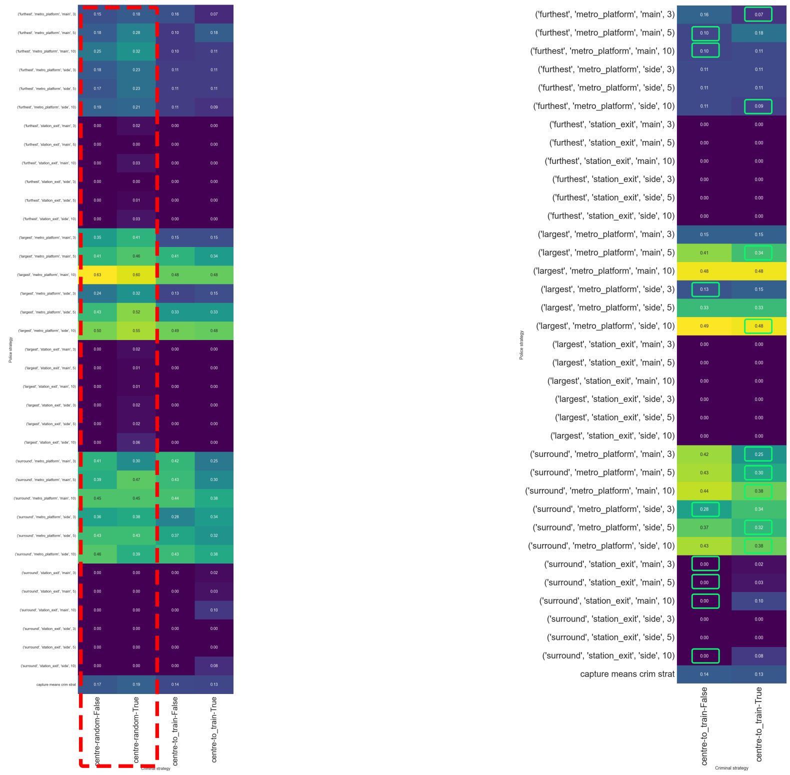
(a) Subset payoff matrix - offender strategies highlighting 'one-line station' as start position



(b) Subset payoff matrix - offender strategies excluding 'one-line station' as start position

Figure 8.7: Payoff matrix highlighting offender behaviour: 'one-line station' as start position (experiment 1)

Next, the remaining four strategies both start at a central metro station, but vary in the offender's rationale state and goal selection. The two strategies highlighted by the red box in Figure 8.8a, show scenarios in which the offender chooses a random end location. In the two non-highlighted strategies the offender attempts to transfer to a train network, which show a roughly 5% lower mean capture rate across all police strategies. Knowing this, the offender will most likely not select its goal randomly, thereby excluding these strategies from the payoff matrix with potential strategies, shown in Figure 8.8b.



(a) Subset payoff matrix - offender strategies highlighting 'random' end locations

(b) Subset payoff matrix - offender strategies excluding 'random' end locations

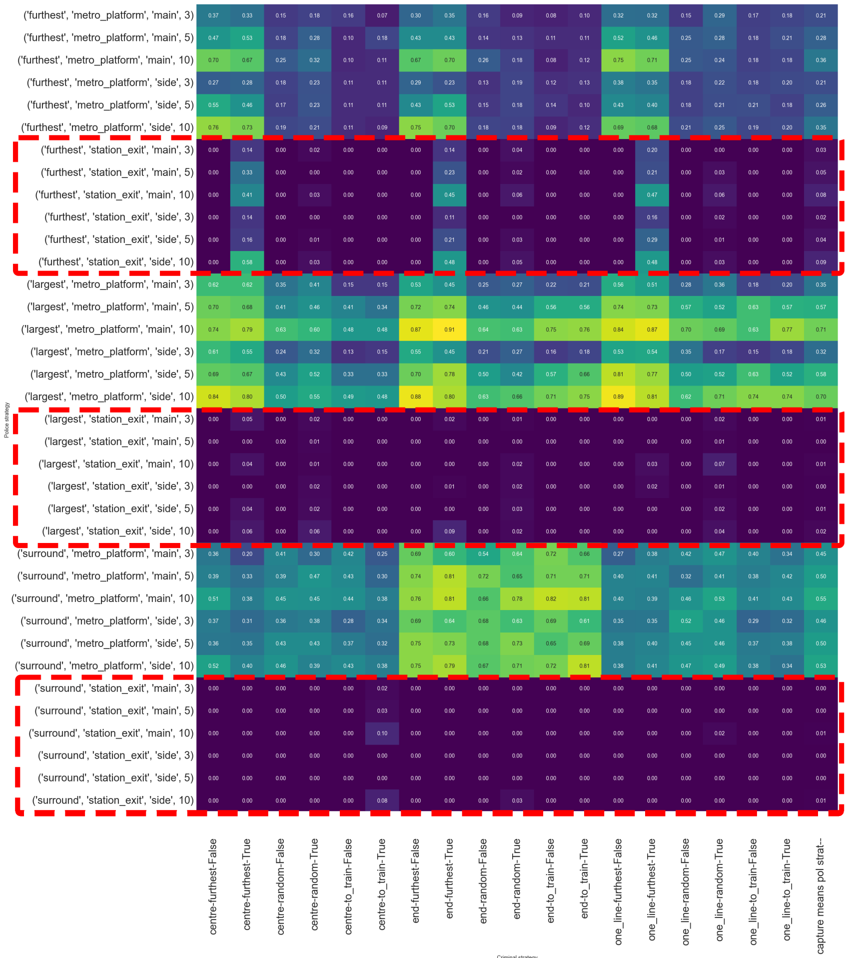
Figure 8.8: Payoff matrix highlighting offender behaviour: 'random' end locations (experiment 1)

Figure 8.8b shows two similar strategies, with the only difference being the offender's initial rationale state. The strategy in which the offender starts with bounded rationality has a 1% lower capture chance than if the offender is rational. Additionally, when looking at the success of both strategies for each police strategy separately, it can be seen that both strategies per similar. The green boxes in the figure identify the most successful offender strategy, per police strategy. This shows, that for multiple police strategies, the offender strategies score the same capture rate. However, where the offender strategy containing a bounded rational state of mind does better in 9 scenarios, the strategy in which the offender starts rationally does better in 8 scenarios. Thus, it can be concluded that the success of these strategies is almost the same, and the outcome relies on the strategy of the police. This means that the dominant strategy for the offender is to start at a central metro station and aim to go to a train station, regardless of their rationale state.

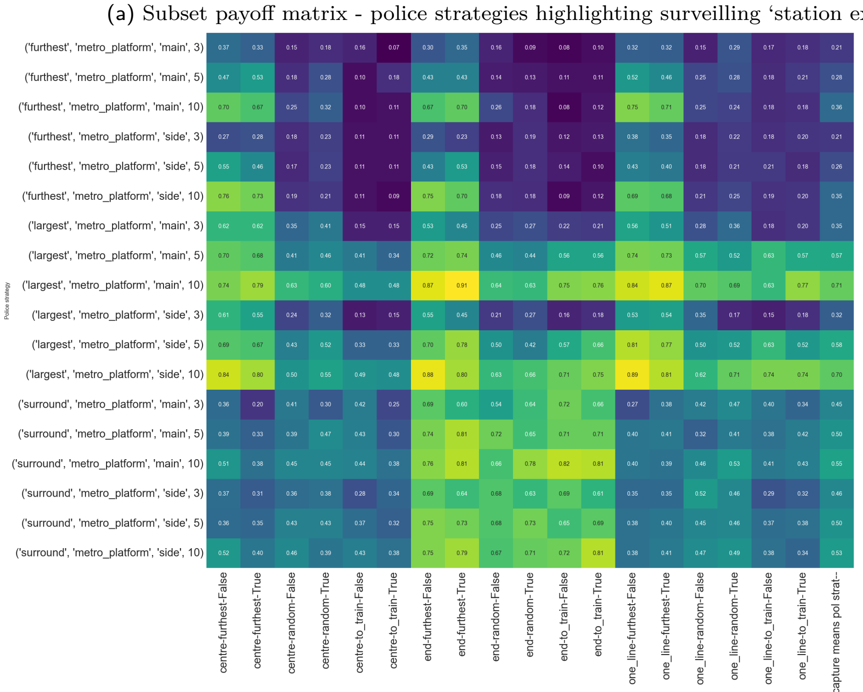
Overall, it can be concluded that the most important factor in lowering the capture rate for the criminal is its goal selection. When going to a far goal, its capture chances increase by 10%. The next most determining factor it the offender's start location. When the offender starts and en end station instead of in the centre or at a metro station with only one line, the capture rate increases by roughly 5%. Thus, it can be concluded that the offender will not start at end stations, and will not aim to go to far stations to escape the crime scene.

8.6.2 Police strategies

For the trends caused by police strategies the rows must be analyzed. In contrary to the offender, the police aim for a high capture. Meaning the yellow cells are desired. The last column combines the capture chances for the police strategies over all possible offender strategies. The first horizontal trends that are apparent are the scenarios in which the police surveil the station exits instead of the metro platforms. These scenarios are characterized by their low capture rates, highlighted by the red boxes in Figure 8.9a. All scenarios that include the surveilance of metro stations have a mean capture value of less than 10%, averaged over all possible offender strategies. In scenarios that contain the same strategy but instead of surveiling the station exits the police surveils the metro platforms, the capture rates increase significantly, shown in the last column of the payoff matrix. Since the strategies in the red boxes are always outperformed by their equivalent strategies that guard the metro platforms, the police will always adopt the latter suveilance method. Thus, the red boxes are removed from the matrix with potential police strategies, shown in Figure 8.9b.



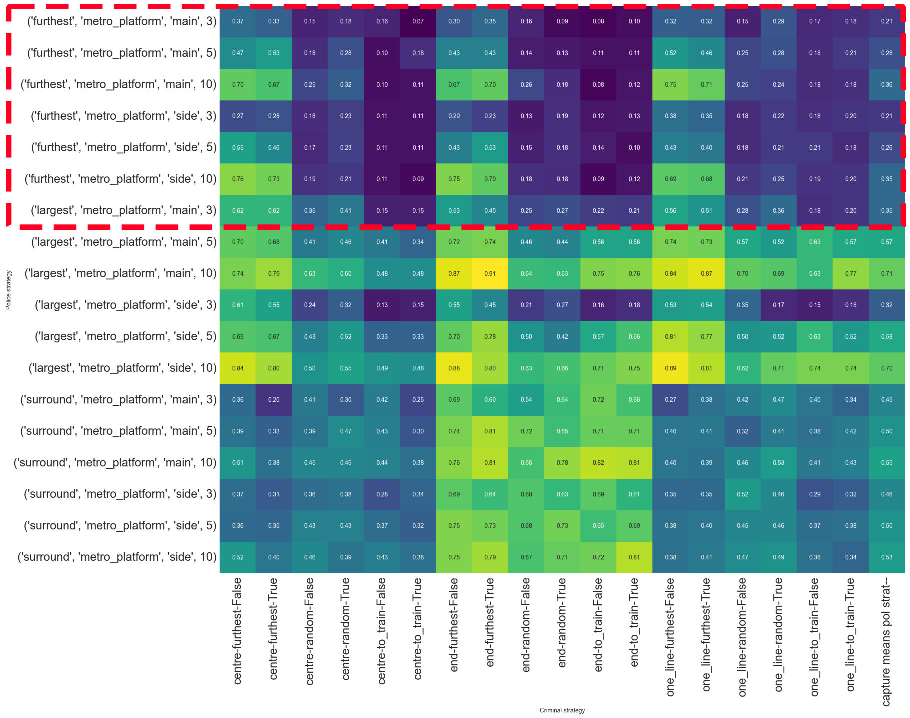
(a) Subset payoff matrix - police strategies highlighting surveilling 'station exits'



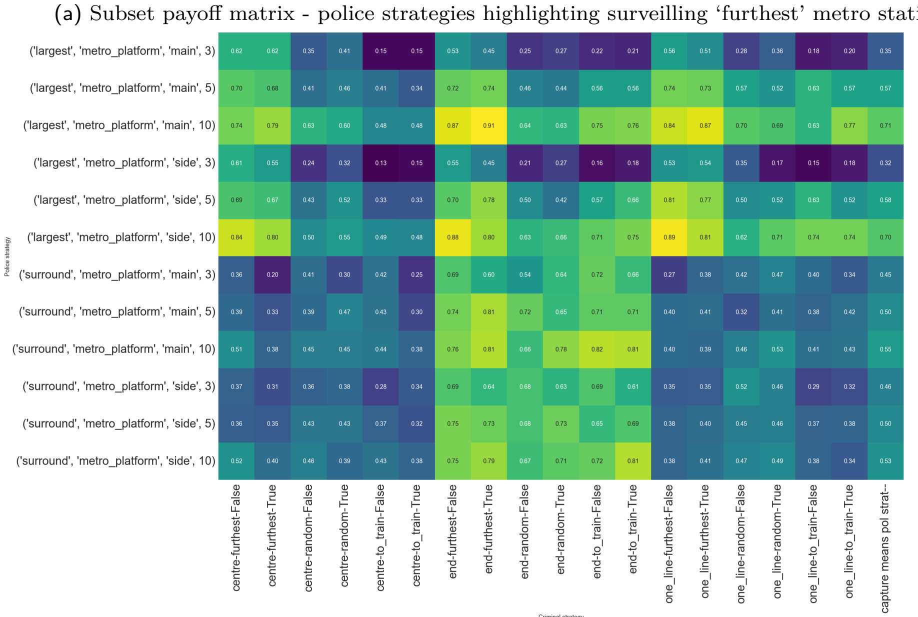
(b) Subset payoff matrix - police strategies excluding surveilling 'station exits'

Figure 8.9: Payoff matrix highlighting police behaviour: surveilling 'station exits' (experiment 1)

Figure 8.10a shows the strategies in which the police always guard the metro platform, as that has been proven to be dominate the removed strategies. The highlighted strategies are where the police guard the metro platforms at far stations. The success of these strategies is dependent on the offender's behavior. This is evident from the lighter columns where the offender also tries to go to a far station, resulting in a high capture chance. In contrast, in the strategies where the offender tries to get to a train or a random goal, the capture chance significantly decreases. The last column shows that for the highlighted strategies the capture chances ranges from 21% to 36%. Whereas for the strategies in which the police go to a large or surrounding metro station, the capture chance ranges between 45% and 71% (with one outlier of 32%). Therefore, it can be assumed that the police will always prefer such strategies, and never choose to guard far stations. Figure 8.10b excludes these strategies from the payoff matrix. This is done in Figure 8.10b.



(a) Subset payoff matrix - police strategies highlighting surveilling 'furthest' metro stations

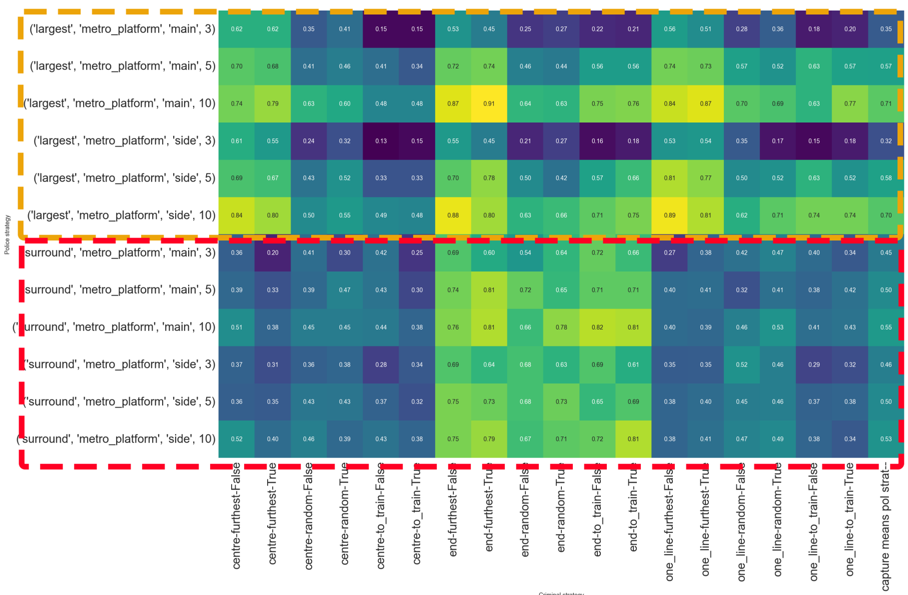


(b) Subset payoff matrix - police strategies excluding surveilling 'furthest' metro stations

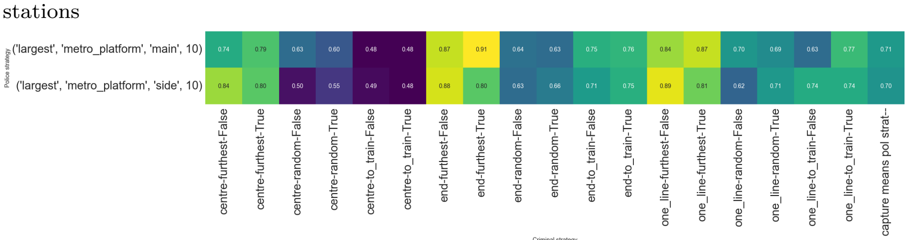
Figure 8.10: Payoff matrix highlighting police behaviour: surveilling 'station exits' (experiment 1)

Figure 8.11a shows the remaining police strategies, differentiating between the surveillance of large metro stations highlighted by the orange box, and the surveillance of surrounding metro stations in the red box. The strategies containing the surrounding method show relatively similar horizontal patterns; performing better when the offender starts at a centre or one line metro station, and performing worse when the offender starts at an end station. When the offender starts at an end location, the capture chance increases to more than 60% the majority of times, evident from the more yellow columns red box. If the offender chooses a metro station in the center or with only one metro line as a starting position, the capture chance lies below 50% the majority of the time, depicted by the darker cells. This means that the surrounding strategies are dependent on the behavior of the offender. Furthermore, the surrounding strategies have a mean capture value between 45% and 55%, averaging at 50%. This implies that the success of these strategies is reasonably stable and behavioural variables such as the number of units and the exits that are guarded do not largely impact the output.

In the orange box, when police employ strategies where they surveil large metro stations, the effect of the offender's strategy decreases. This is noticeable by the relatively similar capture values within one row in Figure 8.11a. This means, that the strategies in the orange box are more robust across all offender strategies. The figure also shows that two strategies always lead to a low capture chance, regardless of the offender's behaviour. It implies that if the police adopt a strategy where they guard the metro platforms of large stations, the number of units and the type of stations exits they surveil influence the outcome. For example, when the police use have three units, the capture chance decreases to roughly 35%, evident from the darker rows. Whereas if the police have 5 or 10 units at their disposal, regardless of which exits are guarded, the capture chance increases to above 55%. Thus, it is likely that the police will choose one of these robust strategies with a high capture rate across all offender's strategies, outlined in Figure 8.11b.



(a) Subset payoff matrix - police strategies highlighting surveillance at 'surrounding' and 'large' metro stations



(b) Subset payoff matrix - police strategies excluding surveilling 'station exits'

Figure 8.11: Payoff matrix highlighting police behaviour: surveilling 'station exits' (experiment 1)

Similar to the offender, the police has strategies which always have a higher capture rate than other strategies. The most dominant variable in these strategies is the surveilance location. The police will always guard the metro platforms, instead of the station exits. Furthermore, the police will also prefer to guard large or surrounding metro stations, rather than far metro stations.

8.6.3 Pure-strategy Nash equilibrium

In Figure 8.4 has shown that the output of the simulation model is dependent on the strategies of both players. For example, when police surveil the furthest goal, the capture chance significantly increases when the offender also has the desire to go to a far goal. Similarly, when the offender starts at the end of a metro line the police can drastically improve their capture chance by guarding surrounding stations, rather than large or far stations.

In a zero-sum non-cooperative game where players are interdependent, optimal outcomes require knowledge of the strategies other players will employ. However, given the different objectives of all players, cooperation in our simulation model is unrealistic. Nevertheless, if assumed that the payoff matrix includes all possible strategies and that all players have full knowledge of these options, the players can anticipate what the other will do. In such a scenario, a pure-strategy Nash equilibrium can be calculated.

