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The Effect of Models of Fugitive Behavior on Police Interception Strategies

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Abstract One of the tasks of police is catching fleeing suspects, where the police interception positions depend on the fleeing suspect's route choices. Various conceptualizations of route choice decision-making of fleeing suspects exist. However, we do not know the effects of these different models of fugitive behavior on the calculated police interception strategy. Therefore, we operationalize two models of route choice and implement these in a simulation. Police interception strategies are obtained by optimization. The resulting sets of routes and the calculated police interception positions are subsequently compared and interpreted. The experiments show that the different route-choice models result in different escape routes and, therefore, different calculated police interception positions. The differences are larger when the road network is complex and contains non-uniform obstacles. In other words, the robustness of the calculated police interception positions for each model largely depends on the network topology.

Keywords Emergency service optimization · Criminal behavior · Simulation · Police interception

1 Introduction

In recent years, only 32% of reported crimes in The Netherlands resulted in the apprehension of a suspect [25]. In the US, this figure is 37% for violent crimes and only 12% for property crimes [14]. Furthermore, 85% of arrests are red-handed, meaning the suspects were caught in the act of committing a crime or immediately after committing a crime with incriminating evidence. The remaining 15% of arrests

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involve costly and time-intensive investigations [10]. Increasing the number of red-handed arrests allows for more effective use of critical resources. Understanding the movement patterns of fleeing suspects and suggesting proper intervention positions for police units can limit the use of police resources and increase the chance of red-handed arrests.

Good interception positions are typically found at chokepoints in the road network, such as bridges and tunnels, where multiple roads converge. Mathematical optimization of the interception position relies on generating escape routes for the suspect [11]. The generated set of routes has to be complete in terms of network coverage and has to include the chokepoints. If not, the mathematical optimization model will not identify the most interesting interception points.

There are various ways to conceptualize the route choices of fleeing suspects to generate a set of escape routes [27, 35]. Without knowledge of their underlying decision-making process, the routes may resemble a random walk through the road network. In contrast, if we had complete information on the suspect's characteristics and decisions, there would be a single deterministic route. In practice, we have incomplete information, where we have some understanding of route choices but not all, leading to a heuristic implementation of the route choice model of a fugitive.

Many theoretical studies implement a random motion for the fleeing suspect [6, 27]. Explicitly encoding behavior through decision rules could lead to more effective interception strategies [30]. Therefore, the central question in this paper is: what is the effect of different models of fugitive behavior on the calculated police interception strategy? To answer this question, we conceptualize and operationalize two modes of fleeing suspect route choices. We compare the resulting sets of routes and the optimized police interception positions. Finally, we evaluate the effectiveness of the police interception positions for different route generation models.

The following section discusses the related literature on modeling behavior in interception problems and, specifically, modeling fugitive route choice behavior. Section 3 describes the methods used in the paper, including a description of the case studies, the models, and the optimization algorithms. The subsequent section details the obtained results. Possible threats to the validity of the results are discussed in Sect. 4.4, and we share our conclusions in Sect. 5.

2 Modeling Behavior

Different fields use different terminology when talking about interception. Game theory and mobile robotics refer to pursuit-evasion games, where the terms *pursuer*, *evader*, or *target* are used [7]. Mathematical optimization refers to similar problems as search problems or interception problems, depending on the objective function [1]. Game theory, mobile robotics, and mathematical optimization take a theoretical approach, reflected in the abstract naming. In contrast, empirical research on police interception refers to *police units* and *suspects* or *fugitives* [9]. In this paper, we will follow the terminology belonging to each field when discussing related literature and use the terms *police unit* and *fugitive* in the case study.

The following subsections discuss how targets are modeled in interception problems and explore various conceptualizations of criminal behavior. Each section first outlines the relevant literature and subsequently discusses its relation to this paper and resulting modeling choices.

2.1 *Modeling Behavior in Interception Problems*

Various methods exist to model targets' behavior in the search, pursuit, and interception literature. Inspired by the mindmap on search in mobile robotics in [7], we use the structure depicted in Fig. 1. The Figure provides options for motion, behavior, and availability of information, which are subsequently discussed.

Motion Pursuit-evasion games and search problems are solved for both stationary and mobile targets. For a comprehensive overview of stationary target interception, see [33]. Most other papers discussed in this section treat mobile targets, as that is the focus of this paper. For a survey of graph-based search of mobile targets, see [1].

