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Crime reduction through simulation: An agent-based model of burglary

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ABSTRACT

Traditionally, researchers have employed statistical methods to model crime. However, these approaches are limited by being unable to model individual actions and behaviour. Brantingham and Brantingham (1993) described that in their opinion a useful and productive model for simulating crime would have the ability to model the occurrence of crime and the motivations behind it both temporally and spatially. This paper presents the construction and application of an agent-based model (ABM) for simulating occurrences of residential burglary at an individual level. It presents a novel framework that allows both human and environmental factors to be simulated. Although other agent-based models of crime do exist, this research represents the first working example of integrating a behavioural framework into an ABM for the simulation of crime. An artificial city, loosely based on the real city of Leeds, UK, and an artificial population were constructed, and experiments were run to explore the potential of the model to realistically simulate the main processes and drivers within this system. The results are highly promising, demonstrating the potential of this approach for both understanding processes behind crime and improving policies and developing effective crime prevention strategies.

1. Introduction

Understanding the processes behind crime is an important research area in criminology which has major implications for both improving policies and developing effective crime prevention strategies (Brantingham & Brantingham, 2004; Groff, 2007a). Recent advances in criminology, such as routine activities theory (Cohen & Felson, 1979), lifestyle exposure theory (Hindelang, Gottfredson, & Garofalo, 1978) and crime pattern theory (Brantingham & Brantingham, 1993) have highlighted a shift from the study of the motivation of offenders to understanding the social and environmental contexts in which crimes occur. However, in order to test these "opportunity theories", it is essential to be able model the complex, dynamic interactions of the individuals involved in each crime event, their interactions with other agents and the environment. Current approaches to modelling crime are limited in their scope/usefulness due to an inability to model the complex micro-level interactions that characterise this system (Groff, 2007a).

The ability to more accurately represent, simulate and thus prevent and reduce crime is at the forefront of crime prevention policies in the UK. For example, in the city of Leeds, the public body responsible for implementing and evaluating crime reduction strategies, Safer Leeds, are involved in developing strategies to reduce residential burglary, which has been consistently the highest when compared to any other local authority in England and Wales (Shepherd, See, Kongmuang, & Clarke, 2004). However, one of the central challenges of modelling a system as complicated as that of residential burglary lies in simulating human behaviour within a computer environment. Humans exhibit soft factors such as seemingly irrational behaviour and complex psychology (Bonabeau, 2002); these characteristics are highly challenging to simulate in a computer model. This is compounded by the fact that burglars can be classified as experts in their field (Nee & Meenaghan, 2006); they possess a range of both behavioural characteristics and specific knowledge that is unique to them. Many studies have interviewed burglars (both incarcerated and active) to gather qualitative evidence regarding their behaviour and motives (Brown & Bentley, 1993; Cromwell & Olson, 2005, chap. 5; Hearnden & Magill, 2003; Nee & Meenaghan, 2006; Wright & Decker, 1996). While these studies have revealed valuable insights into the possible behaviour and motives of offenders (many of which have been incorporated into the design of the model presented here), they often suffer from problems associated with sampling of a small population and lack of rigorous empirical testing. Quantitative studies have helped to establish general trends in burglar behaviour (Bernasco & Luykx, 2003; Massey, Krohn, & Bonati, 1989; Snook, 2004). However, these approaches are limited due to the use of aggregated data and they are unable to represent the micro-level human and environmental factors that dictate whether or not an individual crime event will occur.

One technique that shows considerable promise for overcoming these limitations is agent-based modelling (ABM). ABM represents

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a shift in the social sciences towards the use of models that work at the level of the individual. For a recent overview of applications, see Paredes and Hernández (2008). ABMs are comprised of autonomous, decision making entities called agents that have the ability to interact with each other and their environment (Bonabeau, 2002). Agents can represent individuals, groups of individuals and, if appropriate, inanimate objects such as houses or cars. As the model iterates, each agent has the ability to assess its circumstances, and based on a set of probabilistic rules, makes an informed/educated decision about its future course of action (Bonabeau, 2002). Through this mechanism, more realistic human behaviour can be incorporated (Moss & Edmonds, 2005).

Simulating residential burglary is a particularly challenging problem, largely because the system can be regarded as highly complex. Not only does it contain potentially unlimited entities (broadly categorised as social, environmental and behavioural factors) linked by often unknown and non-linear relationships, this system is highly dynamic, changing both over time and space. For example, an occurrence of a residential burglary is affected by the time of day, a combination of spatial and environmental factors (e.g. low security, easily accessible property) and individual behaviour (opportunistic crime, individual motivation). One of the most attractive elements of ABM is the ability to experiment with different crime theories and reduction policies before implementation in the real system. Examples of this type of application can be found in the areas of urban planning (Al-Ahmadi, Heppenstall, Hogg, & See, 2009) and education (Harland & Stillwell, in press, chap. 16). The development and application of an ABM for simulating residential burglary thus provides a unique opportunity to both further understanding of the processes and dynamics of this system as well as providing a platform for testing out crime reduction policies.

Brantingham and Brantingham (1993) described that, in their opinion, a useful and productive model for simulating crime would include the ability to model the occurrence of crime and the motivations behind it in a dynamic time and space. This paper presents the development and application of an ABM for simulating the occurrence of crime (specifically residential burglary) at an individual level. A particular focus of this paper is the modification and inclusion of the Physical conditions, Emotional states, Cognitive capabilities and Social status (PECS) framework for simulating more realistic human behaviour within a computational/artificial environment. The model is tested through the development of an artificial city loosely based on the real city of Leeds, UK. Previous approaches to crime modelling are discussed in Section 2, illustrating how this approach enhances existing work to date. The PECS framework along with details of how this was integrated into the ABM is outlined in Sections 3 and 4. A series of experiments testing the behaviour and robustness of the model are presented in Section 5. Sections 6 and 7 conclude with a discussion of the results and a critique of the methodology while future work is briefly outlined in Section 8.

2. Previous approaches to crime modelling

The crime system is driven by a large number of interrelating factors. These include, but are not limited to, an offender's individual perception and knowledge of the physical environment, the suitability or attractiveness of the target, the offenders cognitive representation of the environment, the layout of the physical environment and other factors relating to the surrounding community (Brantingham & Brantingham, 1993).

Environmental criminology has employed numerous methods for understanding and examining the most important environmental factors that influence how criminals choose their targets (Brantingham & Brantingham, 1993). Early seminal work by Shaw and McKay (1969) utilised mapping techniques to investigate the link between juvenile delinquency and social or cultural characteristics. The authors found that juvenile delinquency rates were at their highest in city centres and exhibited similar spatial patterns to other indicators of social problems. Advances in geographical information systems (GIS) and the availability of individual-level data have catalysed the development of more advanced mapping analysis techniques such as "hotspot detection (Grubesic & Murray, 2001). For example, Pain, MacFarlane, Turner, and Gill (2006) overlaid crime hotspot maps with streetlight location maps to investigate the impact that street lighting had on crime and fear-of-crime levels; the results were used to inform existing street lighting policies. Although these techniques are invaluable for crime prevention practitioners (due in part to their ability to highlight areas with unusually high crime rates), they fail to provide insights into the dynamics and processes that govern these systems.

In addition to mapping techniques, statistical or mathematical models have also been widely used. Early examples include the use of principal components analysis to investigate the factors related to social deprivation (Giggs, 1970) and cluster analysis to search for associations between crime and environmental factors (Brown, Mcculloch, & Hiscox, 1972) (although these approaches are strongly criticised by Baldwin (1975) who describes them as "unilluminating"). More recent statistical modelling has been centred around the use of regression models. For example, Craglia, Haining, and Signoretta (2001) compared high intensity crime areas to census data whilst Dahlbäck (1998) found high population density and weak social bonds to be associated with high theft rates through application of longitudinal multivariate regression. Other studies using regression include Gaviria and Pagés (2002) research that linked the chance of being a victim to individual and city-wide variables, and Meera and Jayakumar (1995) who attempted to explain the relationship between rising levels of crime and different demographic and economic variables. These approaches have revealed interesting links between crime and other variables, but they are unable to account for the motivations and impact of individual actions upon both other individuals and the environment.

Advances in software engineering catalysed by increases in computer data storage and processing power has precipitated an uptake in computational approaches to the modelling of crime. A recent example can be found in the work of Kongmuang, Clarke, Evans, and Ballas (2005) and Kongmuang (2006) who utilised spatial micro-simulation and spatial interaction models to investigate urban residential burglary rates. This research both successfully estimated offender flows within a city and predicted the risk of being a victim of residential burglary at the individual level. Despite the advances that this technique provided, this work was limited by the inherent inability of micro-simulation to model interactions between individual entities and most importantly cannot represent human behaviour.

A central drawback common to each of the approaches discussed above is that they fail to address the importance of individual incidents located in a specific time and space. Instead, findings are concerned with general, aggregate patterns; this makes it difficult to draw conclusions regarding how the individual behaviour of victims or offenders may be affecting the occurrence and rate of crime. Brantingham and Brantingham (1993) describe that, potentially, the most productive model in criminology will be the model that "places both the actual criminal events at a specific site, situation and time and the individual committing the crime while in a specific motivational state on (or in) an environmental backcloth, that may itself be mostly stable, regular and predictable or may instead be irregular, rapidly changing and unpredictable." Due to their aggregate nature, traditional statistical modelling techniques are limited in their ability to represent local variation present in the "environmental backcloth". Factors such as the individual location of houses (e.g. corner blocks) (Taylor & Nee, 1988), their visibility to neighbours and passers-by (Robinson & Robinson, 1997) and the layout of the local street network (Bevis & Nutter, 1977) will affect their propensity to be burgled; however, these factors cannot be incorporated into models which do not operate at the level of the individual.

To improve our understanding of the trends and characteristics of crime patterns, it is necessary to examine the individual actors who play important roles in discrete crime events. ABM has been applied to a vast number of subject areas including computer systems that assist car drivers (Miller, Hwang, Torkkola, & Massey, 2003), pedestrian movements (Castle & Crooks, 2006; Turner & Penn, 2002), human immune systems (Jacob, Litorco, & Lee, 2004) and simulating processes and dynamics in the retail petrol market (Heppenstall, Evans, & Birkin, 2005). Despite this uptake, the potential benefits of ABM are only just beginning to be realised in criminology; current work is briefly outlined below. For a detailed review of the theory and concepts behind ABM, the reader is directed to Axtell (2000).

