

DRUG POLICY MODELLING PROJECT  
**MONOGRAPH 11**

**SIMDRUG**  
**EXPLORING THE COMPLEXITY OF HEROIN**  
**USE IN MELBOURNE**

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Drug Policy Modelling Project Monograph Series

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## **THE DRUG POLICY MODELLING PROJECT**

This monograph forms part of the Drug Policy Modelling Project (DPMP) Monograph Series.

Drugs are a major social problem and are inextricably linked to the major socio-economic issues of our time. Our current drug policies are inadequate and governments are not getting the best returns on their investment. There are a number of reasons why: there is a lack of evidence upon which to base policies; the evidence that does exist is not necessarily analysed and used in policy decision-making; we do not have adequate approaches or models to help policy-makers make good decisions about dealing with drug problems; and drug policy is a highly complicated and politicised arena.

The aim of the Drug Policy Modelling Project (DPMP) is to create valuable new drug policy insights, ideas and interventions that will allow Australia to respond with alacrity and success to illicit drug use. DPMP addresses drug policy using a comprehensive approach, that includes consideration of law enforcement, prevention, treatment and harm reduction. The dynamic interaction between policy options is an essential component in understanding best investment in drug policy. Stage One has: a) produced new insights into heroin use, harms, and the economics of drug markets; b) identified what we know about what works (through systematic reviews); c) identified valuable dynamic modelling approaches to underpin decision support tools; and d) mapped out the national policy-making process in a new way, as a prelude to gaining new understanding of policy-making processes and building highly effective research-policy interaction.

This monograph (No. 11) reports on the work of the complex systems scientists at ANU. Complexity Theory is a loose cluster of theories and methodologies aiming at understanding the properties of complex adaptive systems. Complex adaptive systems (CAS) are ones characterised by: emergence; path dependency; non state equilibrium; and adaptation. The heroin drug market fits these characteristics nicely. The features of the agent-based model, called SimDrug, include the spatial environment, time scale, and social agents. SimDrug includes different types of social agents: users, dealers, wholesalers, police constables, and outreach workers. Each type represents a minimum set of characteristics and dynamics that allow the whole artificial population to display most of the properties observed in real societies. The model has proved robust and stable. SimDrug has demonstrated the plausibility of using a multi-agent system model to describe the relationships between heroin users, dealers, their surroundings and the two interventions modelled (outreach workers and police). In future developments, we hope that policy makers will be able to use the model to determine potential scenario's as a result of their intervention.

Monographs in the series are:

01. What is Australia's "drug budget"? The policy mix of illicit drug-related government spending in Australia
02. Drug policy interventions: A comprehensive list and a review of classification schemes
03. Estimating the prevalence of problematic heroin use in Melbourne
04. Australian illicit drugs policy: Mapping structures and processes

05. Drug law enforcement: the evidence
06. A systematic review of harm reduction
07. School based drug prevention: A systematic review of the effectiveness on illicit drug use
08. A review of approaches to studying illicit drug markets
09. Heroin markets in Australia: Current understandings and future possibilities
10. Data sources on illicit drug use and harm in Australia
11. SimDrug: Exploring the complexity of heroin use in Melbourne
12. Popular culture and the prevention of illicit drug use: A pilot study of popular music and the acceptability of drugs
13. Scoping the potential uses of systems thinking in developing policy on illicit drugs

DPMP strives to generate new policies, new ways of making policy and new policy activity and evaluation. Ultimately our program of work aims to generate effective new illicit drug policy in Australia. I hope this Monograph contributes to Australian drug policy and that you find it informative and useful.



Alison Ritter  
Director, DPMP

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## COMPLEXITY THEORY IN CONTEXT

The Drug Policy Modelling Project aims to develop new tools for policy makers to improve the ways in which evidence is used. A number of modelling approaches have been explored, and this monograph outlines the complex system scientists work. The first section outlines how drug use and drug markets are complex phenomena. Approaches from complexity – dynamical systems models; network theory; and multi-agent systems – are then outlined. The third section describes the development of a multi-agent system (the model called *SimDrug*) followed by a summary of the preliminary results arising from the model. The monograph concludes with considerations of future development of *SimDrug*.

### Complexity of illicit drug use and markets

*“Still little is known about the structure and dynamics of drug markets at national, regional and global levels[...]. Illicit drugs are commodities at the centre of lucrative, clandestine and transnational markets. Albeit illegal, these markets obey basic supply and demand rules[...] Understanding the rules will help[...] Vigorous research programs into the way drug markets are structured, operate and evolve are required.”* (UNODC, 2004).

