An Agent-Based Framework to Support Crime Prevention

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ABSTRACT
An important research topic within Environmental Criminology is the analysis of the spatio-temporal dynamics of crime. Some of the main challenges in this area are the prediction and prevention of criminal hot spots. This paper presents an agent-based framework that is able to address such challenges. The framework exploits simulation techniques to compare different strategies for guardian movement in terms of their efficiency (low costs) and effectiveness (high prevention rate). In addition, by automated checks, more detailed properties of the different strategies can be studied. As a result, the framework can be used as a tool to assist researchers in their theory building, and potentially also policy makers in their decision making. To illustrate the approach, a number of strategies for guardian movement are compared, and the results are discussed.

Categories and Subject Descriptors
I.6.3 [**Simulation and Modeling**]: *Applications*.
J.4 [**Social and Behavioral Science**]: *Sociology*.

General Terms
Experimentation, Human Factors, Verification.

Keywords
Criminal Hot Spots, Social Simulation, Formal Analysis, Crime Prevention Strategies.

1. INTRODUCTION
Within the field of Environmental Criminology, the analysis of the *displacement of crime* is one of the main research interests [8, 13, 18]. Certain types of crime typically cluster around specific locations in a city, such as busy shopping streets (in case of pick-pocketing) or deserted railway stations (in case of assault). Such locations with a high concentration of criminal activities are usually called *criminal hot spots*. However, these hot spots are not always persistent over longer time periods. A number of factors are known to cause displacement of hot spots from one location to another. For instance, introducing television screens in a railway station may decrease crime rates [8, 13, 18].

This dynamic nature of criminal hot spots makes them a popular topic of scientific research. For example, typical questions that are studied in Environmental Criminology are: Where and when do criminal hot spots emerge? How long do they persist? And how can they be prevented? The classical approach to investigate these kinds of questions is to collect large numbers of empirical data (e.g. from crime report databases), and to use analysis techniques to identify trends in these data [16]. However, a drawback of this approach is that it focuses on past displacement patterns, which does not guarantee that future patterns will be similar.

As an alternative, for a number of years, criminologists have joined forces with researchers from Computer Science and Artificial Intelligence, to explore the benefits of (Agent Based) Social Simulation to investigate crime displacement. Thus, the perspective taken in these approaches is to use a simulated environment to predict dynamics of crime displacement in the future, rather than to analyse past dynamics. Since simulation permits the analyst to perform scalable social "experiments" without much effort, it turns out to be particularly appropriate to analyse phenomena within the criminological domain. Indeed, in recent years, several papers have successfully tackled criminological questions using Social Simulation [1, 3, 7, 11, 12, 15, 17].

As a follow up of that success, the current paper proposes an agent-based framework to support crime prevention[†]. This framework consists of two main components, namely an agent-based simulation model for crime displacement, and a formal analysis method to investigate (simulation) traces in more detail. As such, it extends the existing literature in two ways. First, the simulation model allows the analyst to define different *strategies* for guardian movement, which makes it a test bed to compare strategies against each other. Second, the use of *automated formal techniques* enables the analyst to analyse large numbers of (simulation and empirical) traces in limited time.

The paper is organised as follows. Section 2 reviews existing approaches that aim at studying crime displacement by means of Artificial Intelligence techniques, and positions the current paper. In Section 3, the basic simulation model for crime displacement is presented. Next, in Section 4, a number of crime prevention strategies are introduced that can be used by the guardian agents in the simulation model. Section 5 illustrates the working of this model by means of simulations, and shows how the different strategies perform in different circumstances. Section 6 presents and illustrates the formal analysis method to investigate simulation traces in more detail. Section 7 concludes the paper with a summary and a discussion about future work.

2. RELATED WORK
Over the last decade, various computational modelling approaches have been applied to the domain of crime displacement. A shared element within all of these approaches is that the displacement processes is studied as the result of the interaction between three types of agents: *criminals*, *guardians* and *passers-by*. This choice is mainly inspired by the Routine Activity Theory in Criminology [8], which basically states that crime occurs when a motivated offender encounters a suitable target, while no efficient guardian is present. However, despite this common underlying principle,

[†] In this paper we focus explicitly on assault, although the model is sufficiently generic to study several other types of crime as well.

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there is a large variation in the modelling techniques that are used. Some authors apply agent-based modelling [1, 3, 7, 17], whereas others use population-based modelling [3], cellular automata [12, 15], different spatial analysis techniques [11], or evolutionary c

omputing techniques [17]. Due to space limitations, we will not provide a complete comparison, but an overview is given in [14].

In addition to the differences in modelling techniques, the papers mentioned above also show differences in the specific goals they try to achieve. While some authors try to develop simulation models of crime displacement in existing cities, which can be directly related to real world data (e.g., [15]), others deliberately abstract from empirical information (e.g., [3]). The idea behind the latter perspective is that the simulation environment is used as an analytical tool, mainly used by researchers and policy makers, to shed more light on the process under investigation, and perhaps improve existing policies (e.g., for surveillance) on the long run [10]. Also, some authors take an intermediate point of view (e.g., [1]). They initially build their simulation model to study the phenomenon per se, but define its basic concepts such that it can be directly connected to empirical data, if these become available.