Early agent based crime models were relatively simple but began to show that the technique can hold promise in the field of criminology. For example, Winoto (2003) investigated rational choice and whether a society without crime is attainable, Gunderson and Brown (2000) presented a methodology for predicting both physical- and cyber-crime and Melo, Belchior, and Furtado (2005) modelled police patrol route reorganisation. More recently, even more advanced models have begun to emerge. Notable sources are the recent book entitled "Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems" (Liu & Eck, 2008) and a special issue of the Journal of Experimental Criminology (Groff & Mazerolle, 2008). Models found in these publications, and others, cover a wide range of applications. Simulations which attempt to make predictions about crime rates include drug market dynamics in Melbourne (Dray, Mazerolle, Perez1, & Ritter, 2008), street robbery in Seattle (Groff, 2006, 2007a, 2007b), crime patterns in Cincinnati (Liu, Wang, Eck, & Liang, 2005) and burglary in an abstract environment (Hayslett-McCall et al., 2008, chap. 14). Agent-based crime models are also under development whose aim is not to actually predict crime rates but experiment with criminological ideas. For example, Brantingham, Glasser, Kinney, Singh, and Vajihollahi (2005b), Brantingham, Glässer, Jackson, Kinney, and Vajihollahi (2008, chap. 13), have used the abstract state machine formalism to represent agents who have memory, behaviour and motivations who can be situated in an abstract environment. The resulting simulation can be used as an interdisciplinary tool to assist criminologists in investigating the dynamics of urban crime. In a similar vein, Wang, Liu, and Eck (2008, chap 11) outlined a tool to study the interactions between actors involved in a crime event.

To improve upon the previous models, this research will present a model that includes a larger number of factors and a more accurate model of human behaviour to better represent the real burglary system. These factors include the effect of drug addictions (Wright & Decker, 1996), offenders' perceptions of their physical environment (Brantingham & Brantingham, 1993; Beavon, Brantingham, & Brantingham, 1994) and physical characteristics of the local area (Brown & Bentley, 1993). Furthermore, accurate human behaviour is incorporated via a comprehensive cognitive framework which is the subject of the following section. However, in one respect this model appears less evolved than others: it does not include a realistic urban environment as accomplished in Groff's (and others') work. Because this model is more advanced in other areas, the first challenge is to ensure that the dynamics are fully understood before increasing the complexity. This is noted by Elffers and van Baal (2008, chap. 2) as an extremely important step because an overly-complicated model might be no easier to understand than the real system it is modelling. However, including a realistic backcloth is an eventual goal of this research because it will enable crime predictions that relate to the real world and might be able to influence policy. The final part of the paper will discuss the challenges of including a realistic backcloth in a model such as this.

3. Incorporating human behaviour into an ABM: The PECS framework

An agent's architecture determines how the functionality of the agent is organised and how human or biological traits such as reasoning, beliefs, attitudes and behaviour can be replicated (Singh, 2005). A number of architectures have been proposed to address how these traits should be mimicked; two of these are outlined.

Perhaps the most popular architecture used is the Beliefs–Desires–Intentions (BDI) model. This architecture has been used in several areas, including air traffic management systems (Rao et al., 1995), simulations of geo-political conflicts (Taylor, Frederiksen, Vane, & Waltz, 2004) and frameworks for models of crime reduction (Brantingham et al., 2005b, Brantingham, Glasser, Kinney, Singh, & Vajihollahi, 2005a). Despite its uptake, BDI has been widely criticised. Some authors criticise the three core components (beliefs, desires, and intentions) of the architecture as being too restrictive while others feel that they are overly complicated (Rao et al., 1995). Fundamentally, the architecture assumes rational decision making; this is difficult to justify because people rarely meet the requirements of rational choice models (Axelrod, 1997). Brailsford and Schmidt (2003) see the restriction of the architecture to cognitive processes as a limitation; BDI cannot integrate physical, emotional or social processes or the interactions between them. Balzer (2000, chap. 5) also notes that the core elements are difficult to observe directly: observation can only be achieved in a laboratory setting which is unlikely to relate to real situations.

An alternative, but rarely used, architecture is the PECS framework (Physical conditions, Emotional states, Cognitive capabilities and Social status). Proposed by Schmidt (2000) and Urban (2000, chap. 6), this architecture states that human behaviour can be modelled by taking into account physical conditions, emotional states, cognitive capabilities and social status. Personality is incorporated into the agents by adjusting the rate that internal state variables change and also how these changes are reflected in agent behaviour (Schmidt, 2002). The framework is modular, allowing separate components to control each aspect of the agent's behaviour (Martinez-Miranda & Aldea, 2005). Proponents of PECS cite that as rational decision making is not required and the framework is not restricted to the factors of beliefs, desires, and intentions (Schmidt, 2000), it is an improvement on the BDI architecture.

To illustrate the PECS features, an example proposed by Urban (2000, chap. 6) is adapted here. Consider a person in a shop who is contemplating purchasing some goods. They might experience physical needs (such as hunger), emotional states (such as surprise at the available goods), cognition (such as information about current prices) and social status (which could affect how the agent reacts to the shop assistant). Schmidt (2000) and Urban (2000, chap. 6) argue that every aspect of human behaviour can be modelled using these components although, depending on the application, it might not be necessary to incorporate all of them (Schmidt, 2002).

Despite documented use of the framework being limited, the applications that have incorporated it are diverse. For example, PECS has been used to build emotions into a virtual learning environment (Ammar, Neji, & Gouardères3, 2006; Neji & Ammar, 2007). Here, non-verbal communication was incorporated in the form of emotional facial expressions with the aim of improving the relationship between a human learner and a computer-controlled tutor. In the field of health care, Brailsford and Schmidt (2003) used the framework to improve a simulation of disease screening. The authors noted that through the use of PECS they were able to incorporate individual behaviour; an important determinant of a patient's attendance at a screening session, a factor that is absent from the majority of models in their field.

PECS places behaviour into two categories: reactive and deliberative. Reactive behaviour encompasses actions that are largely instinctive; no deliberation is required. Schmidt (2000) describes how reactive behaviour can be subdivided:

- *Instinctive behaviour*. An automatic reaction to stimulus depending on the internal state of the agent, for example, a parent reacting instinctively to a child's cry. Instinctive behaviour can be easily incorporated using pre-defined rules.
- *Learned behaviour*. Here, rules are learnt dynamically, for example Schmidt (2000) cites the example of a car driver who instinctively brakes if a child runs in front of their car.
- *Drive controlled behaviour*. This behaviour is directed by internal drivers to satisfy needs. Needs range from basic, for example preserving life (such as the need for food or safety) to social needs and intellectual needs. The drivers determine an individual's behaviour as they attempt to satisfy the drive with the greatest intensity. The following function is used to determine drive intensity:

  $$T = f(N, V, X)$$

  where N is the need, V represents environmental influences and X represents other influences. For example, if hungry, an individual will have a strong drive to eat if N is high. However, the environment also plays a part, the drive to eat may be stronger if the person can smell food, even if N is not great.
- *Emotionally controlled behaviour*. As with drives, if emotions are strong enough this will dictate the behaviour of the agent. However, the key difference is that they are stimulated externally, and not by internal state changes. Schmidt (2000) defines the intensity of emotions, E as,:

  $$E = g(I, A, X)$$

  where I represents the importance of the event that has generated the emotion, A the agent's personal assessment of the event and X represents other influences.

Schmidt (2000) also discusses deliberative behaviour. With reactive forms of behaviour the organism is not truly aware of the reasons that cause their behaviour. For example, they are not aware that looking for food is a task which ultimately ensures survival. Agents who engage in deliberative behaviour, however, do so in order to consciously pursue goals. These goals, such as take up a new hobby, can be complex and might involve numerous intermediate targets. As Section 4.1 will illustrate, the model presented here primarily uses reactive forms of behaviour to drive the agents, but the agents then use deliberative techniques to satisfy their goals.

The next section will outline how the PECS framework is implemented in an agent-based model (ABM) to introduce realistic behaviour into the agents (people).

4. An agent-based model of burglary

This section explains the framework of the agent-based model of burglary, in particular the characteristics, behaviours and cognitive maps of the offender agents and the model's physical environment.

4.1. The agents

The model is populated by "people" agents. All agents possess the same basic structure and fundamental needs: the need to generate wealth and the need to sleep (more details will follow). These people agents are further divided into two groups: those who can always generate sufficient wealth through legitimate work (termed 'citizens') and those who do not have sufficient employment and must burgle occasionally (the 'potential burglars'). Potential burglars are assigned random amounts of work each day; however the amount of work does not always fully satisfy their need for wealth. This behaviour is consistent with the literature. For example, Wright and Decker (1996) found that burglars are often employed and this employment can lead to them discovering new, suitable targets that they would be otherwise unaware of. As discussed later, we recognise that this is a vast simplification and do not support the notion that all unemployed people are burglars!

The roles of the agents do not change; a potential burglar agent cannot become a citizen and vice-versa. Although this is a simplification of real life, whereby external circumstances might drive people towards or away from burglary (effectively changing their 'role'), the model is based on the burglar's individual behaviour and their relationship with the physical environment rather than the social or political processes which drive people towards a life of crime. This area of research will, however, inform future work.

The number of agents in each model run can be varied, but for the experiments outlined here, was fixed at 300. This value was chosen to ensure that the majority of the houses in the environment are occupied by an agent. However, there are also unoccupied houses: this allows for future examination of the difference that citizen daily habits have on their burglary risk. When they are created, each agent has a 5% chance of being a burglar agent and a 95% chance of being a citizen. These percentages have been chosen under the assumption that the number of burglars in the population is small. As the model is not trying to predict actual numbers but spatial patterns, this weighting is felt to be reasonable. The total number of agents and the probabilities of being a burglar or citizen can be varied but they are kept constant for all experiments outlined here. This results in approximately 15 burglar agents in each model, although (due to the probabilistic nature of agent generation) the total number in each run will vary slightly.

Wealth is used to encompass factors that require money for satisfaction, for example, the need to buy food, socialise, support a family or sustain a drug addiction. All agents also require sleep which must be sought at home. Levels of wealth and sleep deteriorate at a constant rate throughout the simulation and can be replenished by working, burgling or sleeping. Using these two needs it is possible to create behaviour which can be generally found in the daily patterns of employed people in most cities. An avenue for future research is the transference of this work from a homogenised case-study to an application based on a real city.

