# A Model-Based Reasoning Approach to Prevent Crime

Tibor Bosse and Charlotte Gerritsen

**Abstract.** Within the field of criminology, one of the main research interests is the analysis of the *displacement of crime*. Typical questions that are important in understanding the displacement of crime are: When do hot spots of high crime rates emerge? Where do they emerge? And, perhaps most importantly, how can they be prevented? In this paper, an agent-based simulation model of crime displacement is presented, which can be used not only to *simulate* the spatio-temporal dynamics of crime, but also to *analyze* and *control* those dynamics. To this end, methods from Artificial Intelligence and Ambience Intelligence are used, which are aimed at developing intelligent systems that monitor human-related processes, and provide appropriate support. More specifically, an explicit domain model of crime displacement has been developed, and, on top of that, model-based reasoning techniques are applied to the domain model, in order to analyze which environmental circumstances result in which crime rates, and to determine which support measures are most appropriate. The model can be used as an analytical tool for researchers and policy makers to perform thought experiments, i.e., to shed more light on the process under investigation, and possibly improve existing policies (e.g., for surveillance). The basic concepts of the model are defined in such a way that it can be directly connected to empirical information.

## 1 Introduction

Within the field of criminology, one of the main research interests is the analysis of the *displacement of crime* [14, 20, 26]. Typically, certain locations

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L. Magnani et al. (Eds.): Model-Based Reasoning in Science & Technology, SCI 314, pp. 159–177.
springerlink.com 

in a city seem to attract many criminal activities, but only for a short period. These locations where many crimes occur are called *hotspots*. Questions that are important in understanding the displacement of crime are: When do hot spots of high crime rates emerge? Where do they emerge? And, perhaps most importantly, how can they be prevented? In recent years, computational modeling and simulation have proved to be a useful instrument to answer such questions.

When investigating the literature on computational modeling of displacement of crime, different computational modeling approaches can be distinguished. Among the approaches that are applied, one can find agent-based modeling [6, 9, 13, 24], population-based modeling [9], cellular automata [19, 22], different spatial analysis techniques [18], and evolutionary computing techniques [24].

Although they all share the aim of investigating crime displacement, the perspectives taken in the above papers differ. For example, some authors try to develop simulation models of crime displacement in existing cities, which can be directly related to real world data (e.g., [22]), whereas others deliberately abstract from empirical information (e.g., [9]). The idea behind the latter perspective is that the simulation environment is used as an analytical tool, mainly used by researchers and policy makers, for thought experiments, to shed more light on the process under investigation, and perhaps improve existing policies (e.g., for surveillance) [16]. Also, some authors take an intermediate point of view (e.g., [6, 23]). They initially build their simulation model to study the phenomenon per se, but define its basic concepts in such a way that it can be directly connected to empirical information, if this becomes available.

This intermediate perspective is also taken in the current paper. Its main goal is to develop an agent-based simulation model of crime displacement, which can be used not only to *simulate* the spatio-/temporal dynamics of crime, but also to *analyze* and *control* those dynamics. This second aim distinguishes it from most existing approaches, which are mainly descriptive (instead of prescriptive).

To achieve this goal, we make use of techniques from Artificial Intelligence, and in particular from Ambient Intelligence (AmI). Ambient Intelligence [1, 2, 25] represents a vision of the future where humans will be surrounded by pervasive and unobtrusive electronic environments, which are sensitive, and responsive to their needs. In order to develop such intelligent environments, Bosse et al. [10] introduced a methodology to endow intelligent systems with the possibility to reason explicitly about the mental and physical states of humans. In the current paper, this methodology is reused in order to develop an intelligent system that reasons about crime displacement.

More specifically, this paper will first describe the development of an explicit *domain model* of crime displacement (which describes displacement in terms of states of the world over time, and transitions between these states). On top of that, model-based reasoning techniques (cf. [4]) will be applied to the domain model, in order to analyze which environmental circumstances result in which crime rates, and to determine which support measures are most appropriate (cf. [5]). Hence, both an *analysis model* and a *support model* will be developed.