This intermediate perspective is also taken in the current paper. More specifically, it proposes a simulation model that can be used to compare different strategies in guardian movement in terms of their efficiency and effectiveness, combined with a formal analysis method to study detailed properties of the simulations. Like other approaches in the literature, the simulation model distinguishes three types of agents (criminals, guardians, and passers-by). To make a comparison of strategies possible, the behavioural rules for criminals and passers-by are almost completely re-used from existing approaches (in particular [3]), but the behaviour of the guardians is variable. A preliminary investigation [2] pointed out that there are several possibilities to improve existing guardian movement strategies. Whilst most currently used strategies are reactive (i.e., guardians move to a location after many crimes have been committed there), also anticipatory strategies (i.e., guardians move to a location as soon as they expect that many crimes will be committed there) and hybrid strategies (i.e., combinations of reactive and anticipatory strategies) have a strong potential. The current paper compares a number of these strategies in terms of their efficiency (what are the costs?) and effectiveness (how many crimes are prevented?). This approach distinguishes the current paper from most approaches in the literature, which mainly simulate existing strategies instead of novel strategies. A welcome exception is [17], but this paper addresses short term strategies (i.e., patrol routes) rather than long term (surveillance investment) strategies.

Another element that distinguishes the current paper from existing approaches is the use of formal techniques to analyse simulation traces (see Section 6). This idea is similar to the approach taken in [1], which also addresses verification of dynamic properties of simulation traces. A difference is however that that paper addresses properties related to the spatial patterns of displacement, whereas we here focus on efficiency and effectiveness.

3. SIMULATION MODEL

This section introduces the simulation model for crime displacement processes, inspired by [2, 3]. Note that agent groups are modelled in terms of their density, i.e., at a global, population-based level, not an individual level. This choice was made on the basis of [3], which demonstrates that, to study crime displacement, population-based agent modelling can be a computationally cheap alternative for individual-based (stochastic) agent modelling, while still approximating the same results. Section 3.1 introduces the main aspects of the model and their relations. Section 3.2 provides the formalisation of the model.

3.1 Crime Displacement

As mentioned in the introduction, each large city usually contains a number of *hot spots*, i.e., locations where most of the crimes occur [9, 18]. Such locations may vary from railway stations to shopping malls. These hot spots usually have several things in common, among which the presence of many passers-by (which makes the location attractive for criminals) and the lack of adequate surveillance. However, after a while the situation often changes: the criminal activities shift to another location. This may be caused by improved surveillance systems (such as cameras) at that location, by an increased number of police officers, or because the police changed their policy.

Another important factor in explaining crime displacement is the *reputation* of specific locations in a city [13]. This reputation may be a cause of crime displacement, as well as an effect. For example, a location that is known for its high crime rates usually attracts police officers [9], whereas most citizens will be more likely to avoid it [19]. As a result, the amount of criminal activity at such a location will decrease, which affects its reputation again.

To summarise, in order to model the process of crime displacement, several aspects are important. First, one should have information about the *total number* of agents in the different groups involved, i.e., the number of *criminals*, number of *guardians*, and number of *passers-by*. Next, it is assumed that the world (or city) that is addressed can be represented in terms of a number of different *locations*. It is important to know how many agents of each type are present at each location: the *density* of criminals, guardians, and passers-by. Furthermore, to describe the movement of the different agents from one location to another, information about the *reputation* (or *attractiveness*) of the locations is needed. This attractiveness is different for each type of agent. For example, passers-by like locations where it is safe, e.g. locations where some guardians are present and no criminals. On the other hand, guardians are attracted by places where a lot of criminals are present, and criminals like locations where there are many passers-by and no guardians. Finally, to be able to represent the idea of hot spots, the *number of assaults* per location is modelled. The idea is that more assaults take place at locations where there are many criminals and passers-by, and few guardians, cf. the Routine Activity Theory by [8].

The interaction between the concepts introduced above is visualised in Figure 1[‡]. This figure depicts the influences between the different groups at one location. Here, the circles denote the concepts that were mentioned above in italics, and the arrows indicate influences between concepts (influences on attractiveness have been drawn using dotted arrows to enhance readability).

[‡] Note that Figure 1 does not depict the influence of some *basic attractiveness* of a location for certain groups (i.e., an attractiveness that is independent of the distribution of agents at the location). For the sake of readability, this notion has been left out of the picture, but it often plays a role in reality. For instance, locations like a railway station will be visited more often by passers-by than other locations, simply because people need to go there to reach their desired destination. Therefore, the notion of basic attractiveness will also be considered in this paper.

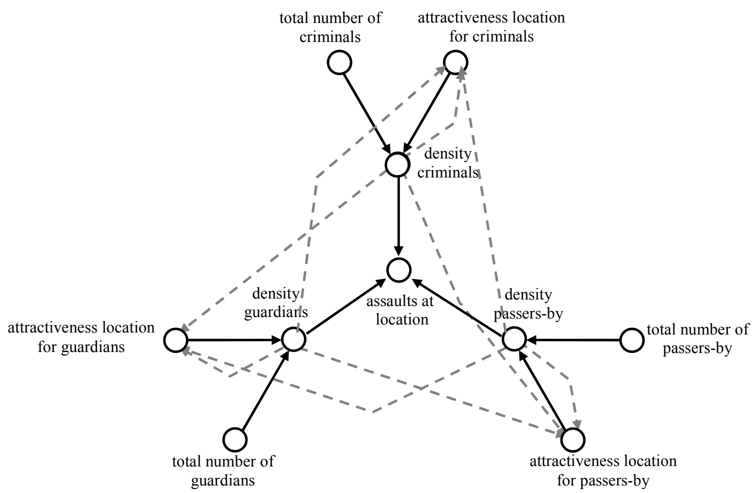

Figure 1. Interaction between criminals, guardians, and passers-by

3.2 Formalisation

To formalise the concepts that were introduced above (in italics), a number of variable names are used; see Table 1.

