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Simulating Burglary with an Agent-Based Model

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Abstract

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 and Brantingham, 2004; Groff, 2007a). In order to test modern opportunity theories it is essential to be able model the complex, dynamic interactions of the individuals involved in each crime event. However, studies to date are limited in their ability to provide consistent support for these theories due to an inability to model complex micro-level interactions (Groff, 2007a).

Agent-based modelling (ABM) represents a shift in the social sciences towards the use of models that work at the level of the individual. Using the ABM paradigm, human agents can be implemented with realistic human behaviour who interact with each other and their environment to create a dynamic system which mimics a real scenario.

This paper presents the development and application of an ABM for simulating the occurrence of residential burglary at an individual level. Experiments are conducted investigate the effectiveness of burglary reduction strategies and criminology theories. The model is able to demonstrate that a commonly used crime-reduction initiative is ineffective at removing crime hotspots.

Keywords

Agent-Based Modelling, Burglary, Computer Simulation, Crime Reduction

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 and Brantingham, 2004; Groff, 2007a). Recent advances in criminology, such as routine activities theory (Cohen and Felson, 1979), lifestyle exposure theory (Hindelang et al., 1978) and crime pattern theory (Brantingham and 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. 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. However, most studies to date are limited in their ability to provide consistent support for these theories due to an inability to model these complex micro-level interactions (Groff, 2007a).

Burglary rates in the city of Leeds in the United Kingdom are consistently the highest when compared to any other local authority in England and Wales (Shepherd, 2004). Safer Leeds, the public body responsible for implementing and evaluating crime reduction strategies in partnership with the West Yorkshire Police and other local government agencies, are developing strategies to reduce burglary in the city. 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. Not only is the system highly complex, but the behaviour of the individual entities is also extremely complicated. Humans exhibit “soft” factors such as seemingly irrational behaviour and complex psychology (Bonabeau, 2002) which are considerably difficult characteristics to simulate in a computer model. In addition, burglars can be classified as “experts” in their field (Nee and Meenaghan, 2006) meaning that there is an entire range of behavioural characteristics which will be unique to them. Many studies have interviewed burglars (both incarcerated and “active”) to gather qualitative evidence regarding their behaviour and motives (Brown and Bentley, 1993; Wright and

Decker, 1996; Hearnden and Magill, 2003; Cromwell and Olson, 2005; Nee and Meenaghan, 2006). Although these studies have revealed valuable insights into the possible behaviour and motives of offenders (many of which have been used in the design of the model presented here), they often suffer from problems associated with sampling a population of "burglars" and have not been empirically tested. Quantitative studies have helped to establish general trends in burglar behaviour (Massey et al., 1989; Snook, 2004; Bernasco and Nieuwbeerta, 2005). However, these approaches also suffer from problems because they use aggregated data rather than attempt to represent the micro-level human and environmental elements that dictate whether or not an individual crime event will occur.

Agent-based modelling (ABM) represents a shift in the social sciences towards the use of models that work at the level of the individual. An agent-based model is comprised of autonomous, decision making entities called agents who can 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 individually assesses its situation and, based on a set of production rules, makes a decision about what action to take (Bonabeau, 2002). In this manner, human agents can be implemented with realistic human behaviour (Moss and Edmonds, 2005). To investigate a specific scenario, the model is configured to represent the scenario and then allowed to run for a number of iterations. The model produces data which describes the history and final state of the system (Axtell, 2000), which can then be analysed. If the model can be considered an accurate representation of the real system under investigation then it is possible to draw conclusions about the real world without the need for direct experimentation.

We must recognise that the burglary system is a highly complex entity. 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 burglary is affected by the time of day, particular spatial and environmental factors (e.g. low security, easily accessible property) and individual behaviour (opportunistic crime, individual motivation), which is the most difficult of all to both model and understand, As it is unethical to experiment with crime theories in the real world, accurate simulations are therefore, an essential tool to aid governments and crime reduction practitioners by allowing theories to be tested before implementation. Such tools are already being used in the context of urban planning (Al-Ahmadi et al., 2008). Computer simulation, and ABM in particular, offers the most attractive approach to modelling the burglary system.

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 PECS (Physical conditions, Emotional states, Cognitive capabilities and Social status) framework for simulating human behaviour within a computational/artificial environment. 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 the model are outlined in sections 3 and 4. A series of experiments testing the behaviour of the model are then presented in section 5. Section 6 concludes with a discussion of the results and a critique of the methodology while future work is discussed briefly in section 7.

2 Previous Approaches to Crime Modelling

The crime system is an incredibly complex one driven by many different interrelating factors. These include, but not exclusively, an offender's individual perception and knowledge of the physical environment, the "suitability" or "attractiveness" of the target, the offender's cognitive representation of the environment, the layout of the physical environment and other factors relating to the surrounding community (Brantingham and Brantingham, 1993).

To address these features and answer questions such as how do criminals choose their targets and what are the surrounding environmental influences (Brantingham and Brantingham, 1993), the field of environmental criminology has employed numerous methods. 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 the 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 has catalysed the development of more advanced mapping analysis techniques such as "hotstpot" detection (Grubesic and Murray, 2001). For example, Pain et al. (2006) overlaid crime hotspot maps with streetlight location maps to investigate the effect that street lighting had on crime and fear-of-crime levels; the results were used to inform on 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 tell us anything about the actual crime event for example, how human behaviour influences crime.

In addition to mapping techniques, statistical or mathematical models have also been widely used. Early examples include the use of principle 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 et al. 1972) (although these approaches are strongly criticised by Baldwin (1975) who describes them as "unilluminating"). More recent statistical models include the logistic regression model by Craglia et al. (2001) who compare high intensity crime areas to census data, Dahlbäck's (1998) longitudinal multivariate regression model which found high population density and weak social bonds to be associated with high theft rates, the regression model by Gaviria and Pagés (2002) which linked the chance of being a victim to individual and city-wide variables and Meera's (1995) regression model which attempted to explain rising levels with demographic and economic variables. These approaches have revealed interesting links between crime and other variables, but they still fail to address the important features outlined earlier which are specific to an individual offender, victim, time and space.

Advances in computer techniques and hardware have also led to modern computer modelling approaches being applied to the study of crime. For example, Kongmuang utilised spatial micro-simulation and spatial interaction models (Kongmuang et al., 2005; Kongmuang, 2006) in her study into urban residential burglary rates. The author was able to successfully predict the risk of being a victim of residential burglary at the individual level and also estimate offender flows within a city. Despite the advances that this technique provided, micro-simulation is inherently limited by its inability to model interactions between individual entities, or indeed account for 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, studies often discover general, aggregate patterns, which makes it difficult to draw conclusions regarding how the *individual* behaviour of victims or offenders affects crime. Brantingham and Brantingham (1993, pp. 6) 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." However, traditional statistical modelling techniques will struggle to incorporate the vast amount of local variation present in the "environmental backcloth" because they inherently work at aggregate scales. Factors such as the individual location of houses (e.g. corner blocks) (Taylor and Nee, 1988), their visibility to neighbours and passers-by (Robinson and Robinson, 1997) and the layout of the local street network (Bevis and Nutter, 1977) will affect their victimisation risk but these factors cannot be incorporated into models which do not operate at the level of the individual.

Therefore, to understand the trends and characteristics of crime patterns more accurately it is necessary to examine the individual actors who play important roles in discrete crime events from which the larger patterns emerge. The technique of agent-based modelling (ABM) has been applied to a vast number of subject areas, including computer systems that assist car drivers (Miller et al., 2003), models of pedestrian movements (Castle, 2006; Turner and Penn, 2002), simulations of human immune systems (Jacob et al., 2004) and models of the retail petrol market (Heppenstall et al., 2005). However, the benefits of ABM are only starting to be felt in criminology; current work is briefly outlined below. For a detailed critique of the use of ABM, the reader is directed to Axtell (2000).