Fig. 1 and Table 1 illustrate how the needs of an agent drives their actions. PECS intensity functions are used to calculate which need is the greatest at each time step. For each agent, the intensity functions take into account the current levels of wealth and sleep, the agent's personal preference for generating wealth or sleeping and the current time of day. It should be noted that not all the possible features of the PECS framework have been included in the model at this stage. For example, social variables do not play a part in the model. As Schmidt (2000) notes, it is important to choose the behavioural factors which are important in the chosen system, not to try to include *all* possible variables. At this stage the effects of

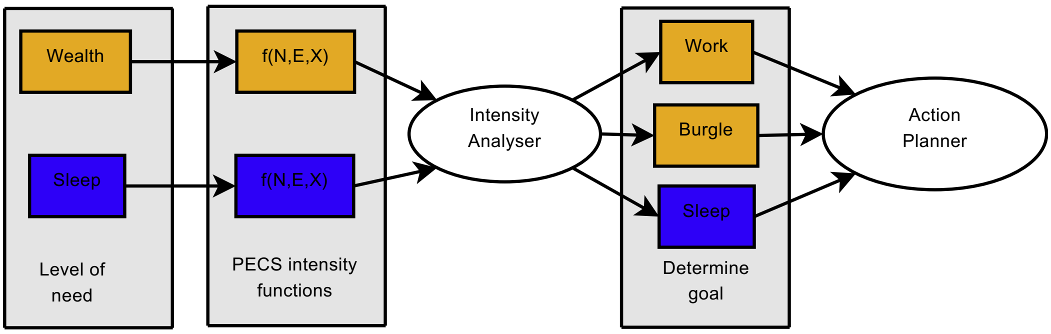

Fig. 1. Agent needs and behaviour. The agents' needs and how their intensities determine the behaviour of the agents, adapted from Schmidt (2000).

Table 1
How actions are generated from PECS needs.

Need	Generate wealth	Sleep
Description of the need	The need to generate wealth: a proxy for any activity which requires wealth to satisfy it.	The need to sleep.
PECS intensity value, I, at time, t.	Based on the time of day, T, the agent's current level of wealth, W and the agent's personal preference for generating wealth, P: $I_t = f(W_t, P_t, T_t)$	Based on the time of day, T, the agent's current level of sleep, S and the amount of sleep the agent needs each day, A: $I_t = f(S_t, A_t, T_t)$
Resulting agent behaviour if intensity is strongest	Try to obtain wealth, either through employment (if available) or through burgling (if not employment is available).	Go home as soon as possible to sleep.

social interactions are deemed too complex to be of use in the model.

Personal preferences allow for the inclusion of heterogeneous agents. For example, a drug addiction which requires considerable wealth to satisfy could be simulated by including agents whose personal preferences for generating wealth are higher than others. At this stage of research, however, personal preferences are not varied so the burglar agents are homogeneous.

Fig. 2 illustrates how T influences the overall intensity of the wealth and sleep needs where time $t = 0$ is set to approximately 7am. The need to work is largest during the day whereas the need for sleep is the strongest during the night.

It is worth noting that, at a first glance, it appears that the model only includes the most basic of human behaviours as stipulated by PECS: that of reactive behaviour. The agents have simple needs that they must satisfy and the strongest of these needs drives their behaviour. However, the behaviour required to satisfy a need is more complex than simple reactive behaviours will allow for. The agents use learned behaviour (they remember where they have visited which influences future choices regarding where to look for burglary targets) and even deliberative behaviour when trying to find a burglary target as they are involved in "conscious pursuit of goals" (Schmidt, 2000). So whilst the agents do not know *why* they need to satisfy their goals (a reactive trait) the methods they use to satisfy them are complex and involve the conscious pursuit of goals with intermediate stages (a deliberative trait).

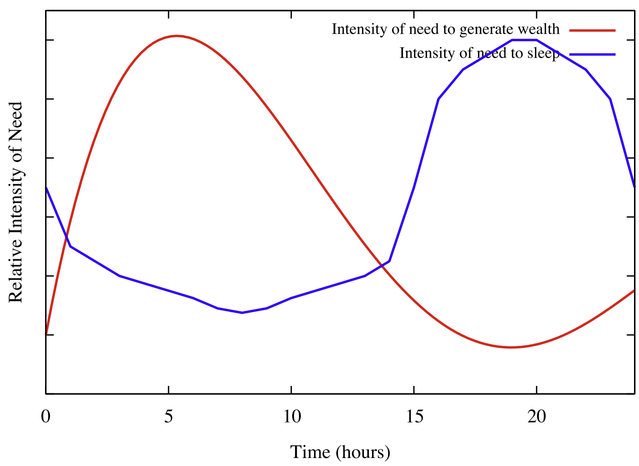

Fig. 2. Need intensities over time. How the time of day affects an agents need to generate wealth or sleep where Time $t = 0$ is defined as approximately 7am.

4.2. Cognitive maps and temporary employment

An important feature of the model is the inclusion of 'cognitive maps'. These maps represent each agent's internal representation of their environment. According to routine activities theory, crime pattern theory and qualitative studies (Cromwell & Olson, 2005, chap. 5; Wright & Decker, 1996), a potential offender is likely to find a suitable target by passing one on their routine travels. The model presented here uses this theory with the cognitive maps adapted from Brantingham and Brantingham (1993) activity spaces concepts. As the agents move around the environment (whether they are looking for a burglary target, or simply travelling to work or home) they remember each house that they have passed. These houses and their locations in the environment are stored internally by each agent as a list. The agents also remember the levels of security and attractiveness of the houses that they have stored in their map. These parameters will be explained in the following sections along with a detailed description of how the agents' cognitive maps are used for burglary.

Assigning potential burglar agents temporary employment allows the agents to visit areas of the environment that they might not do otherwise. This helps them to build up their cognitive maps. Although employment is seen as an essential aspect of the burglary system the different types of employment that agents can engage in (for example industries that service houses such as delivery companies) are not investigated in this iteration of the model development. This will be a future research stream.

4.3. The model environment

The agents populate an artificial environment that is designed to reflect many of the urban features found in modern cities. There is a commercial area in the centre of the environment and this is surrounded by residential properties. This environmental layout does not represent an entire city, rather a small ''micro'' town centre. This type of pattern is repeated throughout modern cities, where commercial and residential areas are fairly mixed (in Leeds, for example, only 30% of employment is found in the city centre Unsworth & Stillwell, 2004). Fig. 3 illustrates the layout of the environment. Although simple and hypothetical, the model environment was designed to allow comparisons with real urban configurations. A central business district represents the centre of employment for city residents, which is a feature found in many modern cities. In this respect the model imitates part of the concentric ring model (Burgess, 1925), although later experiments incorporate communities that are distributed in a less orderly fashion. This corresponds better to British historical housing developments which are often initiated by local councils who build wherever they own land (Baldwin & Bottoms, 1976) and illustrates that the model is highly flexible because the environment can be adapted to reflect the type of city under examination.

The environment is constructed on a grid measuring $41 * 31$ cells. Some squares are ''empty'' and play no part in the model because agents do not move diagonally, only horizontally or vertically. There are three types of cell in the environment: the commercial district, roads, and residential properties. Agents use roads to navigate the environment, always taking the shortest path from their current location to their destination. Each cell in the commercial district represents a single office that provides employment for an unlimited number of agents. The residential properties house the agents (maximum of one agent per house) and also act as burglary targets (one cell represents one house). The houses have two defining characteristics: *security* and *attractiveness*. The security variable is a measure of the level of security of a property, encompassing both physical security and security utilisation; attractiveness is a measure of the wealth of the property. As noted previously, agents remember properties that they pass, along with their security and attractiveness values, by storing them in an internal list (their ''cognitive map''). It has been suggested that burglars in the real world will use environmental cues to determine how attractive or secure a property is. This is accomplished in the model by providing agents with the exact security/attractiveness values of the houses that they pass. A future research direction could be to investigate what would happen if the agents did not know the *exact* security or attractiveness and had to use their intuition to guess the values.

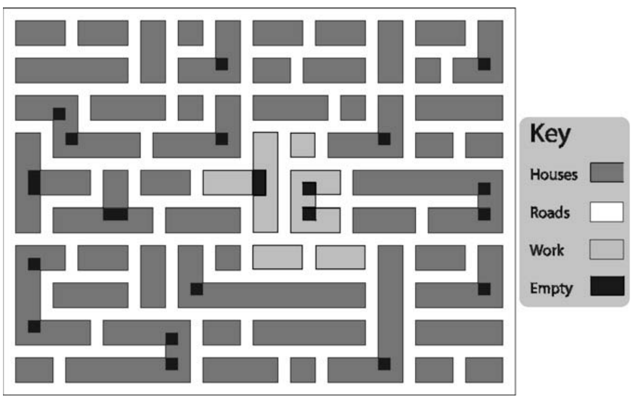

Fig. 3. The model environment. Note that agents in the model cannot move diagonally so empty spaces play no part in the simulation because they cannot be accessed from a road.

Levels of security and attractiveness are dynamic: if a burglary is committed this results in the attractiveness of the victimised property increasing along with smaller increases in the surrounding properties. The victimised property and those adjacent then remain at a higher risk for several days following the burglary. This ''near repeat'' phenomena has been found to exist in the criminology literature (Townsely, Homel, & Chaseling, 2003) and by police force managers (Johnson, 2007). In the UK city of Leeds, there are several proactive crime prevention initiatives which target properties in close proximity to a recent burglary. For this reason, the security levels of the victim and the surrounding properties are increased along with attractiveness after a burglary is committed. These levels of attractiveness and security gradually degrade as the residents become complacent of the risks (from anecdotal evidence); if no further burglaries are committed, the security returns to base levels.

Upon initialisation of the simulation, each agent is randomly assigned a home address and work place (which will be within the commercial district). The experiments presented in this paper place the potential burglar agents both in low-income areas and also distributed evenly throughout the environment. The agents use roads to travel between different addresses and can traverse one square per model iteration. Agents always take the shortest (optimal) route between their origin and destination. Further research will focus on a more accurate representation of travel through the area. Time is measured in the simulation through model iterations; one iteration is classified as 3 min. This means that it will take agents between 10 and 60 min to travel to work depending on their origin. There are therefore 20 iterations per hour and 240 in a day.

4.4. Modelling offender behaviour

There are two main branches of research into understanding how potential burglars behave, their motivations and their responses to environmental cues. These can be broadly classified as qualitative using interview data and quantitative using large data sets and statistical models to establish trends and patterns of potential burglar behaviour. Although different in methodology, these studies draw very similar conclusions; these will be used in the design and implementation of behaviour in the agents. Table 2 outlines findings from studies in the criminology literature and how these will be incorporated into the model to provide a sound theoretical foundation.

The burglary process works as follows:

1. The burglar agent decides that they must commit a burglary to generate wealth because they do not have any temporary employment.
2. The agent chooses a house to visit from the list of all those they know about (the houses that are stored in their cognitive map). A ''roulette wheel selection'' process is used so that each house has a probability of being chosen based on its attractiveness.
3. The agent travels directly to the chosen house using the shortest path. As they pass houses they examine their security to determine whether or not they are suitable for burglary.
4. If the agent reaches their chosen house and has not found a suitable burglary target they choose another house from their cognitive map (using the same roulette-wheel procedure) and begin the process again.