Table 1. Variables in simulation model

Name	Explanation
c	Total number of criminals
g	Total number of guardians
p	Total number of passers by
c(L, t)	Density of criminals at location L at time t.
g(L, t)	Density of guardians at location L at time t.
p(L, t)	Density of passers-by at location L at time t.
β(L, a, t)	Attractiveness of location L at time t for type a agents: c (criminals), p (passers-by), or g (guardians)
ba(L, a, t)	Basic attractiveness of location L at time t for type a agents: c (criminals), p (passers-by), or g (guardians)
assault_rate(L, t)	Number of assaults taking place at location *L* per time unit.

Next, a number of equations are introduced to represent the causal relations between these variables. Most of these ideas are taken over from [2] (and [3]). First, the calculation of the number of agents at a location is done by determining the movement of agents that takes place based on the attractiveness of the location. For example, for criminals, the following formula is used:

$$c(L, t + \Delta t) = c(L, t) + \eta \cdot (\beta(L, c, t) \cdot c - c(L, t)) \Delta t$$

This expresses that the density $c(L, t + \Delta t)$ of criminals at location L on time $t + \Delta t$ is equal to the density of criminals at the location at time t plus a constant η (expressing the rate at which criminals move per time unit) times the movement of criminals from t to $t+\Delta t$ from and to location L, multiplied by Δt. Here, the movement of criminals is calculated by multiplying the relative attractiveness $\beta(L, c, t)$ of the location (compared to the other locations) for criminals with the total number c of criminals (which is constant). From this, the density of criminals at the location at t is subtracted, resulting in the change of the number of criminals for this location. For passers-by, a similar formula is used:

$$p(L, t + \Delta t) = p(L, t) + \eta \cdot (\beta(L, p, t) \cdot p - p(L, t)) \Delta t$$

However, as opposed to [3], the movement of the guardians is not (necessarily) modelled using this formula. Instead, to represent guardian movement, different strategies can be filled in (see Section 4).

Next, the attractiveness of a location can be expressed based on some form of reputation of the location for the respective type of agents. Several variants of a reputation concept can be used. The only constraint is that it is assumed to be normalised such that the total over the locations equals 1. An example of a simple reputation concept is based on the densities of agents, as expressed below.

$$\beta(L, c, t) = p(L, t) / p \quad \text{for criminals}$$
$$\beta(L, p, t) = g(L, t) / g \quad \text{for passers-by}$$

This expresses that criminals are more attracted to locations with higher densities of passers-by, whereas passers-by are attracted more to locations with higher densities of guardians. This definition of reputation is used in [3]. Although this definition is simple, which makes the model well suited for mathematical analysis, it is not very realistic. To solve this problem, in this paper, the following linear combinations of densities are used[§]:

$$\beta(L, c, t) = \beta_{c1} \cdot (1 - g(L, t) / g) + \beta_{c2} \cdot p(L, t) / p + \beta_{c3} \cdot ba(L, c, t)$$
$$\beta(L, p, t) = \beta_{p1} \cdot (1 - c(L, t) / c) + \beta_{p2} \cdot g(L, t) / g + \beta_{p3} \cdot ba(L, p, t)$$

This expresses that criminals are repelled by guardians, but attracted by passers-by. Similarly, passers-by are repelled by criminals, but may be attracted by guardians. In addition, for each type of agent some basic attractiveness can be defined. The weight factors (β_{xy},which may also be 0) indicate the relative importance of each aspect. Again, for the guardians no formula is specified, since this depends on the guardian movement strategy that is selected.

Finally, to measure the assaults that take place per time unit, also different variants of formulae can be used (see [3]). In this paper, the following is used:

$$assault\_rate(L, t) = max(c(L, t) \cdot p(L, t) - \gamma \cdot g(L, t), 0)$$

Here, the assault rate at a location at time t is calculated as the product of the densities of criminals and passers-by, minus the product of the guardian density and a constant γ, which represents the capacity of guardians to avoid an assault. The motivation behind this is that the maximum amount of assaults that can take place at a location is $c(L, t) \cdot p(L, t)$, but that this number can be reduced by the effectiveness of the guardians (which corresponds exactly to the Routine Activity Theory). In principle, this assault rate can become less than 0 (the guardians can have a higher capacity to stop assaults than the criminals have to commit them); therefore the maximum can be taken of 0 and the outcome described above. Based on this assault rate, the total (cumulative) amount of assaults that take place at a location is calculated as:

$$total\_assaults(L, t + \Delta t) = total\_assaults(L, t) + assault\_rate(L, t) \Delta t$$

Although the model is presented here in a purely mathematical notation, its actual implementation has been done in the agent-based modelling environment LEADSTO [5]. This environment is well suited for the current purposes, since it integrates both qualitative, logical aspects and quantitative, numerical aspects, and is compatible with the TTL checker tool for verification of logical formulae [4] (see Section 6). Its basic building blocks are executable rules of the format $\alpha \twoheadrightarrow \beta$, which indicates that state

[§] Note that these attractiveness formulae are not normalised yet. To ensure that the values stay between 0 and 1, each attractiveness value is divided by the sum of the values over all locations. Moreover, the influence by agents from the same group is not considered.

property α leads to state property β. Here, α and β can be (conjunctions of) logical and numerical predicates.

4. GUARDIAN STRATEGIES

This section extends the model presented above with the possibility to specify crime prevention strategies. The idea is that, in addition to the rules that govern the behaviour of criminals and passers-by, the behaviour of the guardians can be specified by selecting one out of multiple strategies.

In current practice, the crime prevention policies that are applied by law enforcement agencies are - mostly - reactive [6, 9]. That is, these agencies often only increase the level of guardianship at locations where crimes have been committed in the past. As a consequence, this often means that such a decision is made too late, because the damage has already been done. Instead, we hypothesise that a more anticipatory strategy (e.g., a strategy to invest in more guardians at locations where one predicts that a hot spot *will emerge*) may be more efficient.

