Chapter 7 Simulation of Dependencies between Armed Response Vehicles and CPTED Measures in Counter-Terrorism Resource Allocation

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Abstract

National and local governments must continuously adapt counter-terrorism strategies to new and evolving threats. With limited budgets, security architects and planners across the world face the same recurrent challenge: specifying a portfolio of effective measures and detailing where and when to deploy those. To perform this difficult task, methods have been proposed that apply a risk-based approach to solve this class of optimisation problems. However, many of those methods either ignore important aspects of the attacker-defender interaction or are too complicated to appeal to practitioners.

Aimed at security specialists, this article uses simulation experiments to examine current responses to an unsophisticated but increasingly frequent manifestation of terrorism: vehicle and knife attacks. In particular, it shows that the optimal configuration of Armed Response Vehicles (ARVs) and measures of Crime Prevention through Environmental Design (CPTED) depends on whether offenders conduct hostile reconnaissance, the way they react to the presence of security measures, and what attributes of the opportunity structure influence their actions most.

Through this study, we demonstrate how information about offender displacement can be used to improve security strategies. We found that security architects and planners should not necessarily prioritise the most crowded and high-profile targets but could also consider deploying CPTED measures to protect nearby secondary targets. As we review the information underpinning our decision-making model, practical challenges in modelling displacement are then highlighted. Finally, a more general observation is made that, despite strong conceptual differences, ARVs and CPTED measures are, in fact, interdependent.

Keywords: armed response vehicle, CPTED, offender decision-making, security architecture, terrorism

Background

Protecting citizens against vehicle and knife attacks

In the last five years, a growing number of attacks have been conducted on European soil with unsophisticated weapons, especially vehicles and knives (Europol, 2017). Compared with explosive attacks, they have required relatively little effort to plan and prepare, making it difficult for security services to disrupt them ahead of their execution. Many of them have been attributed to so-called *lone actors*, a term that refers to single individuals who could have been previously affiliated with a terrorist organisation (Spaaij, 2010), pairs of individuals who act together as 'isolated dyads' (Gill, Horgan and Deckert, 2014) or 'wolf packs' consisting of up to four ideological offenders (Capellan, 2015). Whilst there is still some uncertainty about the level of support and ties perpetrators have had with other terrorist operatives or networks, the change in terrorist modus operandi is evident (Schuurman, 2017).

In the face of new and evolving threats, it is common for authorities, policy-makers, law-enforcement officers and place managers to review and adapt security arrangements (Lord Harris, 2016). At every level of government, those responsible for securing public spaces are confronted with two critical questions: how much should be invested in security? and what security measures should be adopted? Answering these questions can be difficult, as it requires assessing and comparing potential interventions, a challenge compounded by the number and diverse nature of the security measures that could be deployed. To cite a few, those include security education in public and corporate settings (Run-Hide-Tell), overt/covert surveillance technology (Closed-Circuit Television, Automatic Number Plate Recognition), weapon detection systems (metal detector, X-ray scanners), security personnel (ARVs and private security guards) and target hardening features (bollards and barriers) (Borrion et al., 2014).

Already, a number of measures have been deployed in our cities that aim at reducing terrorism risk through preventing offenders from performing potentially harmful actions or reducing the consequences of their actions. Amongst those, police and military personnel represent a major component of contemporary security strategies. On many occasions, terrorists have been neutralised by police (Parodi and Cinelli, 2016; Smith-Park and Goehler, 2017; The Telegraph, 2017). However, the capacity of law enforcement officers to stop a vehicle attack in progress is very limited, especially in countries where they are not armed. Besides, police are not the only possible actors, and attacks have been disrupted by others. In 2005, it was the action of a private security guard at the Stade de France that prevented an explosion inside the French football stadium. Similarly, civilian staff or members of the public can be instrumental in disrupting attacks, alerting others of the dangers or giving shelter to people (Buncombe, 2015; Chrisafis, 2015; Horton and Day, 2017; Tripathi, Borrion and Fujiyama, 2017).

Besides police personnel, measures of Crime Prevention through Environmental Design (CPTED) are also used to prevent offenders from performing harmful actions or reducing the number of casualties and the amount of damage and business disruption (Borrion and Koch, 2018; Ekblom, 2011). Physical obstacles, especially barriers and bollards, have been deployed in many places in response to the rise in vehicle attacks. Following the attack in Westminster, security barriers have been installed on several bridges in London (Forster, 2017). To prevent attacks, trees and plant pots with bulky planters have been preferred over concrete barriers in Florence and Rome (Yalcinkaya, 2017).

Resource allocation methods

Under limited resources, developing a suitable portfolio of security measures is challenging, and difficult choices must be made between very different strategies (Parker et al., 2017).