Abstract state machines have been used as a way of validating and verifying algorithms, modelling their precise operation mathematically. Brantingham et al. (2005a,b) used this formalism to provide a precise mathematical foundation to the multi-agent modelling paradigm. People are represented as autonomous agents with attributes, memory, behaviour and motivations which are then mapped to state machine objects. The environment is represented as an attributed, directed graph which is constructed in such a way as to allow awareness and activity spaces of the agents to be calculated. Although no results are available at present, this approach offers a novel view of how to model agents and investigate modern crime theories at the level of the individual.

As already mentioned, Groff (2007a) has noted that many previous studies have failed to effectively test routine activities theory because they did not account for dynamic, individual-level interactions. To avoid these pitfalls, Groff (2006, 2007a,b) built an agent-based model to test the applicability of routine activities theory to street robbery. The model is based on the city of Seattle, Washington and utilises a graph-based environment which realistically represents the city's road network. Two types of agent exist: citizens (offenders, victims and guardians) and police. All civilian agents are randomly assigned a particular home location and, in the model's most advanced form, the agents spend time away from home by visiting randomly assigned work and activity nodes following pre-defined routes. The offender's decision to offend is stochastic and based on levels of guardianship and the wealth of the potential target at their current location. As would be expected, the model found that the number of street robberies increased with the amount of time spent away from home because citizens had the chance to meet more potential offenders. Interestingly, some street intersections exhibited significant clusters of events even though the travel patterns of the agents were random (Groff, 2007a). Groff justifies these unrealistic random movements by stating that the routine activities theory does not stipulate how the structure of human activities should be organised. The model is an excellent example of how agent-based modelling can be used to investigate crime theories, but it currently lacks consideration of factors that affect the behaviour of an offender, including (for example) drug addictions (Wright and Decker, 1996), perceptions of their physical environment (Brantingham and Brantingham, 1993; Beavon et al., 1994) and physical characteristics of the local area (Brown and Bentley, 1993). The model outlined in this paper will attempt to address several of these issues.

3 Incorporating Human Behaviour Into An Agent-Based Model: The Pecs Framework

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

Perhaps the most popular architecture used is the Beliefs-Desires-Intentions (BDI) model which equips agents with these three components. The architecture has been used in many different areas, including air traffic management systems (Rao and Georgeff, 1995), simulations of geo-political conflicts (Taylor et al., 2004) and frameworks for models of crime reduction (Brantingham et al., 2005a,b). However, some authors criticise the three core components of the architecture as being too restrictive and others feel that they are overly complicated (Rao and Georgeff, 1995). Fundamentally the architecture assumes rational decision making which is difficult to justify because people rarely meet the requirements of rational choice models (Axelrod, 1997). Brailsford and Schmidt (2003) are critical of the architecture because it is restricted to cognitive processes and therefore cannot integrate physical, emotional or social processes and the interactions between them. Balzer (2000) also notes that the core elements are difficult to observe directly: access to them can only be achieved in a laboratory setting which might not relate to real situations.

An alternative, but rarely used, architecture is the PECS framework (Physical conditions, Emotional states, Cognitive capabilities and Social status) which has been proposed by Schmidt (2000) and Urban (2000). The 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 and Aldea, 2005). The PECS framework is presented as an improvement upon the BDI architecture because it does not require rational decision making as an assumption and is not restricted to the factors of beliefs, desires and intentions (Schmidt, 2000). However, the claim that PECS is an improvement over BDI is not fully justified by Schmidt (Amblard, 2001).

To illustrate the PECS features, an example proposed by Urban (2000) will be adapted. 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 will, for example, affect how the agent reacts to the shop assistant). Schmidt (2000) and Urban (2000) believe 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).

Documented use of the framework is limited, but the few studies that were found come from diverse fields. For example, PECS has been used to build emotions into a virtual learning environment (Ammar et al., 2006; Neji and Ammar, 2007). The authors incorporate non-verbal communication in the form of emotional facial expressions to improve the relationship between a human learner and a computer-controlled tutor. In the field of health care, Brailsford and Schmidt (2003) have used the framework to improve a simulation of disease screening. PECS is used to incorporate people's behaviour into a model, a factor that they note is an important determinant of whether or not a patient will attend a screening session and something that is absent from most models in their field.

PECS divides all behaviour into two categories: reactive and deliberative. Reactive behaviour classifies actions that are largely instinctive; it can be modelled using a set of rules without deliberation on the part of the agent. Schmidt (2000) describes how reactive behaviour can be further broken down into the following:

- **Instinctive behaviour**. An automatic reaction to stimulus depending on the internal state of the agent such as a parent reacting instinctively to a child's cry. Instinctive behaviour can be modelled relatively easily using pre-defined rules which are implemented in certain circumstances.
- **Learned behaviour**. Similar to instinctive behaviour but with rules that are learnt dynamically. Schmidt (2000) cites the example of a car driver who will instinctively brake if they see a child running across the road.
- **Drive controlled behaviour**. This type of behaviour is directed by internal drivers to satisfy needs. These range from basic needs required to preserve life (such as the need for food or

safety) to social needs and finally to intellectual needs. These drivers will, therefore, determine a person's current behaviour as they attempt to satisfy the drive with the greatest intensity. Schmidt defines the following function to determine drive intensity:

$$T = f\,(N, V, X) \quad (1)$$

where N is the need, V represents environmental influences and X represents other influences. For example, a drug addict will have a strong drive to take drugs if N is high because they have gone without drugs for some time. However, the environment must also be taken into account, e.g. the drive might be stronger if the addict is surrounded by others who are using drugs even if N is not great.

- **Emotionally controlled behaviour**. Emotions are similar to drives because if they are strong enough, they will affect the behaviour of the agent. Unlike drives, however, they are stimulated externally, not by internal state changes. Schmidt notes that the intensity of emotions, E, are very hard to model, but defines the following formula:

  $$E = g\,(I, A, X) \quad (2)$$

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

Schmidt (2000) also defines types of deliberative behaviour. With reactive forms of behaviour the organism is not truly aware of the reasons that they behave in the way they do. 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 already discussed, Schmidt (2000) believes that it not necessary to model the entire spectrum of human behaviour. However, a fine balance must be reached. The greater the degree of abstraction of a model, the greater the differences will be between the model and the real system (Schmidt, 2000). For this study, it is decided that modelling deliberative behaviour brings additional complexity which is unnecessary. To model the level of human behaviour required for a simulation of urban residential burglary the focus is on drive controlled behaviour with the option of extending to include emotionally controlled behaviour.

4 An Agent-Based Model (ABM) Of Burglary

This section will outline an agent-based model (ABM) which can be used to experiment with residential burglary using the PECS concepts to control the behaviour of the agents.

4.1 The Agents

The model consists of "people" agents who all have the same basic structure. There are two needs which the agents must fulfil: the need to generate wealth and the need to sleep. Most agents can work in order to generate wealth although some do not have full time employment and must choose to burgle occasionally. These "potential burglar" agents are given random amounts of work each day but it is unlikely to be enough for them to survive. This feature 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 suitable targets they would be otherwise unaware of.

Wealth is used to characterise many factors that require money for satisfaction such as 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 loosely represents the daily patterns of employed people in British or American cities.

Figure 1 illustrates how the needs of an agent lead to goals that they will attempt to accomplish. 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, L, the agent's personal preference for generating wealth or sleeping, P, and the current time of day, T. Therefore the intensity function determines the overall need to generate wealth or sleep, N, at time t:

$$N_t = f(L_t, P, T_t) \qquad (3)$$

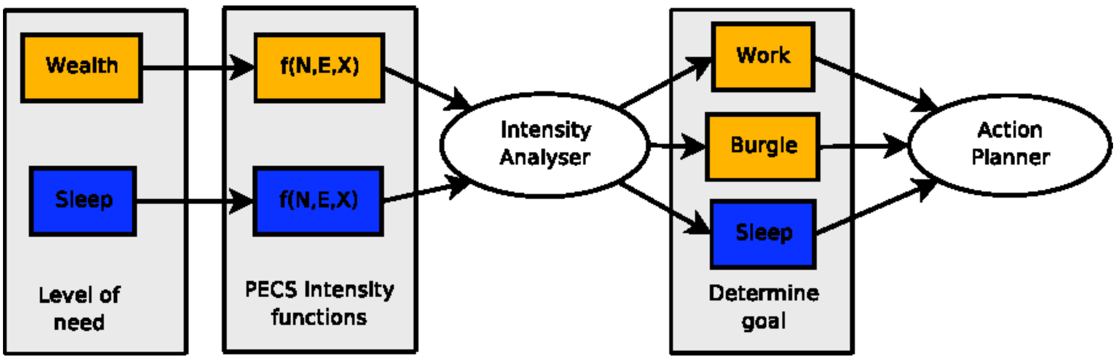

Figure 1 The agents' needs and how their intensities determine the behaviour of the agents, adapted from Schmidt (2000)

Figure 2 illustrates how the 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.