To investigate this, we present multiple strategies for movement of guardians (varying from reactive to anticipatory, and combinations of the two), and analyse for a number of scenarios which strategy yields the lowest assault rate. Most of the selected strategies are based on [2], in which they were already tested against three initial scenarios. In this paper, ten different strategies are explored in total (see also Table 2):

- The first strategy is a *baseline* strategy. In this case guardians do not move at all. Their density at the different locations remains stable over time.
- The second strategy (called *reactive 1*) states that the amount of guardians that move to a new location is proportional to the density of criminals at that location.
- The third strategy (*reactive 2*) states that the amount of guardians that move to a new location is proportional to the percentage of the assaults that have recently taken place at that location.
- The fourth strategy (*reactive 3*) states that the amount of guardians that move to a new location is proportional to the percentage of all assaults that have taken place so far at that location.
- The fifth strategy (*reactive 4*) states that the amount of guardians that move to a new location is proportional to the density of passers-by at that location.
- In the sixth strategy (*anticipate 1*), the amount of guardians that move to a new location is proportional to the density of criminals they expect that location to have in the future.
- In the seventh strategy (*anticipate 2*), the amount of guardians that move to a new location is proportional to the density of passers-by they expect that location to have in the future.
- In the eighth strategy (*anticipate 3*), the amount of guardians that move to a new location is proportional to the amount of assaults they expect that will take place at that location in the future. This predicted amount of assaults is approximated by taking the average of the expected densities of criminals and passers-by.
- The ninth strategy (*hybrid 1*) is a combination of *reactive 2* and *anticipate 2*. Here, the amount of guardians that move to a new location is the average of the amounts of guardians determined by those two strategies.
- The tenth strategy (*hybrid 2*) is a combination of *reactive 3* and *anticipate 2*. Here, the amount of guardians that move to a new location is the average of the amounts of guardians determined by those two strategies.

To formalise these strategies, the following formula is used:

$$g(L, t + \Delta t) = g(L, t) + \eta \cdot \sigma(L, t)\, \Delta t$$

This formula is similar to the formulae used for criminals and passers-by, but the amount of guardians that move per time unit is indicated by the factor $\sigma(L, t)$, which depends on the chosen strategy. The different definitions of σ are shown in Table 2. For example, for the baseline strategy, $\sigma(L, t)=0$, which means that the amount of guardians at time point $t+\Delta t$ is equal to the amount at t.

Table 2. Guardian Movement Strategies

Strategy	Formalisation of σ(L, t)
baseline	0
reactive 1	$(c(L, t)/c) \cdot g - g(L, t)$
reactive 2	$aar(L,t) \cdot g - g(L, t)$
reactive 3	$taar(L,t) \cdot g - g(L, t)$
reactive 4	$(p(L, t)/p) \cdot g - g(L, t)$
anticipate 1	$(c(L, t)+ \eta_2 \cdot(\beta(L, c, t) \cdot c - c(L, t)) \cdot \Delta t)/c \cdot g - g(L, t)$
anticipate 2	$(p(L, t)+ \eta_2 \cdot(\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t)/p \cdot g - g(L, t)$
anticipate 3	$((c(L, t)+ \eta_2 \cdot(\beta(L, c, t) \cdot c - c(L, t)) \cdot \Delta t)/c +$ $(p(L, t)+ \eta_2 \cdot(\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t)/p) / 2 \cdot g - g(L, t)$
hybrid 1	$((aar(L,t) \cdot g - g(L, t))+$ $(p(L, t)+ \eta_2 \cdot(\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t)/p \cdot g - g(L, t)) / 2$
hybrid 2	$((taar(L,t) \cdot g - g(L, t))+$ $(p(L, t)+ \eta_2 \cdot(\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t)/p \cdot g - g(L, t)) / 2$

In the strategies *reactive 2* and *3*, the average assault rate $aar(L,t)$ and the total average assault rate $taar(L,t)$ are calculated by:

$$aar(L,t) = assault\_rate(L,t) / \textstyle\sum_{X:loc} assault\_rate(X,t)$$
$$taar(L,t) = total\_assaults(L,t) / \textstyle\sum_{X:loc} total\_assaults(X,t)$$

As can be seen from Table 2, the idea of the anticipation strategies it that the guardians use formulae that are similar to the formulae for movement of criminals and passers-by to predict how they will move in the near future. Obviously, these predictions will not be 100% correct, since they do not consider interaction between the different types of agents, but our assumption is that they may be useful means to develop an efficient strategy.

Furthermore, different values can be taken for the parameter $\eta 2$ in the anticipation strategies. This parameter represents the speed by which the criminals and/or passers-by move in the predicted scenario (or, in other words, the distance in the future for which the prediction is made). For example, by taking a very high value for $\eta 2$ in the *anticipate1* strategy, guardians get the tendency to move to locations that are predicted to have a high density of criminals in the very far future.

As mentioned earlier, the idea of having different strategies is that the analyst can test which one performs best. A question is however how to define the notion of a ‘good’ strategy. One possibility (see also [2]) is to look at effectiveness, e.g., by considering the strategy that results in the lowest crime rates (*total_assaults*) as the best. However, in reality also the *costs* of crime prevention play an important role. Various mechanisms to improve guardianship exist (e.g., adding and moving security guards, burglar alarms, fencing, lighting), but they all involve costs [6]. Thus, instead of only measuring the amount of assaults that result from each strategy, in the calculation of the ‘best’ strategy one should compensate for the costs involved. For this reason, the following formula (which was not included in [2]) has been added:

$$total\_costs(t + \Delta t) = total\_costs(t) + \textstyle\sum_{X:loc} \sigma(X,t) \cdot \varepsilon\ \Delta t$$

This formula counts the total costs that are spent on crime prevention (for all locations involved) during the simulation. Parameter ε represents the guardian movement costs per time step.