Selecting particular types of measures to implement is only part of the solution though, as security planners must then decide how the selected resources should be distributed in space, time and between stakeholders. For this, different methodological approaches exist that include, but are not limited to, Probabilistic Risk Assessment, Game Theory and Adversarial Risk Analysis. Those are presented below, as they relate to the problem at the heart of this article.

Probabilistic Risk Assessment (PRA) is a quantitative approach widely used to identify and evaluate the composite probability and impact of critical incidents occurring within large industrial facilities and complex technological systems (e.g., Drissi et al. 2013; Park and Lee, 2017; Powell et al., 2008; Rasmussen, 1975). In our context, a formulation of *terrorist risk* has been proposed by Willis et al. (2006) that combines a measure of the threat posed by the offender, a measure of the vulnerability of the defender to the threat, and the consequences of the attack should the attack result in damage.

The application of PRA in terrorist risk assessment usually involves evaluating the differences between the risks faced by different targets under different conditions, with and without specific protection measures. A measure of the risk is then estimated for each target, and a priority to deploy the available resources derived based on the resulting risk distribution (Ayyub et al., 2007; Cox, 2009; Haimes, 2004; Paté-Cornell, 2007; Willis et al., 2007). Cox (2009) commented that if terrorists were aware that PRA is used to deploy resources, they might infer useful information about the vulnerability of the targets, and adapt their actions accordingly. Hence, it is important to model terrorist behaviour in order to estimate what level of risk is likely to remain once protection measures are adopted. One way to do this is to solve a constrained optimisation problem, with one constraint defined by modelling the attacker strategy (e.g., maximising harm).

Alternative approaches have been considered to address this issue. One of them, game theory, is increasingly used to support counter-terrorism resource allocation. It captures two important elements that are, first, strategic interactions between terrorists and defenders (where actions are interdependent) and, second, strategic interactions between rational actors who try to act as they think their counterpart would act and react (Sandler and Arce 2003). In the Stackelberg game, one player acts as a leader and the others as his followers (Stackelberg, 1952). The leader can keep his strategy fixed while the follower reacts independently subject to the leader's strategy. Formally, the Stackelberg game can be modelled as a two-level game model where the players act sequentially. At the first level, the leader (the only active player at that level) plays first and chooses his best strategy, considering that the followers react in an optimal way to his decision. At the second level, the followers react rationally to the leader's strategy by optimising their rewards (e.g. minimise a given cost function or maximise the expected damage). This approach has been applied to develop so-called Stackelberg security games (Kiekintveld et al. 2009) in which the attacker chooses amongst a set of potential targets and the defender seeks to protect them using limited available resources (Nguyen et al., 2016; Wilczyński et al., 2016). Tambe (2012) presented a compact security game model where identical resources can be attributed to any target and the rewards depend on the identity of the attacked target and the defensive protection measures eventually assigned to it.

In a different vein, Powell (2007a) has presented a framework for allocating security resources, and demonstrated that the same principle can be applied to find the optimal solution in four settings. These correspond to cases where (i) the sites to be protected are independent, and the resources available to each site do not depend on what resources were allocated to the others; (ii) resources must be allocated to central interventions in addition to those spent on specific sites (e.g., border defence, intelligence or anti-terrorist operations) which, if successful, would protect all the sites; (iii) threats have not only a strategic component but also non-strategic ones; and (iv) uncertainty about the terrorist target preferences. Bier et al. (2007) have proposed a model where the defender is unaware of the attacker preferences, while the attacker observes the deployment of the protection measures. The model shows that concentration of resources to protect targets with high payoff value yields greater protection overall. Other works dealing with uncertainties related to the attacker's target preferences and value of targets have been proposed by Powell (2007b) and Bier et al. (2008).

In these approaches complete and perfect information is assumed about the aims and aspiration of both the defender and the offender. In practice, however, this information is incomplete (Sandler and Arce, 2003) and the standard approach considering them complete ends up failing (Banks and Anderson 2006). Ezell et al. (2010) adopted a Bayesian approach to model uncertainties about players (attacker and defender) and their preferences. However, finding a balanced solution allows neither defender nor attacker to obtain their best reward (Insua et al., 2009).