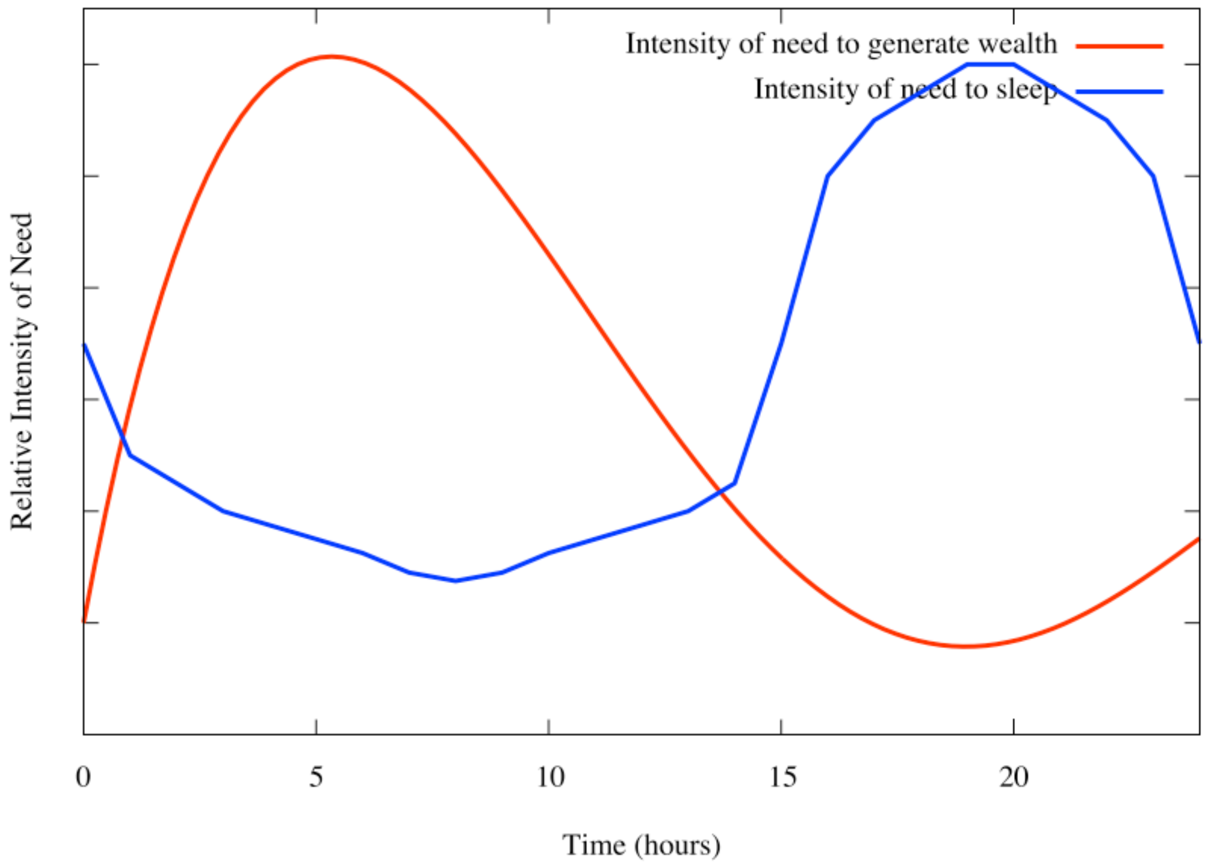

Figure 2 How the time of day affects an agent's need to generate wealth or sleep where Time t =0 is defined as approximately 7am.

In addition to wealth and sleep variables, each agent also contains an individual cognitive map which consists of every property that they are aware of. According to routine activities theory, crime pattern theory and some qualitative studies (Wright and Decker, 1996; Cromwell and Olson, 2005), a potential offender is likely to find a suitable target by passing one on their routine travels. The model presented here works in a similar manner. The cognitive map of each agent is built up from their routine activities to and from work. If an agent subsequently needs to commit a burglary, they travel to the most attractive target in their cognitive map.

4.2 The Model Environment

The model environment is relatively simple but is nevertheless detailed enough to allow comparisons with real urban configurations. Although hypothetical, the environment is designed to reflect many of the features found in modern cities, namely the commercial district in the centre of the city which is the focal point for employment (approximately 30% of all Leeds employment is found in the city centre (Unsworth and Stillwell, 2004)). Figure 3 illustrates the layout of the environment. It consists of three elements: the commercial district, roads and residential properties. Residential properties 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, and attractiveness is a measure of the wealth of the property. These levels are dynamic: if a burglary is committed then the attractiveness of the victimised property increases along with smaller increases in the surrounding properties. The result is that the victimised property and adjacent properties are at a higher risk for the days following a burglary. This "near repeat" phenomena has been found to exist in criminology literature (Townsely et al., 2003) and by police force managers (Johnson, 2007). The victimised property also increases its levels of security in response to the burglary as the residents become aware of the risk. These levels of attractiveness and security gradually degrade so that, if no further burglaries are committed, they will return to base levels.

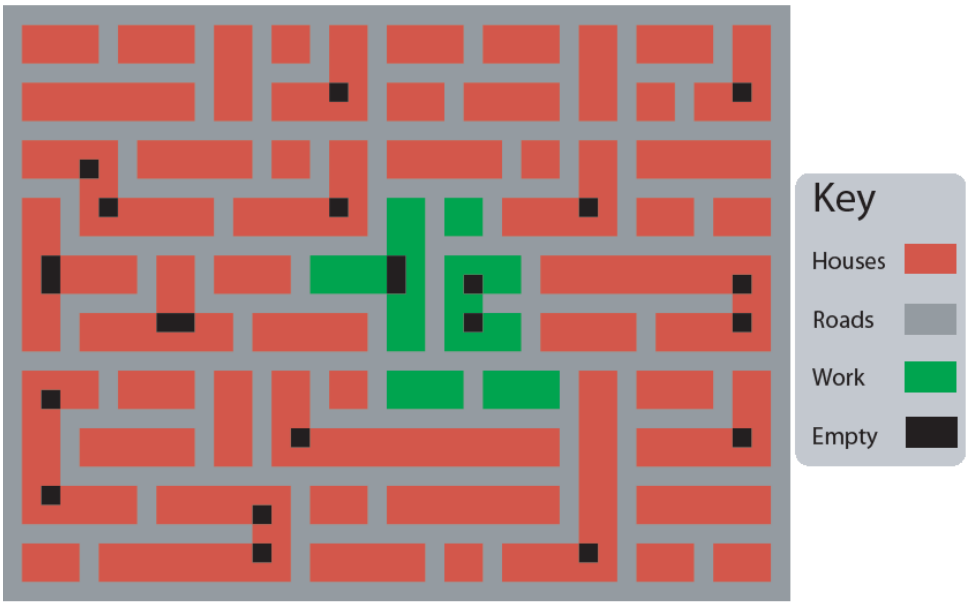

Figure 3 The model environment. Note that agents in the model cannot move diagonally so "empty" spaces play no part in the simulation because they cannot be accessed from a road.

Upon initialisation, each agent is randomly assigned a home address and also the address of their work place which will be within the commercial district. The agents use roads to travel between different addresses and can traverse one square per model iteration. With regards to timing, one model iteration is classified as three minutes so that it will take agents between 10 and 60 minutes to travel to work depending on where an agent lives. Therefore there are 20 iterations per hour and 240 in a day.