Table 2
How the motives of potential burglars and their responses to environmental cues will be implemented in the model.

Behaviour/motive	Implementation in model
Need for money is the primary reason for burglary (Bennett & Wright, 1984; Bernasco & Luykx, 2003; Nee & Meenaghan, 2006; Repetto, 1974; Rengert & Wasilchick, 1985; Wright & Decker, 1996) and usually to buy drugs (Cromwell et al., 1991; Hearnden & Magill, 2003; Scarr, 1973).	Agents in the model burgle to satisfy the desire for wealth. Drug addiction can be represented by increasing the personal preference for generating wealth. Agents with these characteristics will quickly become desperate to generate wealth as if they had a drug addiction to satisfy.
The decision to burgle is made away from the actual crime scene and the potential offender then travels to a target noted previously (Hearnden & Magill, 2003; Nee & Meenaghan, 2006; Wright & Decker, 1996).	Agents build a cognitive map of their environment and choose targets from these known areas.
Few burglars can be classed as "opportunistic" although most interviewees will alter their usual routine if a particularly attractive target presents itself (Nee & Meenaghan, 2006).	During the journey to their chosen target, agents examine properties which they pass and will commit a burglary if the target is deemed suitable.
The expected "yield" is the most important consideration when selecting a target (Hearnden & Magill, 2003; Nee & Meenaghan, 2006) which can range from \$0 to \$12,950 (Snook, 2004).	Potential burglars choose to travel to the most attractive property they are aware of.
Burglars will not usually enter occupied properties (Cromwell et al., 1991; Nee & Meenaghan, 2006; Wright & Decker, 1996).	When occupants are at home a burglar agent will not victimise the property. The burglars agents always "know" if a person is at home; they do not use environmental cues as they might do in the real world.
Most burglars will return to previously burgled properties, usually because they know what goods are available and how to enter the property. (Hearnden & Magill, 2003; Wright & Decker, 1996).	Once a burglary has been committed, the attractiveness of the victimised property increases which encourages the agent to return at a later date.
Properties close to the burglar's home are more likely to become victims (Bernasco & Nieuwbeerta, 2005; Snook, 2004). This is partly because the offender knows the area well and does not need to carry stolen objects too far (Hearnden & Magill, 2003) and also because the potential burglar chooses targets from within their cognitive awareness space (Bernasco & Nieuwbeerta, 2005).	Properties close to a burglar agent's home are more likely to form part of the agent's cognitive map and are therefore a higher burglary risk.
Suitable targets are often found by passing them on their routine activities (Cromwell & Olson, 2005; Wright & Decker, 1996)	The agent's cognitive map is built up from their routine activities and a target is chosen from these known properties.

Two criteria determine whether a target property will be burgled: occupancy and security. An occupied property will never be burgled and the potential burglar is less likely to burgle a secure property particularly if there are possible targets with lower levels of security. These elements are consistent with many findings, including Cromwell, Olson, and Avary (1991), Wright and Decker (1996), Nee and Meenaghan (2006). There are no "unsuccessful" burglaries at present, the burglar either commits a burglary or does not, based solely on the security of the target property and whether or not it is occupied. Therefore if the security of all houses is increased there will be fewer burglaries and the agents' levels of wealth will steadily decrease. In this sense, therefore, the number of burglaries in the model is essentially fixed and the model is only able to compare changing *patterns* of burglary, not overall rates. Allowing for unsuccessful burglaries and other agent behaviours (such as choosing not to burgle at all) will form interesting avenues for future research.

Determining the amount of money which can be generated from a burglary is non-trivial. Snook (2004) found that the average amount was \$900, but the range was \$0–\$12,950 and the value depended on the distance travelled. For simplicity, agents in the model are given the equivalent of one full day of employment. Although this is less than might be expected from real data, it will cause the agents to commit a larger number of burglaries in a given time allowing results to be generated more quickly. This is an important consideration with agent-based models: every agent must make decisions at every iteration which can lead to very large execution times.

The behaviour that is being examined in this model is a simplification of offending behaviour; for example, it is obviously too simplistic to state that an individual will automatically turn to burglary if they have no money. However, there is a scientific basis for not overcomplicating a model. Schmidt (2000) for example, notes that a model does not need to replicate reality, if it did then it would cease to be a model. Furthermore, Elffers and van Baal (2008, chap. 2) note that crime models can become overcomplicated, making it difficult to understand and experiment with the rules that underpin the model. For this model, the inclusion of different types of crime and a complex cognitive framework which gives agents stronger control over how to behave when they lack wealth (rather than always turning to burglary) are seen as unnecessary at this stage. The factors which have been chosen are deemed, from the criminological literature, the most important to the residential burglary system, not a general model of crime and offending.

5. Model experimentation

The model will be applied to testing out crime theories and the effectiveness of varying crime reduction strategies. As highlighted earlier, the environment is artificial, but designed using the UK city of Leeds as its template.

The following experiments will be performed:

- *Control experiment*: The default parameters of security and attractiveness of properties will be used to explore the basic behaviour of the model. The values of the defaults were chosen to coincide with the drive intensity functions which determine how potential offenders should behave (see Sections 3 and 4). The values were calibrated to allow, on average, an offender to commit one burglary per day. This coincides with the expected return of a single burglary which is the equivalent of a single day's work (discussed in Section 4.4).
- *Different types of community*: To simulate the presence of different types of community, such as a deprived area, an affluent area, and an area occupied predominantly by students, the environment will be adapted by modifying the security and attractiveness of property values.
- *Target hardening strategies*: The model is used to test the effectiveness of the crime reduction strategy of target hardening. Target hardening is an intervention scheme whereby government agencies offer additional security protection in the form of physical hardware or verbal/written advice to residents. In the model, target hardening is simulated by increasing the security

of a targeted property up to levels that match the most secure properties in the environment. Two different target hardening strategies are tested. The first is commonly used by local government agencies. The strategy involves targeting the most vulnerable people, which includes new and repeat burglary victims, the elderly, single parents, those renting private houses and people who have recently moved into new properties (see Byron (2003) for a practical example). In the model, vulnerable properties are identified by those that have the highest number of burglaries. The second strategy is an alternative method which is not commonly used in practice. Here, all the properties in a community that has been identified as a high-crime area simultaneously undergo target hardening. The aim of the experiments is to establish which strategy is the most effective at removing a crime hotspot.

- *Different routine activity patterns*: The addresses of potential burglars are altered to change their routine activity patterns. The model is used to generate new crime patterns. This allows us to examine routine activities theory and the effect that different offender daily patterns will have on crime rates.

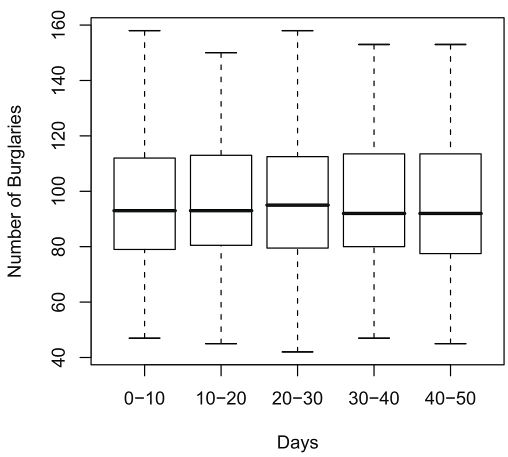

Fig. 4. Crimes committed over different days. Boxplots describe the number of crimes committed at different points over a run of 50 days varying the number of burglars in the model for 100 model runs.

6. Results

6.1. The control experiment

The aim of the control experiment is to check that the model is robust and that it produces sensible results, a process often termed "verification" (Gilbert & Troitzsch, 1999). Default values for security and attractiveness of properties are used throughout the environment and all agents (potential burglars and non-burglars) are assigned randomly to houses. The model is run until it reaches a dynamic equilibrium which refers to the state when aggregate crime patterns are stable although individual crimes are still occurring and, therefore, small local variations are present (van Baal, 2004). For this model, we define dynamic equilibrium as being reached when both the number of crimes committed each day and the mean centre (average) of all burglary locations does not change and we will show that 50 days is sufficient for the model to reach dynamic equilibrium. Fig. 4 illustrates the number of burglaries committed at different intervals. The model was executed 100 times which allows the robustness and sensitivity to initial starting conditions to be assessed. It was noted earlier that the size of the population of burglars varies slightly for each run, but the number of burglaries committed at different intervals remains fairly consistent suggesting that, with respect to the number of burglaries being committed, that the model has reached equilibrium. Further evidence for equilibrium is presented by the spatial distribution of crimes illustrated in Fig. 5; the model reaches dynamic equilibrium in this time because the mean centre of the burglaries does not change. Fig. 5 suggests that, in fact, equilibrium might be reached earlier than day 50, between days 20 and 30 for example. However, later experiments will require time to allow the system to adapt to changes made during the course of a simulation so to ensure that all experiments reach equilibrium all simulations presented will run for 50 days.

Fig. 6 depicts the burglary rates at the end of a typical simulation run. Due to the probabilistic nature of the model, burglary patterns vary between runs. However, burglary levels are routinely highest in the areas closest to the commercial area. These findings are consistent with the principles of crime pattern theory. Brantingham and Brantingham (1993, page 18) note that crime clusters at high activity nodes, along major paths and along edges, where edges represent the boundary between areas that are noticeably

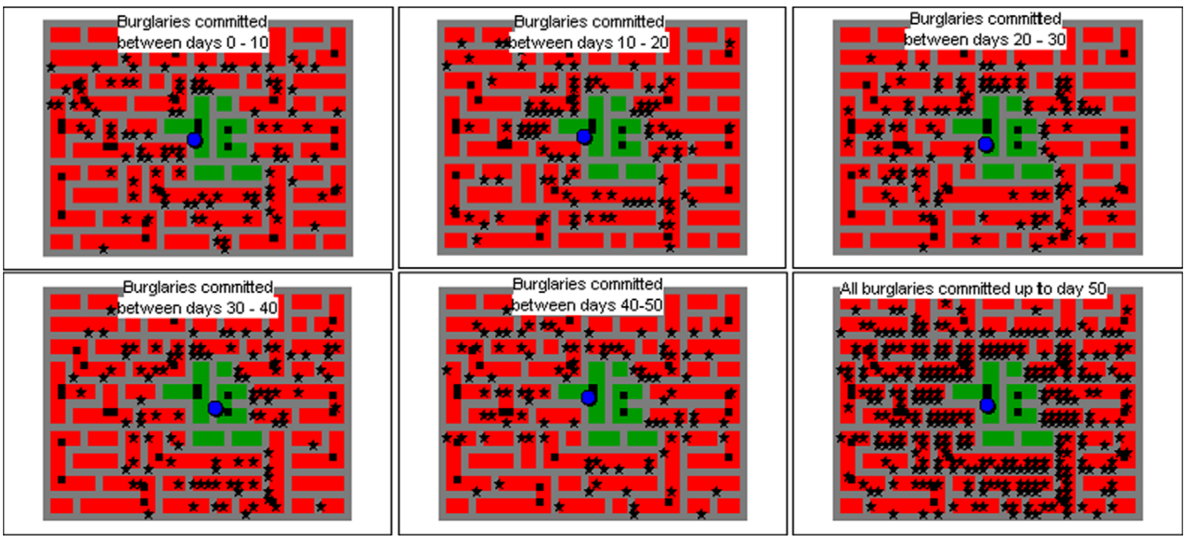

Fig. 5. Control experiment – burglaries. The mean centre of burglary locations at different time points during a typical run.