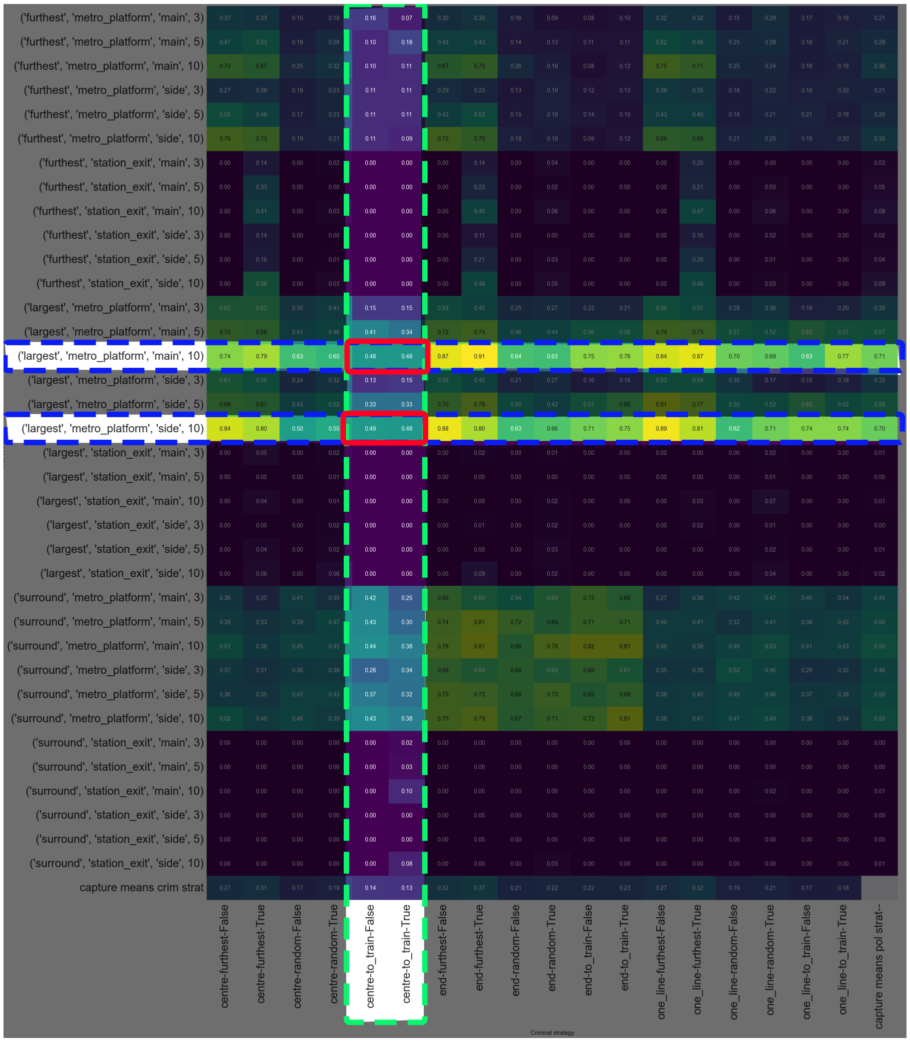
Pure-strategy Nash equilibrium is a concept in game theory that represents a stable state in a strategic interaction game of multiple players, where no participant has an incentive to independently change their strategy (Nash, 1950). Each player's strategy is optimal given the strategies chosen by the other participants. Meaning, that no player can improve their own outcome by changing their strategy, assuming the other player's strategy remains unchanged.

For a pure-strategy Nash equilibrium, it is assumed that both players will always play that strategy (Nash, 1950; Kreps, 1989). This can be found using the min-max strategy, which can be written as:

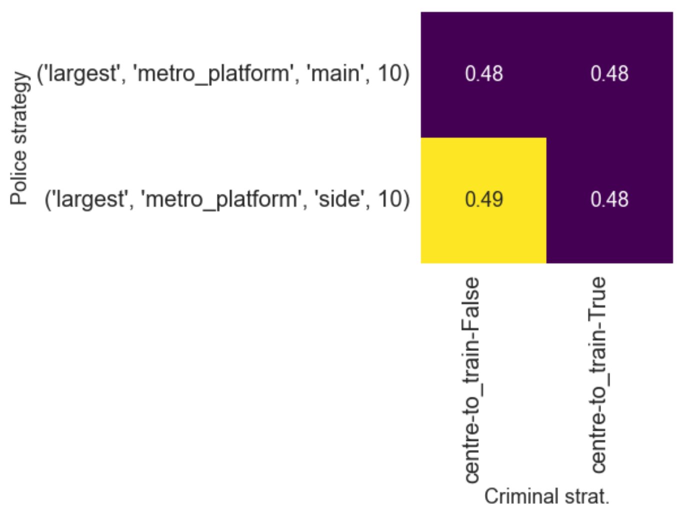
$$\max_{\mathbf{x}} \min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y} = \min_{\mathbf{y}} \max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y}$$

This equation states that in a two-player zero-sum game, the maximum payoff that one player can achieve by selecting a strategy (written as $\max_x$) is equal to the minimum payoff that the other player can ensure, given their choice of strategy (written as $\min_y$). Applied to the fugitive interception simulation model, x represents the strategy of the police, and y represents the offender strategy. A is the payoff matrix representing the capture chance associated with each combination of strategies. The left side of the equation focuses on the police's perspective, aiming to maximize their minimum payoff, while the right side focuses on the offender's perspective, aiming to minimize their maximum loss.

Applied to the matrix in Figure 8.4, the offender desires the lowest possible outcome, and the police the highest. The best-performing strategies for the offender are found in 8.8b. The police's best-performing strategies are identified in Figure 8.11b. Figure 8.12a highlights these strategies, where the blue boxes indicate the best-performing police strategies and the green boxes are the best-performing offender strategies. To check, when the offender employs their best strategies, the police cannot create a higher capture chance than when using the outlined strategies. Similarly, the offender cannot adopt another strategy to lower the capture chances the currently identified, when the police employ its best strategies. This means that the red boxed identify the pure-strategy Nash equilibra for the simulation model of experiment 1. At these points the mean capture value is 0.48 and 0.49, depicted in Figure 8.12b.



(a) Payoff matrix - highlighting best performing strategies for offender and police



(b) Nash equilibirum

Figure 8.12: Payoff matrix highlighting police behaviour: surveilling ‘station exits’ (experiment 1)

For the police, the most successful strategy is to guard metro platforms are large stations. For the offender, the most successful strategy is to start at a central metro station and attempt to transfer to a train station. However, Figure 8.12b identifies four equilibria. The reason for this is that the police's behaviour to guard main or side exits has an insignificant influence on the outcome. Therefore, the most successful strategy is shown for both guarding locations. Similarly, for the offender the effect of its initial mental state, rational or bounded rational, has a minimal effect on the capture chance. Therefore the best strategies for the offender are shown with both mental states. This means that varying between both insignificant variables for the police and offender a second, third and a fourth Nash equilibrium is found. The game will most likely be played around these points.

Table 8.4 shows the Nash equilibria for all experiments, along with strategies for both players.

Exp.	Nash eq.	Offender strategy					Police strategy				
		crim_pos	*crim_start*	*crim_bounded_rat*	*crim_bound_rat_time*	*crim_loose_goal*	*pol_strat*	*pol_guarding*	*Police_entrance*	*units*	*police_undercover*
1	0.48	centre	to train	True/ False	-	-	largest	metro plat.	main / side	10	-
2	0.43	centre	to train	True / False	3	True / False	largest	metro plat.	main / side	10	-
3	0.48	centre	to train	True / False	-	-	largest	metro plat.	main / side	10	True / False
4	0.47	centre	to train	True / False	5	True / False	largest	metro plat.	main / side	10	True / False

Table 8.4: Offender and police strategies for pure-strategy Nash equilibria across all experiments

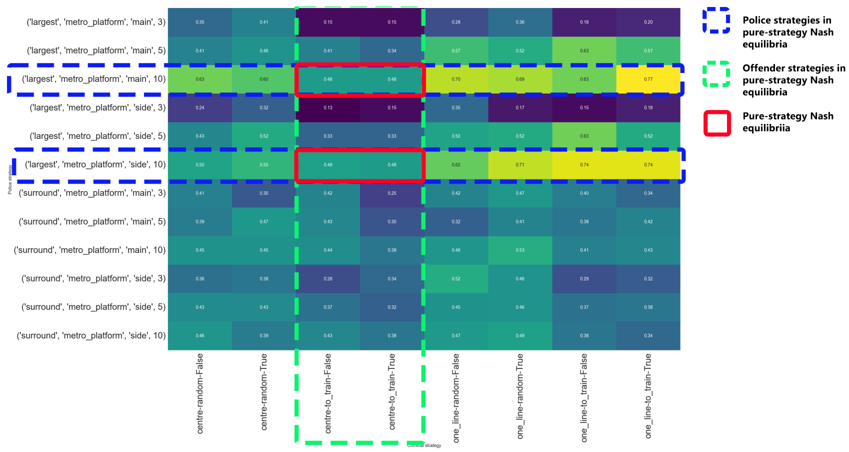
The table reveals that, for all experiments, the Nash equilibrium remains relatively consistent, with a value around 0.45. This means, that the offender and police almost have an equal chance of achieving their desired outcome at the pure-strategy Nash equilibrium across all experiments. However, in experiment 2, where only the offender can interact with information, the pure-strategy Nash equilibrium is 5% lower compared to experiment 1, where none of the players can interact with information. In contrast, experiment 3, where only the police can interact with information, shows a mean capture value identical to that of experiment 1. This suggests that when the offender can interact while the police cannot, the offender has a greater influence on the outcome than when only the police can interact.

Furthermore, across all Nash values, similar strategies are required. The only variable that varies is the *crim_bound_rat_time*. This implies that, regardless of the ability to interact with information, both the offender and the police should adopt the same strategy to reach a Nash equilibrium.

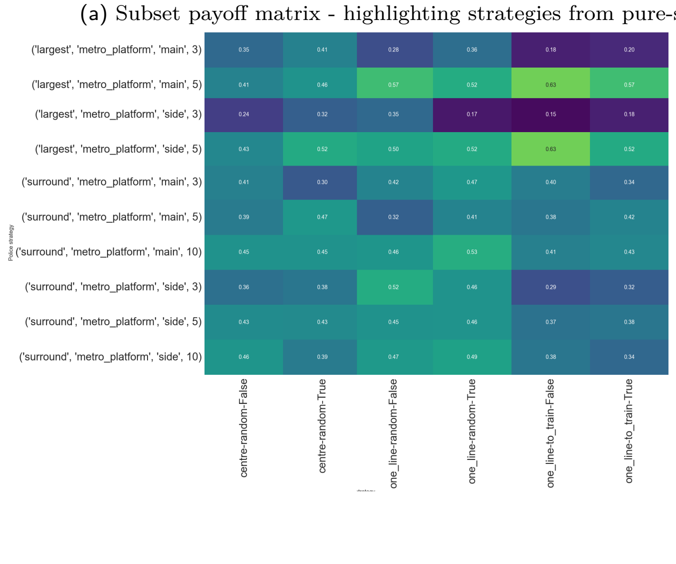
8.6.4 Mixed-strategy Nash equilibrium

To get a more nuanced analysis of strategic interactions in a fugitive interception scenario the strategies of the police and offender can be analyzed by finding mixed-strategy Nash equilibria. Mixed strategies refer to a probabilistic approach that players adopt when making decisions in a game. Unlike pure Nash equilibria, which involve a deterministic choice of actions, mixed-strategy Nash equilibria are when a player chooses multiple strategies with certain probabilities assigned to each (Nash, 1950). Thus, a player does not decide to commit exclusively to one particular action but instead selects multiple actions with certain probabilities. The purpose of this is to achieve the best possible result, considering the actions of other players (Kim and Kim, 1997). A mixed-strategy Nash equilibrium is a combined best strategy for the agents to play.

Section 8.6.3 found multiple pure-strategy Nash equilibria, which means that those strategies create the best payoff for both players when used on their own. However, there will be infinitely many mixed-strategy equilibria with the same game value. At these points an agent will mix the pure-strategy Nash strategies at proportion (p,1-p), where p is any probability between 0 and 1. However, it would be interesting to find what (combination) of strategies would be employed if the pure-strategy Nash strategies are not an option. To find mixed-strategy Nash equilibria with other strategies, the strategies from the pure-strategy Nash equilibria are removed. This is because strategies from the pure-strategy dominate the other strategies. No mixed-strategy Nash equilibria will be found if the dominating strategies are still included in the payoff matrix. They are found to lead to the highest payoff. Therefore, both the police and offender strategies are reduced to fewer options, excluding the strategies from the pure-strategy Nash equilibria identified in Section 8.6.3. This is done in Figure 8.13.



(a) Subset payoff matrix - highlighting strategies from pure-strategy Nash equilibria



(b) Subset payoff matrix A'- excluding strategies from pure-strategy Nash equilibria

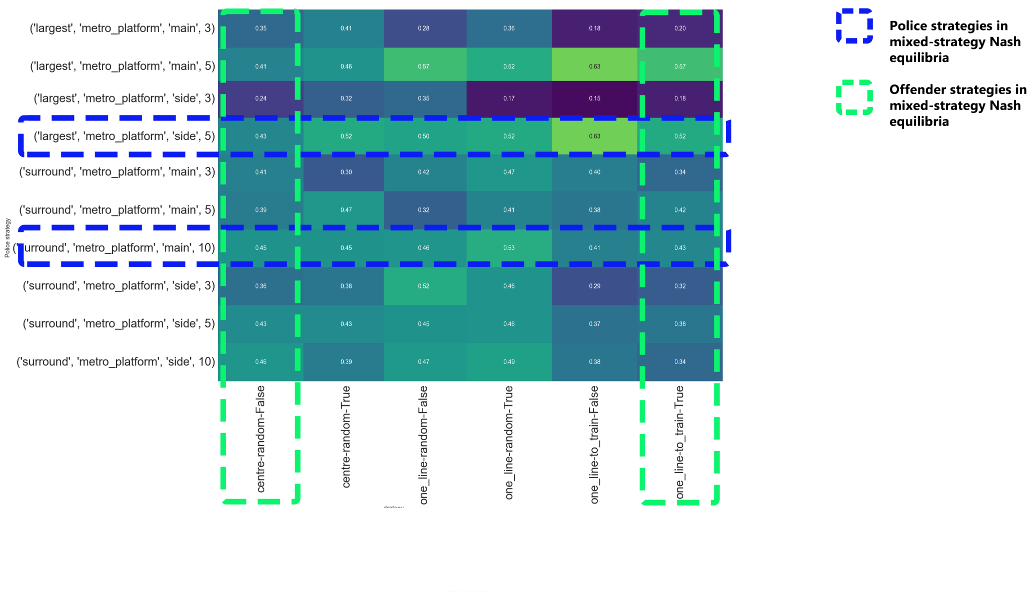
Figure 8.13: Subset payoff matrix A'

Similar to finding the pure-strategy Nash equilibrium, the mixed-strategy equilibria along with its probabilities can be found using this equation:

$$\min_{y \in \Delta_y} \max_{x \in \Delta_x} x^T A y = \max_{x \in \Delta_x} \min_{y \in \Delta_y} x^T A y$$

Added to the previous equation is the Δ. This refers to the set of all valid probability distributions, respective to x and y. The constraints $0 \leq x_i \leq 1$, $0 \leq y_i \leq 1$, $\sum_i x_i = 1$, and $\sum_j y_j = 1$ ensure that x and y are valid probability distributions, which combined do not exceed the value of 1.

Solving this equation to find the mixed-strategy Nash equilibria with a large matrix like matrix A' is difficult. Therefore, an external game-solving tool was used, which can be found here: https://www.math.ucla.edu/ tom/gamesolve.html. Figure 8.14a identifies the strategies that are part of the mixed-strategy Nash equilibrium for payoff matrix A'. Table 8.14b shows the probabilities with which each strategy should be employed. The mixed-strategy Nash equilibrium is at $(0, 0, 0, p, 0, 0, 1-p, 0, 0, 0)$ where $p = 0.18$ for the police and $(q, 0, 0, 0, 0, 1-q)$ where $q = 0.82$ for the offender.



(a) Identification of mixed-strategy Nash equilibrium

Player	Probability	Value of the game
Police (row)	(0,0,0,0.18,0,0,0.82,0,0,0)	0.45
Offender (column)	(0.82,0,0,0,0,0.18)	

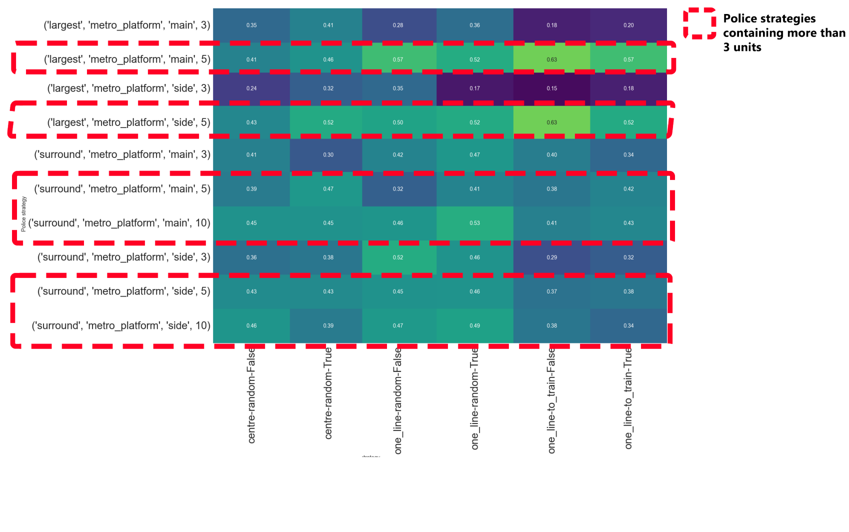
(b) Probabilities mixed-strategy Nash equilibrium

Figure 8.14: Mixed-strategy Nash equilibrium identification & probabilities payoff matrix A'

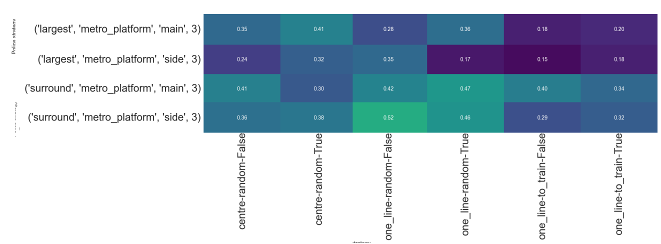
For both players, the mixed-strategy Nash equilibrium is made up out of combining two strategies. The police should surveil metro platforms, and side exits at large stations with 5 units with a probability of 0.18. For the remaining time, with a probability of 0.88, the police is best off guarding metro platforms at main exits at surrounding stations with 10 units. Interesting to see is that the first police strategy is part of the mixed-strategy Nash equilibrium, even though there are other strategies available in the matrix with more units. This emphasizes that finding accurate guarding stations for the police can be more useful in achieving capture than having more units available.

The offender is best off starting at central stations, with a random end goal and behaving rationally, with a probability of 0.82. The remainder of the time the offender should start at a metro station with one line, aim to transfer to a train network and behave bounded-rationally. Interestingly, where the pure-strategy Nash equilibria in Section 8.6.3 were made up of two almost identical strategies, the mixed-strategy Nash equilibrium for payoff matrix A' is made up of two completely different offender strategies.

Figure 8.14a shows that the police strategies containing 5 and 10 units were both part of the mixed strategies. When employing more units, the police can guard more locations thereby increasing the capture chance. However, it would be interesting to see which strategies prove to be most successful when all strategies have the same number of units available. Figure 8.15a highlights the strategies in which more than 3 units are used. Figure 8.15b removes these strategies, showing the remaining strategies in which police only have 3 units available, creating payoff matrix A". For the offender, the same strategies are included in the matrix.



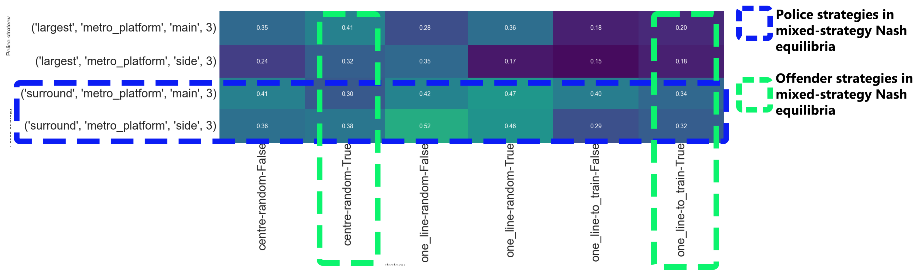
(a) Subset payoff matrix A' highlighting strategies with more than 3 police units



(b) Subset payoff matrix A" with more than 3 police units

Figure 8.15: Subset payoff matrix A"

Figure 8.16a identifies strategies that are part of the mixed-strategy Nash equilibrium for matrix A". Table 8.16b shows the probabilities with which each strategy should be employed. The mixed-strategy Nash equilibrium is at $(0, 0, p, 1-p)$ where $p = 0.67$ for the police and $(0, q, 0, 0, 0, 1-q)$ where $q = 0.22$ for the offender.



(a) Identification of mixed-strategy Nash equilibrium

Player	**Probability**	**Value of the game**
Police (row)	(0,0,0.67,0.33)	0.33
Offender (column)	(0,0.22,0,0,0,0.78)	

(b) Probabilities mixed strategies

Figure 8.16: Mixed-strategy Nash equilibrium identification & probabilities payoff matrix A"

For both players, the mixed-strategy Nash equilibrium of matrix A" consists of two strategies. For the police, both strategies involve guarding surrounding stations, and metro platforms and have 3 units. The difference in the strategies lies in guarding main or side exits. The police are best off guarding main exits at surrounding stations with a probability of 0.67. The remainder of the time, the police should guard side exits. Interestingly, both Nash equilibria found in Section 8.6.3 contained police strategies that guarded large stations, rather than surrounding stations.