Ritter (2005), in her review of illicit drug markets, provides meaningful examples of their inherent complexity. Dorn, Murji, and South (1992), cited in Ritter (2005) describe a qualitative research study of drug markets in the UK. They interviewed a significant number of traffickers, police, police informers and user-dealers. Importantly, they make two central claims. First, they argue that there is no evidence for the large scale organised, top-down hierarchies. Second, the researchers found that the drug markets are constantly fluid and changing. Some of the variables that may drive this diverse and ‘messy’ phenomenon include social background, resources and cultures. The researchers describe people weaving in and out of the trade, with constant interactions with law enforcement resulting in market changes.

Ritter (2005) also mentions, in the USA, research from South (2004) who describes two case studies of heavy recreational drug users. In this context of small-scale dealers, selling drugs becomes a norm with its inherent rules. The author emphasises the fact that better understanding the epistemology of these markets challenges existing notions of drug dealers. May and Hough (2004) describe trends in the American drug market over 10-15 years. They note the change in the market from an open street-based market to a closed market, and associate this with the widespread introduction of mobile phones, coupled with community concern about public space. The authors highlight the dynamical influence of both technology development and law enforcement on the type of market and its operation.

From an economic perspective - while acknowledging the limitations of a pure economic modelling approach - Caulkins and Reuter (1998) argue that price data can be used to test assumptions and characterisations of drug markets. In addition, policy implications can be modelled against price changes. In a more recent paper, the same authors - coming from a psychological, decision-making perspective - describe a model where dealers operate under limited rationality, providing one explanation for the fall in heroin and cocaine prices in the US despite increases in law enforcement intensity (Caulkins & Reuter, 2005). They draw an important distinction between the initial decision to sell drugs, and the decision to continue selling drugs. Using prospect theory, they demonstrate the differences in risks and benefits. From a criminological and anthropological perspective, Mazerolle et al (2004) use cluster analytic



techniques to identify types of drug-dealing places. The six different types identified by Mazerolle were characterised by environmental features such as police calls for service, degree of commercial or residential activity, length of the street block, civil activity and civil disorder.

Complexity of illicit drug markets mirrors the complexity of illicit drug use itself. Unger and colleagues (2004) clearly summarise the challenges we face when trying to understand, describe, and eventually simulate users' behaviour:

*“Drug use is a result of a complex, dynamic interplay of posited risk and protective factors that operate at multiple levels of analysis. At the individual level, biological predispositions, personality traits, and cognitive mechanisms can increase or decrease the likelihood that adolescents will experiment with drugs, as well as the likelihood that they will become physically or psychologically dependent on drugs. At the interpersonal level, social influences from peers, family members, and other role models or networks can influence individuals' perceptions of the social norms surrounding drug use, which then can influence their own use of drugs”* (Unger et al., 2004).

According to Rhodes (2002), a harm reduction praxis founded on a risk environment framework encompasses social contexts that influence health and vulnerability in general as well as drug-related harms in particular. This inevitably leads to a consideration of non-drug and non-health specific factors in harm reduction, and in turn, points to the importance of what might be described as ‘non health oriented interventions’ in harm reduction.

In Australia, the advent of what is known as the heroin ‘drought’ provides a paramount example of the complex interactions at stake and the conflicting analysis drawn by experts coming from different disciplines. According to Dietze and colleagues (Dietze et al., 2003), the supply of heroin in Victoria suffered a dramatic decline between late 2000 and early 2001, after a strong increase in heroin use and related harms in the late 1990s. This change in heroin supply was clearly reflected in decreases in heroin overdoses. Relying on different sources of information, the authors argue that the drought was shadowed by a dramatic increase in amphetamine, benzodiazepine, and prescribed opioid use, resulting in a fairly constant number of injecting drug users in Victoria.

What happened in Australia from late 2000 was unique to that country. Despite a worldwide growth in the availability of stimulants – notably methamphetamine – no other country experienced a comparable shortage of heroin, or the extensive use of stimulants as an alternative to heroin. The Australian heroin drought is held up by the Australian Government as an example of law enforcement having a significant impact on the supply of drugs. As a matter of fact, the Australian Federal Police had seized 606 kg of heroin and dismantled a major drug trafficking syndicate, a few months before the drought. But Bush and colleagues (Bush et al., 2004) argue that this explanation does not stand up to more detailed scrutiny, as other factors were more influential. According to the authors, the most plausible explanation for both the heroin drought and the increase in the availability of stimulants is the strategic decisions and actions of the crime syndicates that supply the Australian market. Interestingly, Agar and Reisinger (2002) develop an equivalent rationale about the heroin drought that occurred in the USA during the mid-1970s. They counter-balance the impact of the “French Connection” breaking up with the rise of methadone-based replacement programs. The authors insist on the complex adaptive properties of the illicit drug use issues.

In order to have a dispassionate look at the question, one must first gather information coming from law enforcement, intelligence, treatment, prevention, and harm reduction sources. Then, this heterogeneous information must be critically analysed before being used to confront and

explore the different plausible scenarios. In a broader context of substance misuse, Fuqua and colleagues (2004) rightfully claim that the whole process needs a transdisciplinary approach to describe such complex systems from more than one vantage point. This claim is particularly relevant in the case of illicit drug use.