The outline of this paper is as follows. First, in Section 2, some background information about the area of Ambient Intelligence will be provided. Next, Section 3 will introduce the basic methodology for the development of intelligent human-aware model-based systems that will be used in this paper. Based on this methodology, Section 4, 5 and 6 will introduce, respectively, the domain model, analysis model and support model for crime displacement. Section 7 will present some preliminary simulation results, and Section 8 will conclude the paper with a discussion.

## 2 Ambient Intelligence

Ambient Intelligence [1, 2, 25] represents a vision of the future where human beings will be surrounded by pervasive and unobtrusive electronic environments, which are sensitive, and responsive to their needs. Such an environment has a certain degree of awareness of the presence and states of living creatures in it, and supports their activities. It analyzes their behavior, and may anticipate on it. Ambient Intelligence (AmI) integrates concepts from ubiquitous computing and Artificial Intelligence (AI) with the vision that technology will become invisible, embedded in our natural surroundings, present whenever we need it, attuned to the humans' senses, and adaptive to them. In an ambient intelligent environment, people are surrounded by networks of embedded intelligent devices that can sense their state, anticipate, and when relevant adapt to their needs. Therefore, the environment should be able to determine which actions have to be undertaken in order to keep this state optimal.

For this purpose, acquisition of sensor information about humans and their functioning is an important factor. However, without adequate additional *knowledge* for analysis of this information, the scope of such applications is limited. As argued by Bosse et al. [10], AmI applications can show a more human-like understanding and base personal care on this understanding when they are equipped with knowledge about the relevant physiological, psychological, and/or social aspects of human functioning. For example, this may concern elderly people, patients depending on regular medicine usage, surveillance, penitentiary care, psychotherapeutical/selfhelp communities, but also, for example, humans in highly demanding tasks such as warfare officers, air traffic controllers, crisis and disaster managers, and humans in space missions; e.g., [17].

Within human-directed scientific areas, such as cognitive science, psychology, neuroscience and biomedical sciences, models have been and are being developed for a variety of aspects of human functioning. If such models of human processes are represented in a formal and computational format, and incorporated in the human environment in devices that monitor the physical and mental state of the human, then such devices are able to perform a more in-depth analysis of the human's functioning. This can result in an environment that may more effectively affect the state of humans by undertaking actions in a knowledgeable manner that improve their wellbeing and performance. For example, the workspaces of naval officers may include systems that, among others, track their eye movements and characteristics of incoming stimuli (e.g., airplanes on a radar screen), and use this information in a computational model that is able to estimate where their attention is focussed at. When it turns out that an officer neglects parts of a radar screen, such a system can either indicate this to the person, or arrange on the background that another person or computer system takes care of this neglected part. Note that for a radar screen it would also be possible to make static design changes, for example those that improve situation awareness (e.g. picture of the environment, [28]). However, as different circumstances might need a different design, the advantage of a dynamic system is that the environment can be adapted taking both the circumstances and the real-time behavior of the human into account.

In applications of this type, an ambience is created that has a better understanding of humans, based on computationally formalized knowledge from the human-directed disciplines. The use of knowledge from these disciplines in Ambient Intelligence applications is beneficial, because it allows taking care in a more sophisticated manner of humans in their daily living in medical, psychological and social respects. In more detail, content from the domain of human-directed sciences, among others, can be taken from areas such as medical physiology, health sciences, neuroscience, cognitive psychology, clinical psychology, psychopathology, sociology, criminology, and exercise and sport sciences.

Although it does not directly fit in the description of Ambient Intelligence, the system envisioned by the current paper has a number of similarities with the types of systems sketched above. That is, it will also take information about humans and their dynamics as input (namely the spatial distribution of individuals over the city, and information about crime rates), it will also be equipped with (formalized) knowledge from human-directed disciplines (in this case criminological knowledge about crime displacement), and it will also generate support measures as output (i.e. advice to reduce crime). Thus, in order to develop the intelligent system for reasoning about crime displacement, it makes sense to reuse approaches from the Ambient Intelligence area. In particular, the methodology from [10] is used, which is introduced below.