For the offender, the strategies for the mixed-strategy Nash equilibrium of matrix A" vary between starting in the centre, with a random goal and behaving bounded-rationally, and starting at a metro station with only one line, transferring to the train network, also behaving bounded rationally. The first strategy should be adopted with a probability of 0.22, and the latter with probability 0.78. Notable, both strategies contain bounded-rational behavior, whereas the ones in Section 8.6.3 showed to have no different outcome based on rationality. This is explainable by the fact that when the offender initially behave bounded-rationally, they are more sensitive crowd flows. They will more frequently diverge from their path based on how busy the station is. When the police only have 3 units available, offenders who frequently change their path are less predictable and are more likely to outmaneuver the police. When more units are available, more stations will be guarded, and therefore a change in the offender's path has a higher likelihood of crossing paths with another police unit, than when there are a total of 3 units.

The value of the game for matrix A" is 0.33, which is significantly lower than that in Table 8.14b where the game value is 0.45. This is attributed to the number of units. The mixed strategies leading to a game value of 0.45 capture chance include 5 and 10 units. Whereas the strategies leading to a game value of 0.33 capture chance both have 3 units available. This shows that the more units available, the higher the capture chance. This is explained by the fact that when more units are available, more stations can be guarded and therefore the interception chance increases. With fewer units, the police can guard fewer stations. This means that the locations where the police guard must be more carefully chosen.

8.6.5 Interaction with information

For this Section the matrices of the different experiments are compared; analyzing the effect information can have on the strategies; and therefore capture the chances of both agents. First, the mean capture across all experiments is shown in Table 8.5. Important to be aware is that this table combines the capture values for all scenarios across the experiment, meaning that all strategies and uncertainties are included and also varied in this number.

Experiment	**μ capture**	**σ capture**	**μ time (min)**	**σtime**
Exp 1	0.23	0.42	33.06	21.95
Exp 2	0.22	0.42	32.93	22.01
Exp 3	0.23	0.42	33.03	22.00
Exp 4	0.23	0.42	32.90	21.89

Table 8.5: Mean (μ) and standard deviation (σ) output for all experiments

This table shows that across all experiments the capture value is the same on average. This implies that interaction with information does not affect the capture chance in a fugitive interception scenario. To further investigate Table 8.6 and Table 8.7 show the interaction variables in relation to the capture rate for scenario 4 for the offender and police respectively.

Frequency diverged from path	**Mean capture**
0	0.23
1	0.49
2	0.18
3	0.30
4	0.16
5	0.26
6	0.23
7	0.56
8	0.42
9	0.04
10	0.11
11	0.17
12	0.00
13	0.00
15	1.00
23	1.00

(a) Offender diverged from path vs. capture

Frequency seen police	**Mean capture**
0	0.22
1	0.41
2	0.30
3	0.34
4	0.21
5	0.27
6	0.25
7	1.00
9	1.00

(b) Offender seen police vs. capture

Table 8.6: Interaction variables for offender experiment 4

Table 8.6 shows that for both interaction variables and increase does not necessarily relate to a decrease in capture chance. Diverging from the path can lead to higher escape chances, however, with frequent diverging this is not guaranteed. Whereas scenarios where the offender diverged 12 or 13 times lead to a capture chance of 0.00, scenarios where the offender diverged 15 or 15 times, the capture was 1. Similarly, when the offender saw the police more than 6 times, the capture rate was 1. This means that, in the case where the offender seems to be surrounded by the police, where the police detection is high and consequently the divergence is also high, the capture chance increases.

Frequency changed goal	**Mean capture**
0	0.22
0.0	0.26
1.0	0.23
2.0	0.19
3.0	0.20
4.0	0.13
5.0	0.15
6.0	0.15
7.0	0.15
8.0	0.10
9.0	0.09
10.0	0.09
11.0	0.05
12.0	0.11
13.0	0.09
14.0	0.13
15.0	0.11
16.0	0.10
17.0	0.13
18.0	0.12
19.0	0.19
20.0	0.16
21.0	0.23
22.0	0.00
24.0	0.14
25.0	0.00
26.0	0.16
27.0	0.00

(a) Frequency police changed goal vs. capture

Gone undercover	**Mean capture**
False	0.23
True	0.29

(b) Gone undercover vs. capture

Table 8.7: Interaction variables for police experiment 4

Similar to the trend observed for offenders, Table 8.7a reveals a counter-intuitive relationship between the frequency of police goal changes and the mean capture chance. In general, an increased frequency of police goal changes is associated with a lower capture chance. However, when the police alter their strategy to go undercover during the simulation model, the capture chance increases.

Furthermore, when comparing the matrix in Figure 8.4 to the matrix for experiment 4 (found in Appendix M, Figure M.4) a pronounced similar pattern can be seen across the combinations of strategies. However, upon visualizing the data through a heatmap, four distinct combinations of strategies stand out.

First, the strategy where police surveil metro platforms at large stations, equipped with 10 units and operating undercover, has a mean capture value of 35% across all offender strategies. However, when combined with a specific offender strategy the mean capture chance decreases to 0. In this strategy, the offender starts its escape at a metro end station, aims for the furthest station, is in panic, and can modify its desired end goal. Surprising is that in this situation the police guard the metro platform, which was previously found to be the most effective variable in achieving a capture, its effect here seems to have decreased.

Second, the scenario where the police are stationed at distant metro stations, surveil the metro platform, are equipped with 10 units, and operate undercover. Combined with an offender who starts at a metro station with a single line and aims to transfer to the train network, the capture chance is 80%. However, under this specific police strategy, the offender significantly reduces its capture chance to approximately 30% when are in panic and are willing to alter its end goal.

Third, in the situation where the offender starts at a metro station with one line, wants to go to a far-end station, is not in panic and is willing to alter their desired end goal, the average capture rate is 25%. The capture rate is lowest when the police also aim for a far station and guard the main station exits, where it decreased to roughly 0%. However, if the police combined this behaviour with having 10 police units at its disposal and being undercover, they can increase the capture changes to 41%.

Finally, the police strategy where they surround the offender, guard the side exits and have 10 units, has an average capture rate of 1% across all offender strategies. However, in combination with a specific offender strategy its capture chance increased so 56%. For this to take place the offender must start at an end location, desire to transfer to a train network, be in panic and not be able to change its end destination.

These outliers in the data imply that the effectiveness of strategies are context-dependent, and their efficacy may vary under different circumstances and combinations for the other player's strategies.

8.7 Uncertainty analysis

Uncertainty analysis is a critical component of scientific research, as it involves the assessment and quantification of the uncertainties in the model on output (Kwakkel, 2017). It measures the variation in the model's output resulting from the modeler's incomplete knowledge or misrepresentation of the model (Cariboni et al., 2007). This paper uses statistical quantities to identify the changes in output that is caused by a variability in input (Geffray et al., 2019).

This fugitive interception simulation model considers five distinct uncertainties within its framework. To explore the impact of these uncertainties across various scenarios, a full factorial design is used which systematically varies each uncertainty. Table 8.8 shows the analysis of how these variations in uncertainties influence the model's outcomes using the mean (μ), standard deviation (σ) and covariance (Cov) (Geffray et al., 2019). For the uncertainty analysis of all experiments see Appendix N.

8.8 Experiment 4: full interaction

Table 8.8: Mean (μ), standard deviation (σ), and covariance (Cov) for uncertainty variables vs. output capture and time (experiment 4)

Uncertainty	Value	μ capture	σ capture	Cov capture	μ time	σ time	Cov time
Offender detection at station exit	50	0.21	0.41	0.22	32.90	21.88	0.04
	70	0.23	0.42		32.88	21.87	
	90	0.24	0.43		32.90	21.90	
Offender detection at metro platform	50	0.20	0.40	0.39	33.55	21.89	-8.64
	70	0.23	0.42		32.86	21.88	
	90	0.26	0.44		32.26	21.87	
Initial call delay	1	0.28	0.45	-0.09	29.97	22.73	4.95
	3	0.23	0.42		32.82	21.747	
	6	0.17	0.38		35.89	20.73	
Police detection by Offender	50	0.23	0.42	-0.01	32.91	22.89	-0.32
	70	0.23	0.42		32.91	21.90	
	90	0.23	0.42		32.86	21.85	
Frequency information update	1	0.23	0.42	0.00	32.88	21.85	-0.32
	3	0.23	0.42		32.88	21.88	
	6	0.23	0.42		32.91	21.88	
	10	0.23	0.42		32.89	21.92	

Increasing the percentage of offender detection at the station exit generally results in higher mean captures. With an increase from 50% to 90% detection at station exit, the mean capture value only increases with 3%, indicating that changes in this uncertainty have a minimal effect on output capture. Similar to the station exit, higher percentages of offender detection at the metro platform lead to higher mean captures. The mean capture values increase by 6% as the detection rate rises by 40%. The initial call delay appears to have the largest effect on the mean capture value. Where a delay of 5 minutes leads to a decrease in 11% capture chances. This, combined with the findings from Figure 8.3, indicate that time plays an important role in an interception with the offender. The faster the police start the interception scenario, the higher the capture chances. The remaining uncertainties have a negligible influence on output. Additionally, it can be seen that the effect on the mean time value is also minimal with varying uncertainties. The reason behind this is that most likely each scenario, regardless of its uncertainties, can have a run where capture happens after ca. 200 minutes. This increases the average simulation time, due to which no significant conclusions can be drawn from the effect of uncertainties on time.

The figure presented below has identified the scenarios based on their unique combinations of uncertainties. This enables the observation of whether distinct combinations of uncertainties result in different behavioural patterns of model output. Large changes in behaviour across different sets of uncertainties could indicate intricate relationships and dependencies within the model uncertainties.

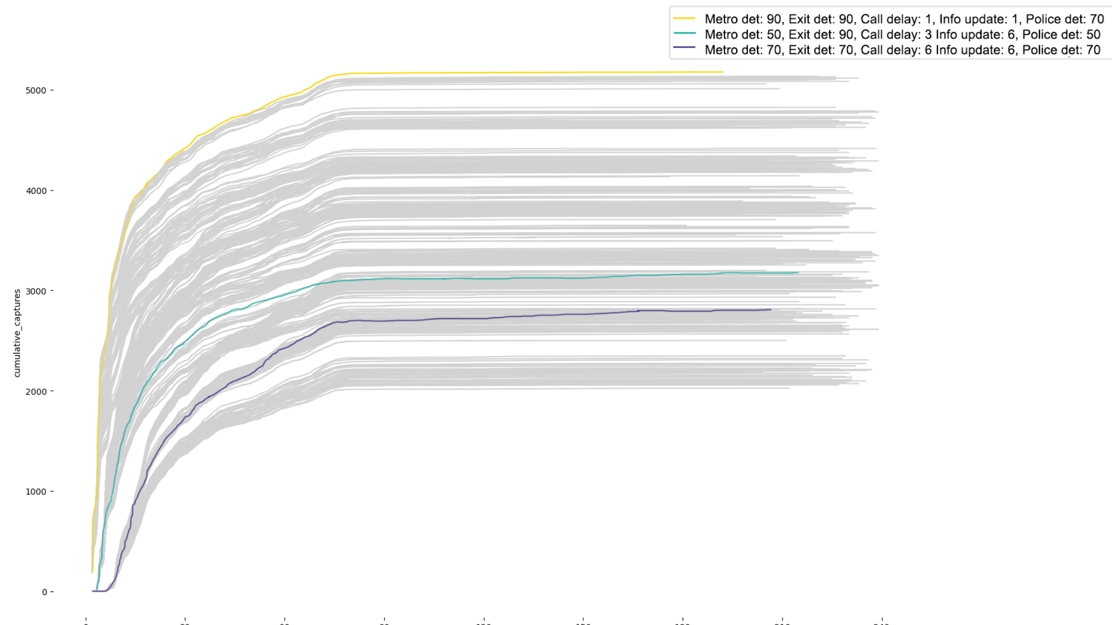


Figure 8.17: Effect of uncertainties on output variables (experiment 4)

In the figure we see that all scenarios show the same behavioural pattern, where the first 45 minutes matter the most for capture, after which the captures reach a steady state. The effect of the initial delay time can be seen throughout all runs. In the scenarios where the delay time is smallest, the captures increase the quickest leading to the highest cumulative captures. Where the delay time is larger, the capture value decreases. Upon close inspection, within the groups that represent the unique call delay times, subgroups can be seen. Each delay time appears to be split up into three parts. This is the difference in values for the uncertainty that the offender is detected at the metro platform, which influences the output the second most as seen in 8.8. Overall, it can be concluded that the combined uncertainties have a great effect on the capture value, more than on output time. However, each uncertainty does not lead to structural model output differences, which indicates that the leading variables for determining output are the input variables.

9 Discussion

9.1 Offender strategies

For the offender, the most crucial variable for ensuring a desired outcome is its selection of an end goal. The second most important feature is the offender's starting position, whose feature importance is 50% smaller, found in Section 8.2. This suggests that the success of the offender is primarily dependent on the choice of route rather than on their behaviour along the way. The simulation model assumes a predefined route, coupled with predefined behaviour. However, in reality, route choice is influenced by behavioural aspects such as rationality, emotional state, and long-term goals of the offender (Tutuarima, 2023).

The offender can choose between three goals: a random goal, a train station, or getting as far away as possible. The matrix in figure 8.5a identified that the strategies in which the offender desires to go to far stations are always outperformed by strategies with other end goals. This can be explained by the guarding stations of the police for two reasons. First, the path the offender needs to travel to get to a far goal crosses potential guarding stations of the police. Namely, for most offender starting positions, the furthest end station is on the other side of the city. This means that the offender must travel through the city centre. If this is combined with the police guarding large metro stations, the offender will most likely pass a station that the police guards. Figure 9.1 shows large stations, with 3 or more metro lines that the police can guard. Evident is that all those stations lie central in the Rotterdam metro network. Meaning that if the offender needs to cross the city to get to a far goal, the police has a high chance of intercepting them if they guard a large metro station.

Figure 9.1: Large metro stations

Second, if the police guard far locations, it is probable that those specific stations are the same as the desired end goal of the offender when they also have a far end goal. If this is the case, this means that the offender is aiming to exit the metro network through the station that the police are guarding. This increases the capture chance. Thus, when the offender aims to go to a far goal, it risks unintentionally traveling toward the police. Either because the police are located at metro stations the offender will pass, or because the offender and police have the same desired end goal. Since two out of three guarding locations for the police lead to a higher capture chance when the offender aims to go to a far goal, it can be assumed that the offender will never employ such strategies.

The two dominant offender strategies found in Figure 8.12b are starting at a central metro station and aiming to transfer to a train network, regardless of the initial mental state. The combination of the starting route and the desired location typically results in a relatively shorter path, given that transfers to the train network are in and around the city center, shown in figure 9.2. This means that the criminal will prefer to take short routes, and attempt to get away from the streets as soon as possible.

Figure 9.2: Metro stations with train connection

Another noteworthy strategy is when the offender starts at an end station. This strategy performs relatively similar to strategies with another starting position, except for when the police guard surrounding metro stations. When this is the case, the capture chance significantly increases. This is can be explained by the fact that when the offender starts at an end station, the surrounding stations are limited. Each end station can only be reached by one metro line. This means that when the police attempt to surround the offender, it has fewer options than when the offender starts at central metro stations with lines in multiple directions. This increases the chances that the offender will pass the same stations that the police guard, thereby increasing the capture rate. Thus, as starting at an end station limits the offender's escape route to one single metro line, they will most likely not start its escape at an end station.

Finally, the matrix reemphasized that the initial mental state of the offender does not have a significant impact on the output. When the offender acts rationally, it is not influenced by external factors. When the offender behaves bounded-rationally, the model is designed in such a way that the offender is affected by crowd flows. In a panic state, the offender may exit or board metros even if the direction is incorrect, as long as it means avoiding an empty platform or an empty train. During this behaviour the offender wants to blend into the crowd; thereby attempting to prevent recognition by the police. Table 9.1 shows the number of times the offender has diverged from its path due to panic, along with the mean capture value for those scenarios. This table implies that the offender's behaviour in following the crowd does not have a direct effect on successfully evading the police. This means that the outcome of a fugitive interception project is not dependent on the rational state of the offender.

Table 9.1: Frequency the offender diverged from its path vs. mean capture (experiment 1)

Frequency diverged	**Mean capture**
0	0.23
1	0.43
2	0.18
3	0.31
4	0.18
5	0.25
6	0.17
7	0.14
8	0.33
9	0.00
10	0.00
14	0.00

9.2 Police strategies

The feature importances in Section 8.2 showed that *pol_guarding* is consistently 500% more important than the next most important feature across all experiments. This means that the outcome of the experiments is heavily dependent on the police's guarding location.

Additionally, when analyzing the police strategies in Figure 8.4, the horizontal pattern emphasized the importance of the guarding location. It showed that capture chances significantly increase when the police guard metro platforms rather than metro stations. This difference can be attributed to the underlying model structure. When an offender passes a metro station, the police have no opportunity to intercept the offender if they are stationed at the station exits. However, if the police are surveilling the metro platforms, the model allows the police to detect the offender in a stationed metro carriage regardless of whether the offender will exit at that location. This means that, when the police are located at the station exits, they can only intercept an offender if the offender uses the station exits. Meaning the station must be the offender's end goal. If the police is located at the metro platform, they can intercept offenders regardless of their final end goal.

Once the police are located at the metro platform, the strategies in which the police surveil far stations prove to be outperformed consistently. When surveilling far stations, the police limit their interception chances as offenders are unlikely to pass far stations during their escape unless it is the offender's intended destination. The model assumes offenders take the most efficient route to their end goal, as discussed in Appendix H. Consequently, if the police guard far stations, they only have a chance of intercepting offenders with the specific goal of reaching a far station. Offenders have three potential goals; random, transferring to a train network, or reaching a far station. Thus, if the police decide to guard far stations, they restrict their capture opportunities to 33% of offender strategies, making this strategy less favorable. In contrast, the strategy in which the police guard large stations, the chance that the offender passes this station increases, shown in Figure 9.1.

To further highlight the importance of goal selection the base case can be used to compare the mean capture value. Table 9.2 shows the capture chance for each police goal selection, based on the offender's goal selection method. Table 9.2a show that when the offender chooses a random goal, the base case has the highest capture rate. This suggests that when the police randomly select a station to surveil, the capture rate increases compared to when the police choose one of the predefined strategies. This is only measured for the scenarios in which the offender also has a random end goal. This outcome can be explained by two reasons. First, it confirms that when the offender and police share the same goal selection, the capture chance increases. This is most likely due to the higher chance that they share the same end station. Second, when the police have a predefined type of goal in mind, all other metro stations that do not qualify as such are neglected and not guarded. However, when the police randomly select its goal, all stations are considered, evidently increasing the chances of interception. This means that when the offender also has a random goal selection, the furthest, largest, and surrounding police strategies do not cover potential intersection points or ending stations. This underscores the importance for the police to position themselves at potential intersection points along the offender's path rather than aiming to capture offenders at their final destinations.

Police end goal	**μ capture**
Base (random)	0.38
Furthest	0.11
Largest	0.24
Surround	0.26

(a) Mean (μ) capture per police end goal when *crim_strat* is 'random'

Police end goal	**μ capture**
-	-
Furthest	0.32
Largest	0.36
Surround	0.25

(b) Mean (μ) capture per police end goal when *crim_strat* is 'furthest'

Police end goal	**μ capture**
-	-
Furthest	0.07
Largest	0.22
Surround	0.24

(c) Mean (μ) capture per police end goal when *crim_strat* is 'to_train'

Table 9.2: Mean (μ) capture for police end goal vs. *crim_strat* (experiment 1)

A noteworthy strategy to discuss is the strategy in which the police guards surrounding metro stations. This strategy shows dependency on offender behaviour. The surrounding strategy consistently performs best when the offender starts at an end goal. However, with other offender starting locations its success decreases. When the offender starts at an end station, its potential next metro stations is limited, which increases the chances that the police can locate the offender. In this case, quickly attempting to surround the offender decreases the dynamic capture circle, which increases the capture chance. This means that, if the fugitive interception scenario starts at an end goal, the police are best off guarding surrounding stations.

If the offender starts at another location; in the centre or at a metro station with one line, the police is best off surveiling metro platforms at large stations. This strategy shows least dependency on the offender's strategy. Additionally, it increases the chances of a crossing with the offender as the offender is most likely to pass large stations, shown in Figure 9.1.