Behavior Many studies implement a random motion for the evader. This approach is usually adopted when there is no understanding of the underlying behavior [30] or when the focus is purely on optimizing search strategies [6]. In the search and rescue literature, random motion is one of the modes of behavior found in empirical data [17, 23]. A lost person trying to find their way may move so erratically that it is close to a random walk. On the other hand, various models, often agent-based, encode rules of behavior of lost persons [17] or evaders [15]. These models can be either based on historical data or grounded in psychological theories. A small, simple set of decision rules can generate complex emergent patterns [12].

Depending on the intended application, evaders are either modeled to be non-reactive, cooperative, or adversarial. Non-reactive evaders move independently of the

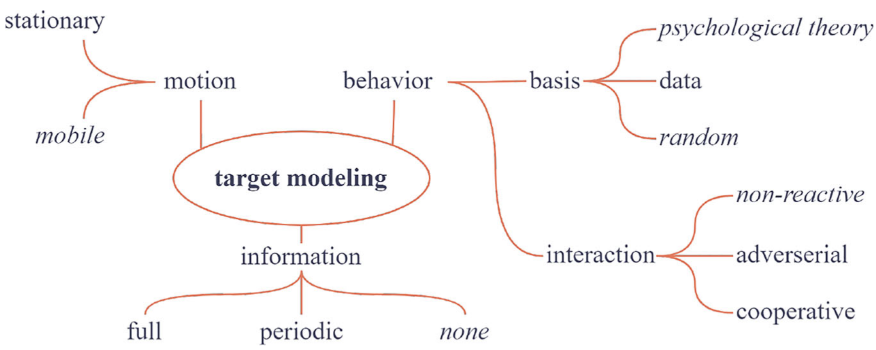


Fig. 1 A graphical overview of the dimensions of target modeling in interception problems. The subset operationalized in this paper is italicized

moves of the pursuer, either randomly or according to some predetermined pattern. This behavior occurs, for example, when the evader does not have any information on the whereabouts of the pursuer. For search and rescue, some modes of behavior of lost persons are non-reactive. Other lost person modes are cooperative: they move to places in the network where they assume that the searchers are likely to look or where they can signal their presence to the searchers. Lastly, adversarial evaders actively evade capture by anticipating and reacting to the pursuer's moves. Adversarial evaders are, for example, found in hide-and-seek [3] and some pursuit-evasion games.

Information Information about the evader's whereabouts can help to find more effective pursuer search strategies and adapt to the evader's strategy. On the other hand, information about the pursuer's location is crucial to optimize an adversarial evader's route to escape capture. Information (in either direction) can either be full [6], based on proximity [20], based on visibility [5] or using a sensor network [28].

In fugitive interception, there is very little exchange of information about each other's positions: the fleeing suspect does not know the locations of the intercepting police units, and vice versa. Spotters, traffic cameras, or phone calls from concerned citizens can provide sparse information about the fugitive's location. Furthermore, very little historical data is available, meaning that data-driven approaches are not applicable. Even with more available data, a model based on historical data would be vulnerable to survivorship bias (as we only have information on successful cases where the suspect was caught) and historical bias (as the data may no longer reflect the current *modi operandi*). Therefore, we opt to build generative models grounded in psychological theory for this application.

The next section explores psychological theories that may be leveraged to build generative models for simulating fugitive escape routes.

2.2 Modeling Criminal Behavior

Little is known about the decision-making of suspects fleeing a crime scene. However, we can draw from the broader field of criminology to generate insights.

The rational choice theory of crime is a leading framework in criminology to understand criminal behavior [8]. The central thesis is that individuals make rational decisions to engage in criminal activities after weighing the potential costs and benefits. Reference [35] goes beyond Rational Choice Theory, proposing two modi of criminal decision-making. Besides the 'cool' rational mode, calculating costs and benefits, there is a 'hot' mode that evaluates options in a more intuitive way. This concept has a long history and is more generally referred to as bounded rationality [31], as heuristic versus analytical [13], as intuitiveâŁ“experiential and analyticalâŁ“rational [12], as system 1 and system 2 [32], as cognition and emotion [19, 22], and as sense and sensibility [36]. Reference [31] explains bounded rationality as "agents use simple rules based on local information—not global information with infinite computing power." Similarly, a criminal in [35]'s 'hot mode' responds to situational characteristics. Premeditation, i.e., preparing a crime, can result in more 'cool' behavior, compared to street offenders in hedonistic contexts [29].