4.3 Modelling Offender Behaviour

Many studies have used interviews to elucidate how potential burglars behave, how they are motivated and how they respond to environmental cues. Alternatively, some studies utilise large data sets and statistical models to establish trends and patterns which suggest how potential burglars behave. Regardless of the methods employed, however, most studies draw very similar conclusions which will all be used to assist in the design of agent behaviour. Table 1 outlines findings from studies in the criminology literature and how these will be incorporated into the model to provide a sound theoretical foundation.

Table 1 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 (Repetto, 1974; Bennett and Wright, 1984; Rengert and Wasilchick, 1985; Wright and Decker, 1996; Bernasco and Luykx, 2003; Nee and Meenaghan, 2006) and usu-ally to buy drugs (Scarr, 1973; Cromwell et al., 1991; Hearnden and Magill, 2003).	Agents in the model burgle to satisfy the desire for wealth. Drug addiction can be represented by altering the rate at which L decreases. Agents with a fast decrease in wealth levels will quickly become desperate to generate wealth as if they had a drug addiction to satisfy.
The decision to commit burglary is made away from the actual crime scene and the potential offender then travels to a target noted previously (Wright and	Agents build a cognitive map of their environment and choose targets from these known areas.

Decker, 1996; Hearnden and Magill, 2003; Nee and Meenaghan, 2006).	
Few burglars can be classed as "opportunistic" although most interviewees will alter their usual routine if a particularly attractive target presents itself (Nee and 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 and Magill, 2003; Nee and Meenaghan, 2006) which can range from \$0 – \$12,950 (Snook, 2004).	Potential burglars choose to travel to the most attractive property they are aware of.
Burglars will not knowingly enter occupied properties (Cromwell et al., 1991; Wright and Decker, 1996; Nee and Meenaghan, 2006).	When occupants are at home a burglar agent will not victimise the property.
Most burglars will return to previously burgled properties, usually because they know what goods are available and how to enter the property. (Wright and Decker, 1996; Hearnden and Magill, 2003).	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 (Snook, 2004; Bernasco and Nieuwbeerta, 2005). This is partly because the offender knows the area well and does not need to carry stolen objects too far (Hearnden and Magill, 2003) and also because the potential burglar chooses targets from within their cognitive awareness space (Bernasco and 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 (Wright and Decker, 1996; Cromwell and Olson, 2005).	The agent's cognitive map is built up from their routine activities and a target is chosen from these known properties.

Determining the suitability of the target is twofold. Firstly, a potential burglar will never burgle a property if the occupants are at home. Secondly, the potential burglar is less likely to burgle a property if it is highly secure or unattractive, particularly if there are possible targets with lower levels of security and greater attractiveness. These elements are consistent with many findings, including Cromwell et al. (1991); Wright and Decker (1996); Nee and Meenaghan (2006).

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 which allows results to be generated more quickly. This is an important consideration with agent-based models: every agent must make decisions at every iteration, so execution times can be very large.

4.4 Experiments to Model Offender Behaviour

The model will be used to experiment with crime theories, an area in which previous studies have had shortcomings (Groff, 2007a), but also to test the effectiveness of various crime reduction strategies. At this stage the environment used is hypothetical, although it has been built in such a way as to allow accurate experiments to take place. The following experiments will be performed:

1. **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. They were calibrated so that, on average, an offender will commit one burglary each day which will generate the same amount of wealth as an employed person.

2. **Different "types" of community**. The environment will be adapted by modifying the security and attractiveness of property values to simulate the presence of different types of community, such as a deprived area, an affluent area, and an area occupied predominantly by students.
3. **Target hardening strategies**: The model is used to test the effectiveness of various crime reduction strategies such as target hardening. Target hardening is an intervention scheme whereby councils 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 which are similar to the most secure properties in the environment. Two different target hardening strategies are tested. The first is commonly used by councils; for a practical example see Byron (2003). 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 (Byron, 2003). 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. All the properties in a community which has been identified as a high-crime area simultaneously undergo target hardening. The aim of the experiments is to establish which strategy is more effective at removing a crime hotspot.
4. **Different routine activity patterns**. The addresses of potential burglars are altered so that their routine activity patterns change. The model is used to generate new crime patterns, which allows us to test the ideas of routine activities theory and what affect different offender daily patterns will have on crime rates.

5 Results Of Model Experimentation

5.1 The Control Experiment

The aim of the control experiment is to check that the model is robust and that it produces sensible results, which is a process often termed as “verification” (Gilbert and 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. Figure 4 illustrates the number of burglaries committed at different intervals over 50 days for 100 model runs. A *percentage* of the population is created as burglars, which means that the total number of burglars in each model run will vary slightly and therefore the total number of burglaries will also vary. However, the number of burglaries committed at different intervals only changes slightly so we can be sure that the model has reached equilibrium and the rates of burglary are accurate.

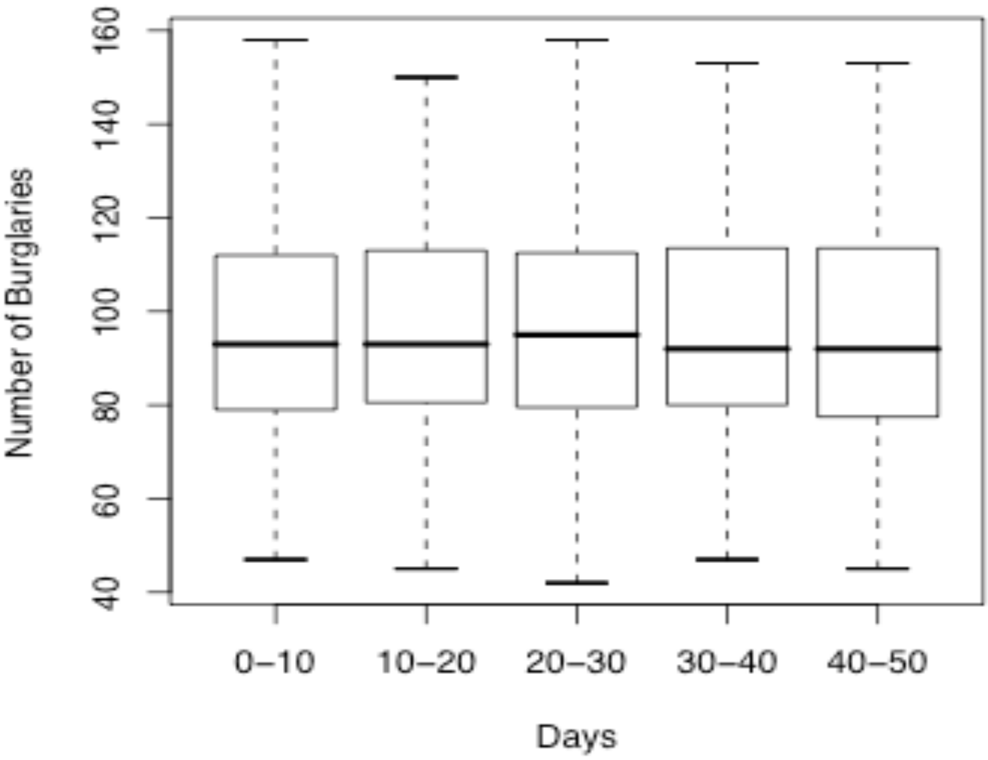

Figure 4 Boxplots describe the number of crimes committed at different points over a run of 50 days varying the number of burglars in the model for 100 model runs

Fifty days was chosen because, as Figure 5 demonstrates, it is clearly enough time to allow the model to reach dynamic equilibrium. 100 individual model runs were chosen because it is a large enough number to ensure that if the model was not robust at least one of these 100 runs would exhibit non-sensible behaviour. Figure 5 illustrates that the number of burglaries committed in a ten-day period and the mean centre of the associated burglary locations also reaches equilibrium rapidly for a typical simulation. Therefore all subsequent experiments will run for a period of 50 days as this is enough time for dynamic equilibrium to establish.