Furthermore, Figure 8.4 showed that the number of units also has an on the capture rate. Table 9.3 shows the mean capture value for each strategy, per *units* value. The table indicates that the mean capture value can increase by 40% for certain strategies when 10 units are deployed, compared to using 3 units. This is logically explainable by the fact that with more policemen on surveillance duty, a greater number of platforms or exits are guarded, consequently increasing the interception chance with the offender. However, simply dispatching more police units to an interception situation also means having fewer policemen available on the street to handle other spontaneous events and more operational costs. Therefore, this paper underscores the importance for the police to strategically position officers and assess situations where deploying more policemen would be advantageous.

Table 9.3: Mean capture chance per police strategy per number of units (experiment 1)

Variable value			**Units**		
pol_strat	*pol_guarding*	*Police_entrance*	*Units* = 3	*Units* = 5	*Units* = 10
Furthest	Metro platform	Main	0.21	0.28	0.36
Furthest	Metro platform	Side	0.21	0.26	0.35
Furthest	Station exit	Main	0.03	0.05	0.08
Furthest	Station exit	Side	0.02	0.02	0.09
Largest	Metro platform	Main	0.35	0.57	0.71
Largest	Metro platform	Side	0.31	0.58	0.70
Largest	Station exit	Main	0.01	0.00	0.01
Largest	Station exit	Side	0.00	0.01	0.02
Surround	Metro platform	Main	0.45	0.50	0.55
Surround	Metro platform	Side	0.46	0.53	0.55
Surround	Station exit	Main	0.00	0.00	0.01
Surround	Station exit	Side	0.00	0.00	0.01

9.3 Importance of time

The parallel plot for police behaviour revealed a negative relationship between the output variables time and capture. This aligns with information obtained from the police, who use dynamic capture circles to estimate where the offender could be. The more time passes, the further the offender could have gotten and the larger the dynamic capture circle. This underscores the importance of quick action by the police, as time significantly influences the chances of a successful capture, supporting Weisburd's (2021) findings. Figure 8.3b showed that a primary indication of the capture chance is determined but the time it takes for the police to receive a phone call about the incident. The faster the phone call, the faster the police could surveil metros. Even though the police do not directly influence on the initial call time, they can use the information about the delay to its advantage. Knowing that the crime has taken place recently means that the offender is closer than if more time has passed between the crime and the initial call. On this, the police can base its decision as to which metro stations to surveil.

Contrasting, there is no such relationship between capture and time for offender behaviour. This can be explained by considering the police's rationale mentioned earlier. The further the offender travels, the more uncertain their location becomes for the police, consequently decreasing the capture chance. This implies that similarly to the opposing objectives of the police and the offender in aiming for capture or escape, they also hold opposing objectives concerning time. As more time passes the more likely an escape.

9.4 Interaction with information

Tables 8.6 and 8.7, in combination with the comparison of matrices in Appendix M, show that the ability to interact with information does not significantly impact the success of strategies employed by either agent. This observation can be attributed to the modeling of the capture dynamics: if the police are in the neighborhood, a capture is likely, and if the police is not close to the offender, a capture is unlikely, regardless of changes in behaviour. Explained, when the police changes goals, it does so in accordance with its predefined strategy. For instance, if the police's strategy involves guarding far stations and it determines that the offender is moving in the opposite direction, it will select a new far station to guard. This logic applies to other strategies as well. Consequently, if the police's initial strategy is ineffective, a change in location is also unlikely to yield success. For example, if the offender has chosen a train station as end destination, the police will never intersect with the offender if it continue to guard far stations. Regardless of how many far stations the police cover, the offender will never get to a far station, thus never risking capture.

This result that interaction has a limited effect on the capture chance can seem counter-intuitive. It could be expected that when the police have more information about the whereabouts of the offender, their chances in a successful capture would increase. This can be explained using the flow diagrams for the agents in Appendix F. These diagrams illustrate that interactions do not alter the fundamental structure of agent behaviour but introduce specific elements. This implies that both offender and police behaviour in the model is predefined and not greatly influenced by interactions.

9.5 Nash equilibria

In the payoff matrix containing all strategies, pure-strategy Nash equilibria were found. This is where the game will most likely be played, as both the police and offender have one strategy that maximizes their desired outcome. There will be infinitely many mixed-strategy Nash equilibria with those strategies. However, when looking at sub-matrices other mixed-strategy Nash equilibria exist. Mixed strategies serve as a tool for strategic optimization, offering players the flexibility to adapt to evolving game dynamics and outmaneuver their opponents. The importance lies in their capacity to introduce probabilities to strategies that, when combined, maximize the players' chances of success in a fugitive interception scenario. For matrix A and A' from Section 8.6.4, both mixed-strategy Nash equilibria were made up of two police strategies. Combining two strategies is simple to adopt, and is advised to do. However, with different combinations of strategies available, other mixed-strategy Nash equilibria will be found.

In the fugitive interception project of this scope, both the police and offender have strategies that perform best when all strategies are considered. However, they remain highly dependent on the strategy of the opposing player. When the police only have 5 and 10 units available, guarding 'large' stations is most successful. When the police is limits to 3 units, 'surrounding' strategies where proven to be most successful. This can be explained by the method of the surrounding strategy. When guarding surrounding stations, the police try to enclose the offender, thereby maintaining a small dynamic capture circle. The idea is that the offender will not have been able to travel far by the time the police guard surrounding stations, thereby increasing the interception chance. Thus, when only 3 units are available, surrounding the offender decreases the possibility of the offender having traveled many stations, and therefore decreases the potential stations the offender could be at.

While the police's strategy changes, so do the offender's strategies. For example, the offender's rationality state leading to success depends on the number of units. When many police units are part of the interception, the offender is best off behaving rationally; thus not altering their behaviour on external factors such as crowds or the sight of the police. When the police have fewer units available, the offender is best off altering its path according to such factors.

However, important to note is that the model currently assumes that all police units do the same. To assign different strategies to the units within one run, the model must be altered. This is further elaborated in Section 10.7.

9.6 Validation of results

Van Horn (1971) describes the act of validation in simulation as the process of making sure that the conclusions drawn from a simulated process are accurate for the system. It provides evidence that the model is an accurate representation of reality. The model's focus is highly specific, examining police and offender strategies in the Rotterdam metro network. While initial behaviours were validated by the police, validating the model's output proved challenging. The police (Appendix B), highlighted the model's significance for them, which could offer an analytical approach to understanding offender behaviour and developing robust police strategies.

First, the police confirmed the model outputs's emphasis on the importance of time. Fast responses, triggered by a quick initial call, increase the chances of success. This understanding is shared among police officers, underscoring the collective effort towards quick responses to incidents. However, validating the simulation results poses a challenge, given the significant role cameras play in real fugitive interception scenarios, which are not included in the simulation model.

The model's implication that certain strategies tend to perform better underscores the significance of proper education of proven robust strategies. Currently, police actions are based on intuition and habit, which could lead to suboptimal strategies if officers are accustomed to less effective behaviour. Moreover, the lack of identified or statistically analyzed strategies within the police further complicates the model's validation. Especially since the model only captures a fraction of the factors involved in real fugitive interceptions.

9.7 Uncertainty analysis

Table 8.8 showed expected effects of variations in uncertainties on output capture. When analysing the mean capture time, it must be kept in mind that for most scenarios some runs end after 2 hours, as seen in 8.17, which increases the mean time value. To get a better understanding of the effect of uncertainties on time the analysis could be redone using the time value where 90% of the runs within a scenario have reached their game time.

Important to highlight are the higher standard deviation values, indicating significant variability in the dataset. This makes it challenging to distinguish whether alterations in one variable directly impact the other, as the variability may be influenced by factors beyond the two variables under consideration. In Table 8.8, the effects of the uncertainties are calculated by grouping the dataset based on the unique values of the uncertainties. This approach is done because assigning constant values to other variables is difficult, aligning with Lempert et al.'s (2003) definition of deep uncertainty. In cases of deep uncertainty, there is uncertainty about probability distributions for important factors. Consequently, variations in other variables are incorporated into the calculations.

A consequence of the high standard deviation is the difficulty in interpreting the covariance. High covariance might indicate a relationship, but due to the high standard deviation the source of variability cannot be limited to that of the relevant uncertainty value. Consequently, no conclusions can be drawn from the covariance, as it could be influenced by unrelated factors.

9.8 Implication of results

This paper attempts to find robust strategies for the police and offender during a figutive interception situation. To do this accurately, a high understanding about offender and police behaviour is required, which can result in realistic input strategies for the model. As this model does has a maximum of five behavioural characterestics for the police and the offender, in combination with the fact that it does not include important realistic factors such as camera footage and the ability to stop metros from moving (Appendix B), the findings of this study are difficult to interpret.

The model emphasizes the significance of time in a fugitive interception scenario. The faster the police can respond, the higher the chance of a successful capture. While the time it takes for the initial phone call to occur is crucial, there are additional factors affecting speed (Appendix B). For instance, the time it takes for the control room to process information about the crime is also important. If the control room can ask targeted questions that immediately provide essential information, it can significantly reduce the police response time. Additionally, the location of police units on the streets plays a role. In this simulation model, police units start at police stations, but in reality, they drive around in the city. If there is an effective distribution of police units across the city, they will reach all corners more quickly, regardless of their assigned guarding locations.

Currently, Rotterdam is equipped with numerous cameras, and the police captures almost 33% of offenders are on camera (Appendix B). However, not even close to the majority of them are captured. This indicates that a successful capture involves more than just the use of camera footage. This knowledge, in combination with this study's findings, that some strategies overall work better than others, can be used to enhance the relative capture chance. Ideally, police strategies are made through the interaction between camera usage, police intuition, and proven robust strategies. This is of practical relevance as it underscores the need for collaboration between technology and experience. As a result, uncertainties in models like this one can be limited, providing more accurate outcomes.

Finally, because we live in a state governed by the rule of law, the police must always be able to justify their actions. In case of accidents, acting on intuition is not a sufficient defense. When the police employ data-based strategies, assumptions and actions can be explained. This can play a crucial role, particularly in preventing ethnic profiling and ensuring the objectivity of the police. Embracing data-driven approaches to enhance transparency and accountability, ultimately contributing to fair and unbiased police strategies, is essential.

9.9 Limitations of study

In this section the five main limitations of the simulation model of this study are discussed. Next, the limitation os the simulation method and game theory analysis are discussed. For the entire list of limitations see Appendix H, Figure H.2.

9.9.1 Limitations of fugitive interception simulation model

The first limitation is the way in which the city of Rotterdam is set up in the simulation. The existing metro stations and police stations in Rotterdam serve as nodes, connected by edges. The edges define the paths that both the metro and the police can take to travel between different points. Consequently, the police follow the same routes as the metro, excluding realistic factors such as traffic conditions and for example shortcuts. Furthermore, in the simulation, the police travel at a constant speed of 50 km/h, and the duration of their journey to a destination is calculated by dividing the length of the edge by the average speed . This simplification disregards real-world scenarios where law enforcement vehicles may utilize higher speeds, activate emergency lights, or suffer from delays due to traffic. Thus, this simplified network in combination with the exclusion of factors affect travel times greatly influences the capture in a fugitive interception project.

A second limitation of this study is the absence of hard data during design and construction phase of the simulation model (Peters and Westelaken, 2014. Consequently, the model relies on information derived from interviews, literature, assumptions, estimations, and interpretations. This introduces model bias, influenced by both the perspectives of the interviewees and the modeler. The assumptions made for the simulation model can be found in Appendix H, Figure H.1. Furthermore, the data and experiences discussed during interviews are primarily drawn from situations where the offender was apprehended. In scenarios where the offender successfully evaded capture, the police often lack information about the fugitive's whereabouts, as their escape strategy remains unknown. This (mainly) one sided knowledge is another source for the modeler bias. It would be valuable to explore strategies that generally lead to escapes, which the police may not be aware of.

A limitation arising from the absence of hard data is the manner in which both offender and police behaviour are modeled. Each agent is assigned a set of behavioural variables, identified as important in literature and interviews. However, real-life offender behaviour is complex and only predictable to a certain extent (Tutuarima, 2023, A. Kalai and E. Kalai, 2010, Jagadeesan et al., 2020, Sooknanan and Seemungal, 2023, Shepherd and Purcell, 2015). This study incorporates only a limited number of behavioural factors that influence the escape and capture plan. In reality, this process is much more elaborate and consists of numerous additional factors that could result in significant strategy variations than this model includes.

In addition to the assumptions about agent behaviour, it is presumed that all players head to predefined destinations. While the police are limited to guarding distant, large, and surrounding stations, offenders have the option to choose far, random, and train stations. Noteworthy, this assumption lacks real-life data about frequently chosen end locations. Furthermore, the police know that offenders also frequently escape to safe houses (Appendix B) to hide after committing a crime until the police redirect their attention elsewhere. The (estimated) existence and locations of these safe houses are not taken into account in the model, although their inclusion could provide valuable insights into how offenders strategize their escape routes.

Next, as previously discussed in this paper, the absence of the role of cameras in this simulatoin game. In reality, the police heavily rely on information obtained through camera footage for their strategies. This means that real life police strategies are, to a large extent, dependent on the insights provided by cameras. However, this study excludes this crucial factor, emphasizing instead the predefined behaviour of both the offender and the police. This was done based on interviews which revealed that when an offender is detected on camera, the likelihood of capture increases to almost 99% (refer to Appendix B). Therefore, the strategies derived from this study cannot be directly translated to real-world scenarios, where cameras play a major role in law police strategies.

Finally, the study uses a deterministic model, whereas humans are stochastic of nature (Ronchi et al., 2013). Even though both agents are modeled with multiple behavioural variables, it cannot be representative of the full range of the behaviours which a person can have in real life (Averill, 2011; Bonau, 2017). Kuligowski (2011) refers to this phenomenon as 'behavioural uncertainty' which is based on randomness which only human behaviour can show.

9.9.2 Limitations of interviews as data collection tool

Using interviews as a data source introduces a potential for bias. Interviewees draw on their own knowledge and perceptions, which are inherently shaped by personal experiences, thereby influencing the reliability of the information gathered. To mitigate this bias, conversations with multiple officers can be employed to verify information and enhance the overall reliability of the data.

A second limitation associated with interviews is their time-consuming nature. The process of recruiting participants, scheduling interviews, conducting them, and subsequently transcribing and analyzing the data demands considerable resources. To overcome this limitation, efficient planning and coordination of interview schedules can help streamline the process.

9.9.3 Limitations of simulation method

While ABM has proven effective in simulating stochastic systems, they come with limitations discussed in Crooks and Heppenstall (2011). Firstly, ABM's flexibility in creating environments, interactions and individual agents gives the modelers substantial freedom, which, if not carefully managed, may result in either oversimplification or excessively detailed representations (Barbaro, 2015; Couclelis, 2000; Abdou et al., 2011). Oversimplification or unnecessary complexity of crucial elements of the scenario can lead to missing key variables in the system. To limit this risk, the study defines a specific scope, as outlined in Section 1.3. Narrowing the scope deliberately excludes insignificant external factors, detailed in Section 4. By doing so, the study aims to concentrate on important aspects of a fugitive interception scenario without the influence of external third parties. This deliberate focus allows for a detailed simulation of the behaviour of actors involved in the scenario while disregarding elements that could significantly impact the model outcomes.

Secondly, ABM's sensitivity to initial conditions and slight changes in interaction rules can limit the predictive certainty, as seen in physical or chemical domains (Couclelis, 2000; Wilson, 200). To prevent the results from being based on the initial conditions of the simulation model, the game has a warm-up up time, explained in Section 6.1. This warm-up period allows the model to evolve to a stable state, reflecting conditions closer to the real-world scenario. Furthermore, a varying initiation time is incorporated, as elaborated in Section 6.1, accounting for the random starting times of offenders in the simulation's state. This inclusion limits the influence of initial conditions on the model's results, creating a more robust and representative depiction of the dynamic nature of fugitive interception scenarios.

A third limitation of ABM is modeler bias, which can significantly impact simulation outcomes. Modeler bias refers to the subjective influence introduced by the modeler's decisions, assumptions, and interpretations during the design and implementation of the simulation. Modeler bias can occur due to multiple things such as the selection of specific variables to include or exclude or the modeling of agent decision-making processes. To overcome these biases expert interviews are done to validate model decisions and agent behaviour in the model.

Lastly, ABM's high computational requirements for running large system models can pose a challenge (Crooks and Heppenstall, 2011; Parry and Bithell, 2011). To address this challenge, the model in this study is structured to save each iteration individually within a scenario. This approach ensures that in the event of a model or computer crash, the progress made up to that point is saved. This design creates a secure environment for the computer to run for extended periods without the concern of a crash. Moreover, the simulation can be paused and resumed at any given moment. Moreover, the network created in the simulation model is saved, which prevents the requirement of setting up every run. If changes are made to the network it is automatically updated and saved. Additionally, the simulation model was set up to be able to multiprocess multiple scenarios at once, lowering computational times. Furthermore, considering that the TU Delft provides access to suitable computing resources, the impact of this computational limitation can be mitigated. The ability to save and resume simulations, coupled with external computing support, contributes to the effective management of computational demands, allowing an extensive simulation model to be made.

9.9.4 Limitations of game theory analysis

The usage of game theory also poses some disadvantages. First, game theory assumes the rationality of all players (Gibbons, 1992). Real-world scenarios, however, are heavily influenced by emotions, biases, and uncertainties, which often hinder strictly rational behavior. Consequently, models based on game theory can be considered oversimplifications, lacking the capacity to fully capture the complexity inherent in real-world situations (Kuligowski, 2011). To address this limitation, the model will include elements of both rational decision-making and randomness, as detailed in Section 3. Additionally, the model includes behavioural uncertainties, which effects on output will be tested. This is done to capture real-world dynamics where not all actions always have the same guaranteed effect.

Another disadvantage of game theory is the assumption of fixed strategies in game theory models, which cause of simplifications in the decision-making of agents (Peters and Westelaken, 2014). In real-world scenarios, players often adapt their strategies based on the actions of others, leading to an ever-changing strategic situation. The challenge here lies in finding ways to incorporate adaptability and strategy changes into the simulation, as overlooking these dynamic aspects may result in a less nuanced representation of an actual fugitive interception game. To incorporate a dynamic decision-making process different behavioural aspects cause different responses to other agents. As these behaviors are varied throughout all scenarios, the effect of certain choices in decision-making can be tested individually.

10
Conclusion

This chapter attempts to answer the research question of this study. Conclusions are drawn from the outcomes of the experiments from the simulation model of a fugitive interception scenario. The results were analysed using game theoretic analyses. First, the sub-questions outlined in Section 1 will be answered. Finally, the societal and scientific relevance of the findings are explored and recommendations for future research are discussed.

10.1 Sub-question 1: Offender strategies

To answer the research question, three sub-questions are formalized. The first two sub-questions consisted of literature studies, expert interviews, the simulation model and the game theoretic analysis. The following sub-question will be discussed in this Section:

Sub-question 1

What strategy can a fleeing fugitive adopt to minimize the probability of an interception by the police when escaping through the metro network of Rotterdam?

To formalize the strategies that a fugitive may adopt during an escape, a literature review and expert interviews are conducted. The escape plan can be divided into two parts; the route and the the behaviour throughout the escape (Appendix B; Zhao et al., 2020; Tutuarima, 2023; Kahneman, 2003). First, the route of an escape plan is determined by the starting location and the desired end destination. Research indicates that certain neighborhoods are more prone to offender activity, while others are more densely populated with offenders. Second, experts pointed out that the type of crime committed provides an initial indication of behaviour throughout the escape. Large crimes like assassinations or armed robberies often involve well-planned escape strategies, characterized by rational behaviour. In contrast, smaller crimes such as theft, vandalism, or harassment tend to occur spontaneously, leading to more unpredictable behaviour.

The police categorize escape plans based on their planning. Offenders with a well-planned escape are identified by rational behaviour, following a predefined plan with a clearly defined destination for hiding. This makes offenders less susceptible to external factors. On the other hand, escapes associated with spontaneous crimes are often linked to bounded rational behaviour. Offenders in these situations may be influenced by factors such as blending into the crowd, taking many turns, or altering their intended destination.

The simulation model for a fugitive interception scenario containing these strategies showed that the success of offender strategies heavily relies on the police strategy. However, offenders committing a crime in the city centre and aiming to transition to a train network (thus exiting the metro network) are overall the most successful in escaping. The success of this strategy can be explained by its route distance. As such a route is often a shorter route compared to other scenarios. This indicates that strategies with the shortest escape routes are the most successful.

Moreover, strategies where the offender's route crosses the centre of Rotterdam were shown to be least successful. For example, when the offender started at the outskirts of metro lines and attempted to move as far away as possible, the capture rate significantly decreased. This is explained by the guarding positions of the police, which are mostly in the centre. Thus, when the offender avoided central stations their escape chances increased, as they did not cross popular stations for the police to guard.