Adversarial Risk Analysis (ARA), an alternative approach integrating classical game theory and PRA, was proposed by Insua et al. (2009) and Rios and Insua (2011) to deal with decision-making problems involving intelligent opponents and uncertain outcomes. Specifically, ARA aims to support defenders seeking to solve a decision-making problem. To that end, they must predict the actions of the attackers, and the outcomes perceived by all the parties (Insua et al., 2009). Forecasting requires considering random consequences that result from the set of selected actions; and deriving a solution requires building a descriptive probabilistic model of the opponent's behaviour that entails strategic thinking: the opponent may behave randomly, perform level-k thinking[ii] (McLay et al., 2012) or use mirroring[iii] (Insua et al., 2009) amongst others (see Insua et al., 2015). Many applications of ARA exist that include simultaneous and sequential models with private information (Insua et al. 2009, Rios and Insua 2011), and aim at securing a military convoy that could be attacked along its route (Wang and Banks, 2011), security resource allocation to protect air traffic control towers (Cano et al., 2016), urban security resource allocation (Gil et al. 2016), and stadium protection (Zawadzki et al., 2017).

Aim and Scope

To many decision-makers, adopting a risk based approach to security planning simply involves prioritizing resources toward high-risk targets or places. As suggested above, this simplistic approach can be ineffective though, and authors have, for example, indicated that resources should be deployed where they can reduce the risk most. Furthermore, there are limitations in using simplistic methods that do not account for the aforementioned dynamic and adaptive aspects of offenders' decision-making processes. Golany et al. (2009), for instance, have pointed out that terrorist planning is not random, and analysts should not underestimate the effects that protecting certain targets can have on others.

Offenders' responses to law enforcement intervention can be of various kinds. Besides deterrence, intervention can give rise to *displacement* in various forms: temporal displacement (change the time at which they commit the offence), tactical displacement (change the modus operandi), target displacement (change from one type of target to another), spatial displacement (switch from one location to another) and functional/offence displacement (switch from one form of crime to another) (Reppetto, 1976; Ratcliffe and Breen, 2011; Weisburd et al., 2006). However, only very few studies have examined displacement of terrorism empirically (Braithwaite and Johnson, 2015; LaFree et al., 2012; Perry et al., 2017; Yang and Jen, 2017).

In the following we explore how post-intervention displacement might affect the risk posed by vehicle and knife attacks in urban environment. Simulation experiments are used to reason about the deployment of ARVs and CPTED measures, and unveil some of the dependencies between these two types of security measures. Ultimately, the demonstration and its findings are designed to illustrate how offender decision-making and displacement can affect the protective impact of counter-terrorism strategies, and assist security architects and planners in the development of city-wide strategies.

Problem Formulation and Modelling

Risk model

A computational model was created for the purpose of our demonstration that represents an ecosystem comprising thirteen places (e.g., pedestrian high streets, squares, etc.). To target those, agents representing violent offenders can choose between two types of weapons (knife and/or vehicle) and three types of attacks (knife attack, vehicle attack or vehicle and knife attack). Altogether, the different combinations of targets and attack types constitute 39 different *attack plans*. On the defender's side, security planners must draw recommendations for the deployment of two new security measures: a set of bollards and one ARV. Finding their optimal location is not straightforward though, as the number of possible options (169 in this case) increases very rapidly with the number of possible locations.

To specify the best possible security strategy, a risk distribution must ideally be estimated for every arrangement of those measures, and the strategy corresponding to the minimum risk identified. Risk is defined here as the *expected* consequences, that is the product of the likelihood and severity of the impact, of potential terrorist attacks (Keeney, 2011; Willis,

2006) across all considered targets, as shown in Equation 1. In the following, we explain how the likelihood and consequences are calculated:

$$R = \sum_{i=1}^{n} R(T_i) \ \ldots\ldots(1)$$

where

n: the number of targets,

$$R(T_i) = \sum_{s \in \boldsymbol{A}} \Pr(s\ occurs\ and\ results\ in\ damage) * \\ \mathrm{E}[Damage\ given\ s\ occurs\ and\ results\ in\ damage]$$

with *s* an attack plan and ***A*** the set of scenarios covering all possible attack plans in the ecosystem considered.

Consequences

Terrorist attacks can have diverse consequences that might be described in terms of fatalities, morbidity, economic cost, social impacts and environmental impact (Keeney et al., 2011). As often in the literature, this article only considers just one of them: fatalities (e.g., Ellis et al., 2016; Phillips, 2014:159; Phillips and Phol, 2012). To calculate the consequences at Target T_i, for i=1,…,n, three functions $f_j(T_i)$ described in Equation 2 are used to represent the expected number of fatalities observed when an attack type j happens at Target i, with $j \in \{V, K, VK\}$ (*V*: vehicle, *K*: knife and *VK*: vehicle and knife).

$$f_V(T_i) = f_V^{max}(T_i)$$
$$f_K(T_i) = f_K^{min}(T_i) + \beta_K(T_i)\,\tau(T_i)$$
$$f_{VK}(T_i) = \begin{cases} f_V^{max}(T_i)\,, if\ the\ ARV\ arrives\ before\ the\ knife\ attack\ starts \\ f_V^{max}(T_i) + \beta_K(T_i)\,\tau(T_i)\,, otherwise \end{cases}$$

where:

$f_V^{max}(T_i)$: the number of fatalities caused by a vehicle attack at Target T_i

$f_K^{min}(T_i)$: the minimum number of fatalities immediately occurring in a knife attack at T_i

$\beta_K(T_i)$: the number of fatalities per unit of time during a knife attack at T_i.