Fig. 6. Control experiment – burglary rates. Burglary rates produced by a control experiment after 50 runs.

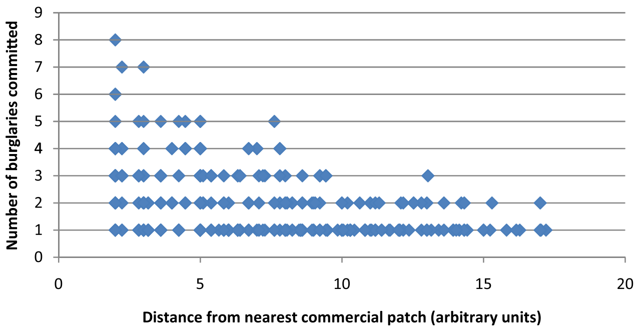

Fig. 7. Burglary distance from centre Graph illustrates the distance from the centre of the environment for each burglary committed. No crimes were committed within three units of the centre because this area is occupied by the commercial district and there are, therefore, no houses to target.

different such as the commercial and residential areas in our hypothetical environment.

Fig. 7 further illustrates that most crimes occur near the centre of the environment. The Pearson correlation coefficient was calculated between the number of burglaries a property received and its distance from the nearest commercial patch and resulted in a value of −0.38. This implies that as the distance from the commercial district increases the number of crimes committed decreases.

6.2. Different "Types" of community

Experimentation in Section 6.1 served to show that the model is stable, producing expected results under default conditions. The next stage is to increase the realism of the model by introducing environmental factors. This added realism is achieved by altering the attractiveness and security of each property to create different communities. Three different areas have been chosen: an affluent area, a deprived area and a student area. These sociotypes have been chosen to reflect the different crime patterns that are prevalent in each of these areas. Offenders travel different distances depending on the affluence of the target (Snook, 2004) and the community type from which an offender originates influences where they are likely to burgle. Shepherd (2006) also found evidence that burglary patterns depended on the type of community. The author discovered that offenders would travel considerable distances to burgle affluent areas, whereas burglaries in deprived

Table 3
The change from the default value for variables associated with different community types.

Type of area	Percentage change from default value	
	Attractiveness (%)	Security (%)
Default	–	–
Rich	150	150
Deprived	50	50
Student	150	50

areas were often committed by local residents travelling short distances. In addition, students were victimised by residents of nearby deprived areas but not from within student communities (Shepherd, 2006). The relative variable values associated with each area are shown in Table 3. These values have been chosen not on the basis of empirical evidence (determining how much more attractive a "student" area is compared to a "normal" area, for example, is non-trivial) but because they are different enough to sufficiently influence the burglars' behaviour and lead to the creation of crime "hotspots". The new areas created, therefore, are not designed to fully represent "student" or "deprived" communities but provide a method of experimenting with how the burglar agents respond to changes in their environment.

Using these different types of area it is possible to investigate how high-crime areas (often called hotspots) arise. Four different layouts for the cityscape were used to ensure that hotspots do not arise as a result of the arbitrary layout of the environment. Fig. 8 illustrates these environments and the burglary rates produced by day 50. Regardless of the layout of the environment or the initial starting positions of the agents, the student areas suffers the highest victimisation rates. This is still evident when there are multiple student areas as illustrated in environment 4.

Further evidence can be supplied through hotspot detection. The nearest neighbour hierarchical spatial clustering algorithm (NNH) is commonly used to search for areas with unusually high crime rates by searching for clusters of points based on their spatial proximity. The CrimeStat application (Levine, 2006) was used on the case-study data. Fig. 9 illustrates the hotspots found by the algorithm when analysing the crimes committed near the end of the simulation (days 40–50). The last ten days are used here because this is the time at which the simulation is judged to have reached equilibrium. The results illustrate that, regardless of the physical layout of the environment, the student areas still suffer the highest levels of burglary victimisation. This is consistent with the criminology literature (Robinson & Robinson, 1997; Tilley, Pease, Hough, & Brown, 1999) and data from the city of Leeds. For example, in Leeds burglary hotspots are highly correlated with areas that house large numbers of students during term-time. In August, when the majority of the student population live outside the city, the burglary clusters move to the poorer areas to the east and west of the city centre.

6.3. Crime reduction: Target hardening strategies

As illustrated in Section 6.2, the layout of the environment does not appear to influence the burglary hotspots found in student areas. Target hardening was therefore applied to environment 1. The strategies were implemented on day 20 and, as with other experiments, the simulation was run to day 50. The area chosen for the block-targeting method covered 50% of the student community (to allow comparisons between the hardened and non-hardened sections). This consisted of 46 properties. In order to test both strategies fairly, it is essential that they increase the overall security of the environment by the same amount. If this is not done

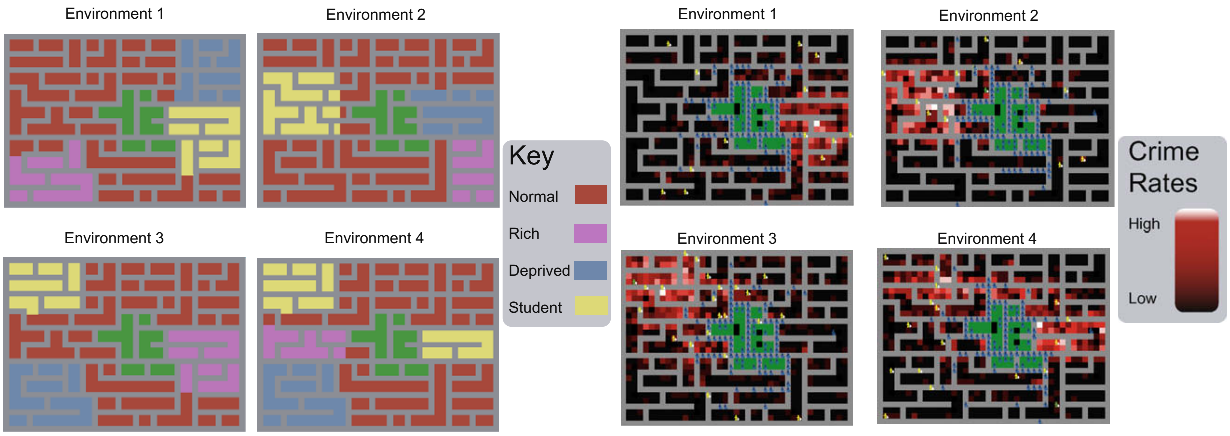

Fig. 8. Altering security and attractiveness. The layout of different environments altering the community type and burglary rates produced by day 50 using different community types.

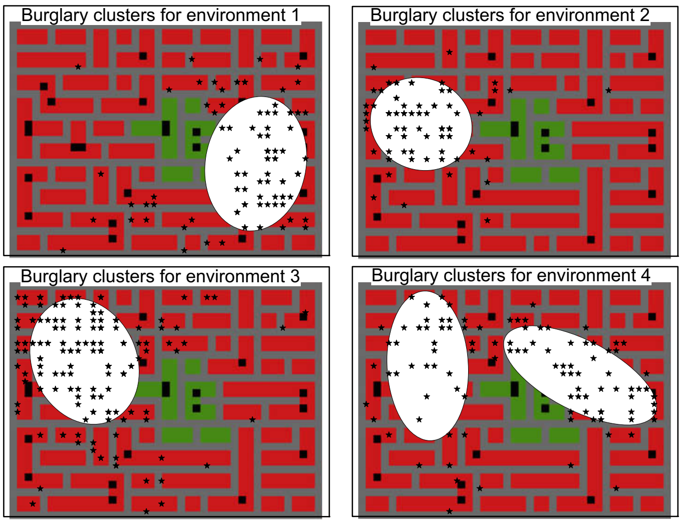

Fig. 9. Security/Attractiveness experiment clusters. Clusters of burglary found by the NNH spatial clustering algorithm.

then the total number of crimes committed might differ between experiments simply because the overall security changes so results will not be comparable across different experiments. Equations in Appendix A demonstrate that the victim-targeting method will increase the security of approximately one house every 2 days to be comparable with the block-targeting method.

Fig. 10 illustrates the results of the victim targeting strategy. The advantage of ABM to view a dynamic history of the model (Axtell, 2000) rather than a single, final equilibrium is utilised here and crime hotspots and burglary rates are illustrated at different points in the simulation. By observing the crime patterns at different points during the simulation we can gain an insight into how crime hotspots arise. The results suggest that the strategy is ineffective at removing the crime hotspot found around the student area. A crime hotspot is established early in the simulation and remains fairly constant throughout. Fig. 11 illustrates the results of the block targeting strategy. It appears that crimes are displaced south towards the remainder of the student area with no target hardening. Although the hotspot produced between days 40 and 50 still covers the target hardened area, only three crimes were committed in the area during that time period. This suggests that if the NNH algorithm was configured differently the hotspot would not cover the north area at all. Interestingly, towards the end of the simulation a new hotspot has started to develop close to the city centre as crimes are displaced away from the student area. This provides further evidence that the hotspot around the student area is less significant.

The patterns produced by the two experiments are very different. When individual houses are targeted, offenders are still attracted to the area because many appealing properties still exist, even if some are now less appealing due to the target-hardening initiative. This suggests that targeting single properties in isolation is unlikely to tackle burglary hotspots because many insecure properties remain in the area. This finding is consistent with the expectations of crime reduction practitioners. Shepherd (2006) notes that the administrators of the Burglary Reduction In Leeds (BRIL) scheme (Safer Leeds, 2007) believe that targeting blocks of properties rather than individuals might have an effect greater than the sum of the parts.