The strategy in which the offender starts at an end station was found to be most dependent on the police strategies. When the police guard surrounding stations, the escape chances for the offender decreased, compared to other police strategies. The chance that the police can adopt this strategy makes starting at an end station unattractive for the offender. Therefore, in the situation where the offender has a limited number of routes and no camera footage is available, the offender will most likely not start at an end station

The predefined rational state of the offender showed to have an effect on output dependent on the number of police units. When the police has 10 units available, the rationale state showed no significant effects on success. This implies that the behaviour of disappearing in the crowd does not have a significant effect on the capture chance in this model. However, in the scenarios in which the police only had 3 units available, the rationale state did have an effect. In such scenarios, the strategies in which the offender behave bounded-rational are found to have a lower capture chance. This implies that, based on the number of police units involved in an interception scenario, the offender should either be more or less influenced by external factors such a crowd flows. Similarly, in experiments where offenders could interact with the police the scenarios in which the offender entered a bounded-rational state after seeing the police for the first time were more successful than scenarios where the offender was not affected by the sight of the police. This suggests that when the offender sees the police, a degree of flexibility during the escape can contribute to achieving success.

To conclude, the strategies adopted by fugitives during escape scenarios, in the Rotterdam metro network, underscore the critical role of route planning and behavior adaptation in preventing capture. These results can also be generalized to other scenarios than the metro. Strategies with shorter escape routes and avoidance of central surveillance locations increase the likelihood of successful evasion. Moreover, flexibility in response to the presence of the police, rather than predetermined behavior, increases the success of escapes. This will be the case for comparable scenarios, which can be used for the police to find robust interception strategies

10.2 Sub-question 2: Police strategies

For sub-question 2 the same approach is used as the first sub-question. Literature and expert interviews provide information for the conceptualization of the strategies in the simulation model. Next, the simulation model is used to determine the effectiveness of each strategy. The results are analyzed using a game theoretic framework.

Sub-question 2

What strategy can the police adopt to maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam?

Limited data and literature are available on the interception strategies the police can adopt during an escape. Therefore, most information for the conceptualization of police strategies is retrieved during expert interviews, summarized in Appendix B.

The simulation model showed, the guarding location to have the highest impact on the outcome in a fugitive interception scenario where no camera footage is available. The police should always guard the metro platforms, rather than the station exits. The most effective strategy involves deploying 10 police units to guard large metro stations, and surveilling the metro platforms and main exits. When guarding the metro platforms, the police can intercept an offender even while they are in the metro. Whereas if the police guard the station exits, the offender will be able to pass that station unseen. Additionally, when surveiling large stations increases the chances of interception, given that a majority of metro routes pass through these locations. This underscores the importance for the police to strategically position units at points where the offender is most likely to pass. It suggests that if the police do not know the final goal of the offender, identifying locations that the offender most frequently crosses can increase capture chances.

In scenarios where the police only surveil the metro exits, the capture chance significantly decreases. This is especially evident when combined with the strategy of guarding surrounding metro stations with 3 or 5 units, resulting in the lowest capture rates. Guarding large stations while only focusing on station exits performs marginally better but still yields poor results.

In contrast, a notable improvement in capture rates occurs when guarding station exits is combined with the strategy of securing the furthest metro stations. This outcome can be explained by that the offender may also employ a strategy to escape through the furthest metro stations. When the police similarly focus on guarding the furthest stations, interception chances at station exits increase. However, the chances that the police is able to correctly identify the desired end location for the offender is relatively small. Therefore, this strategy proves to be useful in this model, but is not advised in real life. Unless the police has an indication of where the offender desires to go.

Furthermore, a crucial factor influencing the outcome of a fugitive interception scenario is time. Generally, the faster the police can apprehend an offender, the greater the chance of a successful capture in future scenarios. Time is influenced by multiple elements, including the timing of crime reporting, police response time, the arrival time of police officers at their designated locations, and the communication time between officers in the control room and those deployed on the streets. This study showed that efficiency in timely elements is of great influence in a fugitive interception project.

All strategies are tested with 3, 5, and 10 units in the simulation model. The first police unit always heads to the crime scene, while the remaining units move towards a goal in an attempt to intercept the offender. All strategies exhibit improved performance when 10 units are available. It is important to realize that having more police units also translates to higher operational costs. Therefore, this study suggests that if an accurate indication of potential points where the offender may be intercepted is identified, fewer units need to be deployed and can therefore help lower costs. This, in turn, allows for more police units to address other emerging issues on the streets.

Furthermore, the results showed that if the police are surveiling locations that the offender crosses, undercover police have an increased capture chance. This implies that remaining unseen by the police can enhance the chances of capture.

To conclude, the police strategies that maximize the probability of an interception with the offender who is attempting to escape through the metro network of Rotterdam, are characterized by the guarding station and the guarding locations. The police creates the highest capture chances when guarding locations which the offender is most likely to pass. The model showed that the chance that the police and offender have the same end goal, is small. Therefore, the police is most likely to intercept with the offender when strategically locating themselves at frequently visited locations.

The findings from this study offer valuable insights that can be generalized to real-world fugitive interception projects beyond the specific context of the Rotterdam metro network. Key factors influencing interception success include the strategic positioning of police units at locations where offenders are most likely to pass. Additionally, the importance of time in responding to a crime report is important in achieving a high capture chance. Additionally, in real-world scenarios, police must find a balance between resource allocation and cost-effectiveness. Incorporating insights from this study into broader fugitive interception strategies can increase the overall effectiveness of police in capturing a fleeing offender across diverse environments and circumstances.

10.3 Sub-question 3: Information & interaction

Sub-question 3

What is the effect of information on the probability of an interception with the offender?

To investigate the impact of information on the strategies employed by the police and the offender, the results of the simulation model are analyzed using a game theoretic approach. The model is divided into four experiments, which alter the ability of the agents to interact with information. In the first experiment, both agents are unable to interact with information. In the second experiment, only the offender can interact with information. In the third, only the police can interact with information, and finally, in the fourth experiment, both agents can interact with information. The introduction of information adds a layer of complexity to the fugivite interception scenario, potentially altering the course of the simulation.

Information exchange between the police and offenders can take various forms, ranging from knowledge of each other's whereabouts to insights into their respective strategies. For instance, the police might receive intelligence regarding the fugitive's next probable location, while the offender could gather information about the police's deployment patterns. Additionally, factors such as the presence of accomplices or access to resources could also constitute valuable pieces of information.

The findings indicate that the ability to react to information about the other player does not significantly affect the capture chance. This can be attributed to the modeling choices made for the agents' behaviour. Initially, police are assigned end goals such as large, far, or surrounding stations. Even with updated information, they will remain to guard stations within the same category. If offenders spot the police, they can either attempt different exits to outmaneuver the police, or they can decide to try and exit the metro network at a neighbouring station. Consequently, both agents are unable to drastically change their behaviour based in incoming information. capture rates are high when police are nearby but low if guarding distant stations. Overall, these modeler choices mean that if the police are in the neighborhood of the offender, the capture rate is high. However, if the police are initially guarding stations that are far away from the offender the capture chances remain low, regardless of information.

This emphasizes the importance of identifying probable locations where the offender will pass. If the police are stationed at places where the offender is likely to pass, it increases the capture rate more effectively than targeting predefined locations unrelated to the offender. Therefore, interaction with the offender becomes crucial when the search area is already confined to likely regions.

Prior to analyzing the results, it was anticipated that the agents' ability to interact with information would have a significant impact on the capture rate. However, interviews revealed that when offenders are identified on metro cameras, they are captured most of the time. Consequently, including camera footage in the study would yield less informative results, so it was omitted. This implies that if the police have information on the offender's whereabouts, it should increase the capture chance, which contradicts the results obtained. Therefore, it is suggested that the model structure in which information is handled be revised, which is further discussed in Section 10.7

10.4 Main research question

In this section the main research question for this study is answered.

Main research question

How can game theory and simulation help in finding optimal interception strategies for the police to increase the catch rate in fugitive interception scenarios?

The findings of the study suggest that the integration of game theory and simulation within a gaming framework holds significant promise for capturing complex insights into a fugitive interception scenario. By employing agent-based modeling, the chaotic and unpredictable behaviors of agents can be effectively simulated. This approach allows for the exploration of numerous scenarios with varying input variables. The relatively rapid computational times facilitate the detection of patterns or trends across scenarios, a task that would be considerably more time-consuming in real-world situations. Additionally, simulation allows uncertain behaviour to be model, which is crucial in a fugitive interception scenario. The decision-making process of agents can be modeled per agent, through which interaction and inter-dependencies among agents can be analyzed.

Through game theoric analysis, robust strategies can be found within a complex system where players both aim to achieve opposing, desired outcomes. It offers insights into the dynamics of interactions between players, finding effective strategies to maximize gains and minimize losses. By understanding the interaction of strategies and potential outcomes, the police and offender can make informed decisions during a fugitive interception scenario to gain a competitive advantage. In this study, pure-strategy and mixed-strategy Nash equilibria were used to identify robust strategies for the police, leading to the highest capture rate.

This study's combination of a simulation model and a game theoretic analysis does not yield surprising results. For instance, the model found the guarding locations for the police and the route distance for the offender to be crucial elements in an interception scenario. The fact that these results are logical means that the model functions correctly. This validation not only confirms our understanding of interception dynamics. It also validated this model, thereby laying the groundwork for future research where increasingly complex scenarios can be explored using simulation and game theory.

In conclusion, simulation is well-suited for capturing the complexity and uncertainties in fugitive interception scenarios. It also allows for the exploration of various input variables and behavioral uncertainties. On the other hand, game theory is useful for identifying optimal strategies within competitive environments, and analyzing the dynamics between players and their strategic choices. Combining simulation and game theory new insights can be found beyond what either method can provide individually. By modeling the stochastic nature of a fugitive interception scenario, the success of the offender and police behaviour can be found. This can help the police during decision-making to adopt more robust strategies while considering the stochastic nature of the environment and strategic interactions with the offender.

While the study has the potential for increasing capture rates, the model needs refinement and adaptation for the results to be able to be implemented by the police. To overcome the current challenges and limitations identified in this study, further research and data gathering must be done. The recommendations outlined in Section 10.7 provide the full list of suggestions for future research.

10.5 Generalization

Even though the focus of this study is highly specific and may not perfectly replicate real-world scenarios within a metro station, its findings are relevant. First, the challenge of lacking camera footage extends to various other situations, such as other methods of public transportation. In cases where offenders use bus or train networks as an escape route from a crime scene, the police does not have available camera footage to base is interception strategies on (Appendix B). Additionally, in public parks, shopping centers, or remote areas surveillance cameras are limited. This can make it challenging for the police to identify and track an offender. These scenarios underscore the need for finding robust strategies for the police during an interception scenario when camera footage is not available.

Second, the study also focuses on scenarios where the offender only has a limited number of escape routes. Similar scenarios can be found on highways, in small towns or rural areas with fewer transportation options, where the offender's escape routes may be restricted. Similarly, in enclosed spaces such as airports, or big buildings, the offender may have fewer paths to take. Understanding and anticipating these constrained route scenarios is important for the police to strategically station resources and increase the likelihood of successfully capturing an offender.

In this model, the incorporation of knowledge about probable strategies of the other player might appear unrealistic. However, in reality, the police frequently use profilers to deduce likely characteristics of the offender. Through this approach, the police can develop a relatively accurate profile of the offender, upon which they base their strategies. For instance, if the offender is known, the police may know in which neighborhood the offender lives, and those areas can be closely surveilled. If the offender appears to have committed the crime spontaneously, strategies can be formulated accordingly.

In conclusion, while this study focuses on a specific scenario within a metro station, its findings hold broader relevance in understanding and addressing challenges encountered by police in various contexts. Overall, this study underscores the importance of developing adaptable and informed strategies that consider diverse constraints to improve the effectiveness of police strategies in interception scenarios.

10.6 Scientific and societal contribution

This study addresses the knowledge gap in finding robust police strategies for a fugitive interception scenario that considers behavioural uncertainties. Much of the existing literature focuses on pursuit-evasion games involving moving robotic objects, simplifying decision-making to predefined processes. In contrast, this model aims to simulate offender and police behaviour, allowing them to respond dynamically to their environment and interact with each other. By taking this approach, the study applies a systematic perspective to a complex stochastic problem characterized by intuitively driven actions.

This study aims to increase the capture chances for the Dutch National Police during a fugitive interception scenario. The study's findings reveal varying degrees of success among different strategies Despite the model's simplification of the real-life system, which limits the generalizability of the study's findings, the approach of a simulation model combined with game-theoretic analyses can contribute to the development of effective and robust interception strategies by the police.

The simulation model is based on offender and police strategies seen in real life. This contribution provides a more comprehensive understanding of the dynamics inherent in a fugitive interception scenario. This can lead to the elimination of biases such as ethnic profiling in police work. Additionally, by increasing the catch rate through strategic objective decision-making, the research aims to contribute to the reduction of overall crime rates and foster increased trust in the Dutch National Police.

10.7 Recommendations for further research

Throughout the model conceptualization, model validation, results, and discussion multiple recommendations for future research are identified. The recommendations are listed below, grouped by area.

Simulation model

- Network: expand the model to more detailed network. The metro network of Rotterdam proved to be inadequate for this study as most offenders who enter the metro are captured. Additionally, it reduced the strategies of the police by eliminating factors such as driving speed, vehicle changes or places to hide. This can be achieved by incorporating Open Street Map data into the model and allowing the fugitive interception scenario to be executed in a more detailed network.
- Time: time was shown to be an important uncertainty in the model. In future research, time could be included by including the police control room and its processes.
- Behaviour: further elaborate on the behavioural patterns found in offender and police behaviour. This will create more usable results and more realistic strategies. To achieve this, expert interviews are advised.
- Interaction between agents: The effect of interaction between agents is less than initially expected. To further analyse this the model structure regarding information handling could be revised. This can be done by integrating a more dynamic mechanism for incorporating real-time data on offender whereabouts. Additionally, the effect of information on an agent's behaviour could be modeled more accurately. This revision would enhance the model's accuracy in reflecting real-world interception scenarios and allow for a more nuanced analysis of the impact of information interaction on capture rates.
- Experimental design: As the model has many offender and police strategies, combined with five model uncertainties, significant conclusions from the statistical analysis are difficult. More runs and further research for the accuracy of uncertainties must be done to increase the significance of the results.

Offender behaviour

- Goal: reconsider the end goals of the offender, such as safe houses, or places where the police lose sight of the offender. By making these more realistic the strategies resulting from the study will become more generalizable. Expert interviews could shed light on these locations.
- Crime: the nature of the crime can give a first indication of the escape behaviour of the offender. Including and elaborating on this can create more complete offender behaviour.

- Route: to further analyze offender behaviour their complete routes could be analyzed, aiming to find locations that are often crossed. This can be done through the use of heat maps.

Police behaviour

- Goal: in this simulation model, the agents' end goals were based on metro station characteristics. Future research could include known locations where offenders often pass, are captured or known to live, and are identified through interviews and data.
- Strategies: currently the police all adopt similar strategies. However, using the Shapley value a fair allocation for the police units can be found, which includes different strategies.
- Mixed strategies: currently the police are advised one type of strategy, meaning all units do the same. However, using a mixed-strategy analysis the police can more accurately be given probability advice on which strategies to adopt. In such a case, the police units within one simulation run can adopt different strategies to one another.
- Data: currently limited data exist on the exact locations where a crime is committed and where the offender is captured. Future research could analyze this providing more information in the route choice behaviour of the offender and police.

Analysis of results

- Zero-sum: the game theoretic analysis was simplified by considering it a zero-sum game. However, in reality, factors such as time and the number of units also influence police costs, thereby affecting the attractiveness of strategies and their payoffs.
- Mixed-strategy Nash equilibrium analysis: this study finds a limited number of mixed-strategy Nash equilibria. Further analysis could find more mixed-strategy Nash equilibria, which creates a more thorough understanding of the strategies to employ in various scenarios.

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A
Informed consent form

U bent uitgenodigd om deel te nemen aan een studie genaamd MSc thesis: Fugitive Interception Project. Deze studie wordt uitgevoerd door Cécile van Heukelom, MSc student Engineering and Policy Analysis aan de Technische Universiteit Delft, in samenwerking met de Nederlandse Politie. Het is belangrijk om te weten dat ik alleen een geheimhoudingsverklaring getekend heb en geen screening ben ondergaan. Mocht u deze willen inzien is dat mogelijk. Let hier alstublieft op bij het beantwoorden van vragen.

Het doel van dit onderzoek is het verkrijgen van inzichten in de vluchtstrategieën van verdachten en achtervolgstrategieën van de politie nadat er een misdaad is gepleegd. Door middel van uw ervaringen en antwoorden hoop ik mijn kennis over deze factoren te kunnen verfijnen en valideren. De verkregen informatie wordt anoniem gebruikt voor kennis input voor de theoretische basis van het simulatiemodel. lk zal open vragen stellen met betrekking keuzegedrag van verdachte en politie en de gevolgen van dien.

Uw identiteit zal vertrouwelijk zijn. lk zal veilig en anoniem interview transcripties, notities, email gesprekken en meeting samenvattingen opslaan, alleen toegankelijk voor mij. De uiteindelijke MSc thesis zal publiek beschikbaar zijn en geen transcripties van de gesprekken met u bevatten of enige verbanden naar uw identiteit. Ook zal een aparte versie voor de Politie beschikbaar komen: hier worden bovenstaande factoren hetzelfde gewaarborgd.

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 geval van een vragenlijst via email wordt u gevraagd expliciet te vermelden dat u dit formulier heeft gelezen en of u wel/niet uw toestemming geeft. In geval van face-to-face (of online) gesprekken zult u gevraagd warden om expliciet akkoord te gaan met de inhoud van dit formulier door dit te benadrukken.

Voor vragen kunt u mij (c.m.v.vanheukelom@student.tudelft.nl) of mijn dagelijkse afstudeerbegeleider Ir. Irene van Droffelaar (i.s.vandroffelaar@tudelft.nl) aan de Technische Universiteit Delft benaderen. Irene is in dienst bij de Nederlandse Politie via het Nationaal Politielab Al. Door dit document te ondertekenen bevestigt u dat u dit document heeft gelezen en toestemt met de hierboven beschreven voorwaarden.

Naam deelnemer: Handtekening deelnemer: Datum:

B Interviews

Due to confidentially, the summaries of the interviews are omitted from the public version of this thesis.

C
Actor analysis

This appendix gives a thorough description of the problem and its actors. Information about this has been acquired through interviews, of which the summaries can be found in Appendix B and Paoletti's master thesis in which the process of emergencies within the police is analysed (2022).

When calling for police assistance, police officers in the Control Room (CR) are the first one comes in contact with. The officer in the Control Room, manages the call and communication with police units on the streets. In cases where a crime has occurred and the offender has fled, the dispatcher gathers information like crime type, specific details, urgency, people involved, suspect's travel direction, and time. As the city of Rotterdam is highly equipped with safety cameras, police officers in the CR attempt to identify the location of the crime and the caller by scanning the camera footage. However, in the situation where an offender has fled using the metro network, the reach of police cameras ends.

The police do not have their own cameras within the metro system, as these are exclusively maintained by the RET (Rotterdam Electrical Tram). Consequently, police officers in the CR inform the RET CR personnel and request access to their camera footage (this is always granted). This highlights the police's heavy reliance on the RET cameras for situational awareness.

Meanwhile, police officers use tools like an intelligence center for data on past crimes and escape routes, and software to get an indication of the urgency of the crime and behaviour of the fleeing offender. Through dynamic capture circles officers in the CR try to estimate where the offender can be, and where an interception is likely. This, in combination with the urgency of the crime decides how many police offers will be dispatched and to where. Paoletti found that high-urgency incidents involve around 6 - 10 units, whereas incidents with lower urgency on average use 2 -3 police units on the streets (2022). Hence, the actions and effectiveness of the police units on the streets are highly dependent upon the knowledge and assessments made by the CR officers. Important to mention is besides technology supporting their decisions, officers in the CR use intuition and experience to assess the situation.

Additionally, the CR police officers possess the authority to instruct RET CR personnel to execute specific actions, such as halting metro departures or permanently shutting metro doors. To accomplish this, the RET CR personnel can directly interfere with driving metros.

However, a capture remains highly dependent on the police officers on the street. These street officers are guided by the information received from the CR. However, also in their behaviour a leading factor is instinct. With experience officers become 'streetwise, meaning they have created individual habits and strategies to handle situations and accomplish success (Appendix B).

In situations where the scale of the incident exceeds the capacity of the street-level and CR police officers, the regional police officers can be informed. These officers possess greater authority and automatic approval for undertaking specific actions. Regional officers can directly assign tasks to the police units operating on the streets and do not need to pass police officers in the CR. Similarly, for when an incident is too large for the regional police and it is given to national police. The visualization of these dependencies can be seen in Section 4.

D
Literature review

This Appendix shows the search terms per research question, its results and the inclusion and exclusion criteria.