## 3 Methodology

In this section, the adopted approach to develop intelligent human-aware systems is presented in detail, cf. [10]. Here, human-aware is defined as being able to analyze and estimate what is going on in the human's mind (a form of mindreading) and in his or her body (a form of bodyreading). Input for these processes are observed information about the human's state over time, and dynamic models for the human's physical and mental processes. For the mental side, such a dynamic model is sometimes called a Theory of Mind (e.g., [3]) and may cover, for example, emotion, attention, intention, and belief. Similarly for the human's physical processes, such a model relates, for example, to skin conditions, heart rates, and levels of blood sugar, insulin, adrenalin, testosterone, serotonin, and specific medicines taken. Note that different types of models are needed: physiological, neurological, cognitive, emotional, social, as well as models of the physical and artificial environment[1].

A framework can be used as a template for the specific class of Ambient Intelligence applications as described. The structure of such an ambient software and hardware design can be described in an agent-based manner at a conceptual design level and can be given generic facilities built in to represent knowledge, models and analysis methods about humans, for example (see Figure 1):

- human state and history models
- environment state and history models
- profiles and characteristics models of humans
- ontologies and knowledge from biomedical, neurological, psychological and/or social disciplines
- dynamic process models about human functioning
- dynamic environment process models
- methods for analysis on the basis of such models

Examples of useful analysis methods are voice and skin analysis with respect to emotional states, gesture analysis, and heart rate analysis. The template can include slots where the application-specific content can be filled to get an executable design for a working system. The analysis method used in the current paper mainly addresses displacement of crime, i.e., it calculates how a certain distribution of persons over space would lead to movement of criminal activities.

A general approach for embedding knowledge about the interaction between the environment and the human(s) in Ambient Intelligence applications is to integrate dynamic models of this interaction (i.e. a model of the *domain*) into the application. This integration takes place by embedding domain models in certain ways within agent models of the intelligent application. By incorporating domain models within an agent model, the intelligent agent gets an understanding of the processes of its surrounding environment, which is a solid basis for knowledgeable intelligent behavior. Three different ways to integrate domain models within agent models can be distinguished.

[1] In this paper, the main focus is on social/environmental states and models, i.e., locations of persons, and decisions to move to other location. Nevertheless, the model is sufficiently generic to be extended with the other types of states as well.

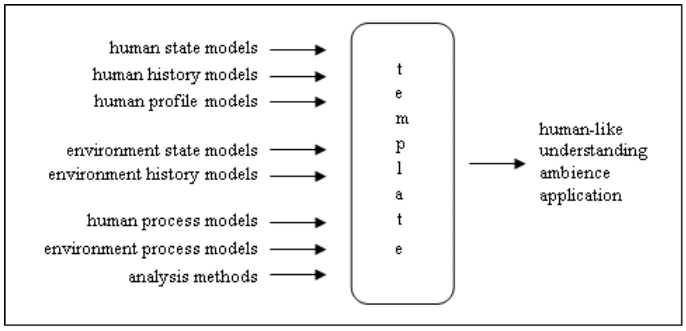


**Fig. 1** Framework to develop intelligent human-aware systems.

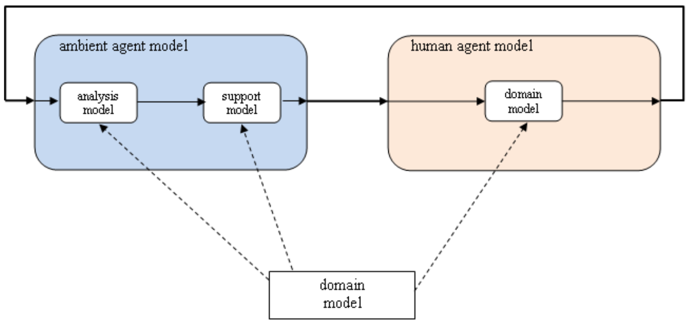


**Fig. 2** Overview of the multi-agent system architecture.

A most simple way is to use a domain model that specifically models human behavior in the following manner:

- *domain model directly used as agent model*
  In this case a domain model that describes human processes and behavior is used directly as an agent model, in order to simulate human behavior. Note that here the domain model and agent model refer to the same agent.