5. SIMULATIONS

To compare the different guardian movement strategies, a large number of simulations have been performed, using different parameter settings. In this section, five of the most interesting scenarios and their results are discussed. These five scenarios are described in Section 5.1. Two example simulation traces are presented in detail in Section 5.2, and the overall results of the simulations are discussed in Section 5.3.

5.1 Scenarios

For the simulations described in this paper, five different scenarios were used[**]. Each of the scenarios involves four locations (called L1, L2, L3, and L4). To enforce the development of hot spots, in each scenario the basic attractiveness of the locations for passers-by changes over time, resulting in different phases. Some scenarios consist of two different phases, whereas others consist of five phases. The scenarios and their consecutive phases are shown in Table 3. Here, for each phase, the cells indicate the basic attractiveness values of the different locations.

Table 3. Simulation Scenarios

scenario	phase 1	phase 2	phase 3	phase 4	phase 5
1	L1=0.25 L2=0.25 L3=0.25 L4=0.25	L1=0.7 L2=0.1 L3=0.1 L4=0.1	---	---	---
2	L1=0.25 L2=0.25 L3=0.25 L4=0.25	L1=0.7 L2=0.1 L3=0.1 L4=0.1	L1=0.25 L2=0.25 L3=0.25 L4=0.25	---	---
3	L1=0.25 L2=0.25 L3=0.25 L4=0.25	L1=0.7 L2=0.1 L3=0.1 L4=0.1	L1=0.4 L2=0.4 L3=0.1 L4=0.1	L1=0.1 L2=0.7 L3=0.1 L4=0.1	---
4	L1=0.25 L2=0.25 L3=0.25 L4=0.25	L1=0.7 L2=0.1 L3=0.1 L4=0.1	L1=0.4 L2=0.4 L3=0.1 L4=0.1	L1=0.3 L2=0.3 L3=0.3 L4=0.1	L1=0.25 L2=0.25 L3=0.25 L4=0.25
5	L1=0.25 L2=0.25 L3=0.25 L4=0.25	L1=0.7 L2=0.1 L3=0.1 L4=0.1	L1=0.4 L2=0.4 L3=0.1 L4=0.1	L1=0.1 L2=0.4 L3=0.4 L4=0.1	L1=0.1 L2=0.1 L3=0.4 L4=0.4

To give an example, in scenario 2, all locations start out with the same basic attractiveness for passers-by (i.e., *ba(L1,p,0)* = *ba(L2,p,0)* = *ba(L3,p,0)* = *ba(L4,p,0)* = 0.25). After a while (in phase 2, which starts at time point 25), the basic attractiveness of location L1 is temporarily increased (i.e., *ba(L1,p,25)* = 0.7, *ba(L2,p,25)* = *ba(L3,p,25)* = *ba(L4,p,25)* = 0.1). This may be caused, for example, because a circus is coming to town. Some time later (phase 3), the circus moves away to another city and the basic attractiveness of all location becomes equal again (0.25).

Other parameter settings were chosen as follows (for all scenarios). The total population consists of 800 criminals, 400 guardians, and 4000 passers-by. Initially, these agents are distributed equally over the four locations (i.e., each location contains 200 criminals, 100 guardians, and 1000 passers-by). The attractiveness settings for criminals are β_{c1}=0.4, β_{c2}=0.6, β_{c3}=0 (i.e., the biggest part of their behaviour is determined by the desire to assault, and a smaller part by the desire to not get caught, whereas no basic attractiveness plays a role for them). The attractiveness settings for passers-by are β_{p1}=0.1, β_{p2}=0.1, β_{p3}=0.8 (to enforce a high influence of basic attractiveness). In all strategies, the speed factors (η) are set to 0.5 for all agents. Furthermore, $\eta 2$=10 in all *anticipate* and *hybrid* strategies. Only for *anticipate 3* two variants are shown: one with $\eta 2$=10 (called *anticipate 3a* from now on) and one with $\eta 2$=30 (called *anticipate 3b*), which turned out to improve the results for that strategy. The value of γ (the capacity of guardians to avoid an assault) is set to 1950, and the movement cost parameter ε is set to 250 (since these values produced most realistic patterns). Finally, Δt=0.1, and the total simulation time is 100 steps.

[**] All scenarios and parameter settings were chosen after a number of brainstorm sessions with experts in criminology. Although the exact numbers do not correspond to actual empirical data, they were selected in such a way that the resulting patterns are realistic. In addition to the simulation experiments presented in this paper, a large number of other experiments have been performed as well (with different ratios, #locations, and so on), but the overall trends were similar to the results shown here.

5.2 Example Simulation Traces

To illustrate the types of patterns that result from the simulations, the dynamics of two example simulation traces are shown in detail. Both traces address scenario 2.