Table D.1: Search terms per sub-research question

Search terms	**Databases**	**Search results**
('criminal AND behaviour') AND ('escape' OR 'capture') AND ('modeling' OR 'simulation')	ScienceDirect	24757
	Scopus	20
	JSTOR	2733
('police AND behaviour') AND ('escape' OR 'capture') AND ('modeling' OR 'simulation')	ScienceDirect	32135
	Scopus	17
	JSTOR	3345

Table D.2: Inclusion & exclusion criteria

Inclusion criteria	Publications must be peer-reviewed
	Publications must have search terms in the title, abstract or key words
	Publications must be in English (translated)
Exclusion criteria	Non-English & Non-Dutch publications
	Publications that are not fully accessible
	Publications that focus on mental illness
	Publications that focus on cybercrime

Table D.3: Relevant literature for offender escape behaviour organized by strategy component

Strategy component	**Source**	**Summary**
Start and end location	Gladwell, 2006; Gemeente Rotterdam, 2022; Sooknanan and Seemungal, 2023; Ino et al., 2009; Shepherd and Purcell, 2015; Boggs, 1965; Zhoa et al., 2021; Escobar et al., 2023	Neighbourhoods can be more prone to criminality based on social contextual indicators. Equally, individuals in neighborhoods where society shows high criminal behaviour are more likely also to show criminal behaviour.
Rationality	Kahneman, 2003; Zhao et al., 2020; Kempenaar, 2022; Tutuarima, 2023	Rational behaviour refers to planned behaviour, often paired with organized crime. Rational behaviour is considered behaviour where the person is not in panic.
Bounded rationality	Kahneman, 2003; Jones, 1999; Zhao et al., 2020; Kempenaar, 2022; Tutuarima, 2023; Escobar et al., 2023; Jiabo et al., 2022	Bounded rationality refers to a state of mind where person is in panic. People in panic show chaotic movements and mostly do not have a predefined route.
Loose goal	Carpio et al., 2022;Bode et al., 2015;	Criminals can show unpredictable behaviour, also in the direction where it is escaping to.

Table D.4: Relevant literature for police interception behaviour organized by strategy component

Strategy component	**Source**	**Summary**
Surveillance location	X. Wang et al., 2018; Zhao et al., 2020	The importance and difficulty of correct location of police officers.

E
Police stations

The police stations included in the model are shown in the list below, along with their abbreviations.

- Politie Stadhuis (SH)
- Politie Rotterdam maashaven (MH)
- Politie Marconiplein (MP)
- Politie Noord (N)
- Politie Zuidplein (ZP)
- Politie Veilingweg (V)
- Politie Krimpen aan den Ijssel (KIJ)
- Politie Slinge (SL)
- Politie Schiedam (SCH)
- Politie Hoogvliet (HV)
- Politie Spijkenisse (SN)
- Politie de veranda (VN)

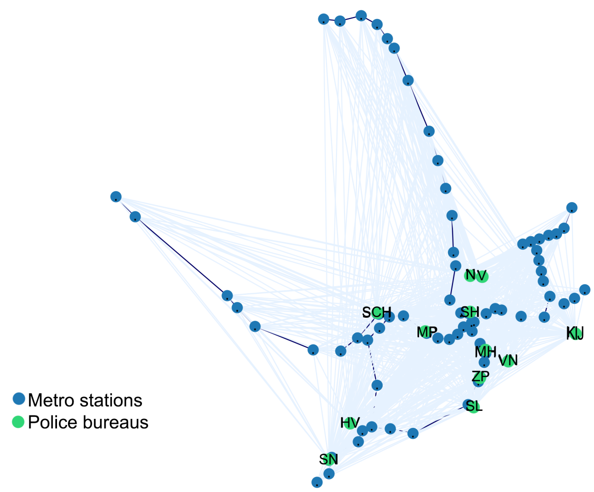


Figure E.1: Police stations in Rotterdam in networkX

F Agent flow diagram

Divided the offender into two parts: in metro and not in metro. For all situation there is an no interaction version and an interaction version.

F.1 Offender not in metro

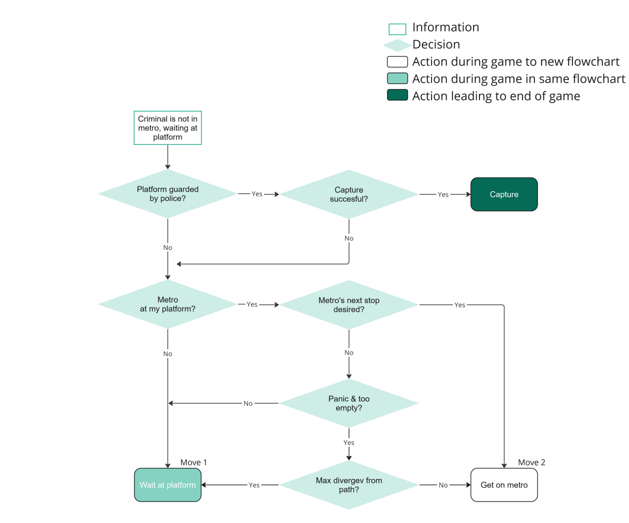


Figure F.1: Flow diagram offender not in metro - no interaction with information

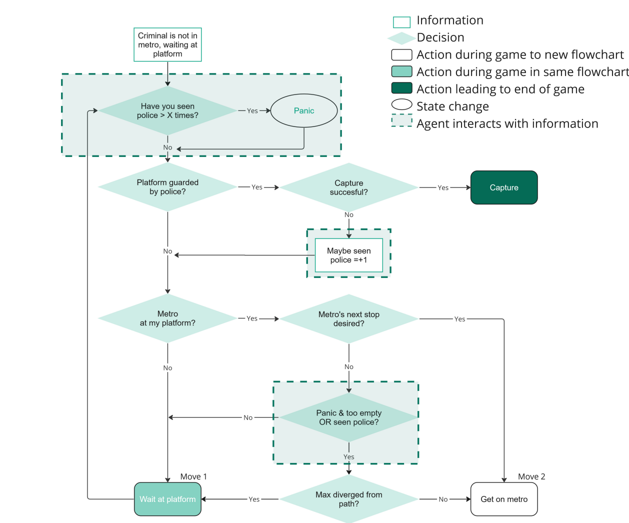


Figure F.2: Flow diagram offender not in metro - interaction with information

F.2 Offender in metro

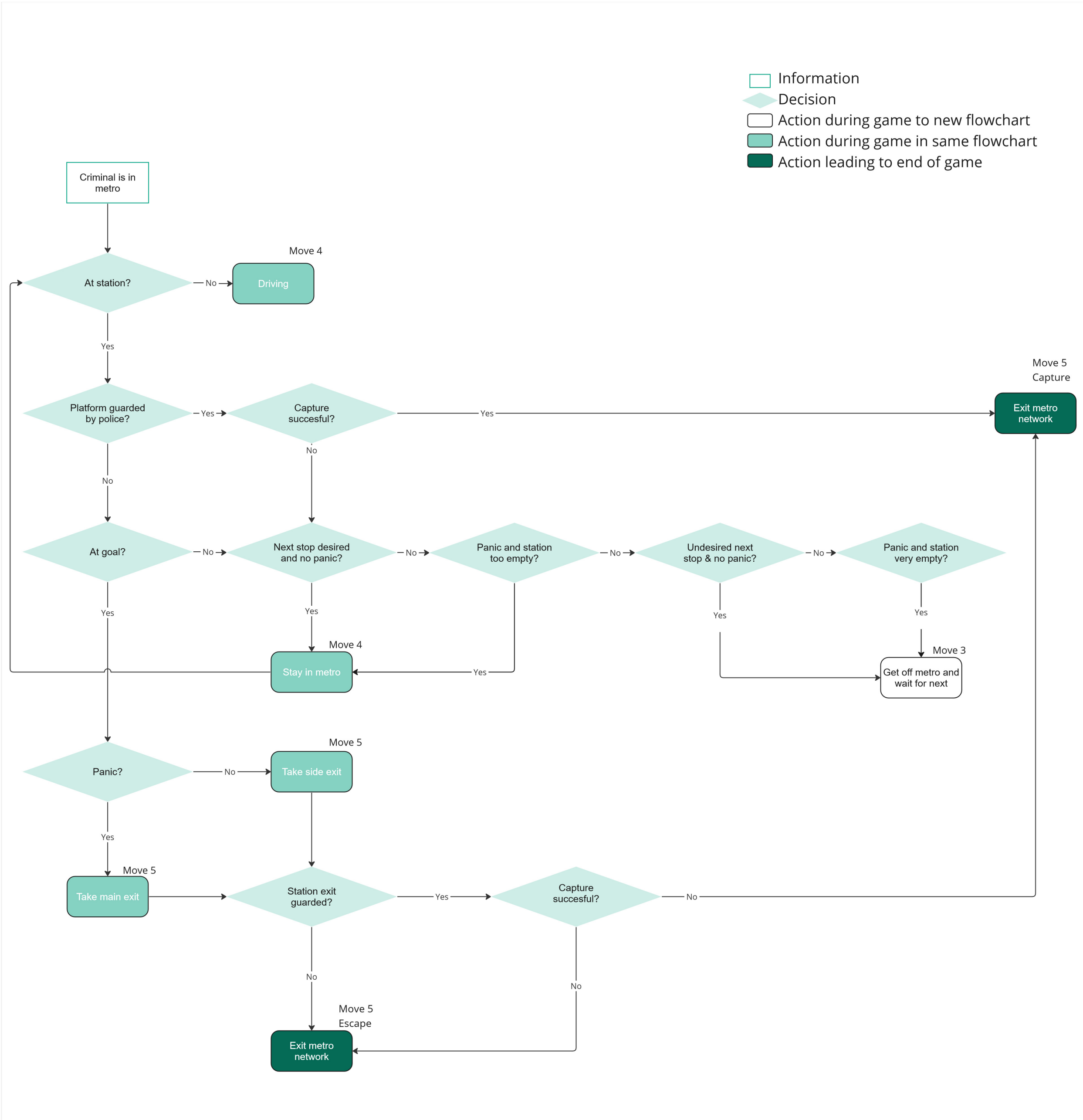


Figure F.3: Flow diagram offender in metro - no interaction with information

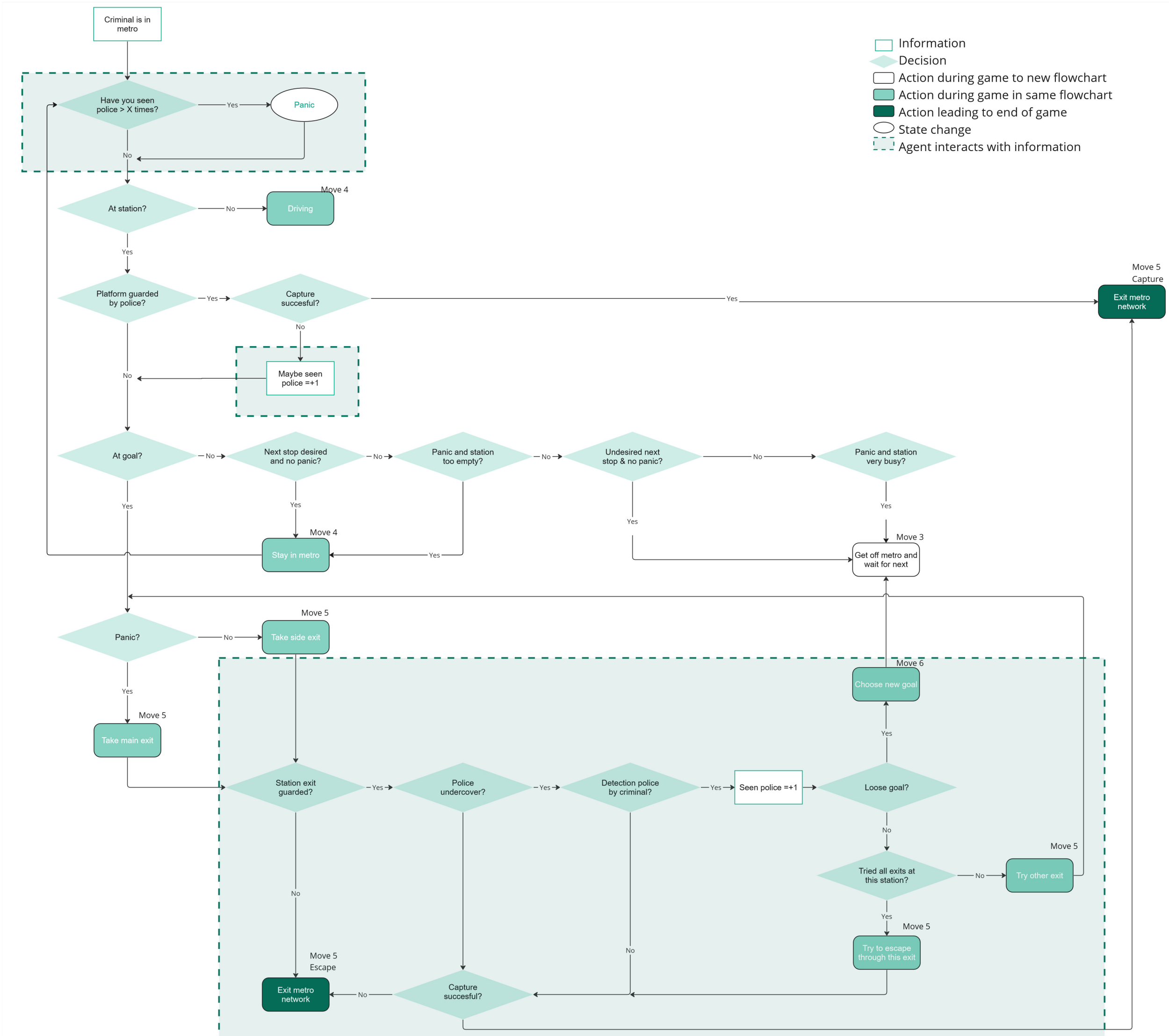


Figure F.4: Flow diagram offender in metro - interaction with information

F.3 Police

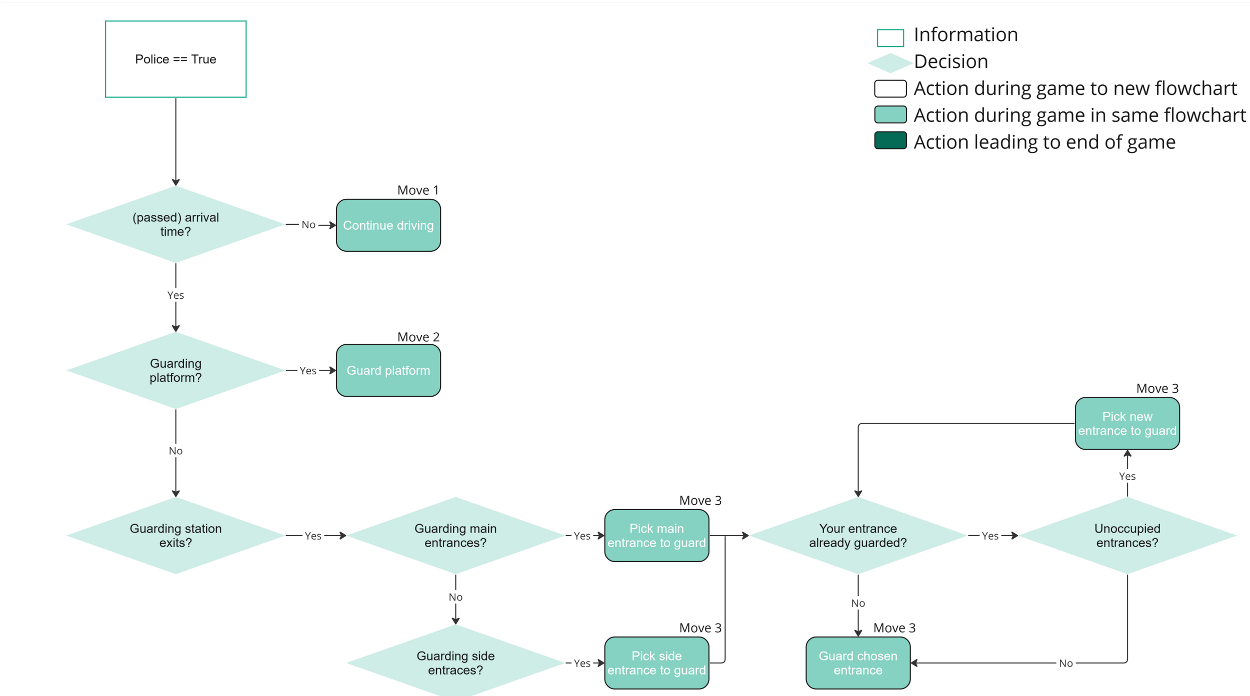


Figure F.5: Flow diagram police - no interaction with information

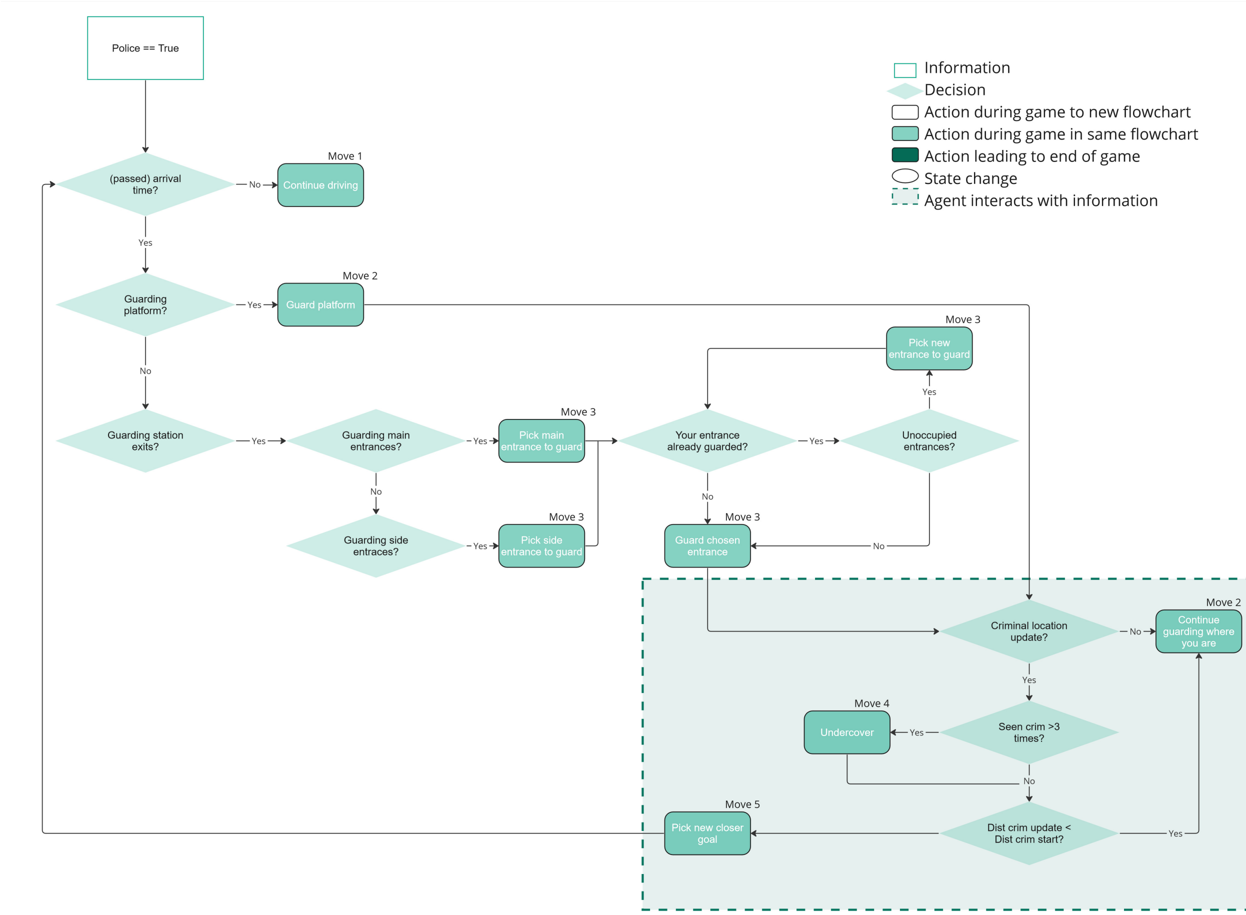


Figure F.6: Flow diagram police - interaction with information

G Model variables

Table G.1: Model input variables

Type	Variable name	Variable definition
Input variables for offender behaviour	crim_pos	Offender starting location
	crim_strat	Offender end goal
	crimd_bounded_rat	Offender panic state. If in panic, offender is bounded rational.
	crim_max_div	The maximum times the offender can diverge from its predefined path.
	crim_loose_goal	Whether the offender is willing to change its final destination.
	crim_bound_rat_time	The number of times the offender has to see the police before they become in panic.
Input variables for police behaviour	pol_strat	Police end goal.
	pol_guarding	Police guarding location, either at the metro platform or at the station entrances.
	pol_entrance	Whether police guards main entrances or side entrances.
	units	Number of police units.
	P_max_at_station	Allowed number of police units who can be at one station.
	pol_undercover	Police undercover.
Input uncertainties	offender_detection_police	Percent chance that the offender detects the police when at the same location.
	crim_Mguard_percent	Percent chance that the police detects the offender on a metro platform.
	crim_Sguard_percent	Percent chance that the police detects the offender at station entrance/ exit.
	init_call_delay	The delay time with which the police receives a call about the crime.
	info_update_freq	Frequency with which the police receives information updates about offender.