Such an agent model can be used in interaction with other agent models, in particular with *ambient agent models* to obtain a test environment for simulations. For this last type of (artificial) agents, domain models can be integrated within their agent models in two different ways, in order to obtain one or more (sub)models; see Figure 2. Here the solid arrows indicate information exchange between processes (data flow) and the dotted arrows the integration process of the domain models within the agent models.

As shown in Figure 2, the following submodels can be obtained based on a domain model:

- *analysis model*
  To perform analysis of the human's states and processes by reasoning based on observations (possibly using specific sensors) and the domain model.
- *support model*
  To generate support for the human by reasoning based on the domain model.

Note that here the domain model that is integrated refers to one or more human agents, whereas the agent model in which it is integrated refers to an artificial agent (the intelligent system). In the following sections, this methodology will be applied to the domain of crime displacement. First a domain model is presented which represents the spatio-temporal dynamics of crime. Next, an analysis model is presented, which is able to reason about the domain model in order to predict crime rates for particular situations. And finally, a support model is presented, which is able to suggest to the user the most appropriate measures to reduce crime rates. For example, in case the analysis model predicts that the crime rates at the railway station will increase with 20% in the next year, and that these rates can be kept stable by increasing the amount of police by 5%, then it may propose to invest in 5% more police forces.

## 4 Domain Model

This section presents the domain model for crime displacement. The important concepts used are introduced in Section 4.1, and their formalization is described in Section 4.2.

### *4.1 Crime Displacement*

As explained in the introduction, most large cities in the world contain a number of *hot spots*, i.e., locations where the majority of the crimes occur [15, 26]. 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 [20]. 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 [15], whereas most citizens will be more likely to avoid it [27]. As a result, the amount of criminal activity at such a location will decrease, which affects its reputation again.

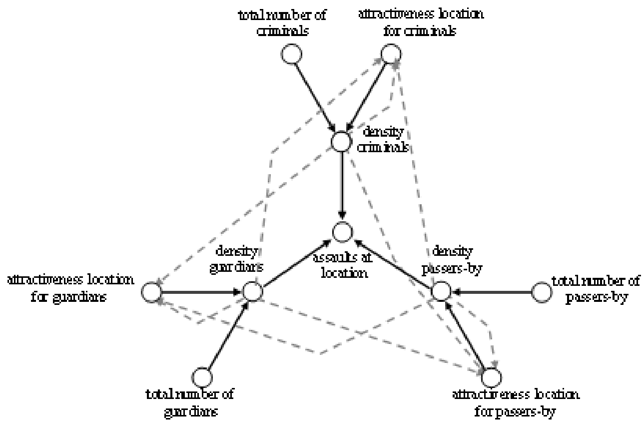


**Fig. 3** Interaction between criminals, guardians, and passers-by.

To summarize, 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 modeled. 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 [14].

The interaction between the concepts introduced above is visualized in Figure 3[2]. This figure depicts the influences between the different groups at

[2] Note that Figure 3 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.

**Table 1** Variables used in the domain 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 $t$. |
| $\beta(L,a,t)$ | Attractiveness of location $L$ at time $t$ for type $a$ agents: $c$ (criminals), $p$ (passers-by), or $g$ (guardians) |
| $\mathrm{ba}(L,a,t)$ | Basic attractiveness of location $L$ at time $t$ for type $a$ agents: $c$ (criminals), $p$ (passers-by), or $g$ (guardians) |
| $\mathrm{assault\_rate}(L,t)$ | Number of assaults taking place at location $L$ per time unit. |

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).

## *4.2 Formalization*

In order to build the domain model for crime displacement, the concepts that were introduced above (in italics) are formalized in terms of mathematical variables. The variable names that are used are summarized in see Table 1.

Next, a number of mathematical equations are introduced to represent the causal relations between these variables. Most of these ideas are taken over from [8] (and [7, 9]). 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 $\eta$ (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 $\Delta t$. 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 [9], the movement of the guardians is not (necessarily) modeled 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 normalized 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.

$$\beta(L,c,t) = p(L,t)/p \qquad \text{for criminals}$$

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

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 [9]. 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[3]:

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

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

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 ($\beta_{xy}$, 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 [9]). In this paper, the following is used:

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

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 $\gamma$, 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

[3] Note that these attractiveness formulae are not normalized 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.