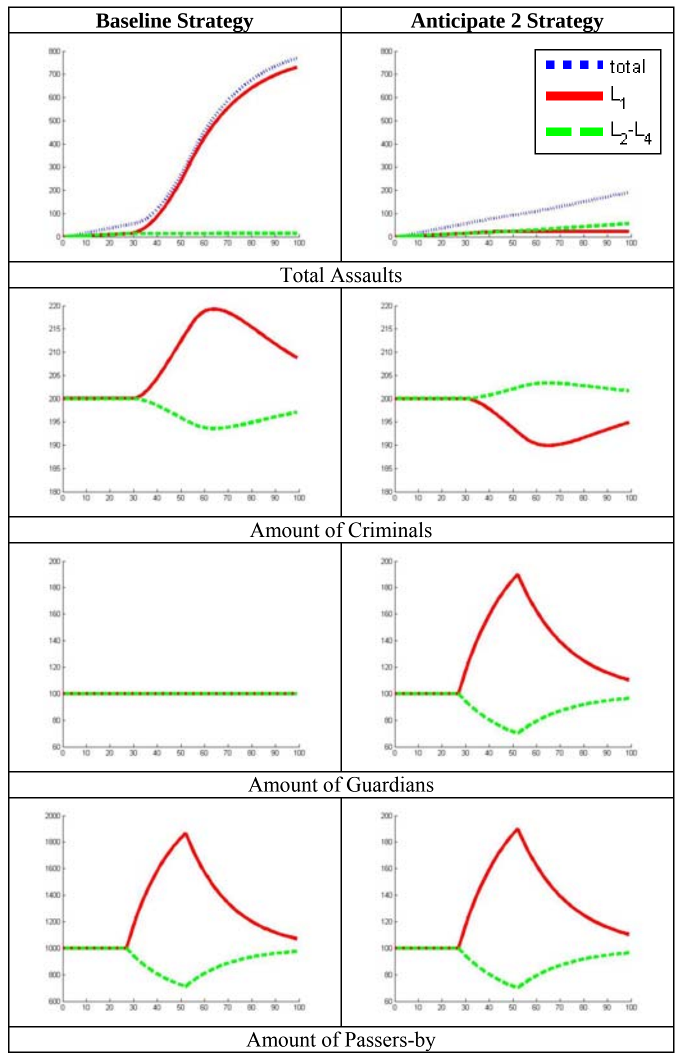

Figure 2. Simulation Traces for Scenario 2

In trace 1 (the left column of Figure 2), the results of the *baseline* strategy are depicted graphically. The results of the *anticipate 2* strategy are shown in trace 2 (the right column of Figure 2). This figure shows, from top to bottom, the total (cumulative) number of assaults, and the amount of criminals, guardians, and passers-by at the different locations. In all graphs, the solid red line indicates location L1 and the dashed green line shows the results for locations L2, L3 and L4 (these locations have the exact same values, and are therefore shown as one single line). The dotted blue line in the upper graphs shows the total amount of assaults, i.e., the sum of the assaults at the four locations.

As can be seen in Figure 2, over the first 25 time points, there is no difference between both strategies: there is a stable situation, with an equal distribution of criminals over the four locations (and therefore also an equal distribution of passers-by and guardians). As a result, the amount of assaults increases linearly (and slowly). However, after time point 25 (the moment that the circus comes to location L1), this location becomes very attractive for passers-by (as can be seen in the lower graphs, for both strategies). The difference between the two strategies is that *anticipate 2* immediately anticipates on this changed situation: many guardians are sent to L1. This causes many criminals to move away from that location. Instead, the *baseline* strategy does not result in any movement of guardians. As a result, many criminals can move to L1, and commit assaults without being stopped.

Although this is only one example scenario, it clearly illustrates the difference between (in this case, *baseline* and *anticipation*) strategies. Guardians that act according to a reactive strategy mainly show behaviour that is similar to the anticipation strategy, but are a bit more 'hesitating' in their actions. A more complete comparison between the strategies is shown in the next section.

5.3 Simulation Results

All 10 strategies introduced in Section 4 have been tested against the five scenarios (among others). Figure 4 shows for each strategy what was the total amounts of assaults (where the numbers of the five scenarios are accumulated). As this figure shows, the crime rates differ significantly between the 10 strategies. The strategies *reactive 1* and *anticipate 1* (which react to the current or predicted amount of criminals, respectively) do not seem to add much compared to the *baseline* strategy. All other strategies seem to be beneficial. The lowest assault rates are found for the strategies *reactive 2* (which reacts to recent assault), *anticipate 2* (which anticipates on expected passers-by) and *hybrid 1* (which is a combination of these two strategies). Interestingly, the *hybrid 1* strategy is even more effective than the two strategies of which it was composed separately. Apparently, this strategy exploits the useful properties of both strategies.

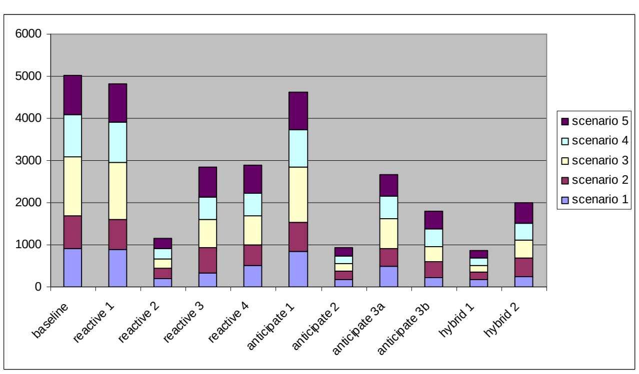

Figure 3. Total amounts of assaults

As explained earlier, the effectiveness of the strategies must be weighed against their efficiency. For this reason, the total costs of each strategy have also been counted, see Figure 4. This figure shows that, although very effective, the *reactive 2* and *hybrid 1* strategies are not very cost-efficient. For obvious reasons, the *baseline* strategy does not involve any costs††.