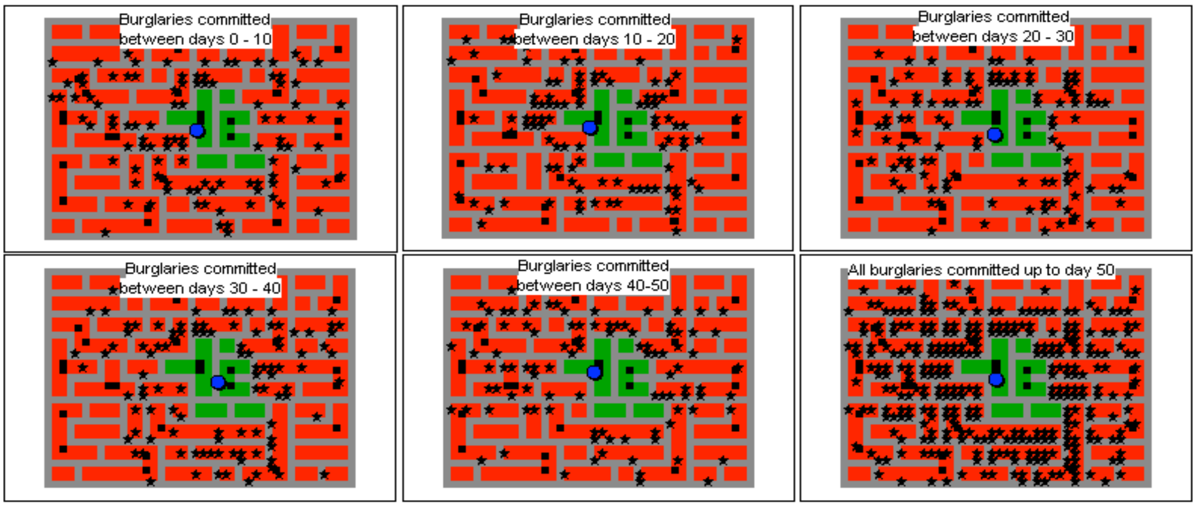

Figure 5 The mean centre of burglary locations at different time points during a typical run.

Figure 6 depicts the burglary rates at the end of a typical simulation run. Burglary patterns will vary slightly between runs, which is to be expected due to the probabilistic nature of the model. 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 different such as the commercial and residential areas in our hypothetical environment.

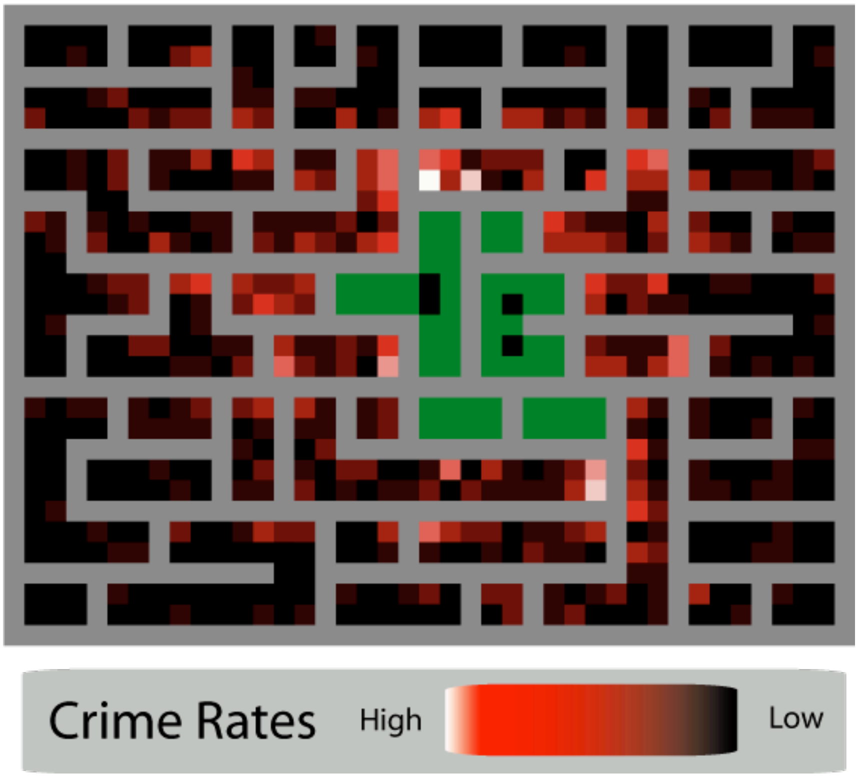

Figure 6 Burglary rates produced by a control experiment after 50 runs

Figure 7 further illustrates that most crimes occur near the centre of the environment. The Pearson's 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.

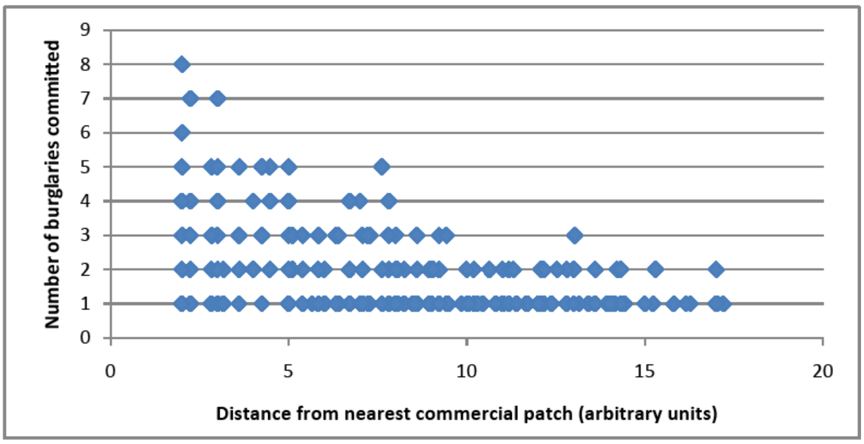

Figure 7 Graph illustrates the distance from the centre of the environment for each burglary committed. No crimes were committed within 3 units of the centre because this area is occupied by the commercial district and there are, therefore, no houses to target.

5.2 Different "Types" of Community

It has been shown that the model produces the expected results under default conditions and it is therefore possible to increase the accuracy 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 because crime patterns in the real world have been shown to be very different in each one. Offenders have been found to travel different distances depending on the affluence of the target (Snook, 2004) and, as will be illustrated later, the community type that an offender originates from will influence 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 sometimes travelled considerable distances to burgle affluent areas whereas burglaries in deprived 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 2.

Table 2: The percentage change from the default value for variables associated with different community types

	Percentage change from default value	
Type of Area	**Attractiveness**	**Security**
Default	n/a	n/a
Rich	150%	150%
Poor	50%	50%
Student	150%	50%

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. Figure 8 illustrates these environments and also the burglary rates produced by day 50. It appears that, regardless of the layout of the environment or the initial starting positions of the agents, the student areas always suffer the highest victimisation rates. This is even evident when more than one student area exists (which is the case in environment 4).

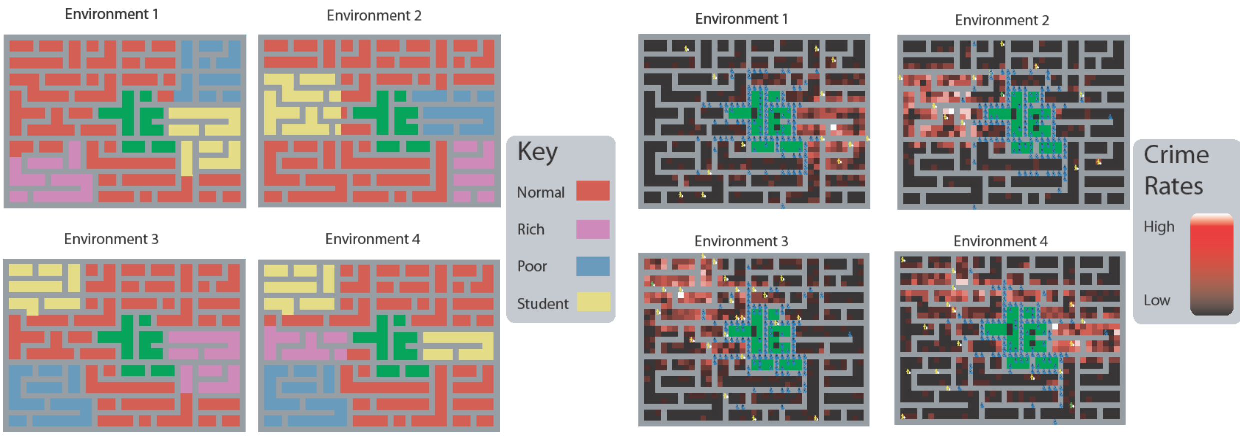

Figure 8 The layout of different environments altering the community type and burglary rates produced by day 50 using different community types

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. A fixed distance of 1 mile and a medium search radius were used as parameters in the CrimeStat application (Levine, 2006) which was used to apply the algorithm.