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:

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

Although the domain model is presented here in a purely mathematical notation, its actual implementation has been done in the agent-based modeling environment LEADSTO [11]. This environment is well suited for the current purposes, since it integrates both qualitative, logical aspects and quantitative, numerical aspects. The basic building blocks of LEADSTO are executable rules of the format $\alpha \twoheadrightarrow \beta$, which indicates that state property $\alpha$ leads to state property $\beta$. Here, $\alpha$ and $\beta$ can be (conjunctions of) logical and numerical predicates.

## 5 Analysis Model

This section extends the domain model introduced in the previous section to an analysis model. The analysis model (and the support model, see next section) are created by taking the domain model as a basis, and applying model-based reasoning to it. In particular, two types of reasoning are applied (taken from [4]): forward and backward reasoning. In short, these types of reasoning make use of the following kinds of (simplified) rules (where $X$ and $Y$ are variables in a model, e.g. as in Figure 3):

- If we believe $X$ and believe that $Y$ depends on $X$, then we also believe $Y$.

$$\text{belief}(X) \wedge \text{belief}(\text{depends\_on}(Y, X))\, \text{belief}(Y)$$

- If we desire $Y$ and believe that $Y$ depends on $X$, then we also believe $X$.

$$\text{desire}(Y) \wedge \text{belief}(\text{depends\_on}(Y, X))\, \text{desire}(X)$$

To illustrate the idea, assume that we focus on an existing city, of which the average number of criminals, guardians, and passers-by at the different locations is known (to a certain extent). Thus, specific numbers can be assigned to the variables *density_criminals*, *density_guardians*, and *density_passers_by* in Figure 3 (which correspond to $c(L, t)$, $g(L, t)$, and $p(L, t)$ in Table 1). Then, via forward reasoning (the first rule shown above), the model can predict how the number of assaults will change over time.

One step further, instead of taking the actual densities of guardians at the different locations, the analysis model can also be used to investigate how the crime rates would change in case the densities of guardians were different. To this end, the analysis model is extended with the possibility to specify particular crime prevention *strategies*. The idea is that, in addition to the rules that govern the behavior of criminals and passers-by, the behavior 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 [12, 15]. 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 hypothesize 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 be able to investigate this, the analysis model in equipped with multiple strategies for movement of guardians (varying from reactive to anticipatory, and combinations of the two). The selected strategies are based on [7, 8], in which they were already tested against some initial scenarios. In total, the analysis model contains ten different strategies (see also Table 2):

1. 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.
2. 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.
3. 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.
4. 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.
5. 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.
6. 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.
7. 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.
8. 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.
9. 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.
10. 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 formalize 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 $\sigma$ 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 considered by the analysis model.

| **Strategy** | **Formalization of** $\sigma(L,t)$ |
|---|---|
| *baseline* | 0 |
| *reactive 1* | $(c(L,t)/c) \cdot g - g(L,t)$ |
| *reactive 2* | $\mathrm{aar}(L,t) \cdot g - g(L,t)$ |
| *reactive 3* | $\mathrm{taar}(L,t) \cdot g - g(L,t)$ |
| *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* | $((c(L,t) + \eta 2 \cdot (\beta(L,c,t) \cdot c - c(L,t)) \cdot \Delta t)/c+$ <br> $(p(L,t) + \eta 2 \cdot (\beta(L,p,t) \cdot p - p(L,t)) \cdot \Delta t)/p)/2 \cdot g - g(L,t)$ |
| *hybrid 1* | $((\mathrm{aar}(L,t) \cdot g - g(L,t))+$ <br> $(p(L,t) + \eta 2 \cdot (\beta(L,p,t) \cdot p - p(L,t)) \cdot \Delta t)/p \cdot g - g(L,t))/2$ |
| *hybrid 2* | $((taar(L,t) \cdot g - g(L,t))+$ <br> $(p(L,t) + \eta 2 \cdot (\beta(L,p,t) \cdot p - p(L,t)) \cdot \Delta t)/p \cdot g - g(L,t))/2$ |