$\tau(T_i)$: the duration of the knife attack at T_i, with $\tau(T_i) \in [0, \tau^{max}(T_i)]$

The rationale for these functions is detailed in the remainder of this section. Vehicle attacks are conducted over a short period of time, and normally end when the vehicle encounters a physical obstacle like a car, wall, tree or bollard, or when the offender tries to escape, rather than because of the real-time intervention of a police officer (BBC, 2018; CNN, 2018; Crouch and Bengtsson, 2017). For this reason, we approximate the expected number of fatalities caused by a vehicle attack as a constant that depends upon the properties of targets (e.g., number of pedestrians) at the location of the attack. Knife attacks must be modelled differently. At the start of the attack, the offender might be able to rapidly harm a number of individuals (f_K^{min}) before pedestrians start fleeing the crime scene. Although the efficiency of an offender with a knife is a lot lower than for a vehicle attack, they are less likely to be stopped by physical obstacles. Because of this, they could continue harming pedestrians for as long as they are not neutralised, which is why the number of fatalities depends upon the duration of the knife attack $\tau(T_i)$. Above a certain response time, though, we assume that attacks are stopped by another responder as represented in Equation 3. The resulting model for knife attacks is depicted in Figure 7.1.

<FIGURE 7.1 HERE>

Figure 7.1: Number of fatalities as a function of police response time, for a knife attack

$$\tau_K(T_i) = min\left(\tau_K^l(T_i), \tau_K^{max}(T_i)\right), l = 1 \ldots L \qquad \ldots\ldots(3)$$

where:

l : the index representing individual ARVs *(L=1 in our case)*

$\tau_K^l(T_i)$, the response time of the l^{th} ARV, which is assumed to be proportional to the distance it must cover to reach the attack site.

To sum up, the two types of protection measures considered in this article are of varying effectiveness (Table 7.1): bollards can be deployed to stop vehicles whereas ARVs are more effective against offenders using a knife. For the third type of attack, bollards are effective in the first phase (that is, against the vehicle) whilst ARVs are potentially effective in the second phase if they are situated close enough to the target.

Table 7.1: Types of attacks and counter-measures considered in our problem.

<TABLE 7.1 HERE>

Likelihood

Multi-criteria decision-making model

Having explained how the consequences of an attack are modelled, we now turn our attention to the other component of the risk equation: the likelihood that the attack occurs and results in damage. Due to the probabilistic nature of the model, the probability estimates are calculated by running Q=1,000 simulations, counting how many times each attack plan is executed, and normalising the results, as described in Equation 4:

$$\forall s \in \boldsymbol{A} : P(s\ occurs) \times P\ (s\ results\ in\ damage | s\ occurs)\ \times 0.01Q \quad \ldots\ldots(4)$$

For the simulations, offender selection of attack plans is guided by a decision-making model relying on three criteria:

- C_F: Gain associated with the fatalities expected to be caused by the attack

- C_N: Gain associated with the iconic nature of the target or places hit or threatened by the attack
- C_D: Loss associated with the effort expected to be involved in the conduct of the attack

For each offender, a vector of scores, u, representing the perceived utility score of each attack plan $s \in \boldsymbol{A}$, is then calculated using a weighted sum approach. The selected attack plans, $\boldsymbol{A}^*$, are those with the greatest utility scores, as shown in Equation 5:

$$\forall s^* \in \boldsymbol{A}^* : \ u(s^*) \geq \ \gamma . \max\big(u(s)\big) \quad \ldots\ldots(5)$$

where γ=0.9 is an arbitrary coefficient defining a threshold above which it is assumed that offenders perceive the utility scores to be equally high. When *N* attack plans are considered sufficiently attractive by an offender, the individual conditional probabilities are inversely proportional to *N*.