Figure 9 illustrates the hotspots found by the algorithm when analysing the crimes committed near the end of the simulation (days 40 – 50). The results illustrate that, regardless of the physical layout of the environment, the student areas always suffer high levels of burglary victimisation. This is consistent with the criminology literature (Robinson and Robinson, 1997; Tilley et al., 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.

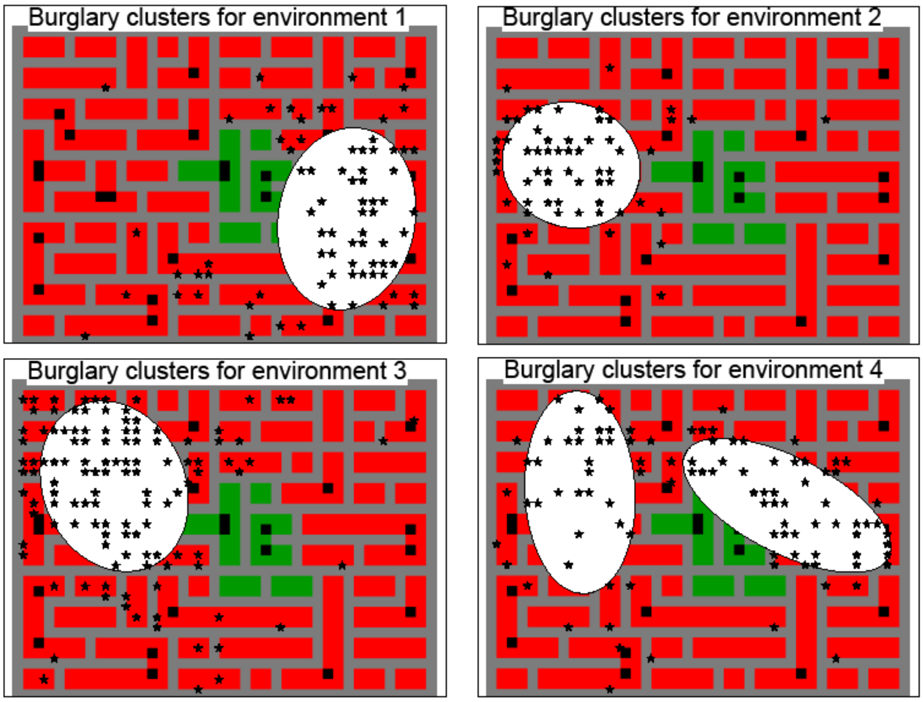

Figure 9 Clusters of burglary found by the Nearest Neighbour Hierarchical spatial clustering algorithm

5.3 Crime Reduction: Target Hardening Strategies

As illustrated in section 5.2, the layout of the environment does not appear to influence the layout of burglary hotspots found in student areas. Therefore we will apply target hardening to environment 1. The strategies will begin implementation on day 20 (which is long enough to allow high-crime areas to develop) and, as with other experiments, the simulation will terminate on day 50. The area chosen for the block-targeting method covers half the student community (to allow comparisons between the hardened and non-hardened sections) which consists 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. Equations in Appendix A demonstrate that the victim-targeting method will increase the security of approximately one house every two days to be comparable with the block-targeting method.

Figure 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. Figure 11 illustrates the results of the block targeting strategy. It appears that crimes are displaced south towards the remainder of the student area which did not undergo target hardening. Although the hotspot produced between days 40-50 still covers the target hardened area, only three crimes were committed in the area during that time period which suggests that if the NNH algorithm were 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.

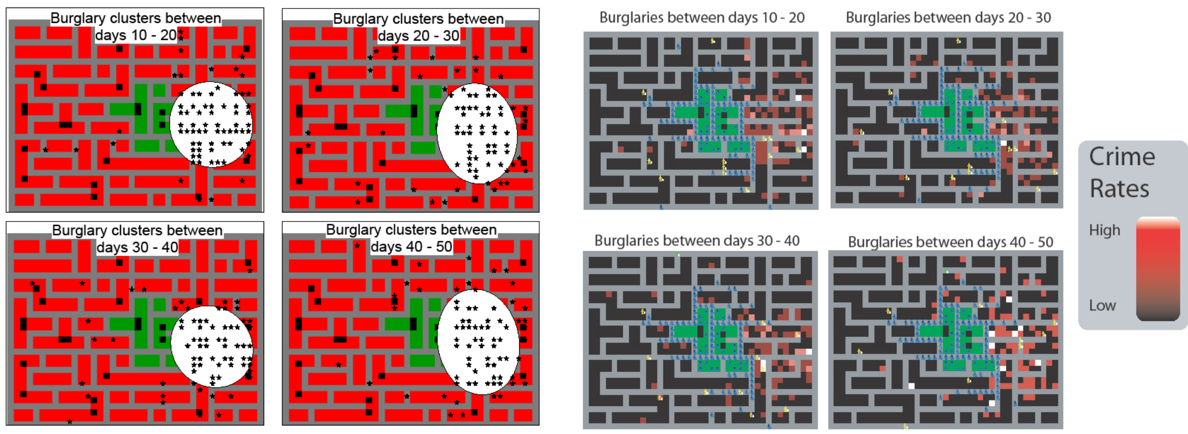

Figure 10 Results of the individual victim target-hardening initiative: Hotspots produced by the NNH algorithm and burglary rates

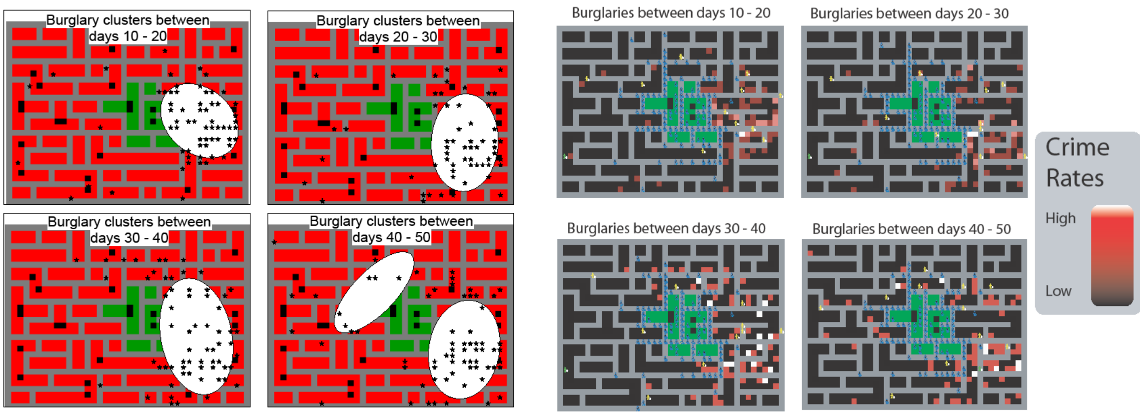

Figure 11 Results of the entire community target-hardening initiative: hotspots produced by the NNH algorithm and burglary rates.

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”.