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

$$\mathrm{aar}(L,t) = \mathrm{assault\_rate}(L,t)/\Sigma_{X:loc}\,\mathrm{assault\_rate}(X,t)$$

$$\mathrm{taar}(L,t) = \mathrm{total\_assaults}(L,t)/\Sigma_{X:loc}\,\mathrm{total\_assaults}(X,t)$$

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 *anticipate 1* 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 analysis model can test which one performs best. A question is however how to define the notion of a "good" strategy. One possibility 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 [12]. 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 [4]) has been added:

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

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

## 6 Support Model

On top of the analysis model presented above, also a support model for crime prevention has been developed. This model takes as input certain information about the future scenario for which the user desires support. Based on this information, it generates advices about which strategies are recommended to prevent crime in this scenario.

More specifically, the model first needs to have some information about the state of the world. In particular, the user needs to specify the geography of the city (i.e., which locations are relevant?), and the initial densities of the different types of agents for each location. In addition to this, the user needs to define a scenario, i.e., (s)he needs to indicate the total time span for which the system is to provide support, and to specify for each location how its basic attractiveness will change during this time span. For instance, in case a circus will temporarily come to town, the basic attractiveness of the location of the circus is likely to increase. Finally, the user has to specify the maximum amount of money (s)he desires to spend.

To summarize, the support model takes the following information as input (which needs to be entered by the user of the system):

- geography of the city (i.e., which locations are relevant?)
- initial densities of the different types of agents ($c(L,t)$, $g(L,t)$, $p(L,t)$) for each location
- total time span of the scenario
- basic attractiveness for the different types of agents ($\text{ba}(L,c,t)$, $\text{ba}(L,g,t)$, $\text{ba}(L,p,t)$) for each location over time
- maximum budget

On the basis of these settings, the support model requests the analysis model to perform simulations for all possible strategies, to determine for each of these strategies to which crime rates it would lead, and what its costs would be. After that, the support model selects the "best" strategies, and presents information about those strategies to the user. The strategies that are assessed as best are those strategies of which the costs are lower than the maximum budget. Moreover, concerning the remaining strategies, in case some strategy s1 turns out both more expensive and less effective than some strategy s2, then this strategy s1 is removed from the selection. Upon request, the model can also provide the user more detailed information about the dynamics of the effect of a particular strategy in the scenario.

## 7 Results

A prototype implementation of the model has been developed. To illustrate the behavior of the prototype, below (part of) the dynamics of an example execution are shown in detail.

This example addresses a scenario where there are three locations, and 3900 agents. The population considered consists of 600 (potential) criminals, 300 guardians, and 3000 passers-by. Initially, these agents are distributed equally over the three location (i.e., at each location, there are 200 criminals, 100 guardians and 1000 passers/by). Moreover, all locations start with the same basic attractiveness (= 0.33 on a $[0, 1]$ scale). After 50 time steps the attractiveness of the locations changes: location 1 becomes very attractive (=0.6), location 2 becomes slightly less attractive (= 0.3), and location 3 becomes much less attractive (= 0.1). The scenario lasts 100 time steps and the maximum budget the user can spend is 100.

When executing the system based on these settings, for the analysis model would predict the dynamics of the scenario for each of the different strategies, as mentioned above. As an illustration, such a prediction is visualized for one particular strategy (in this case, the *reactive 2* strategy, see Table 2) in Figure 4. Figure 4 shows, from top left to bottom right, the assault rate, and the amount of criminals, guardians, and passers-by at the different locations. In all graphs, the red line indicates location L1, the green line indicates location L2, and the blue line indicates location L3. The black line in the upper left graph shows the total amount of assaults, i.e., the sum of the assaults at the three locations.