Weighted sum score

Before presenting the results of the simulation, it is useful to examine Equation 6 which explains how the utility scores associated with individual attack plans, *s*, are calculated (Ehrgott, 2005:p.65).

$$\forall s \in \boldsymbol{A} : u(s) = \sum_{c \in \boldsymbol{C}} \omega_c \, a_{s,c} \quad \ldots\ldots(6)$$

with:

- $\boldsymbol{C} = \{C_F, C_N, C_D\}$
- ω_c: a weight reflecting the importance given by the offender to criterion $c \in C$
- $a_{s,c}$: the performance value of the attack plan s for the criterion c

The performance values, $a_{s,c}$, are based on the offender's perception of the terrorist opportunities, including:

- Expected number of fatalities at Target T_i given the attack plan is attempted with attack type j, for $i = 1, \ldots, n$ and $j \in \{V, K, VK\}$.
- Expected level of publicity generated because of the iconic nature of the target, as perceived by the offender.
- Expected distance the offender would have to travel from the target T_i to implement the attack plan *s*, as perceived by the offender.

As in real life, it is anticipated that the knowledge individual agents have about criminal opportunities can have a significant impact on their actions (Clarke and Newman, 2006, Gill et al., 2018). Because they are unaware of the presence and/or exact location of the ARV, the number of fatalities they expect to be caused by a knife attack at Target T_i is arbitrarily set as the maximum value of the function: f_K^{max}. Similarly, offenders who have not conducted hostile reconnaissance prior to the attack do not know whether bollards are present at given sites, which too should influence their decisions. This is verified in the results presented in the following section.

Simulation

Model parameters

Urban environment

Every city, every neighbourhood has its own unique layout and urban fabric. To make our findings applicable to different contexts, the simulated environment was created with generic characteristics shared by many places. For this, the underlying premise was that many urban environments can be partitioned into primary, secondary and tertiary zones:

Primary zones (Z^*) contain high-profile sites that attract large crowds. They include renowned shopping streets and tourist sites such as the recently targeted Palace of Westminster in London, UK. In the simulation those are assigned large values for the following the performance value of the attack plan s $\{a_{s,C_F}\ ;\ a_{s,C_N}\}$, and are therefore considered attractive targets.

Secondary zones (Z^{**}) consist of buffers surrounding primary zones. Although not as high profile as the latter, the proximity of secondary zones to primary zones has two implications: those places are likely to have fairly high pedestrian flow; and an attack against them might still generate a lot of publicity by association with nearby places. For this reason, sites that are situated in secondary zones and lead to iconic sites are assigned medium-values for a_{s,C_F} and a_{s,C_N}. An example of those is the bridge that leads to the Palace of Westminster.

Tertiary zones (Z^{***}), by definition, are located further away from primary zones, and do not share boundaries with them. They are generally less populated than other zones, and attacks in such places (e.g., some wards in the London Borough of Lambeth, east of Westminster Bridge) would generate less publicity because of the absence of iconic targets nearby. Because of this, these zones are assigned low a_{s,C_F} and a_{s,C_N} values.

The way those types of zones are spatially distributed depends directly on the locations of iconic and populated places, which vary between cities. In many cases, though, an individual walking on a straight line in any direction would likely go through the following sequence of zones:

$$\cdots : Z^{**} : Z^{***} : Z^{**} : \boldsymbol{Z}^{*} : Z^{**} : Z^{***} : Z^{**} : \cdots$$

For our demonstration, the problem can therefore be analysed in a generic mono-dimensional environment consisting of thirteen zones following the above spatial pattern. They include three primary zones, six secondary zones and four tertiary zones. For each target, Table 7.2

lists the maximum value of a_{s,C_F} (i.e., the component of the utility score that is based on the number of fatalities) for the three types of attacks, a_{s,C_N} (i.e., the component of the utility score that concerns the publicity generated by a successful attack against an iconic target), and a_{s,C_D} (i.e., the component of the utility score that is based on the effort associated with travelling to the target). Displayed in Figure 7.2, the specified parameter values are consistent with the heuristic rules enounced above.

Table 7.2: Utility components based on the criminogenic properties of the thirteen targets.

<TABLE 7.2 HERE>

<FIGURE 7.2 HERE>

Figure 7.2: Utility components (based on the number of fatalities and publicity) associated with the three types of attacks at the thirteen targets

Offender profiles

In addition to these potential targets, six offender profiles are created that correspond to diverse triplets of weights. As represented in Table 7.3, the weights are normalised so their sums are always equal to one. The first profile (OP_1), for instance, corresponds to offenders with a preference for fatalities over publicity from iconic targets, whereas this is the opposite for the last profile (OP_6)

Table 7.3: Weight distribution for the six simulated offender profiles

<TABLE 7.3 HERE>

Simulation method

In order to develop scenarios simulating the decision-making process of the offenders, the utility scores of different attack plans (i.e., combination of a target and an attack type) must be calculated for each offender profile. Regarding offenders as rational agents, we assume they would select the attack plans with the highest utility. Since their judgment is unlikely to be perfectly rational, though, we consider that attack plans with fairly similar utility scores (within 10%) are all equally likely to be selected.