In this paper, we operationalize these 'cool' and 'hot' modes using the relevant behavioral factors found by [34]. Her work synthesizes general route choice literature, specifically evacuation literature, and interviews with domain experts. We implement the following factors:

- Camera avoidance: a prepared suspect avoids passing by cameras that the Police can access.
- Obstacle avoidance: traffic lights, roundabouts, bridges, and tunnels are—to a varying extent—less attractive due to unpredictability and becoming potential choke-points [26].
- Number of lanes and maximum speed: a stressed suspect prefers a higher number of lanes and maximum speed so they can get away from the crime location as quickly as possible [21].
- Inertia: a stressed suspect is more likely to continue on the road they are on [2, 24].

Relevant personal attributes (risk aversion and familiarity with the road network) and contextual factors (time of day and crime location) are not considered in this research. Interaction with other traffic is also not considered. Instead, we develop simpler, generalized models that generate a wide range of options, minimizing the risk of dual use of the route generation models by bad-faith actors.

3 Method

3.1 Models

We implement two models of fleeing suspect route choices ('cool' and 'hot').[1] Both models aim to reach a predetermined set of escape nodes from the incident location, but the road preferences vary. Although unrealistic for fugitive behavior, a random walk model is used as a benchmark because it is commonly used in literature, and it is a quick method of generating a broad set of routes.

3.1.1 Cool Mode

The well-prepared, cool model prioritizes avoiding cameras to avoid detection. Traffic lights are avoided because they may add an unpredictable delay and traffic. Roundabouts are avoided if possible because they are difficult to navigate and oversee. Tunnels and bridges are avoided because they create a lock-in, they are difficult to

[1] All data and code can be found at: https://github.com/irene-sophia/fug_behavior.

oversee, and they are seen as a likely police position. In practice, all major tunnels and bridges are overseen by cameras at their entrance and exit, leading to a cumulative perceived delay of 35 or 65 s.

3.1.2 Hot Mode

The stressed, ad-hoc, hot model prioritizes avoiding traffic lights, which mimics turning when encountering a red light. Roundabouts and bridges are, analogous to the cool model, avoided if possible because they are difficult to navigate and oversee. The hot model avoids tunnels more due to feeling trapped. Additionally, the hot model prefers roads with more lanes and higher speed limits for easier maneuverability and perceived faster escape.

3.1.3 Directed Random Walk

The 'hot' and 'cool' models are contrasted with a directed random walk. This method is commonly used and computationally cheap. Like the other models, the random walk starts at the location of the incident, as defined in Sect. 3.4. At each intersection, the fugitive chooses the next node to travel to, following a stochastic process where each neighboring node has an equal probability of being chosen. The fugitive does not turn around unless the node only has one neighboring node (i.e., a dead end).

Each factor identified as important for fugitive route choices is assigned a weight representing its 'added travel time'. In other words, it defines how much shorter a route must be to be more attractive than a longer route that avoids the obstacle. The order and approximate values follow from interviews with domain experts. Table 1 presents the perceived delays of each obstacle. Locations of cameras and obstacles are obtained from open data[2] and OpenStreetMap.

After adding the perceived delays to the travel time of the respective links of the road network, the perceived best routes are generated for each model. Next, a noise of either 2 or 5% (Cool mode) or 5 or 10% (Hot mode) is added to routes, meaning that the suspect takes a wrong turn every X% of the intersections. After a wrong turn, the new best path is determined from their next position. This noise accounts for three factors: (1) simulating human error, especially in stressful situations; (2) accommodating adjustments for unexpected obstacles like red lights; and (3) accounting for factors not explicitly modeled. As a result, we observe a distribution of routes around the optimal paths.

[2] Camera locations were obtained from (1) Utrecht, The Netherlands: https://data.utrecht.nl/dataset/cameraregister-utrecht, public security cameras, (2) Manhattan, New York, USA: https://banthescan.amnesty.org/decode/, traffic cameras, (3) Winterswijk, The Netherlands: https://www.politie.nl/informatie/locaties-cameraplan-anpr-126jj-sv.html, traffic cameras.