As can be seen in Figure 4, over the first 50 time points, the number of the different types of agents at the locations stays equal. After time point 50, the amounts change. The guardians move away from location 3 to location 1, which is the most attractive location. The criminals move away from location 1 because they want to move away from the guardians. The passers by move towards location 1 since they want to be at the safest location (i.e. the location with the highest amount of guardians and the lowest amount of criminals). In this case, the strategy used by the guardians seems to work well, because the total number of assaults (i.e., the black line in the upper left graph) grows

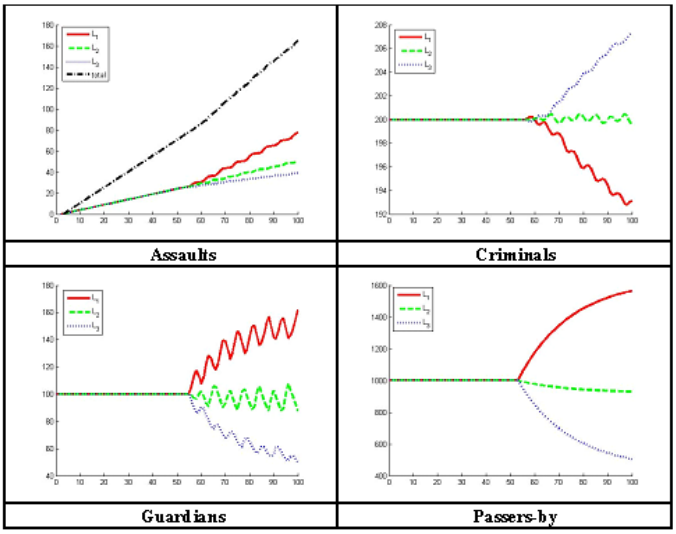


**Fig. 4** Results of an example simulation run by the analysis model.

**Table 3** Recommendation by the support model.

| Recommended strategy | Predicted costs | Predicted % crime prevented |
|---|---|---|
| *anticipate 1* | 30.38 | 7.7 |
| *anticipate 2* | 93.16 | 70.9 |
| *anticipate 3* | 45.10 | 40.6 |

not much faster than it did during the first 50 time points. When comparing this, for instance, with a baseline strategy in which the guardians are static (which is also tested by the analysis model but not shown in Figure 4), this turns out to be a significant improvement.

All in all, the analysis model tries out all possible strategies and provides the results to the support model. Based on this, the support model selects the most promising strategies (in the context of the user's preferences), and presents them as a recommendation to the user. Table 3 shows what this recommendation looks like for the current scenario.

As can be seen from Table 3, the system predicts that the three *anticipate* strategies are "best", i.e., they have costs that are below the budget of the user and are nevertheless effective. Moreover, the system predicts that strategy *anticipate 1* will be cheapest, but that strategy *anticipate 2* will be most effective.

Although this is only a single example scenario, it clearly illustrates that the model is able to generate an appropriate advice on police investment, which may actually be used by policy makes in order to reduce crime rates.

For a more detailed comparison between the different strategies in various scenarios, see [7, 8].

## 8 Discussion

This paper presented a model-based reasoning approach to analyze crime displacement. The approach was inspired by an existing methodology from Ambient Intelligence [1, 2, 25], which proposes that intelligent human-aware systems are composed of three separate components, namely a *domain model*, an *analysis model*, and a *support model* [10]. Although the context of crime displacement has some differences with standard AmI domains (e.g., we focus on group processes instead of individual processes, and use statistical data from police databases rather than sensor data), this methodology turned out very useful for our purposes. In the context of crime displacement, the role of the domain model was to simulate the dynamics of crime displacement, but on top of that, the analysis model proved useful to reason about such simulations for different settings, and the support model was able to generate advice on the basis of the results of this reasoning. The advice consists of a selection of guardian movement strategies that are recommended for a particular scenario, augmented with additional information about the costs and effectiveness of these strategies. A prototype version of the model has been implemented, and some initial tests have pointed out that the model provides realistic advices.

Despite these encouraging results, on should be careful not to overgeneralize them. Currently, they were achieved in simulations that used several specific parameters and simplifying assumptions. Nevertheless, after further testing, the model may provide useful input for policy makers, in order to elaborate their thoughts about efficient strategies, and possibly improve existing surveillance policies.

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