6.4. Different routine activity patterns

The final experiment increases the realism of the model further by investigating the effect that changing the addresses of the po-

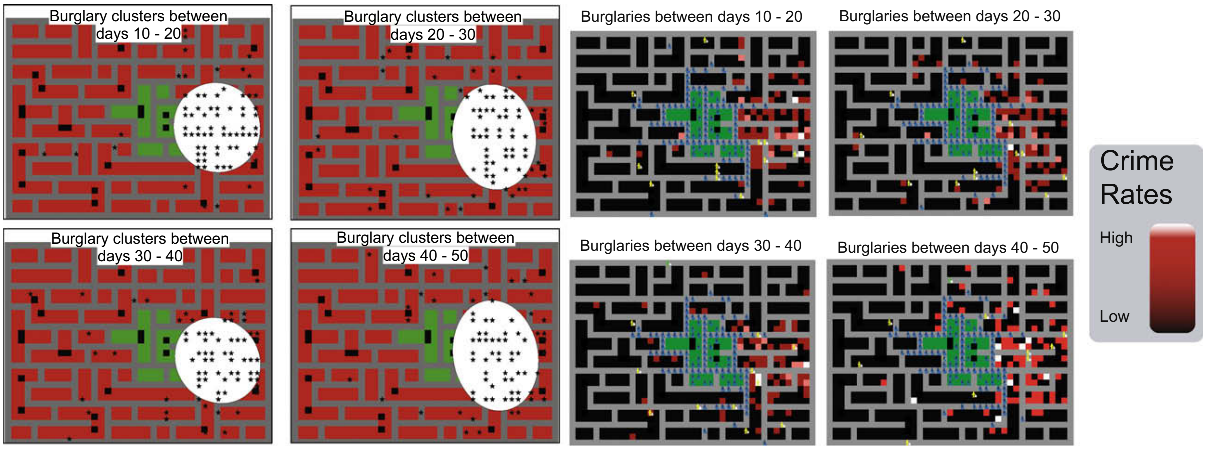

Fig. 10. Individual target-hardening results. Results of the individual victim target-hardening initiative: Hotspots produced by the NNH algorithm and burglary rates.

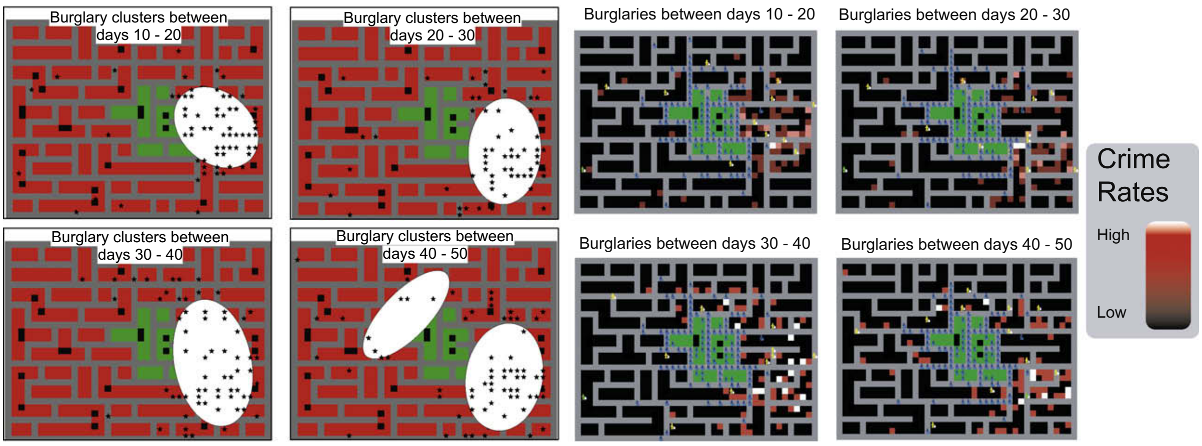

Fig. 11. Block target-hardening results. Results of the entire community target-hardening initiative: hotspots produced by the NNH algorithm and burglary rates.

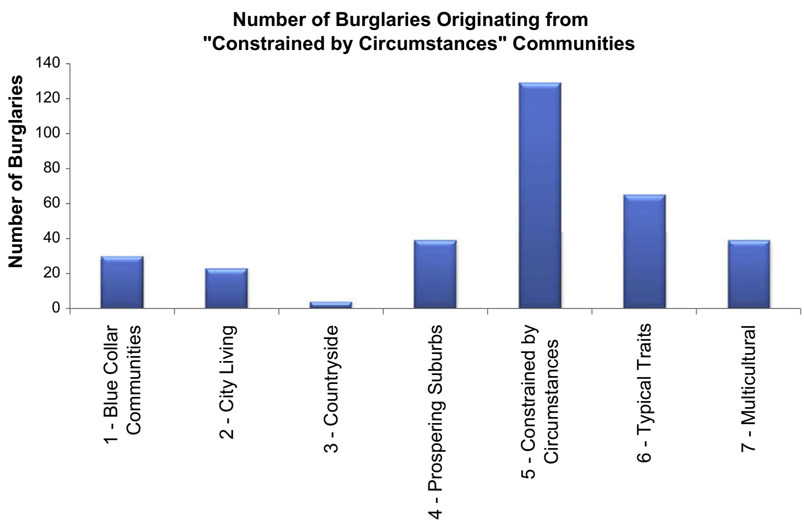

Fig. 12. Burglaries originating from "Constrained by Circumstances" communities. Graph illustrating the number of crimes committed in different community types which have originated from "constrained by circumstances" communities using 2006/07 crime data and the ONS Output Area Classification.

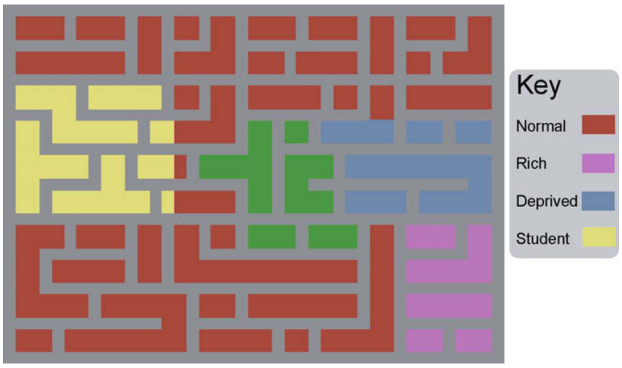

Fig. 13. Environment 2.

tential burglars has on crime rates. In the experiment it is hypothesised that most potential burglars live in the most deprived areas. This notion follows that of the literature: numerous studies have made reference to the link between crime and deprivation (Baldwin & Bottoms, 1976; Bowers & Hirschfield, 1999; Brantingham & Brantingham, 1993; Hesseling, 1992; Sampson, Raudenbush, & Earls, 1997; Shover, 1991; Wilkström, 1991). There is also supportive data from the city of Leeds. Using the Office of National Statistics Output Area Classification (Vickers & Rees, 2006) and over 700 pairs of the addresses of convicted burglars and their victims it was possible to estimate which "type" of community most burglars originated from. Fig. 12 illustrates that the most deprived communities ("constrained by circumstances") export the most crimes. We can hypothesise, therefore, that most burglars live in constrained by circumstances communities.

The locations of the potential burglars in the model were altered from living in randomly chosen patches to the poorest area. This represents a shift in the model towards the inclusion of real geographies and people. This change will obviously also impact on the routine activity patterns of potential burglars. We would therefore expect to observe higher burglary rates in the poorest neighbourhood and on the routes into the commercial district. Environment 2 (illustrated by Fig. 13) was chosen because in this environment the student area and the deprived area are a large distance apart. Therefore if the burglary hotspot still covers the student area we can conclude that the daily activities of the offenders does not influence the location of burglary hotspots in the model.

Fig. 14 illustrates the burglary patterns over different intervals of a typical simulation and also the hotspots produced by the NNH clustering algorithm. Although there are large numbers of burglaries committed in the deprived area, overall the student area exhibits significantly more crimes than all other areas. Initially crimes are spread throughout the area where the offenders live and on the routes between the deprived area, the commercial area and the student area. However, as the simulation progresses and the potential offenders begin to recognise the attractiveness of the student area it absorbs the majority of crimes. This has implications for criminological theory and crime reduction practitioners, a point discussed further in the following section.

7. Conclusions

The aim of this paper has been to demonstrate the strengths, flexibility and applicability of an individual-based model combined with a behavioural model (the PECS framework) for simulating residential burglary. Within the scope of modelling crime theory, there are few published examples of this type of work; the research presented here represents initial modelling attempts to capture the complex micro-level dynamics of this system using an advanced behavioural model. Alternative approaches to modelling crime were outlined, including some existing agent-based models of crime. However there are many factors that are absent in other approaches which this research is able to account for.

Incorporating a detailed behavioural framework into an individual-level model is a relatively new approach in criminology. The PECS framework (Schmidt, 2000; Urban, 2000, chap. 6) was chosen because it does not require rational decision making as an assumption, a drawback of the BDI approach (Schmidt, 2000), and can (theoretically) be extended to model the entire spectrum of human behaviour. PECS uses the concept of intensity functions to determine, in any given situation, which drive is the strongest and how the agent will behave. Two drives were used in this model: the need to generate wealth and the need to sleep. Although the range of drives is limited, they are adequate to loosely represent the daily behavioural patterns of people employed in British or American cities. In addition, the intensity functions can be enhanced to amalgamate different types of behaviour. For example, drug addiction can be simulated by increasing the desire to generate wealth: in the model a burglar with a drug addiction will therefore be forced to commit more risky burglaries to satisfy their greater needs.

Findings from both qualitative and quantitative studies (outlined in Table 1) were utilised to ensure that the behaviour of

Fig. 14. Routine activities experiment results. Results of routine activities experiment: hotspots produced by the NNH algorithm and burglary rates.

offenders in the model reflected findings from the real world. One of the most interesting features of the model are the cognitive spaces which are individual to each agent and are built up dynamically during the simulation. Potential offenders do not have global knowledge of their environment and they must choose to victimise a property that they know about already, finding new properties as they travel around the environment (whether on legitimate business or not). This feature reflects modern thinking in criminology and has yet to be included in this type of model.

Four experiments were designed to test the validity of the model and then experiment further with it. In particular, two target hardening approaches were tested. The first, which is an approach commonly used in practice, targeted single properties that were deemed a high burglary risk and the second targeted an entire block of properties. Cluster analysis confirmed that targeting individual properties in isolation was insufficient at removing the hotspot as offenders in the model were simply able to burgle nearby houses that have not undergone target hardening. Targeting an entire block, however, successfully removed the hotspot because the entire area became unattractive to burglars. This demonstrates that the model, through matching empirical findings, is both robust and able to simulate the important processes and trends within the system.