Table 1 Operationalization of the behavioral models. The times and factors indicate the perceived delays by the fugitive

Perceived delay	'Cool' model	'Hot' model
Camera	+30 s	–
Traffic light	+10 s	+20 s
Roundabout	+5 s	+5 s
Tunnel	+5 s	+10 s
Bridge	+5 s	+5 s
Lanes	–	1: ×1.2, 2:×1, ≥3: ×0.8
Speed limit (km/h)	–	≤30: ×1.2, ≥30:×1, ≥50: ×0.9, ≥80: ×0.8

3.2 *Optimization*

We model the optimization problem as a variation on the Flow Interception Problem [4, 18]. The target position for each police unit is optimized to maximize the number of intercepted routes. A route is intercepted if (1) the route passes a target position of a police unit and (2) that police unit can reach its target position before the escape route passes through. The optimization problem is NP-hard, meaning that solving real-world instances involves computation times of years. Optimizing the route of each police unit, where they can intercept the fugitive at any intermediate time, or dynamically reacting to incoming information about the fugitive's whereabouts would further increase the complexity and required computation time.

We solve the optimization problem using a genetic algorithm supplemented with the auto-adaptive framework from Borg, which co-evolves the probabilities of the evolutionary operators used for population adaptation based on their relative success in finding fitter offspring [16]. Reference [11] show that this optimization approach quickly finds near-optimal solutions. To further ensure the quality of the solutions, the algorithm is run with five seeds for 20,000 function evaluations, only preserving the best solution.

3.3 *Design of Experiments*

We examine the effect of different fleeing suspect route choice models on the resulting simulated escape routes and the calculated police interception positions. Finally, we cross-evaluate the calculated interception positions on different sets of simulated escape routes. For this, we use the following design of experiments, graphically displayed in Fig. 2:

1. A set of 1000 routes is generated by looping through all escape nodes and generating the shortest route (based on the adjusted perceived travel time).

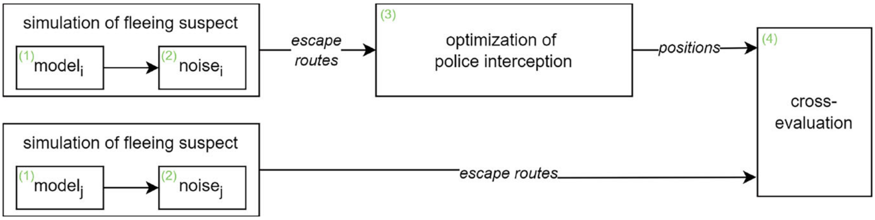


Fig. 2 Graphical overview of the design of experiments. The green numbers in parentheses refer to the numbered items in Sect. 3.3

2. These routes form the input to a pyDSOL discrete-event simulation model.[3,4] An entity is created for each route. In the pyDSOL model, each entity follows its predetermined route unless it takes the wrong turn (determined by the 'noise' parameter). A wrong turn is a random choice of the neighboring links, excluding the planned and previous ones. Each combination of model and noise generates a set of routes constituting the first set of results.
3. These routes are the input of an optimization model that determines the positions for a set of police units that maximizes the number of intercepted routes. The calculated interception positions form the second set of results.
4. The positions are evaluated against different models to test their robustness. In other words, we determine the number of intercepted routes resulting from a different model using the positions optimized for the original model.

3.4 Road Networks

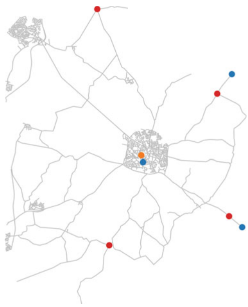
The experiments are performed for three case studies (Table 2). Utrecht, The Netherlands represents a typical European city with a historical center surrounded by modern neighborhoods. Winterswijk, the Netherlands represents a rural area with sparse roads surrounding a town. Escaping by crossing the border to Germany is possible in the north, east, and south. Manhattan, New York, USA represents a modern grid layout city with traffic lights and cameras at most intersections. The police start locations are the local police stations.

4 Results and Discussion

The simulation results in Table 3 display the escape routes in red and green, indicating whether they are intercepted by the calculated police interception positions (blue

[3] pyDSOL core: https://github.com/averbraeck/pydsol-core.
[4] pyDSOL model: https://github.com/imvs95/pydsol-model.

Table 2 Case study road networks used in this study. Incident locations are marked in orange; escape nodes in red, and police starting positions in blue

Utrecht	Winterswijk	Manhattan
Typical European city	Rural area	Modern, grid city
Incident: city center	Incident: city center	Incident: union square
Escape: reach the highway	Escape: cross the border	Escape: get off the peninsula
		

dots). The following sections discuss the results: first, the escape routes, then the calculated positions, and last, the robustness evaluation.