In the first stage, agents could arrive from anywhere, making each target equally likely to be the closest or the farthest from the start of their journeys. Because of this, $\boldsymbol{a}_{\boldsymbol{s},C_D}$ is not included in the calculation of the utility scores at this point. In the second stage, potential interventions are introduced, and the utility score of the attack plans are revised to reflect their impact on offenders. Offender behaviour is then simulated for each security arrangement by applying the same decision-making method to the revised utility scores. At that point, the location of offender is taken into account. Finally, the risk estimates are then calculated and the effect of the measures quantitatively determined by comparing them with the worst case situation.

As shown in the decision tree represented in Figure 7.3, the computation is conducted for i) the case where offenders have conducted hostile reconnaissance and therefore know about the presence of bollards when selecting their attack plans, and ii) the case where offenders take decisions with incomplete information. In the latter, agents might opt for a new attack plan if they discover that the intended target is not as vulnerable as they initially thought.

<FIGURE 7.3 HERE>

Figure 7.3: Generic decision tree showing the simulated sequences of actions for M different security plans, with and without hostile reconnaissance (HR) activities.

Results and Discussion

Computation

Initial state

The first set of scenarios generated in the simulation represent the decisions and actions of terrorists with offender profile OP1 in the *status quo* situation (i.e., without extra security measures). Owing to the parameters of the decision-making model and the criminogenic characteristics of the targets, the results show that all terrorist agents perceive the highest utility score to be that of a vehicle and knife attack in Zone 7: $u(VK7) = 0.975$. Similar attacks in the two other primary zones (Z3 and Z11) score highly too, with $u(VK3) \sim u(VK11) \sim 0.8$. The difference between them is sufficiently large, though, to presume that terrorists would conduct the attack in Zone 7.

<FIGURE 7.4 HERE>

Figure 7.4: Utility scores of the three attack types at the 13 targets for offender profile OP1, no additional security measures.

Introduction of bollards

Considering the above results, we introduce bollards in Zone 7, where they reduce the risk most. New simulations are then run, accounting for the responses of the agents to this intervention. Unlike previously, the second set of scenarios shows that each attack plan depends upon the offender profile.

When they collect tactical information through hostile reconnaissance, agents are able to assess the situation and select their targets remotely. Those with profiles OP1, 2, 3 and 5 all perceive that a vehicle and knife attack in Zone 11 has the highest utility, whilst those with profile OP4 would conduct a similar attack but in Zone 3 where the anticipated gain associated with the iconic nature of the target is greater. Agents with the last profile (OP6), however, opt for a different course of action, preferring to conduct a knife attack at their current location in Zone 7.

As seen in Table 7.4, the situation is different when no hostile reconnaissance is conducted. In this case, the agents travel to Zone 7 where they realise that bollards have been deployed, and revise their assessment of the different options. The first class of agents decide to move to Zone 8 or 11 where they attempt to conduct a vehicle and knife attack, as both attack plans have the same utility score. Instead of targeting Zone 3, those with less focus on fatalities (OP4 and 6) rather stay in the same location (Zone 7) but switch to a knife attack.

Table 7.4: Attack plans selected before and after the introduction of bollards, with and without hostile reconnaissance

<TABLE 7.4 HERE>

K: knife attack– V: vehicle attack – VK: vehicle attack immediately followed by knife attack

Amongst the three attack plans selected in the second set of scenarios (Table 7.4), VK11 represents the best alternative when the distance to cover does not have a strong impact on the utility score. It would be selected, for example, if the offender places limited weight on $\boldsymbol{a}_{s,C_D}$ and thus on the distance to the target. In contrast, the other attack plans (VK8 and K7) emerge as good trade-offs between the perceived cost of travelling to another target and the benefits resulting from the anticipated fatalities and publicity. In two cases (OP1 and OP4), we can see that the conduct of hostile reconnaissance significantly changed the attack plan.

Before-and-after comparison reveals that the form of displacement observed is directly related to the profiles of the agents. As explained in Table 7.4, the introduction of bollards might create geographical displacement from Zone 7 to Zones 3, 8 and 11, depending on the importance given to the iconic nature of the target. Alternatively, this might also induce tactical displacement, such as swapping a vehicle for a knife to overcome bollards (OP4 and OP6). An interesting observation from this set of simulation is that, not all targets are situated in primary zones. The offender profile whose utility scores are displayed in Figure 7.4 (OP1) might instead attack targets in the secondary zone near the initial target.