5.4 Different Routine Activity Patterns

The final experiment increases the realism of the model even further and will investigate the effect that changing the addresses of the potential burglars has on crime rates. In the experiment it is hypothesised that most potential burglars live in the most deprived areas. Numerous studies have made reference to the link between crime and deprivation (Baldwin and Bottoms, 1976; Shover, 1991; Wilkström, 1991; Hesseling, 1992; Brantingham and Brantingham, 1993; Sampson et al., 1997; Bowers and Hirschfield, 1999) and there is also supportive data from the city of Leeds. Using the Office of National Statistics Output Area Classification (Vickers and Rees, 2006) and over 700 pairs of the addresses of convicted burglars and their victims it is possible to estimate which “type” of community most burglars come from. Figure 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.

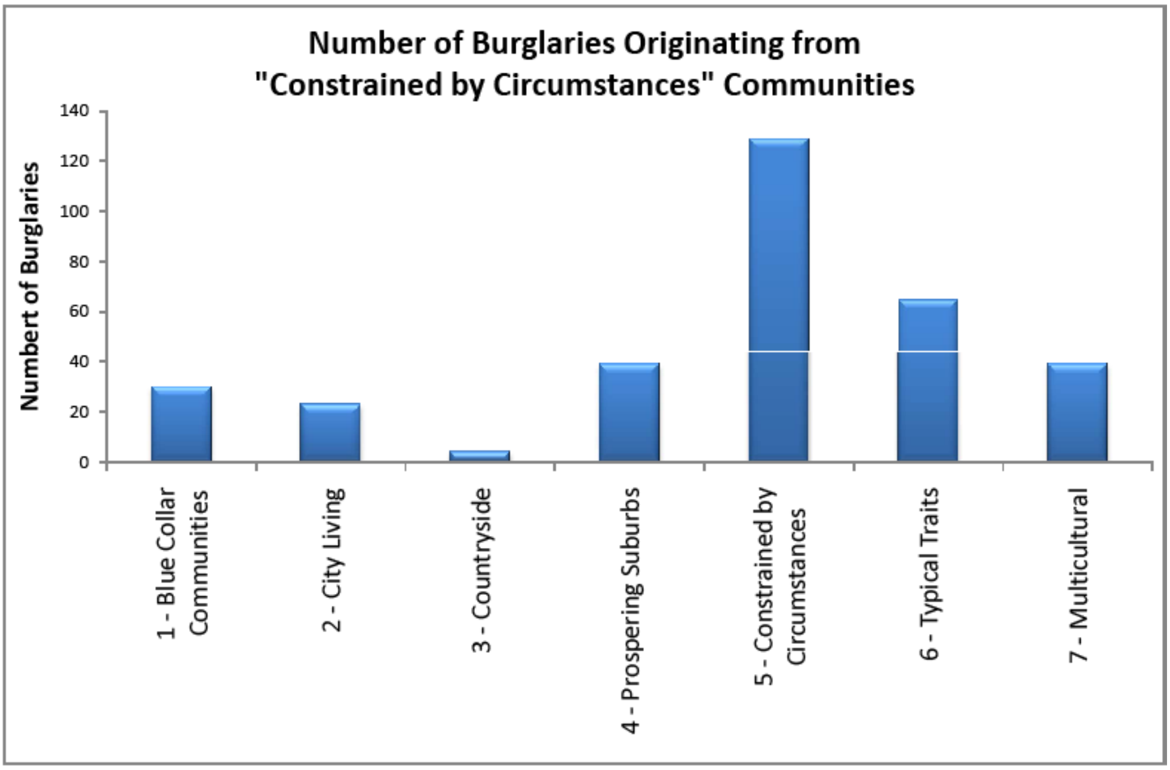

Figure 12 Graph illustrating the number of crimes committed in different community types which have originated from "constrained by circumstances" communities using 2006/07 crime data and the ONS Output Area Classification

Thus the locations of the potential burglars in the model are altered so that instead of living on randomly chosen patches they live in the poorest area. This represents a shift in the model towards the inclusion of real geographies and people. The change will impact on the routine activity patterns of potential burglars because instead of travelling from homes scattered around the city, most burglars will travel to the city centre from the deprived area. We would therefore expect to observe higher burglary rates in the poorest neighbourhood and on the routes into the commercial district. Environment 2 from previous experiments (illustrated by Figure 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.

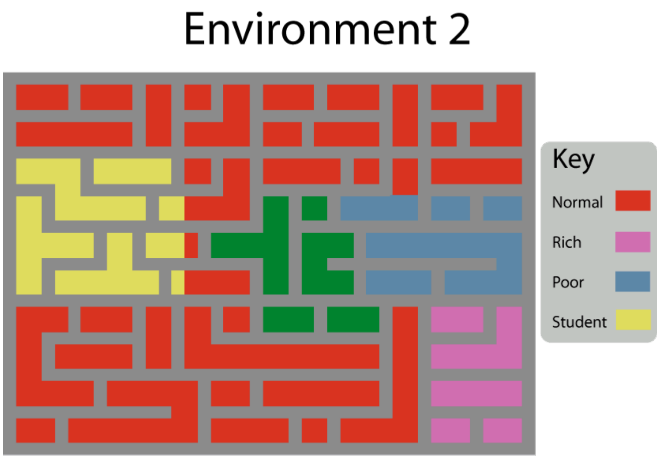

Figure 13 Environment 2 is used in the routine activity experiment.

Figure 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.

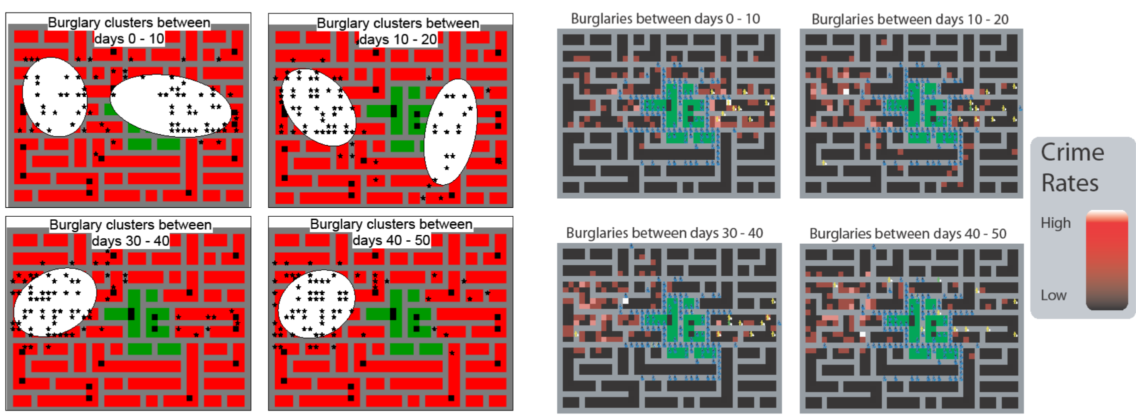

Figure 14 Results of routine activities experiment: hotspots produced by the Nnh algorithm and Burglary rates

6 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). Within the scope of modelling crime theory, there are no published examples of this type of work; the research presented here therefore 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 but they fail to address the crime event as an individual incident located in a specific time and space.

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 and Bottoms, 1976) and illustrates that the model is highly flexible because the environment can be adapted to reflect the type of city under examination.

Incorporating a detailed behavioural framework into an individual-level model is a relatively new approach in criminology. The PECS framework (Schmidt, 2000; Urban, 2000) 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. Also, 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 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. 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 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 who had not undergone target hardening. Targeting an entire block, however, successfully removed the hotspot because the entire area became unattractive to burglars. The "block targeting" technique is something that some practitioners are already aware of so this model is able to provide further evidence for the better technique.

It should be noted, however, that although a crime hotspot in the model was displaced, 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. This is not necessarily a limit of the model; it could be a drawback of ABM in general. It is not possible to include *every* feature of a real system in a model and thus some aspects cannot be accounted for. 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.

7 Future Work

One of the major benefits of the ABM approach is its flexibility; the extensions that could be made to this work are unlimited. 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, family members etc. 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. There are also a number of ways in which the environment itself could be enhanced. These range from including ideas regarding collective efficacy (Sampson, 1997) or "broken windows" theory (Wilson and Kelling, 1982) to incorporating real GIS data similar to that of Groff (2007a,b). In addition, the availability of vehicle transport (such as cars or public buses) could be included by adding different layers to the environment.