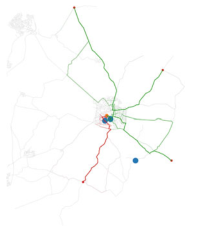
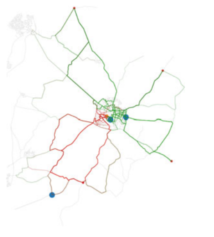
4.1 Simulated Escape Routes

The escape routes resulting from the various models are presented in Table 3. Below, we discuss the results, first in general and then individually for each city.

In general, the characteristics of the simulated escape routes depend on the underlying road network. However, directed random walks are an exception, as they tend to stay near the starting point and rarely reach the designated escape nodes. Additionally, the Cool and Hot models show different road preferences across all networks. With increasing noise, routes spread out more, visiting more nodes, but the differences between Cool and Hot persist.

Utrecht shows several equivalently attractive roads near the incident in the city center. A few major arteries fan out from the city center towards the escape nodes, but the chosen arteries differ between the Hot and Cool models. For instance, comparing the southwest of Utrecht for the Cool model with 2% noise and the Hot model with 5% noise shows clear differences. In Winterswijk, only a few roads lead to the designated escape nodes, resulting in similar Hot and Cool graphs, with noise being the main distinguishing factor. In Manhattan, low-noise models gravitate towards the major riverside roadways due to the relative absence of traffic lights and cameras. The preferred roads differ between the Hot and Cool models. The Hot model is relatively less sensitive to noise (comparing Cool and Hot with 5% noise) since

Table 3 Resulting escape routes, with intercepted routes in green and not intercepted routes in red, where the transparency of the road segment represents the number of routes passing through. Calculated interception positions are blue

Model	Utrecht	Winterswijk	Manhattan
Random walk			
Cool, 2% noise			
Cool, 5% noise			
Hot, 5% noise			
Hot, 10% noise			

there is a traffic light at virtually every intersection, and cameras are slightly more sparsely distributed. Therefore, when the Hot model takes a non-optimal turn due to the modeled noise, making a U-turn is more attractive than taking a detour. At higher noise (10%), the model is pushed out of that equilibrium, and the routes spread out widely due to the grid layout with nearly equivalent.

In summary, the cool and hot models result in different road preferences. The specific characteristics are dependent on the network features and topology.

4.2 Calculated Interception Positions

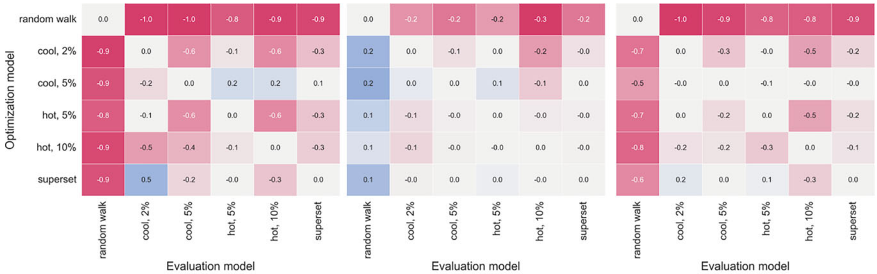
The calculated positions are shown as blue dots in Table 3. The positions are optimized to maximize the number of intercepted routes. Note that a route is only intercepted if the associated police unit can reach the position before the route passes it. The initial police positions are shown in Table 2.

Since the random walks remain stuck near the incident, the calculated interception positions are also near the incident, at very different positions than other models. The calculated positions for Utrecht are along major city roads, further from the incident. Yet, the specific positions vary across models. One consistently calculated position, located centrally in the East, proves effective regardless of the suspect's model. Similarly, in Winterswijk, a position near the incident remains constant across all models: one nearby police unit can quickly intercept many routes towards the north and east of the network, while others disperse across the network depending on the model used for the suspect. In Manhattan, the calculated interception positions are consistent across Cool and Hot models and are concentrated along the major roadways along the river.

In summary, the Cool and Hot models result in different calculated police interception positions. The specific positions are dependent on the road network features and topology. Some consistently well-performing positions are found.