Introduction of the ARV

In the following we consider the effect of introducing the armed response vehicle in the environment. Because offenders are not cognisant of its location, this mobile police unit would not affect target selection. Despite this, the ARV can potentially reduce the impact of attacks involving the use of a knife if it can arrive at the crime scene before other responders. This is represented in Figure 7.5 where the consequences caused by Offender OP1 are plotted for different initial locations of the police vehicle. Because this is calculated from the perspective of the defender, the consequences only concern the component of the (dis)utility score associated with the fatalities caused by the attack ($\boldsymbol{a_{s,C_F}}$), and do not take into account publicity or distance to target. To put these values into context, a_{s,C_F} is divided by max($\boldsymbol{a_{s,C_F}}$) = 1.15 which corresponds to the consequences that would be observed if a vehicle and knife attack is conducted in Zone 7, and no additional security measures were deployed there. To reduce the risk posed by the first type of offenders, the figure shows that the ARV should be stationed in Zone 11, as it yields the greatest expected risk reduction.

<FIGURE 7.5 HERE>

Figure 7.5: Normalised consequences of ($a_{s,C_F}/a_{VK7,C_F}$) associated with attack plans VK8 and VK11, for different positions of the Armed Response Vehicle (0: no ARV).

Discussion

Limitations

Before drawing conclusions from this study, the results should be placed into context and the main limitations of this work highlighted. The computational model supporting the analysis was developed to assist our reasoning about counter-terrorism resource allocation. As such, it cannot be considered a high-fidelity representation of the real-world phenomenon. First, the simulated events were restricted to attacks involving vehicle and/or knife. Second, the tenets of the simulation are grounded in a (bounded) rational-choice theoretic framework – *terrorists are considered to opt for the attack plans that are perceived to have the highest utilities* – which does not capture all the complex mechanisms potentially involved in target selection. Third, the choice of a weighted sum model to estimate the utility scores, whilst not uncommon in the field of decision-making, was mainly driven by its simplicity. Fourth, the various parameters in the decision-making equation (e.g., weights and criteria) could be criticised too. Fifth, the simulated environment is described in a one-dimensional space, and the proposed classification and spatial pattern of zones underpinning it have not been validated. With little ecological validity, it should be understood that the simulation cannot offer any reliable predictive capability to decision-makers.

In spite of its limitations, the model can still be regarded as a useful tool that can aid reasoning about terrorist displacement and improve security planning. In practice, policy-makers and practitioners are routinely required to take decisions, and cannot wait for the evidence required to inform those to become available. Because of this, the knowledge that supports security planning often consists of heuristics that assume some level of rationality in offender behaviour (Davis and Cragin, 2009). Furthermore there is anecdotal evidence that the three selected factors (i.e., anticipated number of fatalities, amount of publicity and effort/time) have played a role in the planning of previous terrorist attacks (Clarke and Newman, 2006; Dhami et al., 2016; Gill et al., 2018). Another argument in support of this generic toy model is that enriching it with a realistic spatial backcloth would not necessarily improve our analysis if the underlying mechanisms are not well understood or modelled (Elffers and van Baal, 2008). For all these reasons, we argue that the model can offer interesting perspectives in this exploratory study.

Findings

CPTED measures must be allocated before ARVs

Within the admittedly narrow scope of our counter-terrorism problem, we have found the following heuristic principles to be useful (albeit not necessarily optimal) in deciding where ARVs and bollards should be spatially distributed:

- First, bollards should be assigned to places where the risk of vehicle attacks can be reduced most.
- Second, the risk map should then be re-estimated based on the new situation (given the introduction of bollards), and ARVs assigned to places from which the *aggregated* risk of vehicle and knife attacks or knife attacks can be reduced most.

In the simulated setting, the strategy derived from applying those principles yielded a 14% reduction in the fatality score compared to allocating all the resources to the zone with the highest risk or allocating the ARV before the bollards. A rapid analysis suggests that the gain that was achieved can be entirely attributed to the integration of knowledge about offender displacement into risk estimation.

CPTED measures can induce different forms of displacement

Other than complete deterrence (which was not modelled here), two different effects of deploying bollards were observed in the simulation that are geographical displacement and tactical displacement. Geographical displacement[iv] mainly increased the probability of vehicle and knife attacks against high-profile and populated targets that would not have otherwise been targeted, whereas tactical displacement resulted in reduction of the number of fatalities at the same targeted site. The latter occurred when the agents, realising that bollards prevented them from conducting a vehicle attack, chose instead to conduct the attack with a knife.

Another interesting observation was that the type of displacement that occurred not only depended upon the offender profile but also on the place where target selection had been conducted, which itself was influenced by whether the agent had conducted hostile reconnaissance. When this was not the case, some of the agents, realising that bollards were introduced to secure the target they had selected, were then unlikely to select sites located further away. For example, the 2017 New York vehicle-ramming attack succeeded even though the city had already been protected using physical fortifications such as bollards (Jasiński, 2018). The attack occurred just few blocks away from where bollards were installed (Tate, 2017), which appeared to have been more convenient to the terrorist rather than looking for a suitable target further away.