This model represents an advance over existing models and we have demonstrated, through experiments, that realistic results can be obtained. 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 to a more advanced framework and incorporate real data.

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*.

Amblard, F. (2001). Book review: The modelling of human behaviour. *Journal of Artificial Societies and Social Simulation* 4(4).

Ammar, M. B., Neji, M., and Gouardères3, G. (2006). Conversational embodied peer agents in affective e-learning. In Rebolledo-Mendez, G. and Martinez-Miron, E. (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 Conte, R., Hegselmann, R., and Terna, P. (eds.), *Simulating Social Phenomena*, pp. 21-40. Springer-Verlag, Berlin.

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, available at 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. and Bottoms, A. E. (1976). *The Urban Criminal: A Study in Sheffield*. Tavistock Publications, London.

Balzer, W. (2000). SMASS: A sequential multi-agent system for social simulation. In Suleiman, R., Troitzsch, K. G., and Gilbert, N. (eds.), *Tools and Techniques for Social Science Simulation*, chapter 5, pp. 65-82. Physica-Verlag.

Beavon, D. J. K., Brantingham, P. L., and Brantingham, P. J. (1994). The influence of street networks on the patterning of property offenses. In Clarke, R. V. (ed.), *Crime Prevention Studies*, volume 2. Criminal Justice Press, New York.

Bennett, T. and Wright, R. (1984). *Burglars on Burglary: Prevention and the Offender*. Glower, Aldershot, UK.

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

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. and 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. and 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. and Brantingham, P. (1993). Environment, routine, and situation: Toward a pattern theory of crime. In Clarke, R. and Felson, M. (eds.), *Routine Activity and Rational Choice*, volume 5 of *Advances in Criminological Theory*. Transaction Publishers, New Brunswick, NJ.

Brantingham, P., Glasser, U., Kinney, B., Singh, K., and Vajihollahi, M. (2005a). A computational model for simulating spatial aspects of crime in urban environments. *2005 IEEE International Conference on Systems, Man and Cybernetics* 4:3667-3674.

Brantingham, P., Glasser, U., Kinney, B., Singh, K., and 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*, pp. 101-117. Paris.

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

Brown, B. B. and 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., and 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 Park, R. E., Burgess, E. W., and McKenzie, R. D. (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*. Home Office, London.

Castle, C. J. E. and Crooks, A. T. (2006). Principles and concepts of agent-based modelling for developing geospatial simulations. *UCL Centre For Advanced Spatial Analysis Working Papers Series* Paper 110.

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

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

Cromwell, P. and Olson, J. N. (2005). The reasoning burglar: Motives and decision-making strategies. In Cromwell, P. (ed.), *In Their Own Words: Criminals On Crime (An Anthology)*, chapter 5, pp. 42-56. Roxbury Publishing Company, 4th edition.

Cromwell, P. F., Olson, J. N., and Avary, D. W. (1991). *Breaking and entering: an ethnographic analysis of burglary*, volume 8 of *Studies in Crime, Law and Justice*. Sage Publications, Newbury Park, London.

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.

Gaviria, A. and Pages, 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 Carter, H. and Davies, W. K. D. (eds.), *Urban Essays*, pp. 101-143. Longman, London.

Gilbert, N. and Troitzsch, K. G. (1999). *Simulation for the Social Scientist*. Open University Press, Buckingham, Philadelphia.

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.

Grubesic, T. and Murray, A. (2001). Detecting hot-spots using cluster analysis and GIS. Paper presented at the 5th Annual International Crime Mapping Research Conference, Dallas, Texas, USA.

Hearnden, I. and Magill, C. (2003). *Decision-making by house burglars: offender's perspectives. Home Office Research Findings 249*. Home Office, London.

Heppenstall, A. J., Evans, A. J., and 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., and Garofalo, J. (1978). *Victims of personal crime : an empirical foundation for a theory of personal victimization*. Ballinger, Cambridge, MA.

Jacob, C., Litorco, J., and 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, University of Leeds, School of Geography, Leeds LS2 9JT, UK.

Kongmuang, C., Clarke, G., Evans, A., and Ballas, D. (2005). Modelling crime victimisation at small-area level using a spatial microsimulation technique. Paper Presented at the RSAIBIS 35th Anual Conference, available at http://www.geog.leeds.ac.uk/people/c.kongmuang/SimCrimeIS.doc [accessed - May 2006].

Levine, N. (2006). Crime mapping and the CrimeStat program. *Geographical Analysis* 38:41-56.

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

Massey, J. L., Krohn, M. D., and 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. and Jayakumar, M. D. (1995). Determinants of crime in a developing country: A regression model. *Applied Economics* 27:455-461.

Miller, B. W., Hwang, C. H., Torkkola, K., and Massey, N. (2003). An architecture for an intelligent driver support system. In *Intelligent Vehicles Symposium*, pp. 639- 644. IEEE.

Moss, S. and Edmonds, B. (2005). Towards good social science. *Journal of Artificial Societies and Social Simulation* 8(4).

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

Neji, M. and Ammar, M. B. (2007). Agent-based collaborative affective e-learning framework. *The Electronic Journal of e-Learning* 5(2):123-134.

Pain, R., MacFarlane, R., Turner, K., and 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.

Rao, A. S. and Georgeff, M. P. (1995). BDI agents: From theory to practice. In Lesser, V. and Gasser, L. (eds.), *Proceedings of the First International Conference on Multi-Agent Systems (ICMAS-95), San Francisco, USA*. MIT Press.

Rengert, G. and Wasilchick, J. (1985). *Suburban Burglary: A Time and a Place for Everything*. Charles Thomas Publishers, Springfield, Illinois.

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

Robinson, M. B. and 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 (BRIL) programme. http://www.leeds-csp.org.uk/view.asp?id=54 [accessed - Nov 2007].

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

Scarr, H. A. (1973). *Patterns of Burglary*. U.S. Govenrment Printing Office, Washington, DC.

Schmidt, B. (2000). *The Modelling of Human Behaviour*. SCS Publications, Erlangen, Germany.

Shaw, C. R. and McKay, H. D. (1969). *Juvenile Delinquency and Urban Areas*. The University of Chicago Press, Chicago.

Shepherd, P., See, L., Kongmuang, C., and Clarke, G. (2004). *An Analysis of Crime and Disorder in Leeds, 2000/01 to 2003/04*. School of Geography, University of Leeds.

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

Shover, N. (1991). Burglary. In *Crime and Justice: A review of research*, volume 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., and Waltz, E. (2004). Agent-based simulation of geo-political conflict. In *16th Conference on Innovative Applications of Artificial Intelligence*. AAAI Press, San Jose, CA.

Taylor, M. and 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., and Brown, R. (1999). *Burglary prevention: Early lessons from the Crime Reduction Programme.* Policing and Reducing Crime Unit Crime Reduction Research Series Paper 1. Home Office, London.

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

Turner, A. and 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. and Stillwell, J. (eds.) (2004). *Twenty-first century Leeds: geographies of a regional city*. PLACE Research Centre, St John College, York.

Urban, C. (2000). PECS: A reference model for the simulation of multi-agent systems. In Suleiman, R., Troitzsch, K. G., and Gilbert, N. (eds.), *Tools and Techniques for Social Science Simulation*, Chapter 6, 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. and Rees, P. (2006). Introducing the national classification of census output areas. *Population Trends* 125.

Wilkström, P. (1991). *Urban Crime, Criminals and Victims: The Swedish Experience in an Anglo-American Comparative Perspective*. Springer-Verlag, New York.

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

Wright, R. T. and Decker, S. H. (1996). *Burglars on the Job: Streetlife and Residential Break-ins*. Northeastern University Press, Boston.

Appendix A

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

$$46 * 30 * 4 = 5520$$

where 4 is the arbitrary number of units which represent 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 – 40 is:

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

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

840x ⍰ 10 = 5520

$$x = 0.6571$$

so each day (between days 20 – 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.