4.3 Robustness Evaluation

We cross-evaluate the effectiveness of calculated police interception positions for each model (i) by examining the number of intercepted routes generated by other models (j). The results, shown in Fig. 3, are scaled to the number of intercepted routes using the same optimization and evaluation model ($i = j$). Therefore, each row indicates the robustness of the calculated positions across different models of suspect route choices. Negative values (pink) indicate that the interception positions calculated based on the optimization model perform worse on the routes generated using the evaluation model compared to the routes generated using the optimization model (when $i = j$). A positive score (blue) means that relatively more routes are



(a) Utrecht (b) Winterswijk (c) Manhattan

Fig. 3 Results of the robustness evaluation

intercepted, suggesting that the routes of the evaluation model are less spread out than those of the optimization model.

Irrespective of the road network, the random walk model generates distinctly different routes, so positions based on this model perform poorly on other sets of routes and vice versa. An exception is Winterswijk, where any set of calculated positions performs well for random walk routes, likely due to their proximity to the incident location, where the random walk routes concentrate.

The bottom row and rightmost column display the superset of routes, combining the Cool 2%, Cool 5%, Hot 5%, and Hot 10% routes. The results confirm that interception positions calculated for this superset are generally robust across models. While they do not significantly outperform other optimization models, they offer a reliable approach if the mode of behavior is unknown.

The heatmap of Utrecht (Fig. 3a) shows that positions calculated based on the set of escape routes generated using one model do not perform well on another set of routes. Numerous potential escape nodes and equally attractive roads leading to them result in considerable differences in calculated positions across models. Notably, the Cool 5% model shows higher robustness compared to others. The Winterswijk heatmap (Fig. 3b) is relatively homogeneous, with most values around 0. This can be explained by, first, the generally good interception position in the city center and, second, the limited number of roads that lead to the escape nodes. The Manhattan heatmap (Fig. 3c) also shows a somewhat uniform pattern. Generated escape routes converge on riverside roadways, leading to a concentration of calculated positions. However, the Hot 10% model is an exception due to its broad set of escape routes covering most nodes in the road network. Consequently, the calculated positions based on this model are less concentrated on the riverside roadways. This results in poor performance when applying positions from the Hot 10% model to other models and vice versa.

In summary, the robustness of the calculated police interception positions for each model largely depends on network topology. In compact networks with few escape nodes and distinct attractive roads leading to them, funnels emerge that form good interception positions. However, in more uniform road networks, understanding the suspect's route choice is crucial for successful interception.

4.4 Discussion

This paper shows that the effectiveness of police interception depends on the route choice model of the fugitive. The specific characteristics of escape routes and interception positions largely depend on the case study network. Therefore, further research should explore more types of road networks and identify network characteristics that consistently lead to effective interception positions.

This paper presents a first attempt to operationalize conceptual models of fugitive escape route decision-making. Additional state information that might influence fugitive behavior, such as the type of crime (ram raid, robbery, pickpocketing, etc.) and the traffic situation, can be added. Additionally, the model of behavior might switch during the escape, for example, shift to 'cool' after some time or shift to 'hot' when unexpected things occur. Expert interviews can help to determine relevant characteristics to add to the choice model. However, there is a limit to predictability: the police do not know the exact psychological state of the fleeing fugitive, and empirical data on fugitive routes does not exist. Additionally, limited computation time for real-time decision support constrains the complexity of the models that can be used.

5 Conclusion

Knowledge of the specific route choice model of the fleeing suspect is critical for finding effective interception positions in complex networks with non-uniformly distributed features and obstacles. This paper conceptualizes and operationalizes three models of fleeing behavior to examine the resulting routes, calculated police interception positions, and the robustness of the models. We show that

- A random walk model - often used to simulate fleeing suspects in interception problems - leads to distinctly different escape routes and, therefore, calculated interception positions compared to models based on psychological theory. Therefore, a random walk model is unsuitable for decision support in real-world police interception.
- Despite their similarities in implementation, the Cool and Hot models result in different simulated escape routes and, therefore, calculated police interception positions. The differences are larger when the road network is complex and has non-uniformly distributed obstacles.
- The calculated interception positions are robust to different models of a fleeing suspect when the road network is either (1) relatively simple with few roads leading to the escape nodes, or (2) when police units can quickly reach intersections close to the incident, or (3) the positions of the escape nodes create a funnel where escape routes converge.

Further research should focus on extending the library of plausible models of fleeing suspect route choices based on data and interviews with domain experts. Additionally, exploring a wider range of road networks should identify network characteristics that consistently lead to effective interception positions.

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