Table G.2: Model output variables

Variable name	Variable definition
Capture	if offender is caught during game.
Game over	whether the game is has ended with a capture or escape, or whether nor the offender nor the police were able to achieve their goal.
time	Time until game over.
offender__seen__police	How often offender has seen police without capture. And thus, if offender has changed to panic state during simulation model.
offender__passed__police	How often offender has passed police, can also be without having seen police.
offender__diverged__from__path	How often offender has changed its predefined path.
offender__tried__exits	How often offender has turned around to try to escape through other exit to get away from police.
police__gone__undercover	If police has gone undercover during simulation model
Police__changed__goal	How often police has changed goal based on information updates about offender.

H Model assumptions

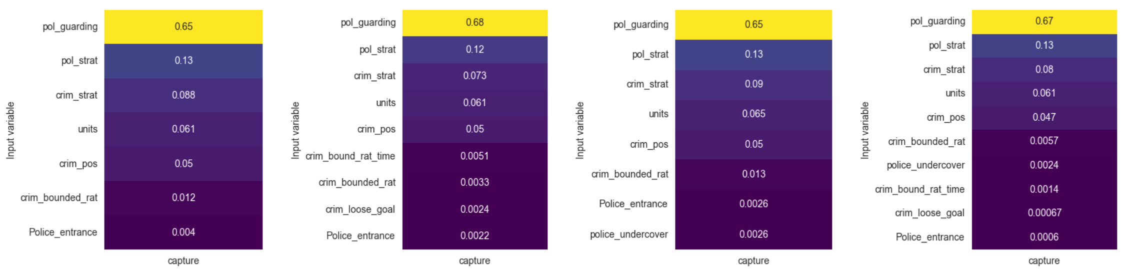
Table H.1: Assumptions

Component	Assumption	Effect
Escape route offender	Offender wants to get away from crime scene.	Offender's end goal is at least five stops away from its starting location. Otherwise the simulation model is too short and police does not have time to reach offender.
Offender escape route	Offender wants to get to a predefined destination	Offender can diverge from its path a maximum number of times. If that maximum has been reached they will not diverge anymore because they want to get to goal.
Offender escape route	Offender wants to get to a predefined destination	If the offender is at its final destination and sees police, it can decide to alter his predefined destination. In that case, they will go to an earlier or later stop. So the max change in metro stops is 1 when changing goals. This process can repeat itself.
Offender in panic	Offender wants to follow the crowd	Offender in panic follow the crowd and can either get off or on a metro if they find it too empty somewhere.
Offender in panic	Offender wants to get to a predefined destination	If the offender is in panic and it can still follow its planned route, it will. Meaning, they will not make unnecessary turns. For example: the original plan is A, but in panic, it would do B. If the offender is in panic and option A can be done, it will do A. However, if option A cannot be done it will do.
Police route	Police drive at a constant speed and in a direct line to their goal	External uncertainties such as shortcuts, speed alterations, traffic jams, etc. are not taken into account.
Offender information	Police will only move to the new guarding location if the offender is not going in their direction	If the offender is closer to the police than when it started, the police will not move. It does not take into account if the offender could be in a metro which takes a turn right in front of them.
First police unit	The first police unit goes to the crime scene.	They stay there and cannot guard other metro stations later in the game.
Offender in panic	A offender in panic does not become calm during an escape	Offender who has become panicked cannot become unpanicked again.
Police guarding locations	Police agents spread out	Initially police units will not go to the same location.
Offender route	Offender takes most efficient route to destination	Offender will not be in metro longer than needed, to confuse police.

Table H.2: Limitations

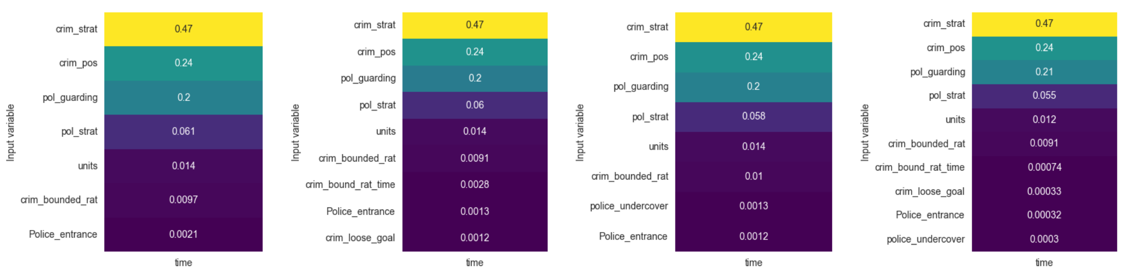
Component	Limitation	Effect
Camera usage	Metro stations do not have camera's that can be used for the simulation model.	Not realistic
Network	NetworkX only knows the nodes of the police stations and the metro stations	The police drive in a direct.
Detection	There is no difference between checking the platform or checking a train at a platform	If police stands at platform offender can be seen whether he remains in train or gets out.
Network	The networkX network only knows the metro stations and police stations.	Police starts at police stations and drives at an average speed in a direct line to its goal. Traffic therefore does not play a role in the model.
Metro platforms	Police know from which direction the offender comes, and always wait at correct platform	No differentiation is made between platforms in metro stations.
Busyness station	The busyness of station is estimated using the busyness during weekdays. Additionally, the busyness is for the metro platforms, and not calculated for in the metro	If it is a busy station during weekdays, this station is always assumed to be busier than less busy stations, regardless the time. Also, if a station is assumed to be busy, all the metro's that arrive are also assumed to be busy. The same goes for empty stations.
Detection chance	The police and offender both have a detection chance of spotting the other.	For example, if the detection chance is 70%, then this means that at the platform there is a 70% chance of detecting the offender. However, at the exits the police must also guard the correct doors so the detection chance lowers to 70% * (the number of exit doors guarded/ total number of exit doors).
Police strategy	all police adopt the same strategy (furthest, largest or surround).	Combinations between strategies are not checked.
Network	Network X only knows the nodes of the police stations and metro stations	Police use the same edges as the metro, but drive across it with more speed.
Network	Network X counts distances between nodes	The direct distance between two points is calculated, meaning the driving time does not consider one-way routes or other external factors which could lead to an increased distance.
Metro station	Metro stations have at least one main and side exit	Metro stations have at least two exits. If metro has three or more exits then two are main exits and the others are side exits.
Police moves	The police travel by car	The police cannot enter a metro, and will always take a car to the next metro station, regardless of the time it would take.
simulation model	Offender cannot leave platform	If an offender is at a metro platform and sees police, they can get on a 'wrong' metro to evade the police. They cannot hide or go to another platform. This means the offender can only be 'lucky' as to whether they will be detected by the police.
Police units	One unit is one officer	When one unit guards a metro station, then one unit is modeled to cover one exit. Even though in reality police officers often travel by two, meaning two exits could can be surveilled.

I Feature importance



(a) Exp 1 (b) Exp 2 (c) Exp 3 (d) Exp 4

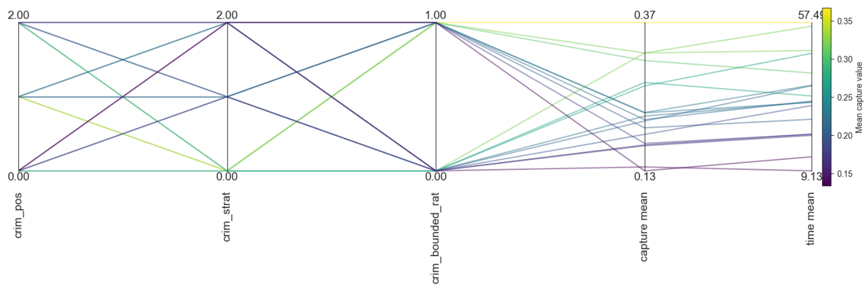
Figure I.1: Feature importances for output capture across all experiments



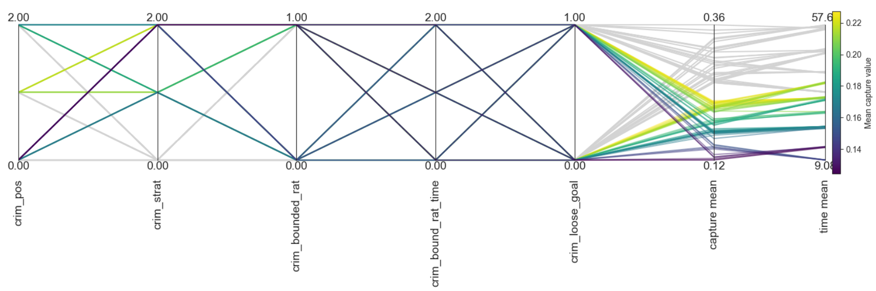
(a) Exp 1 (b) Exp 2 (c) Exp 3 (d) Exp 4

Figure I.2: Feature importances for output time across all experiments

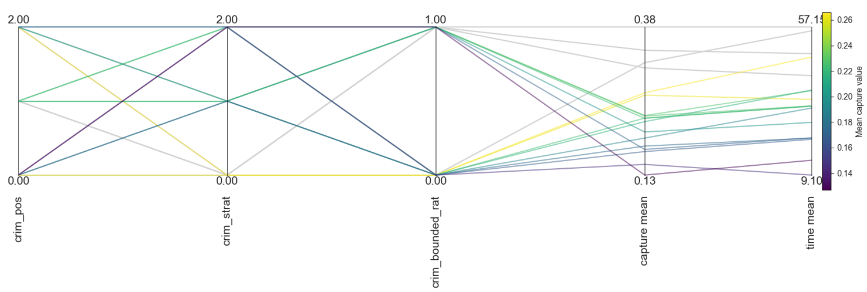
J
Parallel plots



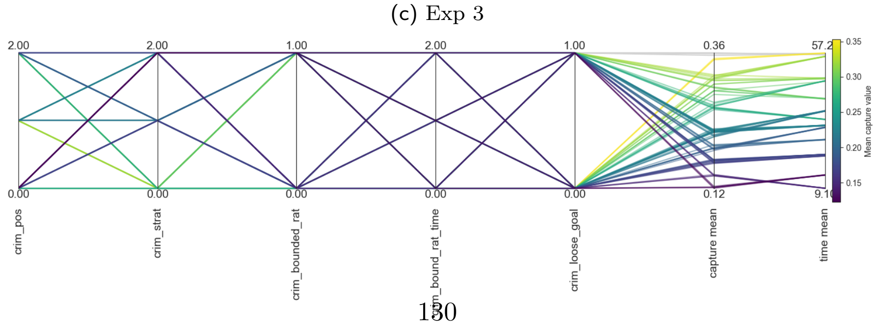
(a) Exp 1



(b) Exp 2

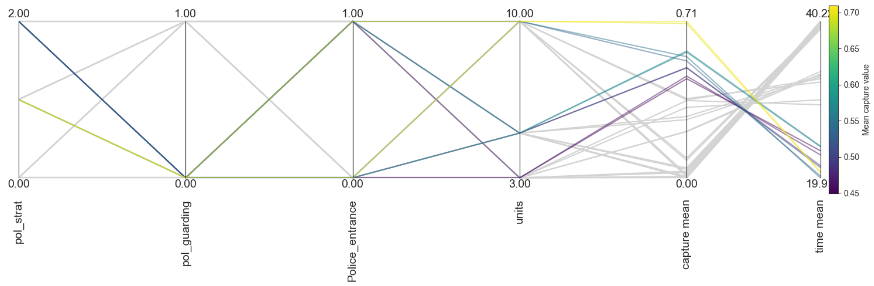


(c) Exp 3

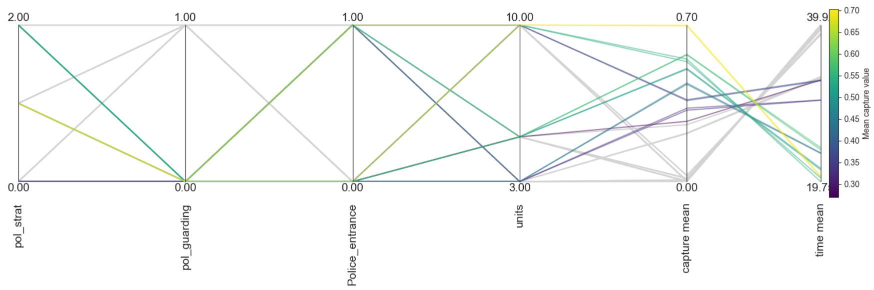


(d) Exp 4

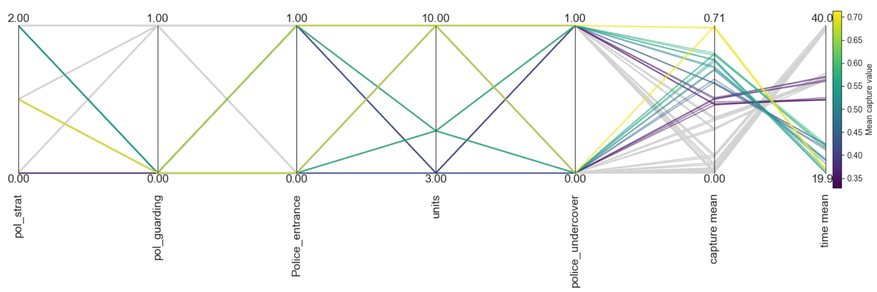
Figure J.1: Parallel plots offender behaviour vs. capture and time across all experiments



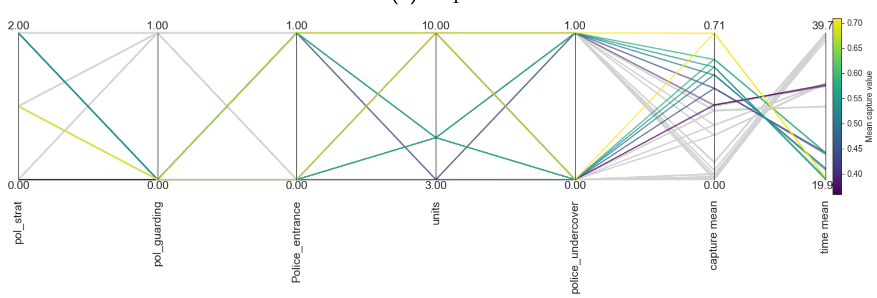
(a) Exp 1



(b) Exp 2



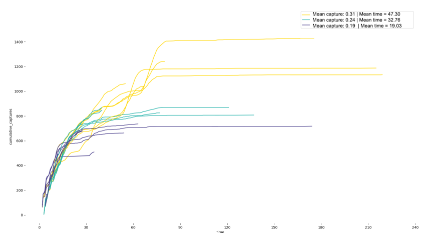
(c) Exp 3



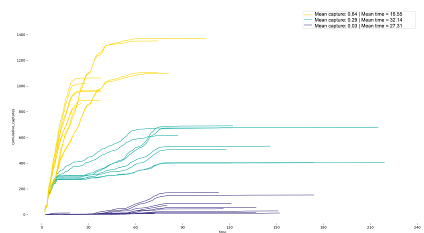
(d) Exp 4

Figure J.2: Parallel plots police behaviour vs. capture and time across all experiments

K Relationship output variables

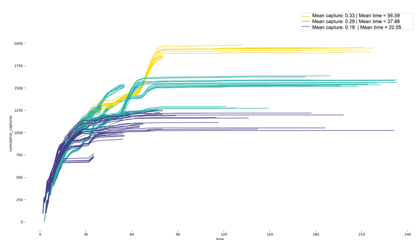


(a) fig: Relationship output variables capture and time for offender behaviour

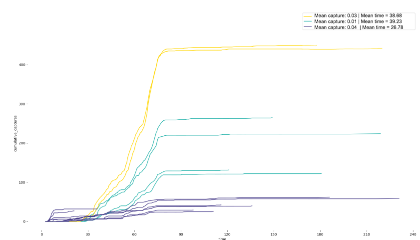


(b) fig: Relationship output variables capture and time for police behaviour

Figure K.1: Relationship output variables for offender and police behaviour (experiment 1)

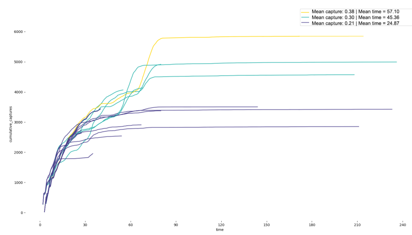


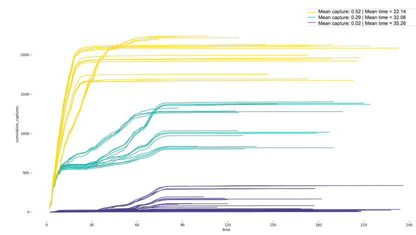
(a) fig: Relationship output variables capture and time for offender behaviour



(b) fig: Relationship output variables capture and time for police behaviour

Figure K.2: Relationship output variables for offender and police behaviour (experiment 2)

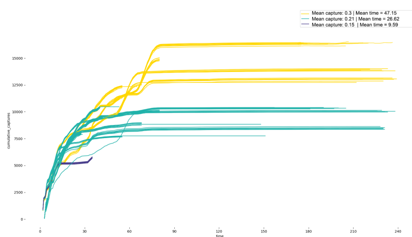


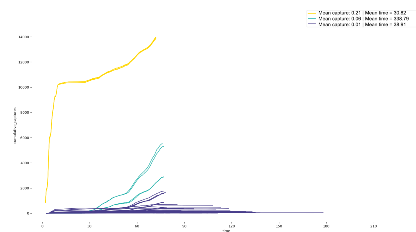


(a) fig: Relationship output variables capture and time for offender behaviour

(b) fig: Relationship output variables capture and time for police behaviour

Figure K.3: Relationship output variables for offender and police behaviour (experiment 3)





(a) fig: Relationship output variables capture and time for offender behaviour

(b) fig: Relationship output variables capture and time for police behaviour

Figure K.4: Relationship output variables for offender and police behaviour (experiment 4)

L
Sensitivity analysis

L.1 Experiment 1: no interaction

Table L.1: Mean (μ), standard deviation (σ), and covariance (Cov) for offender behavioural variables vs. output capture and time (experiment 1)

Variable	Value	μ capture	σ capture	Cov capture	μ time	σ time	Cov time
Offender start position	Centre(0)	0.20	0.40	0.10	23.85	18.89	3.11
	End (1)	0.26	0.44		41.82	22.94	
	One line (2)	0.22	0.42		33.30	19.98	
Offender strategy	Furthest (0)	0.31	0.46	-0.04	47.42	23.56	-8.73
	Random (1)	0.20	0.40		30.57	19.62	
	To train (2)	0.18	0.38		21.35	12.58	
Bounded rational	False(0)	0.22	0.41	0.01	31.94	20.69	0.57
	True (1)	0.24	0.43		34.21	23.11	

Table L.2: Mean (μ), standard deviation (σ), and covariance (Cov) for police behavioural variables vs. output capture and time (experiment 1)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Police strategy	Furthest (0)	0.17	0.37	0.03	36.36	22.18	-1.92
	Largest (1)	0.27	0.45		32.22	20.99	
	Surround (2)	0.25	0.43		30.61	22.25	
Police Guarding location	metro platform(0)	0.44	0.50	-0.1	26.45	21.07	3.32
	station exit(1)	0.02	0.14		39.74	20.77	
Police entrance location	main(0)	0.23	0.42	0.0	33.08	22.01	-0.01
	side(1)	0.023	0.42		33.04	21.89	
Police units	3	0.17	0.33	0.13	34.27	22.23	-2.43
	5	0.23	0.42		32.83	21.80	
	10	0.29	0.45		32.08	21.76	

L.2 Experiment 2: offender interaction

Table L.3: Mean (μ), standard deviation (σ), and covariance (Cov) for offender behavioural variables vs. output capture and time (experiment 2)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender start position	Centre (0)	0.20	0.40	0.01	23.73	18.82	3.14
	End (1)	0.26	0.44		41.62	22.98	
	One line (2)	0.22	0.41		33.25	20.20	
Offender strategy	Furthest (0)	0.29	0.46	-0.04	47.28	23.88	-8.67
	Random (1)	0.20	0.40		30.52	19.60	
	To train (2)	0.18	0.38		21.35	12.58	
Bounded rational	False(0)	0.22	0.41	0.00	31.90	20.67	0.52
	True (1)	0.23	0.42		33.98	23.26	
Time till bounded rational	1	0.22	0.42	0.00	32.95	22.03	-0.01
	3	0.22	0.42	32.92	21.99		
	5	0.22	0.42		32.93	21.99	
Loose goal	False(0)	0.22	0.42	0.00	33.04	22.05	-0.05
	True (1)	0.23	0.42		32.83	21.96	