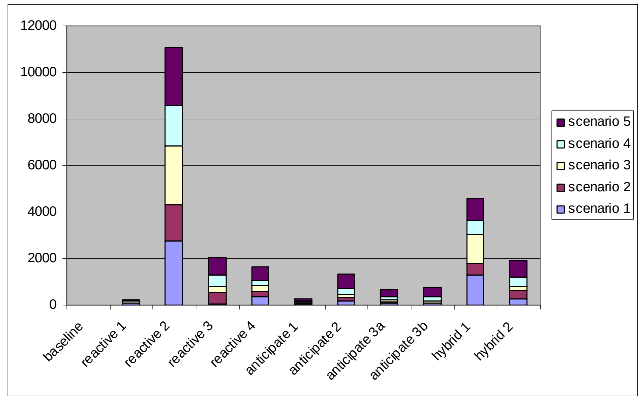

Figure 4. Total amounts of costs

When we want to weigh the costs of a particular strategy *S* against its benefits, also a notion of *benefits* is needed. This is defined as the amount of assaults that are prevented by strategy *S*, compared to a situation in which the baseline strategy is used:

$$total\_prevented\_assaults_S(t) = \sum_{X:loc} (total\_assaults_{baseline}(X,t) - total\_assaults_S(X,t))$$

Based on this definition, the *cost-benefit ratio* of a particular strategy *S* in a given scenario is defined as follows (where *lt* is the last time point of the scenario).

$$ratio_S = total\_costs_S(lt) / total\_prevented\_assaults_S(lt)$$

An overview of the cost-benefit ratios for the different strategies is provided in Figure 5. Here, the baseline strategy is omitted because it is used as a benchmark for the other strategies. It becomes clear that, for the given scenarios, the anticipatory strategies have the lowest cost-benefit ratio, whereas the reactive strategies have the highest ratio.

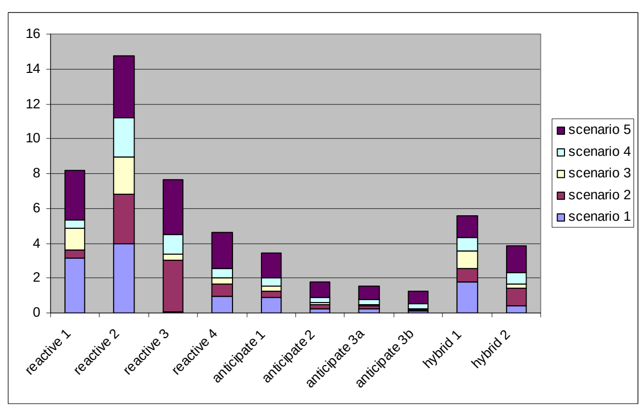

Figure 5. Cost-benefit ratios

†† Note that only the costs for moving guardians are counted; for simplicity, variable costs for maintenance of existing guardianship (e.g., depending on their job description, or work times) are ignored.

In practice, the question which strategy is 'best' of course depends on the preferences of the law enforcement agency (e.g., how much money can be invested?). However, the above results have illustrated that the presented simulation model can give insight in the costs and benefits of different strategies, which may provide useful information for policy makers.

6. FORMAL ANALYSIS METHOD

As illustrated above, simulation may be a useful instrument in that it enables the researcher to perform large numbers of (pseudo-) experiments to explore certain questions. For example, based on the simulation results, it could be concluded that anticipatory strategies are usually more cost-efficient than reactive strategies. However, these results do not provide much explanation on individual cases; e.g., they do not shed any light on why some strategy performs better in one scenario than in another. To answer such questions, it is needed to study individual simulation traces in detail. However, if the number of traces is large, is not trivial to filter out those traces that are worth investigating.

For this purpose, this section introduces an automated approach to classify the simulation traces based on their behavioural patterns. The main idea is that different traces are distinguished by checking certain dynamic properties against them, cf. [4]. These dynamic properties are formalised in terms of logical statements, and are automatically verified against simulation traces. A typical example of a property that may be checked is "whether the amount of assaults is equally spread over the different locations". By running a large number of simulations and verifying such properties against the resulting simulation traces, the modeller can separate the interesting cases from the less interesting ones within limited time. As a next step, the interesting simulation traces can be inspected by hand, to explain the unexpected behaviour.

For the presented model of crime displacement, a number of such dynamic properties have been formalised in the Temporal Trace Language (TTL) [4]. This predicate logical language supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to *states* of the world, *time points* and *traces*, i.e. trajectories of states over time. In addition, *dynamic properties* are temporal statements that can be formulated with respect to traces based on the state ontology Ont in the following manner. Given a trace γ over state ontology Ont, the state in γ at time point t is denoted by state(γ, t). These states can be related to state properties via the formally defined satisfaction relation denoted by the infix predicate |=, comparable to the Holds-predicate in the Situation Calculus: state(γ, t) |= p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties can be formulated in a formal manner in a sorted first-order predicate logic, using quantifiers over time and traces and the usual first-order logical connectives such as $\neg$, $\wedge$, $\vee$, $\Rightarrow$, $\forall$, $\exists$. A special software environment has been developed for TTL, featuring both a Property Editor for building TTL properties and a Checking Tool that enables formal verification of such properties against (simulated or empirical) traces. This tool can also import simulation traces produced by the LEADSTO environment [5]. For more details about TTL, including complexity results, see [4].

Various dynamic properties for the model have been formalised in TTL. Below, a number of them are introduced, both in semi-formal and in informal notation (note that they are all defined for a given trace γ, a time interval between tb and te, and an integer n):

P1 - Maximal Adaptation Time

For each time point t (between tb and te) on which the basic attractiveness of some location l increases, it takes at most n time points until the assault rate is back to the level it had before t.