Hence, it is not surprising that complexity theory has attracted an increasing number of scientists working in the domain of population health and epidemiology. For example, August and colleagues (2004) describe the complexity of prevention program implementation. The authors outline the challenges faced by developers of prevention programs in transporting scientifically proven or evidence-based programs (efficacy) into natural community practice systems (effectiveness). The intricacy of multiple interactions between individuals, the various timelines linked to different aspects of drug policy interventions, and contrasting social rationalities observed among field practitioners (prevention, law enforcement, harm reduction, treatment) contribute to the creation of a complex and unpredictable system.

## **Complexity theory and human ecosystems**

Rather than a well-structured scientific corpus, Complexity Theory tends to gather a bundle of theories and methodologies aimed at understanding properties of complex adaptive systems (Richardson and Cilliers, 2001). According to Holland (1995), these systems display the following characteristics:

- **Emergence:** a system-level phenomenon is emergent if it requires new categories to describe it, which are not required to describe the behaviour of the underlying components. In other words, interactive individual components instantiate emerging patterns at the level of the system.
- **Path dependency:** due to the highly non-linear relationships between individual components or parts of the system, a given system-level phenomenon can be achieved – in theory - through an infinite number of combinations at the micro-level.
- **Non state equilibrium:** the Complex Adaptive Systems display an ever-changing dynamic equilibrium, driving the system back and forth between chaotic and ordered states. On the edge of chaos, these systems are very sensitive to any perturbation from the individual components.
- **Adaptation:** the evolution of the system is driven by the co-evolution of its individual components. They adapt to their environment and modify it in a recursive way. If the components are cognitive beings, the adaptation relies mainly on the individual and collective learning processes.

Human ecosystems constitute a subset of complex adaptive systems. They correspond to real life systems characterised by very strong and long-term interactions between human communities and their environment. According to Stepp et al. (2003), human ecosystems not only process matter and energy flows, but – and more specifically – information flows as well. Therefore, they display very specific characteristics. Batten (2000) demonstrates how they are inherently complex and adaptive, due to the ability of human beings to switch from rational deductive reasoning to inductive pattern recognition, in order to solve (with more or less success) any given problem. In addition, our ability to communicate and learn from others creates the conditions for co-

evolutionary processes where positive feedback loops follow negative ones, punctuation dispels equilibrium, chaos threatens order, and chance gives a hand to necessity.

As a matter of fact, Complexity Theory falls in between the world of trustworthy deterministic demonstrations and the realm of reassuring statistical certitudes. Hence, our understanding of complex adaptive systems is highly uncertain due to two different causes: unpredictable non-linear interactions and ill-defined predicates. Unpredictable non-linear interactions are the *raison d'être* of these systems. Arthur (1994) proposed a very simple but paramount metaphor to demonstrate their impact. He describes the behaviour of regular patrons to a virtual bar called El Farol. They have to decide independently each week whether or not to go to their favourite bar next Thursday. Space is limited, so the evening is enjoyable only if the bar is not too crowded. Because of the self-referential condition, no individual decision model exists that could provide a deductive solution to the problem. Irrespective of past attendance figures, and because of their bounded rationality, patrons are forced to reason inductively. But the intriguing overall result of corresponding computer simulations is that – regardless of the ever changing set of individual decisional rules – the average attendance at the bar fluctuates around a critical value, creating a very stable system-level pattern. Thus, the complex interactions between perfectly deterministic individual behaviours drive the system into an emergent simplicity.

Ill-defined predicates – more frequently encountered than usually admitted – rely on our limited ability to infer robust causality links among given sets of elementary processes. For example, Durkheim (English translation, 1979), in his famous study of suicide, concluded that no matter how much a researcher knows about a collection of individuals, *“it is impossible to predict which of them are likely to kill themselves. Yet the number of Parisians who commit suicide each year is even more stable than the general mortality rate”*. A process that seems to be governed by chance when viewed at the level of the individual turns out to be strikingly predictable at the level of society as a whole. One would argue that statistics prevail in this case, but others would admit that we don't know enough yet about the intimate social dynamics that control such a deviant behaviour. Finally, we have to agree with Bradbury (2000) that human ecosystems are inherently unpredictable as a whole: *“their futures are not determined. Their global behaviours emerge from their local interactions in complex, historically contingent and unpredictable ways”*.

In the 1980s, Complexity Theory appeared like a Promethean gift on the altar of science. Twenty years down the track, a unified theory is still to be written but insights into complex adaptive systems are more likely thanks to three different scientific streams, namely, Multi-Agent Systems, Dynamical Systems, and Network Theory.