Table L.4: Mean (μ), standard deviation (σ), and covariance (Cov) for police behavioural variables vs. output capture and time (experiment 2)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Police strategy	Furthest (0)	0.15	0.36	0.03	36.00	22.26	-1.79
	Largest (1)	0.27	0.44		32.22	21.04	
	Surround (2)	0.25	0.43		30.62	22.36	
Police Guarding location	metro platform(0)	0.44	0.50	-0.11	26.46	21.12	3.27
	station exit(1)	0.01	0.08		39.53	20.90	
Police entrance location	main(0)	0.22	0.42	0.0	32.92	21.95	-0.01
	side(1)	0.022	0.42		32.94	22.06	
Police units	3	0.17	0.37	0.13	34.24	22.22	-2.79
	5	0.23	0.42		32.78	21.97	
	10	0.28	0.45		31.78	21.76	

L.3 Experiment 3: police interaction

Table L.5: Mean (μ), standard deviation (σ), and covariance (Cov) for offender behavioural variables vs. output capture and time (experiment 3)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender start position	Centre (0)	0.20	0.40	0.01	24.01	18.97	3.07
	End (1)	0.26	0.44		41.55	23.01	
	One line (2)	0.23	0.42		33.33	20.16	
Offender strategy	Furthest (0)	0.31	0.46	-0.04	47.37	23.79	-8.70
	Random (1)	0.20	0.40		30.49	19.55	
	To train (2)	0.18	0.38		21.38	12.58	
Bounded rational	False(0)	0.22	0.41	0.01	31.90	20.63	0.57
	True (1)	0.24	0.43		34.17	23.25	

Table L.6: Mean (μ), standard deviation (σ), and covariance (Cov) for police behavioural variables vs. output capture and time (experiment 3)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Police strategy	Furthest (0)	0.17	0.37	0.03	36.29	22.43	-1.88
	Largest (1)	0.27	0.45		32.16	20.92	
	Surround (2)	0.25	0.43		30.64	22.22	
Police Guarding location	metro platform(0)	0.44	0.50	-0.1	26.41	21.00	3.32
	station exit(1)	0.02	0.14		39.70	20.94	
Police entrance location	main(0)	0.23	0.42	0.0	33.06	22.06	-0.01
	side(1)	0.23	0.42		33.00	21.94	
Police units	3	0.17	0.38	0.13	34.28	22.12	-2.50
	5	0.23	0.42		32.77	21.91	
	10	0.29	0.45		32.03	21.91	
Police undercover	False(0)	0.23	0.42	0.0	33.01	22.00	0.01
	True(1)	0.23	0.42		33.05	22.00	

L.4 Experiment 4: full interaction

Table L.7: Mean (μ), standard deviation (σ), and covariance (Cov) for offender behavioural variables vs. output capture and time (experiment 4)

Variable	Value	μ capture	σ capture	Cov capture	μ time	σ time	Cov time
Offender start position	Centre (0)	0.20	0.40	0.01	23.89	18.89	3.05
	End (1)	0.26	0.44		41.49	22.88	
	One line (2)	0.22	0.42		33.11	19.98	
Offender strategy	Furthest (0)	0.30	0.46	-0.04	47.19	23.67	-8.63
	Random (1)	0.20	0.40		30.48	19.52	
	To train (2)	0.18	0.38		21.36	12.57	
Bounded rational	False(0)	0.22	0.41	0.00	31.77	20.61	0.56
	True (1)	0.24	0.42		34.03	23.05	
Time till bounded rational	1	0.23	0.42	0.00	32.93	21.91	-0.03
	3	0.23	0.42		32.92	21.87	
	5	0.23	0.42		32.83	21.86	
Loose goal	False(0)	0.23	0.42	0.00	32.91	21.90	-0.01
	True (1)	0.23	0.42		32.88	21.87	

Table L.8: Mean (μ), standard deviation (σ), and covariance (Cov) for police behavioural variables vs. output capture and time (experiment 4)

Variable	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Police strategy	Furthest (0)	0.16	0.36	0.03	36.11	22.21	-1.85
	Largest (1)	0.27	0.45		32.01	20.83	
	Surround (2)	0.25	0.43		30.56	22.21	
Police Guarding location	metro platform(0)	0.44	0.50	-0.11	26.36	20.88	3.29
	station exit(1)	0.01	0.12		39.53	20.87	
Police entrance location	main(0)	0.23	0.42	0.0	32.90	21.89	-0.01
	side(1)	0.23	0.42		32.88	21.88	
Police units	3	0.17	0.37	0.13	34.15	22.06	-2.65
	5	0.23	0.42		32.72	21.84	
	10	0.28	0.45		31.80	21.69	
Police undercover	False(0)	0.23	0.42	0.0	32.77	21.82	0.06
	True(1)	0.23	0.42		33.01	21.94	

M
Payoff matrix

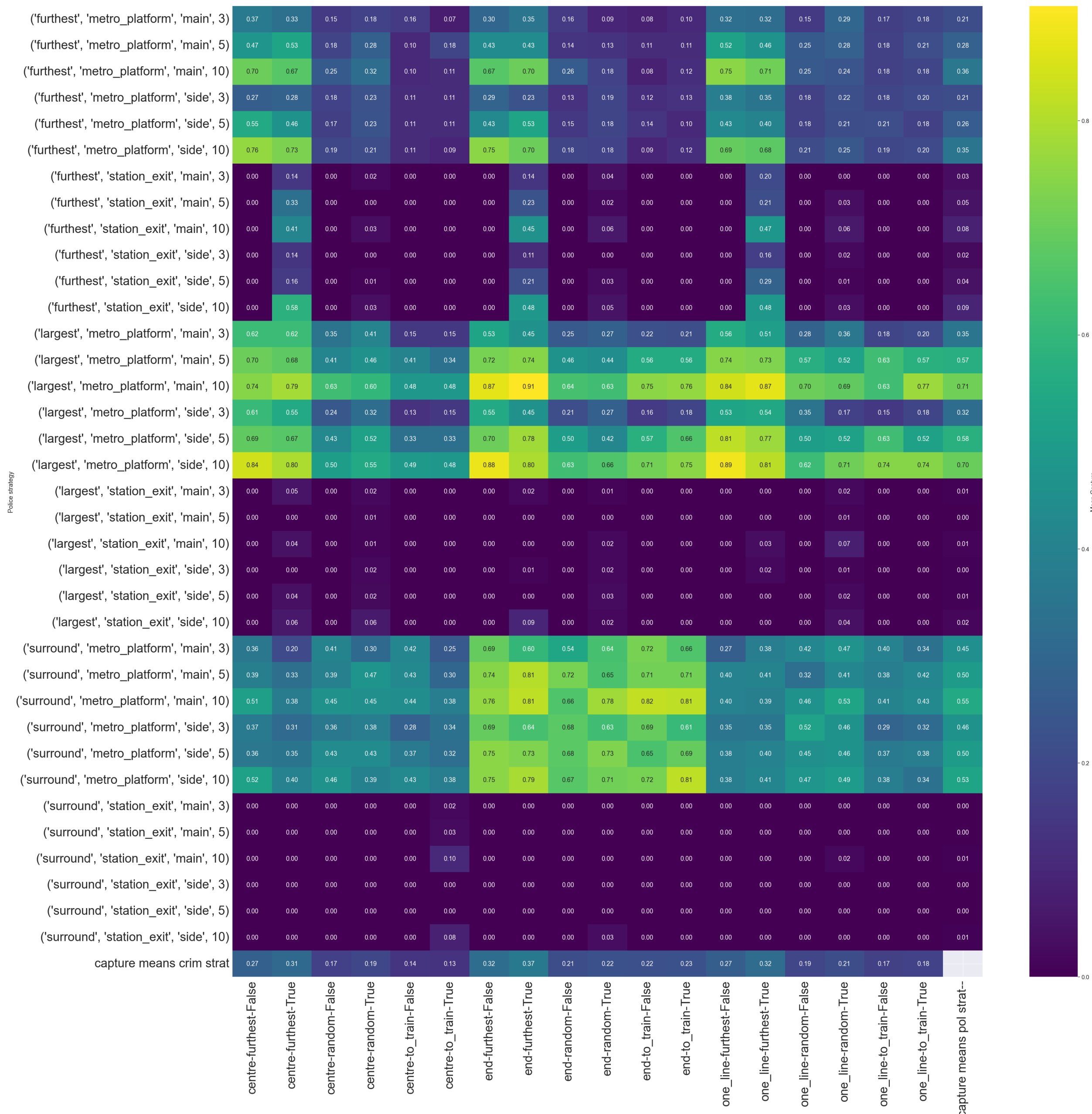


Figure M.1: Payoff matrix police vs. offender strategies (experiment 1)

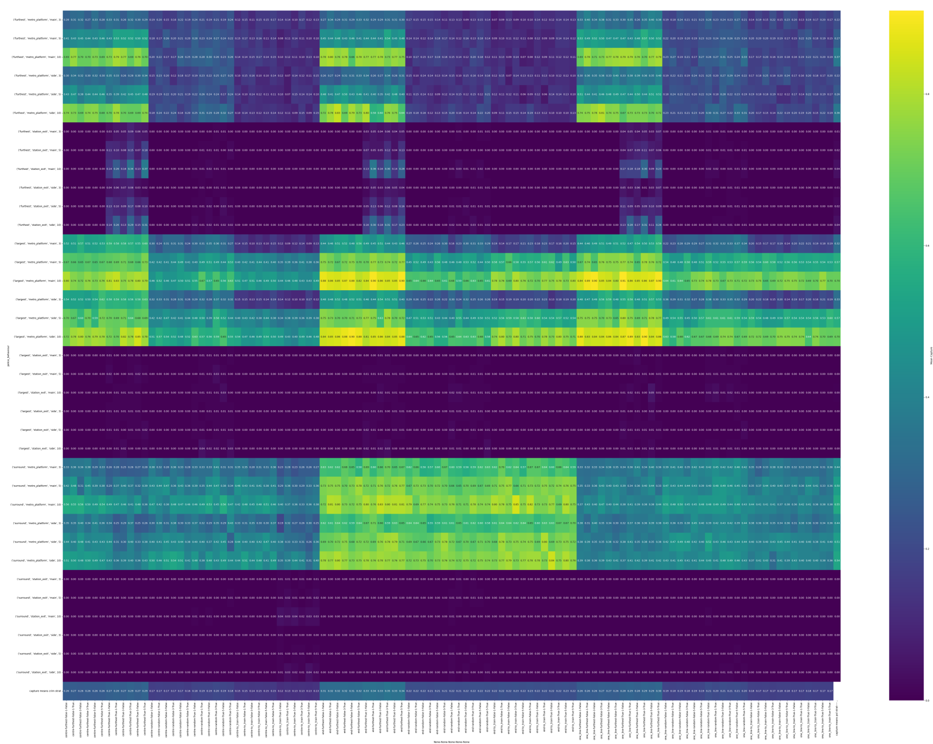


Figure M.2: Payoff matrix police vs. offender strategies (experiment 2)

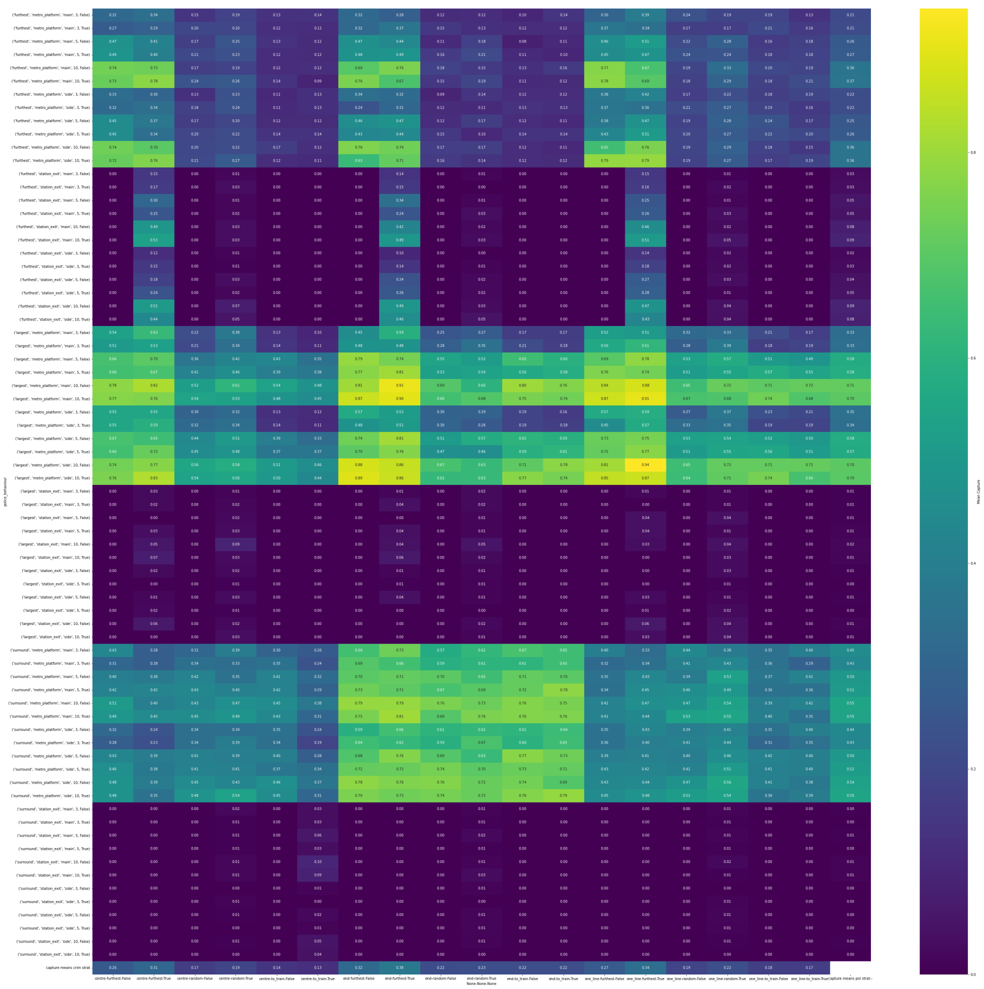


Figure M.3: Payoff matrix police vs. offender strategies (experiment 3)

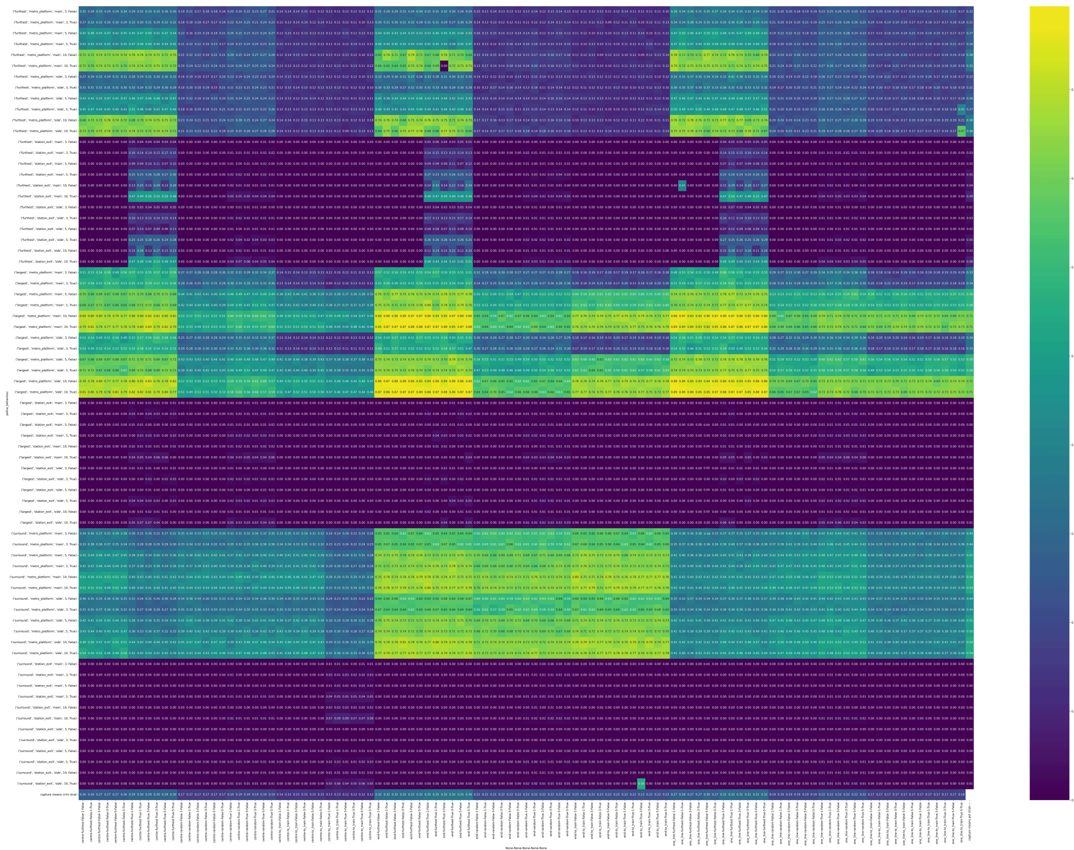


Figure M.4: Payoff matrix police vs. offender strategies (experiment 4)

N Uncertainty analysis

N.1 Experiment 1: no interaction

Table N.1: Mean (μ), standard deviation (σ), and covariance (Cov) for uncertainty variables vs. output capture and time (experiment 1)

Uncertainty	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender detection at station exit	50	0.21	0.41	0.22	33.17	22.04	1.23
	70	0.23	0.42		33.02	21.99	
	90	0.25	0.43		32.99	21.83	
Offender detection at metro platform	50	0.20	0.40	0.37	33.37	22.01	-8.25
	70	0.23	0.42		32.95	21.90	
	90	0.26	0.44		32.50	21.92	
Initial call delay	1	0.28	0.45	-0.09	30.27	22.85	4.9
	3	0.23	0.42		32.83	21.76	
	6	0.18	0.38		36.10	20.80	

N.2 Experiment 2: offender interaction

Table N.2: Mean (μ), standard deviation (σ), and covariance (Cov) for uncertainty variables vs. output capture and time (experiment 2)

Uncertainty	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender detection at station exit	50	0.21	0.41	0.21	32.94	22.02	-0.23
	70	0.22	0.42		32.96	22.03	
	90	0.24	0.43		32.90	21.96	
Offender detection at metro platform	50	0.19	0.40	0.38	33.57	21.97	-8.19
	70	0.23	0.42		32.90	22.01	
	90	0.25	0.43		32.34	22.02	
Initial call delay	1	0.27	0.45	-0.09	30.05	22.84	4.85
	3	0.23	0.42		32.90	21.87	
	6	0.17	0.37		35.86	20.87	
Police detection by Offender	50	0.23	0.42	-0.04	32.96	22.04	-0.41
	70	0.22	0.42		32.94	21.98	
	90	0.22	0.41		32.90	21.99	

N.3 Experiment 3: police interaction

Table N.3: Mean (μ), standard deviation (σ), and covariance (Cov) for uncertainty variables vs. output capture and time (experiment 3)

Uncertainty	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender detection at station exit	50	0.21	0.41	0.23	32.98	22.01	0.48
	70	0.23	0.42		33.06	22.02	
	90	0.25	0.43		33.05	21.96	
Offender detection at metro platform	50	0.20	0.40	0.40	33.73	22.06	-9.63
	70	0.23	0.42		33.06	21.98	
	90	0.26	0.44		32.29	21.93	
Initial call delay	1	0.28	0.45	-0.09	30.07	22.84	4.97
	3	0.24	0.42		32.99	21.92	
	6	0.18	0.38		36.03	20.78	
Frequency information update	1	0.23	0.42	0.00	33.04	22.00	0.00
	3	0.23	0.42		32.98	21.97	
	6	0.23	0.42		33.09	22.08	
	10	0.23	0.42		33.00	21.94	

N.4 Experiment 4: full interaction

Table N.4: Mean (μ), standard deviation (σ), and covariance (Cov) for uncertainty variables vs. output capture and time (experiment 4)

Uncertainty	**Value**	**μ capture**	**σ capture**	**Cov capture**	**μ time**	**σ time**	**Cov time**
Offender detection at station exit	50	0.21	0.41	0.22	32.90	21.88	0.04
	70	0.23	0.42		32.88	21.87	
	90	0.24	0.43		32.90	21.90	
Offender detection at metro platform	50	0.20	0.40	0.39	33.55	21.89	-8.64
	70	0.23	0.42		32.86	21.88	
	90	0.26	0.44		32.26	21.87	
Initial call delay	1	0.28	0.45	-0.09	29.97	22.73	4.95
	3	0.23	0.42		32.82	21.747	
	6	0.17	0.38		35.89	20.73	
Police detection by Offender	50	0.23	0.42	-0.01	32.91	22.89	-0.32
	70	0.23	0.42		32.91	21.90	
	90	0.23	0.42		32.86	21.85	
Frequency information update	1	0.23	0.42	0.00	32.88	21.85	-0.32
	3	0.23	0.42		32.88	21.88	
	6	0.23	0.42		32.91	21.88	
	10	0.23	0.42		32.89	21.92	