The effect of CPTED measures on displacement should be better understood

Applying the aforementioned method to distribute ARVs and CPTED measures requires estimating the spatial distribution of risk before taking each resource allocation decision. In practice, this can be a challenge as the introduction of bollards can cause displacement and affect the risks at other targets. Similarly, determining the aggregated risk of attacks involving knives is not straightforward as the distribution of profiles (weights) amongst likely offenders is generally unknown.

To inform the selection of an effective strategy, security architects and planners should ideally be able to predict what forms of displacement are likely to occur, or at least reduce the uncertainty about it. For this, detailed tactical information about offenders might be required. Assuming a weighted sum model is ‘good enough’ to represent offender decision-making, the following components would then still need to be determined: (1) what criteria offenders take into account; (2) how much weight offenders give to different criteria; and (3) how much offenders perceive different targets to score against those criteria.

Whilst the physical mechanisms by which individual CPTED measures work are relatively clear, their effects on offenders’ perception of criminal opportunities and decisions are much more difficult to ascertain, as they might depend on their assessment of current and future situations (Ezell, Behr and Collins, 2012; Lodge and Wegrich, 2014; Schuurman, Bakker, Gill and Bouhana, 2017). Moreover, research suggests that the extent to which offenders recognise CPTED measures into their assessment and decision-making process is still questionable (Armitage and Joyce, 2016). This implies that the methods used for counter-terrorism resource allocation should allow high levels of uncertainty to be considered in the modelling of displacement; and further research conducted to understand what forms of displacement are more likely to be induced by specific CPTED measures (Armitage, 2014; Guerette and Bowers, 2009; Johnson, Bowers and Guerette, 2012; Johnson, Guerette and Bowers, 2014), particularly when research findings on CPTED are highly variable indicating the presence of variability in outcomes of CPTED interventions, too (Cozen and Love, 2015).

CPTED measures should also be introduced at the periphery of primary targets

The last point to be made in this section concerns an observation in the simulation (Table 7.4). Whilst most forms of geographical displacement consisted of targeting the next 'best' primary target, it is noteworthy that the first agent also selected a secondary target in Zone 8. From their perspective, this choice represents a good trade-off between the three criteria. This can be explained by the proximity to the target considered as the most attractive. Once in Zone 7, the agent was not far from the secondary targets in Zone 8, and an attack against those generate some publicity because of their proximity to the high-profile targets in the primary zone.

These findings are in good agreement with some of the recent lone actor terrorism incidents. The terrorist who had driven on the pavement of Westminster Bridge on 22 March 2017 might have initially intended to target Parliament. Realising that the place was protected, they may have decided to target the crowd on the bridge, which was the closest and next 'best' option (BBC, 2017a). In the following attack, the attackers initially planned to cross London Bridge but turned round when they saw the police and then crashed near a local pub in Borough Market (BBC, 2017b). With the attack being diverted from the initially selected target, the terrorists continued their attack at the next 'best' target, which was Borough Market.

Conclusions

Although ARVs and CPTED measures could potentially mitigate terrorist attacks, this research has shown that there exist practical challenges that need to be addressed before their deployment in urban environment. First, the complexity and configurational effects of CPTED measures are often overlooked and oversimplified by policy-makers and planners, which impacts on the ability of these actors to assess risk and develop appropriate strategies given specific situations, places, and times (Armitage, 2013; Cozens and Love, 2015;

Ekblom, 2010:46; 2011; chapter 5 in this volume). Second, the effects of CPTED measures on displacement are difficult to assess and anticipate. There exist very few studies that have empirically demonstrated the effectiveness of CPTED measures. For this reason, the benefits that sophisticated optimisation methods could offer for the prevention of terrorist attacks cannot be fully realised. Third, the results of the simulation showed that the presence of bollards could lead to both geographical and tactical displacement. In real life, this outcome is likely to have ethical implications since it might place less protected targets at higher risk of being attacked. To address this issue, policy-makers and planners should consider the costs and benefits of deploying CPTED measures to protect not only in high-profile and crowded zones but also in nearby zones where terrorists may displace their attacks.

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[ii] "A level-k defender chooses a strategy as a best response to a level-(k-1) attacker, who responds to a level-(k-2) defender and so forth" (McLay et al., 2012).

[iii] In a mirroring procedure, the defender chooses a strategy whilst considering the analysis conducted by the opponent, while taking account of the fact that the latter may be simultaneously performing an analysis of the defender decision making process.

[iv] Geographic displacement being entirely correlated with target displacement in this study, it was not possible to analyse them separately.