### **Multi-agent systems**

Scientists using Multi-Agent Systems tend to focus on the individual components interacting within a given system. This is a purely bottom-up approach where representations of the individual components – the agents – display a large autonomy of action. Hence, system-level behaviours and patterns emerge from a multitude of local interactions. Intentionality is deliberately placed at the level of the agents to the detriment of the system itself, greatly limiting its ability to control its own evolution. In the case of human ecosystems, agents can represent individual actors or relevant social groups and communities (Bousquet and LePage, 2004). Ferber (1999) proposes the following definition of a Multi-Agent System (MAS) that should include:

- An environment (E), often possessing explicit metrics.

- A set of passive objects (O). Objects can be located, created, destroyed or modified by the agents.
- A set of active agents (A). Agents are autonomous and active objects of the system.
- A set of relationships (R) linking objects and/or agents together.
- A set of operators (Op) allowing the agents to perceive, create, use, or modify the objects.

According to the same author, an agent is a physical or virtual entity that demonstrates the following abilities: autonomy, communication, limited perception, bounded rationality, and decision-making processes based on satisfying goals and incoming information. A Multi-Agent Based Simulation (MABS) is the result of the implementation of an operational model (computer-based), designed from a MAS-based conceptual representation of an observed system. The strength of MAS approaches lie in their ability to represent socially and spatially distributed problems. Meaningful examples of application come from ecology (Janssen, 2003), sociology (Conte and Gilbert, 1995), and economics (Tesfatsion, 2002). Cederman (2005) asserts that generative process theorists in social science - shifting from traditional nomothetic to generative explanations of social forms, and from variable-based to configurative ontologies – may find in Multi-Agent Systems relevant tools to explore the emergence of social forms in the Simmelian tradition, thanks to common foundations in both epistemology and ontology.

The main criticism associated with Multi-Agent Based Simulations is their inability to generate optimal system-level solutions. Klugl and Dornhaus (2002) rightfully argue that some properties of the original system may make the approach not advisable:

- If it is not clear, what parts of the system can be identified as agents. Components with simple non-autonomous behaviour or systems with fixed direct connections between components with well defined input-output behaviour can be tackled with better developed methods.
- If the considered space has a large extension or the agent numbers are huge, then an abstraction of homogeneous space and homogeneous societies may still be satisfying. A macro simulation approach might to be sufficient.
- If a formal analysis of the model without simulation is necessary then a modelling method resulting in an exact and explicit model is necessary. Such a modelling method does not yet exist for multi-agent models.

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## **Dynamical systems**

Scientists using Dynamical Systems tend to focus on the flows of information, mass and energy within a given system. Practically, modellers describe systems as a set of modules or compartments interlinked by flows and controls. The compartments are used to represent the stocks (aggregated variables) of information, mass, or energy available at any time. It is thus possible to link social, ecological and economic components into an integrated model. Each sub-system dynamic is controlled by other sub-systems. For instance, stocks of a resource are controlled by the harvest, which in turn is controlled by capital (Ford, 1999). The theoretical assumptions supporting Dynamical Systems include the concepts of state equilibrium and resilience. As a consequence, complex adaptive systems under study move from one stable state

to another according to external forces or internal tensions. According to its degree of resilience, the system is attracted to another stable state or not (Holling, 2001). Dynamical System Modelling (DSM) is the result of the implementation of an operational model (computer-based), designed from a DS-based conceptual representation of an observed system.

Coming from historical sociology, Turchin (2003) asserts that using DSM, based on differential equations, to model complex adaptive systems has several advantages. First, it has been greatly standardised, so that a model written as a system of differential equations is much easier to grasp than the computer code describing the same assumptions. Second, analytical results are available for most simple or medium-complexity models. Even if we do not have an explicit analytical solution (which is the case for most nonlinear models), we can obtain analytical insights about qualitative aspects of long-term dynamics predicted by these models. Third, numerical methods for solving differential models have been highly standardised. Thus, other researchers can rather easily check on the numerical results of the authors. Ecological modelling provides various examples of Dynamical Systems use (Anderies, 2000; Janssen et al., 2000).

Obviously, Dynamical Systems offer a system-wide interpretation of the local interactions between individual components. Hence, a strong intentionality is placed at the global level that dictates its own evolution. Associated with Control Theory, it is possible to use Dynamical System Modelling in order to infer optimal predictions. But Gilbert and Troitzsch (1999) perceive several flaws in this system-wide approach:

- *Global analysis.* The mathematical model describes global phenomena occurring at the system level. Thus, variables and parameters are located at the same macro-level of analysis.
- *Opacity of the parameters.* Sometimes, the system of differential equations needs global parameters, difficult to estimate from observation or simply unrealistic to establish.
- *Absence of action.* Mathematical models consider actions through their consequences at the global level or through their probability of occurrence. Hence, emerging phenomena cannot be detected.
- *Qualitative deficiency.* Mathematical models are inherently unable to take into account qualitative information coming from the real system.