The final experiment examined what happened if the home locations of potential burglars were altered. The effect was that the agents' routine activities no longer took them through the student area. However, as the simulation progressed a hotspot nevertheless formed around the student area. This suggests, for criminologists, that although routine activities are important we should not discount the pull of highly attractive areas which might drive offenders away from their routinely travelled routes. Obviously a greater investigation is required before making any firm conclusions, but the experiment nevertheless demonstrates the utility of using even simple types of agent-based models in criminology.

It should be noted that the total number of crimes in the environment remains unchanged. In other words, there is spatial crime displacement but no other types of displacement such as a change in modus operandi (MO), crime type (for example the offender could move from burglary to drug dealing) or indeed the decision to stop burgling altogether. Furthermore, the vast complexity of human behaviour and the urban environment are extremely difficult (or even impossible) to capture in a computer model, thus models such as these will never be able to account for everything that can affect the real system. These are not necessarily limits of a model, but a drawback of ABM in general. We do not subscribe to the notion that this renders the individual-level approach useless; rather we recognise the drawbacks of the approach and consider these when making conclusions regarding the applicability of the results to the real world.

8. Future work

One of the major benefits of the ABM approach is its flexibility. Incorporating additional needs, such as the need to socialise, will provide the agents with a greater range of behaviour and allow us to implement different types of citizen such as students, unemployed people, and family members. These different types of people could also influence the behaviour of the potential burglars, by acting as capable guardians for example. Anchor points could also be included (such as friends' houses or the addresses of drug dealers) which would generate interesting cognitive environments. The model at this stage does not consider the possibility for citizens to become opportunistic burglars, which could represent a significant portion of burglaries committed. Consideration of how the model framework could be modified to incorporate these types of behaviours and more heterogeneous agents is ongoing.

There are also a number of ways in which the environment itself could be enhanced. These range from including ideas regarding collective efficacy (Sampson et al., 1997) or "broken windows" theory (Wilson et al., 1982) to incorporating real GIS data similar to that of Groff (2007a, 2007b). In addition, the availability of vehicle transport (such as cars or public buses) could be included by adding different layers to the environment. There are a number of challenges associated with incorporating a more realistic environment, however. Initially, it is necessary to obtain low-level, accurate physical and social environmental data to act as inputs to the model. Furthermore, accurate individual-level crime data is necessary to use in evaluating the accuracy of the model (comparing simulation results to real data). Assuming these data are available, the next challenge is to adapt the model to function in a much more complex virtual environment. Routines to allow agents to travel on the transport system must be implemented and it is likely that the complexity of the agents must be increased to allow them to perceive their new environment correctly. Regardless of the difficulties, including a more realistic urban backcloth is an ultimate goal of this research (with the proviso that the simple model is fully understood first). This will allow for crime predictions in the real world which could ultimately influence policy.

This type of model has obvious benefits and has the potential to form an integral part of a tool for policy makers to test the impact of varying scenarios. The next stage is to translate the simple model into a more advanced framework and to incorporate a real environment.

Acknowledgements

We would like to thank Safer Leeds, the local Crime and Disorder Reduction Partnership, for providing invaluable crime data and their experiences in crime reduction.

Appendix A

The simulation is run for 50 days, so the overall increase in security produced by the block-targeting method (which covers 46 houses and is instigated on day 20, thus running for 30 days) can be calculated as:

$$46 * 30 * 4 = 5520$$

where 4 is an arbitrary number of units which represents a 150% increase in security. Method 1 is also implemented on day 20, and will target the x most vulnerable properties every day. The strategy stops at day 40 so that the simulation is allowed 10 days to reach equilibrium. Therefore, to ensure that both methods lead to the same overall increase in security, the number of houses targeted each day by method 1, x, between days 20 and 40 is:

$$x\left(\sum_{20}^{i=0} 4(i+1)\right) = 840x$$

and this security increase is applied for a further 10 days (between days 40 and 50), so:

$$840x * 10 = 5520$$
$$x = 0.6571$$

so each day (between days 20 and 40) there is a 66% chance that a house will be targeted which will, on average, increase the overall security of the environment by the same amount as the block targeting strategy.

References

Al-Ahmadi, K., Heppenstall, A. J., Hogg, J., & See, L. (2009). A Fuzzy Cellular Automata Urban Growth Model (FCAUGM) for the City of Riyadh, Saudi Arabia. Part 1: Model structure and validation. *Applied Spatial Analysis and Policy, 2*(1), 65–83.

Ammar, M. B., Neji, M., Gouardères3, G. (2006). Conversational embodied peer agents in affective e-learning. In G. Rebolledo-Mendez, E. Martinez-Miron (Eds.), *Workshop on motivational and affective issues in ITS. 8th International conference on ITS 2006* (pp. 29–37).

Axelrod, R. (1997). Advancing the art of simulation in the social sciences. In R. Conte, R. Hegselmann, & P. Terna (Eds.), *Simulating social phenomena* (pp. 21–40). Berlin: Springer-Verlag.

Axtell, R. (2000). Why agents? On the varied motivations for agent computing in the social science. Center on social and economic dynamics working paper no. 17. <http://www.brookings.edu/es/dynamics/papers/agents/agents.htm> Accessed January 2007.

Baldwin, J. (1975). British areal studies of grime: An assessment. *The British Journal of Criminology, 15*(3), 211–227.

Baldwin, J., & Bottoms, A. E. (1976). *The urban criminal: A study in Sheffield*. London: Tavistock Publications.

Balzer, W. (2000). SMASS: A sequential multi-agent system for social simulation. In R. Suleiman, K. G. Troitzsch, & N. Gilbert (Eds.), *Tools and techniques for social science simulation* (pp. 65–82). Physica-Verlag.

Beavon, D. J. K., Brantingham, P. L., & Brantingham, P. J. (1994). The influence of street networks on the patterning of property offenses. In R. V. Clarke (Ed.). *Crime prevention studies* (Vol. 2). New York: Criminal Justice Press.

Bennett, T., & Wright, R. (1984). *Burglars on burglary: Prevention and the offender*. Aldershot, UK: Glower.

Bernasco, W., & Luykx, F. (2003). Effects of attractiveness, opportunity and accessibility to burglars on residential burglary rates of urban neighborhoods. *Criminology, 41*(3), 981–1002.

Bernasco, W., & Nieuwbeerta, P. (2005). How do residential burglars select target areas? *British Journal of Criminology, 45*(3), 296–315.

Bevis, C., & Nutter, J. (1977). Changing street layouts to reduce residential burglary. Paper presented to the American Society of Criminology, Atlanta.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*, 7280–7287.

Bowers, K., & Hirschfield, A. (1999). Exploring the link between crime and disadvantage in north-west England: An analysis using geographical information systems. *International Journal of Geographical Information Science, 13*(2), 159–184.

Brailsford, S., & Schmidt, B. (2003). Towards incorporating human behaviour in models of health care systems: An approach using discrete event simulation. *European Journal of Operational Research, 150*(1), 19–31.

Brantingham, P., & Brantingham, P. (1993). Environment, routine, and situation: Toward a pattern theory of crime. In R. Clarke & M. Felson (Eds.), *Routine activity and rational choice. Advances in criminological theory* (Vol. 5). New Brunswick, NJ: Transaction Publishers.

Brantingham, P. L., & Brantingham, P. J. (2004). Computer simulation as a tool for environmental criminologists. *Security Journal, 17*(1), 21–30.

Brantingham, P., Glasser, U., Kinney, B., Singh, K., & Vajihollahi, M. (2005a). A computational model for simulating spatial aspects of crime in urban environments. In *2005 IEEE international conference on systems, man and cybernetics* (Vol. 4, pp. 3667–3674).

Brantingham, P., Glasser, U., Kinney, B., Singh, K., & Vajihollahi, M. (2005b). Modeling urban crime patterns: Viewing multi-agent systems as abstract state machines. In *Proceedings of the 12th international workshop on abstract state machines, Paris* (pp. 101–117).

Brantingham, P., Glässer, U., Jackson, P., Kinney, B., & Vajihollahi, M. (2008). Mastermind: Computational modeling and simulation of spatiotemporal aspects of crime in urban environments. In L. Liu & J. Eck (Eds.), *Artificial crime analysis systems: Using computer simulations and geographic information systems* (pp. 252–280). IGI Global.

Brown, B. B., & Bentley, D. L. (1993). Residential burglars judge risk: The role of territoriality. *Journal of Environmental Psychology, 13*, 51–61.

Brown, M. J., Mcculloch, J. W., & Hiscox, J. (1972). Criminal offences in an urban area and their associated social variables. *The British Journal of Criminology, 12*, 250–268.

Burgess, E. W. (1925). The growth of the city. In R. E. Park, E. W. Burgess, & R. D. McKenzie (Eds.), *The city* (pp. 47–62). The University of Chicago Press.

Byron, C. (Ed.). (2003). *Supplement 8 to findings 204. Reducing burglary initiative project summary: Stockport*. London: Home Office.

Castle, C. J. E., & Crooks, A. T. (2006). Principles and concepts of agent-based modelling for developing geospatial simulations. UCL working papers series, Paper 110. London: Centre for Advanced Spatial Analysis, University College. <http://eprints.ucl.ac.uk/archive/00003342/01/3342.pdf>.

Cohen, L., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588–608.

Craglia, M., Haining, R., & Signoretta, P. (2001). Modelling high-intensity crime areas in English cities. *Urban Studies, 38*(11), 1921–1941.

Cromwell, P., & Olson, J. N. (2005). The reasoning burglar: Motives and decision-making strategies. In P. Cromwell (Ed.), *In their own words: Criminals on crime (an anthology)* (4th ed., pp. 42–56). Roxbury Publishing Company.

Cromwell, P. F., Olson, J. N., & Avary, D. W. (1991). *Breaking and entering: An ethnographic analysis of burglary*. *Studies in crime law and justice* (Vol. 8). Newbury Park, London: Sage Publications.

Dahlbäck, O. (1998). Modelling the influence of societal factors on municipal theft rates in Sweden: Methodological concerns and substantive findings. *Acta Sociologica, 31*, 37–57.

Dray, A., Mazerolle, L., Perez1, P., & Ritter, A. (2008). Policing Australias heroin drought: Using an agent-based model to simulate alternative outcomes. *Journal of Experimental Criminology, 4*(3).

Elffers, H., & van Baal, P. (2008). Realistic spatial backcloth is not that important in agent based simulation: An illustration from simulating perceptual deterrence. In L. Liu & J. Eck (Eds.), *Artificial crime analysis systems* (pp. 19–34). Springer.