P1(γ:TRACE, tb,te:TIME, n:INTEGER) ≡
∀t:TIME ∀x1,x2,y1:REAL ∀l:LOCATION
[tb ≤ t & t ≤ te &
state(γ, t) |= has_basic_attractiveness_for(l, passers_by, x1) &
state(γ, t+1) |= has_basic_attractiveness_for(l, passers_by, x2) &
x2 > x1 & state(γ, t) |= assault_rate_at(l, y1)]
⇒ [∃d:INTEGER ∃y2:REAL
state(γ, t+d) |= assault_rate_at(l, y2) & 0<d & d≤n & y2≤y1 &
[∀y3:REAL ∀t2:TIME t < t2 & t2 < t+d &
state(γ, t2) |= assault_rate_at(l, y3) ⇒ y3 ≥ y1]]

This property can be used to find out how long it takes until a particular hot spot has disappeared. This can be useful in cases where policy makers have strict constraints in the amount of time they allow a hot spot to persist. The results of checking this property against the simulated traces are displayed in Figure 6. This figure shows, e.g., that *reactive 2* is very quick in eliminating the hot spot in scenario 1, but is much slower (also compared to the other strategies) in scenario 4, involving multiple hot spots.

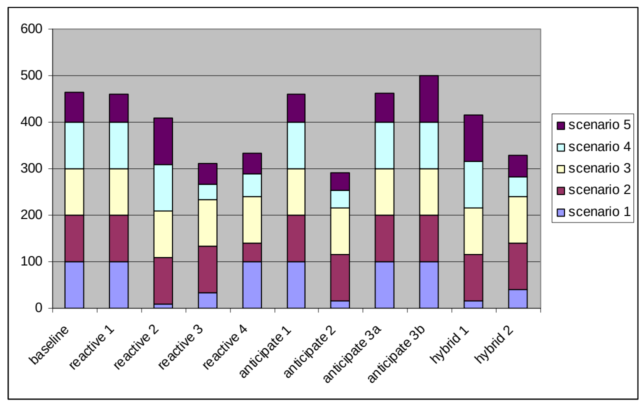

Figure 6. Maximal adaptation times

Another relevant property is the following:

P2 - Equal Spread of Assaults

For each time point t (between tb and te), the assault rate at the largest hot spot is at most n% of the assault rate at the smallest hot spot.

P2(γ:TRACE, tb,te:TIME, n:INTEGER) ≡
∀t:TIME ∀x1,x2:REAL∀l1,l2:LOCATION
[tb ≤ t & t ≤ te &
is_largest_hot_spot_at(l1, t, γ) &
is_smallest_hot_spot_at(l2, t, γ) &
state(γ, t) |= assault_rate_at(l1, x1) &
state(γ, t) |= assault_rate_at(l2, x2)] ⇒ x1 ≤ (1+n/100)*x2

In this formula, is_largest_hot_spot_at is an abbreviation, which is formalised as follows (and similarly for is_smallest_hot_spot_at):

is_largest_hot_spot_at(l1:LOCATION,t:TIME,γ:TRACE) ≡
∃i:REAL state(γ, t) |= assault_rate_at(l1, i) &
∀l2:LOCATION ∀i2:REAL
[state(γ, t) |= assault_rate_at(l2, i2) ⇒ i2≤i]

Property P2 can be used to select strategies that enforce small differences between the crime rates of different locations. Due to space limitations, the checking results are not shown here, but they were comparable with the results shown in Figure 3. I.e., the strategies *reactive 2*, *anticipate 2*, and *hybrid 1* yielded the smallest differences (with *anticipate 2* as absolute winner: this strategy always kept the difference in assault rates below 10).

Finally, property P3 can be used to find out the maximal rate at which guardians move for each scenario. Again, the results are not shown here, but they were comparable with Figure 4 (although with small differences, since 'maximal' is not the same as 'total').

P3 - Maximal Movement Rate

For each time t (between tb and te), the total movement rate is at most n.

P3(γ:TRACE, tb,te:TIME, n:INTEGER) ≡
∀t:TIME ∀x:REAL
[tb ≤ t & t ≤ te & state(γ, t) |= total_movement_rate(x) ⇒ x ≤ n]

To conclude, the formal method presented here can be used as an addition to the simulation model, in order to find more detailed properties of individual simulation traces that can not (easily) be verified by looking at the simulation runs. Moreover, besides simulation traces, the checker tool can also import traces that are constructed from empirical data, if these are available. This way, the method can be exploited to analyse existing displacement data.

7. DISCUSSION

Computational modelling of crime displacement is a hot topic since a number of years. Various modelling approaches have been taken, with different perspectives and goals [1, 3, 7, 11, 12, 15, 17]. The current paper extends the state-of-the-art by proposing an agent-based framework to analyse displacement processes. The framework consists of a simulation model to compare crime prevention strategies, and a formal method to analyse detailed properties of the strategies. Using this framework, various crime prevention strategies were analysed under different circumstances. The results suggest that a hybrid strategy is most effective, but that purely anticipatory strategies are more cost-efficient.

Despite these encouraging results, they should not be over-generalised. They were achieved in simulations that used several specific parameters and simplifying assumptions. For example, in practice it is not always feasible to determine exact numbers for the attractiveness of a location for certain groups, or for the amount of assaults that are performed. Nevertheless, the results of such simulations may be useful input for policy makers, in order to elaborate their thoughts about efficient strategies (cf. [10]), as also confirmed by our colleagues in the Department of Criminology. In that light, an advantage of comparing multiple strategies is that one can select the most feasible one in a particular case.

As a first step to support such policy making, for future work it is planned to incorporate the presented simulation model within an intelligent support agent. Such an agent will use input from databases on citizen activities and crime records, in order to provide the police advice on how to handle in a given situation. Another further extension that will be addressed is the use of more intelligent strategies for the criminals. Although the currently used formula approximates (for large numbers) the behaviour of criminals in the real world, it would be interesting to explore how a more sophisticated formula would influence the results.

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