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## **Network theory**

Scientists using Network Theory tend to focus on the structure of interactions between individual components of a system. Network Theory embodies the idea of objects and relationships at the most fundamental level. Practically, a *graph* is a set of *nodes* (also called vertices) that are joined by *edges* (also called links). A *directed graph* is a graph in which each edge has a direction. Finally, a *network* is a directed graph in which each edge or node has attributes. Network parameters include: the number of nodes in the network (size); the number of connections per node (connectivity); the template for the neighbourhood of each node (neighbourhood); function(s) that describe the interaction between nodes (rule scheme); and the method for changing the state of each node (updating). Several specific networking structures (random graphs, small worlds, scale-free networks) have been described and related to existing natural, social, or artificial systems (Watts, 2003). Network Theory assumes that many aspects of a system's behaviour and properties arise from its network structure. Hence, the theory offers a holistic view upon a given

system where interacting parts are represented at the same time as the global body. Research on ‘how?’ and ‘why?’ networks self-organise in time is at its very early stage, and intentionality is placed within the structure itself that dictates the evolution of the system. Hence, collective properties like cohesion, consensus, or cooperation can be interpreted through structural indicators (Stocker et al., 2001).

Understanding collective social behaviour, once individual attitudes are known, requires taking into account the interactions among the individuals of the group and acknowledging that these interactions are mediated by a network of social relations. For this reason, many sociologists interested in social networks developed early collaborations with network theorists. This is the case in epidemiology where diffusion processes are usually run over networks mimicking social communities (Meyers et al., 2005). But in the same way that the actions of individuals are affected by the social network, the network is not an exogenous structure but is created by individual choices. However, there are not many specific models of social dynamics that explicitly incorporate the concept of co-evolution of individual and network (Eguiluz et al., 2005). Most recent work from Robin and colleagues (2005) provides some theoretical insight into self-organisation of networks from elementary dyadic or triadic relationships between nodes.

Beyond the capacity of Network Theory (NT) to provide a consistent analytical framework for studying multidimensional and evolving structures, some weaknesses currently remain:

- Limited agency: nodes are not agents. They can be given some decisional rules or optimisation algorithms, but their autonomy is inherently limited.
- Spatial fixity: networks can display spatially distributed properties but they hardly cope with the eventual mobility of the entities represented by the nodes.
- Temporal dynamics: the two previous limitations prevent network-only based simulations to provide realistic evolution of a system over a long period of time.

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### **Cross-breeding perspectives**

Recent developments in the field of Complexity Theory indicate that future research will increasingly involve cross-breeding methodologies. Thanks to the incremental flexibility and calculation capacities of the new generation of computers, coupling Multi-Agent Systems with Network Theory, or blending Dynamical Systems and Network Theory, are already being explored by pioneering research teams. Influential outsiders coming from anthropology (Lansing, 2003), epidemiology (Agar and Reisinger, 2003), or system thinking (Lissak and Richardson, 2001) are instrumental in driving such evolution.

### **Complexity theory and illicit drug use**

Gorman and colleagues describe drug use-related problems as heterogeneously distributed with respect to population and geography. Therefore, the authors propose to consider these problems as essentially based on local interactions. More specifically, they perceive a local community as “*an interacting set of systems that support or buffer the occurrence of specific substance misuse outcomes*” (Gorman et al., 2004). As a consequence, our understanding of these systems requires the creation of adequate models that can capture the primary community structures and relationships that

support drug use and related outcomes. According to the authors, researchers in the field of addictions must turn to complexity theory approaches in order to better explore the systems they try to understand and better anticipate implications of drug use for public policy and prevention programming:

*“The dynamics of the impact of alcohol and illicit drugs depend on space, time, the topologies of social systems as well as a range of actual and potential bounded (culture, age, gender, ethnicity, religiosity, etc.) phenomena. For example, the economic geography of drug markets likely differs between Friday night and Monday morning. In addition, the effects of the parameters in the system—social capital, collective efficacy, concentrated poverty, etc.—are rarely precisely quantifiable, and can interact in complicated nonlinear ways. Models that capture the behaviour of these complicated community systems and control strategies that modify them must, therefore, combine available data, statistics, and spatiotemporal dynamics”* (Gorman et al., 2004).

Drawing from Dynamical Systems and Control Theory, the authors observe that - given the unique nature of each nonlinear and dynamic system - interventions are most effective when they are context specific and informed by context-specific data. Moreover, system analysis may reveal that there are numerous possible solutions available, and that in each case the potential outcomes are uncertain, thereby calling for caution in policy development. In fact, the best global solution may be a collection of local solutions tailored to local circumstances and needs. Obviously, such an approach may not have a great deal of intuitive appeal to policymakers, who favour large scale standardised interventions that promise to deliver assured, definite, and extensive outcomes.