Gaviria, A., & Pagés, C. (2002). Patterns of crime victimization in Latin American cities. *Journal of Development Economic, 67*(1), 181–203.

Giggs, J. A. (1970). The socially disorganised areas of barry: A multivariate analysis. In H. Carter & W. K. D. Davies (Eds.), *Urban essays* (pp. 101–143). London: Longman.

Gilbert, N., & Troitzsch, K. G. (1999). *Simulation for the social scientist*. Buckingham, Philadelphia: Open University Press.

Groff, E. (2006). Exploring the geography of routine activity theory: A spatio-temporal test using street robbery. Ph.D. thesis, University of Maryland.

Groff, E. (2007a). Simulation for theory testing and experimentation: An example using routine activity theory and street robbery. *Journal of Quantitative Criminology, 23*, 75–103.

Groff, E. (2007b). 'situating' simulation to model human spatio-temporal interactions: An example using crime events. *Transactions in GIS, 11*(4), 507–530.

Groff, E., & Mazerolle, L. (2008). Simulated experiments and their potential role in criminology and criminal justice. *Journal of Experimental Criminology, 4*(3), 187–193.

Grubesic, T., & Murray, A. (2001). Detecting hot-spots using cluster analysis and gis. In *Paper presented at the 5th annual international crime mapping research conference, Dallas, Texas, USA*.

Gunderson, L., & Brown, D. (2000). Using a multi-agent model to predict both physical and cybercriminal activity. *IEEE International Conference on Systems, Man, and Cybernetics, 4*, 2338–2343.

Harland, K., & Stillwell, J. (in press). Commuting to school: A new spatial interaction modelling framework. In Stillwell, J., Duke-Williams, O., Dennett, A. (Eds.), *Technologies for migration and commuting analysis: Spatial interaction data applications*. Springer.

Hayslett-McCall, K. L., Qiu, F., Curtin, K. M., Chastain, B., Schubert, J., & Carver, V. (2008). The simulation of the journey to residential burglary. In *Artificial crime analysis systems*. IGI Global.

Hearnden, I., & Magill, C. (2003). *Decision-making by house burglars: Offender's perspectives. Home office research findings* (Vol. 249). London: Home Office.

Heppenstall, A. J., Evans, A. J., & Birkin, M. H. (2005). A hybrid multi-agent/spatial interaction model system for petrol price setting. *Transactions in GIS, 9*(1), 35–51.

Hesseling, R. B. P. (1992). Using data on offender mobility in ecological research. *Journal of Quantitative Criminology, 8*(1), 95–112.

Hindelang, M. J., Gottfredson, M. R., & Garofalo, J. (1978). *Victims of personal crime: An empirical foundation for a theory of personal victimization*. Cambridge, MA: Ballinger.

Jacob, C., Litorco, J., & Lee, L. (2004). Immunity through swarms: Agent-based simulations of the human immune system. *Lecture Notes in Computer Science, 3239*, 400–412.

Johnson, D. (2007). Predictive analysis: Utilising the near repeat phenomena in Bournemouth. Paper presented at the fifth national crime mapping conference, London.

Kongmuang, C. (2006). Modelling crime: A spatial microsimulation approach. Ph.D. thesis. Leeds, UK: School of Geography, University of Leeds.

Kongmuang, C., Clarke, G., Evans, A., & Ballas, D. (2005). Modelling crime victimisation at small-area level using a spatial microsimulation technique. Paper presented at the RSAIBIS 35th anual conference. <http://www.geog.leeds.ac.uk/people/c.kongmuang/SimCrime2520Paper_RSAIBIS.doc> Accessed May 2006.

Levine, N. (2006). Crime mapping and the crimestat program. *Geographical Analysis, 38*, 41–56.

Liu, L., & Eck, J. (Eds.). (2008). *Artificial crime analysis systems: Using computer simulations and geographic information systems*. IGI Global.

Liu, L., Wang, X., Eck, J., & Liang, J. (2005). Simulating crime events and crime patterns in a ra/ca model. In F. Wang (Ed.), *Geographic information systems and crime analysis* (pp. 197–213). Reading, PA: Idea Publishing.

Martinez-Miranda, J., & Aldea, A. (2005). Emotions in human and artificial intelligence. *Computers in Human Behaviour, 21*, 323–341.

Massey, J. L., Krohn, M. D., & Bonati, L. M. (1989). Property crime and the routine activities of individuals. *Journal of Research in Crime and Delinquency, 26*(4), 378–400.

Meera, A. K., & Jayakumar, M. D. (1995). Determinants of crime in a developing country: A regression model. *Applied Economics, 27*, 455–461.

Melo, A., Belchior, M., & Furtado, V. (2005). Analyzing police patrol routes by simulating the physical reorganization of agents. In J. S. Sichman & L. Antunes (Eds.), *MABS. Lecture notes in computer science* (Vol. 3891, pp. 99–114). Springer.

Miller, B. W., Hwang, C. H., Torkkola, K., & Massey, N. (2003). An architecture for an intelligent driver support system. In *Intelligent vehicles symposium (pp. 639–644)*. IEEE.

Moss, S., & Edmonds, B. (2005). Towards good social science. *Journal of Artificial Societies and Social Simulation, 8*(4). <http://jasss.soc.surrey.ac.uk/8/4/13.html>.

Nee, C., & Meenaghan, A. (2006). Expert decision making in burglars. *British Journal of Criminology, 46*, 935–949.

Neji, M., & Ammar, M. B. (2007). Agent-based collaborative affective e-learning framework. *The Electronic Journal of e-Learning, 5*(2), 123–134. <http://www.ejel.org>.

Pain, R., MacFarlane, R., Turner, K., & Gill, S. (2006). 'when, where, if, and but': Qualifying gis and the effect of streetlighting on crime and fear. *Environment and Planning A, 38*, 2055–2074.

Paredes, A. L., & Hernández, I. C. (Eds.). (2008). *Agent based modelling in natural resource management*. INSISOC, Spain.

Rao, A. S., & Georgeff, M. P. (1995). BDI agents: From theory to practice. In V. Lesser & L. Gasser (Eds.), *Proceedings of the first international conference on multi-agent systems (ICMAS-95)*. San Francisco, USA: MIT Press.

Rengert, G., & Wasilchick, J. (1985). *Suburban burglary: A time and a place for everything*. Springfield, IL: Charles Thomas Publishers.

Repetto, T. G. (1974). *Residential crime*. Cambridge, MA: Ballinger.

Robinson, M. B., & Robinson, C. E. (1997). Environmental characteristics associated with residential burglaries of student apartment complexes. *Environment and Behaviour, 29*, 657–675.

Safer Leeds (2007). Burglary reduction in leeds programme (bril). <http://www.leeds-csp.org.uk/view.asp?id=54> Accessed November 2007. <http://www.leeds-csp.org.uk/view.asp?id=54>.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*, 918–924.

Scarr, H. A. (1973). *Patterns of burglary*. Washington, DC: US Govenrment Printing Office.

Schmidt, B. (2000). *The modelling of human behaviour*. Erlangen, Germany: SCS Publications.

Schmidt, B. (2002). How to give agents a personality. In *Proceedings of the 3rd workshop on agent-based simulation*, April 7–9. Passau, Germany.

Shaw, C. R., & McKay, H. D. (1969). *Juvenile delinquency and urban areas*. Chicago: The University of Chicago Press.

Shepherd, P. J. (2006). Neighbourhood profiling and classification for community safety. Ph.D. thesis. Leeds, UK: School of Geography, University of Leeds.

Shepherd, P., See, L., Kongmuang, C., & Clarke, G. (2004). An analysis of crime and disorder in Leeds, 2000/01 to 2003/04. School of Geography, University of Leeds.

Shover, N. (1991). Burglary. *Crime and justice: A review of research* (Vol. 14, pp. 73–113). University of Chicago Press.

Singh, K. (2005). An abstract mathematical framework for semantic modeling and simulation of urban crime patterns. Ph.D. thesis, University of Dehli.

Snook, B. (2004). Individual differences in distance travelled by serial burglars. *Journal of Investigative Psychology and Offender Profiling, 1*, 53–66.

Taylor, G., Frederiksen, R., Vane, R., & Waltz, E. (2004). Agent-based simulation of geo-political conflict. In *16th conference on innovative applications of artificial intelligence*. San Jose, CA: AAAI Press.

Taylor, M., & Nee, C. (1988). The role of cues in simulated residential burglary. *The British Journal of Criminology, 28*(3), 396–401.

Tilley, N., Pease, K., Hough, M., & Brown, R. (1999). Burglary prevention: Early lessons from the crime reduction programme. *Policing and reducing crime unit crime reduction research series paper 1*.London: Home Office.

Townsely, M., Homel, R., & Chaseling, J. (2003). Infectious burglaries: A test of the near repeat hypothesis. *British Journal of Criminology, 43*, 615–633.

Turner, A., & Penn, A. (2002). Encoding natural movement as an agent-based system: An investigation into human pedestrian behaviour in the built environment. *Environment and Planning B, 29*, 473–490.

Unsworth, R., & Stillwell, J. (Eds.). (2004). *Twenty-first century Leeds: Geographies of a regional city*. St John College, York: PLACE Research Centre.

Urban, C. (2000). PECS: A reference model for the simulation of multi-agent systems. In R. Suleiman, K. G. Troitzsch, & N. Gilbert (Eds.), *Tools and techniques for social science simulation* (pp. 83–114). Physica-Verlag.

van Baal, P. (2004). *Computer simulations of criminal deterrence: From public policy to local interaction to individual behaviour*. Boom Juridische uitgevers.

Vickers, D., & Rees, P. (2006). Introducing the national classification of census output areas. *Population Trends*, 125.

Wang, X., Liu, L., & Eck, J. (2008). Crime simulation using gis and artificial intelligent agents. In Liu, L., Eck, J. (Eds.), *Artificial crime analysis systems: Using computer simulations and geographic information systems*. Information Science Reference.

Wilkström, P. (1991). *Urban crime, criminals and victims: The Swedish experience in an Anglo-American comparative perspective*. New York: Springer-Verlag.

Wilson, J. Q., & Kelling, G. L. (1982). Broken windows: The police and neighborhood safety. *The Atlantic Monthly, 249*(3), 29–38.

Winoto, P. (2003). A simulation of the market for offenses in multiagent systems: Is zero crime rates attainable? In J. S. Sichman, F. Bousquet, & P. Davidsson (Eds.), *MABS. Lecture notes in computer science* (Vol. 2581, pp. 181–193). Springer.

Wright, R. T., & Decker, S. H. (1996). *Burglars on the job: Streetlife and residential break-ins*. Boston: Northeastern University Press.