In a broader context of health geography, Gatrell (2005) considers the primary characteristics of Complexity Theory, with particular emphasis given to networks, non-linearity, and emergence. The author acknowledges its capacity to move away from reductionist accounts and to propose new perspectives on sociality and connectedness. Research on health inequalities, spatial diffusion, and resurgent infections, have much to learn from Complexity Theory provided that modelling results are inferred from “*good empirical work*”. Gatrell rightfully underlines the fact that:

*“Metaphors and some of the methods used in complexity theory are essentially visual. Despite the disappearance of the graphical [...] from much of the research literature, the ‘seeing eye’ and the ability to detect and describe pattern remains at the forefront of many research methods, including health geography”* (Gatrell, 2005).

Agar and Reisinger (2003) have developed over the years an empirical theory of illicit drug epidemics, called ‘Trend Theory’. They first look for a rapid increase in incidence. The assumption is that this rapidly increasing curve is an emergent property of systems that are themselves undergoing rapid change. Thus, they look at relevant segments of a society (clusters) where major ongoing changes may be linked to the drug. They also assume that changes are underway in the system of production for the illicit drug. Finally, they assume that change is also ongoing in the networks that link the production system with the population. Trends are dynamic and must be understood over time as they develop. Agar and Reisinger admit that:

*“The most difficult part of trend theory work is that each ‘data point’, if you will, represents a complicated research effort. A massive amount of different material must be gathered, where most of it does not directly ask or answer the questions that we have. [...] With any luck, the effort to build a trend theory will help in some way as the drug field continues to struggle with that key epidemiological question: why these people in this place at that time?”* (Agar and Reisinger, 2003)

In a previous paper, the same authors recognise that complexity underlies Trend Theory (Agar and Reisinger, 2002), in as much as complex adaptive systems consist of different actors in

different sub-systems, all in continual change over time as they evolve with their environment. Complexity theory also indicates that measures of the system as a whole – like epidemiological indicators of heroin addiction – are often emergent processes. Agar and Reisinger believe that explanation of a phenomenon of interest is not available in the location where that phenomenon takes place. Instead, events – most of them at remote social locations – unfold and interact over time, and the local phenomenon is only one of a number of factors involved. An explanation of a trend calls for a model of how that system works. A heroin trend increases when distant systems, by both chance and design, enter into interlocking feedback loops.

Epidemiologists have pioneered the use of Complexity Theory in Population Health. Outbreaks have been simulated through percolation processes into artificial networks or by means of emerging properties of artificial societies composed of interacting agents. For example, recent work from Meyers and colleagues (2004) demonstrates how contact network epidemiology better explains the heterogeneity of SARS outbreaks worldwide, compared with traditional compartmental modelling. Likewise, Valente and colleagues (2004) use network level measures (centralisation, density, transitivity) to explore the impact of social networks on drug use among adolescents. In this case, network analysis provides a technique to map specifically who has adopted evidence-based programs and where they are in the network. Hence, the network map provides important monitoring information indicating how well the practice is spreading.

Agar and Wilson (2002) provide a compelling example of Multi-Agent Based Simulation in the context of youthful heroin experimenters in the Baltimore metropolitan area. The model is used to explore the impact of circulating stories of drug reputation on individual attitudes towards the drug. Based on ethnographic work, the model demonstrates a dampening effect of increased social connections, contrary to epidemiologic expectations. As described by the authors:

*“To summarise, [...] five hundred agents begin with normal, randomly distributed risk and a shared attitude set to some number with a parameter. The agents move around and, if they encounter heroin, they compare attitude to risk. If attitude is higher than T-risk, they try the heroin. And, if they try it, they have good or bad experiences, with some probability, and those experiences, should they occur, change their attitude by some amount. Agents also change their attitude, depending on the “buzz” around the drug that they pick up as they move around the world. After a tick of the model, any adjacent agent might influence their attitude. The chances they do so, and the amount of the influence, will depend on the combined effect of both agents’ experiences. Chances and amount also depend on whether the two agents are strangers or friends” (Agar and Wilson, 2002).*

Mason and colleagues (2004) describe a slightly different approach to modelling environmental impact on urban youth drug use. The approach incorporates individual, social, and geographical parameters to systematically understand the ecology of risk and protection for urban youth. Geographic Information Systems (GIS) derive spatial relationships and use data on specific locations where the teenagers are active, their subjective ratings of these locations, and objective environmental risk. These social network and GIS data are merged to form a detailed description and analysis of the social ecology of urban adolescent substance use.

Even Chou and colleagues (2004), despite a strong empathy for statistical methods – a shared language between experts involved in trans-disciplinary drug use research – recognise that:

*“While the statistical models discussed later are based on assumptions of linear associations, nonlinear association can also be handled by some of these models. It should be noted that to understand and appreciate the dimensions of the process or phenomenon being studied, data-driven selection of either a linear model or a nonlinear model is*



*critical. Using linear tools to study non-linear processes can yield misleading conclusions that impact the planning, implementation, and assessment of intervention programs” (Chou et al., 2004).*

Finally, Agar (2005) building on his previous work, recently argues for ‘emic’ models, models grounded in what matters in the world of those being modelled. But most models are ‘etic’, in the sense that they are built on an outsider’s view of the people and the world being modelled. In a pure positivist stand, etic models represent how the modeller thinks the world works; emic, how people who live in such worlds think things are. In a very inductive and post-normal move, Agar equips his artificial agents with rules of decisions coming from individual responses to ethnographic surveys. By doing so, he tries to explore and better understand the reasons for an early experimenter becoming dependent, based on social ties. The author recognises that despite his commitment, some etic-based knowledge pervaded his model but he emphasises the importance of a strong empirical experience to back up such complex modelling. This is the only current example of post-normal modelling in the domain of population health, unlike environmental studies where participatory modelling experiences are rapidly developing (Bousquet et al., 2004).

## **SIMDRUG – MODEL DESCRIPTION**

### **Background**

In September 2004, during the inaugural DPMP workshop, the Complexity Theory group was asked to present advantages and limitations of using this approach for modelling illicit drug use and markets. Two key issues shaped the boundaries and content of the present project:

- Finding a case study that would contain – a priori – as much complexity as possible and would provide the information needed to build a consistent model.
- Fitting into the actual structure of the DPMP project in order to interact efficiently with relevant experts and to avoid undesirable overlapping with other on-going research.

Dynamical Systems were already used by the epidemiological and system thinking groups, our group had to choose between Network Theory and Multi-Agent System for our initial approach. Looking at the Australian illicit drug markets through a cross-scale approach, it seemed that urban districts constituting a ‘drug scene’ involved most of the actors (with exception of importing syndicates and production cartels) while displaying a maximal complexity. As a matter of fact, this intermediate scale fits in between statistical accounts at the State or National levels, and ethnographic accounts of street-based interpersonal interactions and individual motivations. Social heterogeneity, spatial mobility, and abrupt changes characterise drug scenes. Global patterns and trends emerge from multiple interactions both distant and local.

Rapidly, the ‘Melbourne heroin scene’ was perceived as the best option because of the following features:

- A well documented history of heroin use in Melbourne CBD and surrounding suburbs (hot spots) showing the cultural dimension of the local heroin scene.
- A trans-disciplinary team (sociology, psychology, epidemiology, and economics) already working on the case study and having developed a comprehensive database.
- A legitimate questioning of local authorities on balancing law enforcement, treatment and harm reduction programs.
- A retrospective view upon the conflicting explanations that arose after the so-called ‘heroin drought’.

Most of the potential agents in the system were clearly identified but various aspects of their interdependent links were ill-defined, hence we decided to opt for a Multi-Agent System approach rather than a Network Theory one. Beside, the trans-disciplinary communication that would be needed advocated for a rather more intuitive modelling approach. The ‘building blocks’ methodology attached to Multi-Agent Systems, and the visual paradigms (UML design) used to describe the modelling components, appeared to be highly relevant. The trans-disciplinary expert panel involved: P.Perez (design), A.Dray (modelling), A.Ritter (psychology), P.Dietze (epidemiology), T.Moore (economics), and L.Mazerolle (criminology).

## Model description

The model is created with the Cormas<sup>®</sup> platform (Bousquet et al., 1998), developed from the VisualWorks<sup>®</sup> commercial software. Cormas<sup>®</sup> provides a SmallTalk<sup>®</sup>-based environment to the developer where spatial visualisation, graphic results, and sensitivity analysis tools are already encapsulated. Hence, the modeller can concentrate on the development of the application only, without bothering with peripheral but time consuming tasks.

### Time scale

We have decided to work on a daily basis, meaning that one modelling time step is equivalent to a 24h-day in reality. A first compromise among the group of experts was established around a fortnightly structure, but later developments showed that injecting behaviours needed more accurate time steps. Each simulation is run over a 5-year period. As a matter of fact, even if the ‘heroin drought’ period is our main target, we assume that different processes (with different response times) were at stake. Thus we take 1998-2002 as the reference period. In terms of validation, this time bracket gives us the opportunity to test the robustness of the model by comparing a series of micro (agent level) and macro (system level) indicators with corresponding observed data. The model must be able to consistently reproduce pre-drought, crisis, and post-drought dynamics of the system.

### Spatial environment

We have decided to work on an archetypal representation of Melbourne based on a regular 50\*50 square mesh. The size of the grid has been chosen according to the number of users (3000) and dealers (150) to be modelled and located in the environment. At this stage, there is no need to work on a real GIS-based representation since we mainly focus on social behaviours and interactions. Each cell - elementary spatial unit - corresponds to a *street block*. A *suburb* is defined as an aggregation of neighbouring cells. Five suburbs are created with different sizes and shapes, regardless of realistic features. In fact, the environmental mesh is a Cellular Automata able to process a large amount of information at the level of each cell. Two special cells represent the *Police Station* and the *Treatment Centre*.

#### Street block

The main characteristics (or attributes) of a *street block* are: the number of **overdoses**, **fatal overdoses** and **crimes** locally recorded. The following table summarises the list of attributes and their corresponding meaning.

**Table 1: Street block attributes, variable type and description**

Attribute	Type	Description
crime	integer	Number of crimes committed in the block
overdoses	integer	Number of non fatal overdoses
fatalOverdoses	integer	Number of fatal overdoses
wealth	integer	Cash value available for successful crimes
risk	integer	Indicator of environmental risk
conductivity	boolean	Attractiveness for drug dealing

Each street block has a **wealth** value, interpreted as a synthetic parameter indicating the social and material capital of the place. Initial values of wealth are randomly attributed and range between \$100 and \$500. Each time a crime is committed in a street block, its wealth value decreases by 5%. Conversely, after a 10-day period without crime, the wealth value increases by 3% (**updateWealth**). Wealth values are limited to a maximal value of \$500. The initial wealth values come from ethnographic surveys of arrested offenders and correspond to the average money they can get from receivers. The increase and decrease rates are not calibrated yet.

The concept of risk environment is encapsulated into the **risk** attribute. An empirical linear equation is used to calculate risk values at each time step:

$$risk = (10 * nb\ of\ crimes) + (10 * nb\ of\ overdoses) + nb\ of\ users\ on\ the\ street\ block$$

At the beginning of the simulation, each street block is initialised with a risk value of 0. Risk values are used to calculate social dissatisfaction at the level of the suburb (see below), and to calculate the **conductivity** of a given street block to drug dealing. The following rules apply:

One street block becomes *conductive* (i) if there is a dealer or (ii) if risk > 20 or (iii) if there are at least 4 conductive street blocks around.

One street block becomes *non-conductive* if there is no dealer and (i) if the risk = 0 or (ii) if there is at least 4 non-conductive street blocks around.

### **Suburb**

Each suburb is able to calculate an average risk over its belonging street blocks. This overall risk is interpreted as a measurement of the social dissatisfaction (**suburbProtest**) of the local residents. When the corresponding value reaches a score of 5 or above the police station needs to intervene (see below).

### **Police Station**

There is only one Police Station for the whole system. Constables without identified mission return to the Police Station. Likewise, arrested users, dealers, and wholesalers are transferred to the Police Station before being retrieved from the system (**removeDetainees**). At each time step, the Police Station sends constables to suburbs with **suburbProtest** values > 5 (**crackOnDealer**). In reality, operations against wholesalers are often initiated by special units (drug squads) and rely on external intelligence or insider's information. Hence, we decided that the Police Station has a 0.25% chance to get reliable information and to send constables to the corresponding address (**crackOnWholesaler**).

**Table 2: Police attributes, variable type and description**

<b>Attribute</b>	<b>Type</b>	<b>Description</b>
arrestedUsers	integer	Number of arrested user-dealers
arrestedDealers	integer	Number of arrested dealers
arrestedWholesalers	integer	Number of arrested wholesalers
seizure	integer	Quantity of drug seized from wholesalers
allConstables	constable objects	List of constables

### Treatment centre

We created one Treatment Centre that receives users who decide to undergo a treatment program. The overall capacity of the Centre corresponds to 1000 patients. Three programs are available, differentiated by their duration and estimated success rates (based on Australian treatment outcome data):

**Table 3: Treatment programs, duration and abstinence rate**

Treatment	Duration (days)	Success rate
Detoxification (residential)	8	3%
Therapeutic community (TC) (residential)	76	30%
Methadone maintenance (non residential)	200	25%

Outreach workers (see below) without mission come back to the treatment centre. Likewise, users undergoing detoxification or TC programs move to the treatment centre.

### Social entities

SimDrug includes different types of social agents: *users*, *dealers*, *wholesalers*, *constables*, and *outreach workers*. Obviously, these computer entities don't accurately mimic individual behaviours of their real life counterparts. In fact, each type represents a minimum set of characteristics and dynamics that allows the whole artificial population to display most of the properties observed in real societies. The trans-disciplinary work plays a paramount role in defining a consensual set of simplified rules for the corresponding agent to 'behave' realistically.

Another issue deals with the creation of a closed or open system. In a closed system, the initial set of agents remains in the system during the whole simulation, with the exception of individuals who die in the meantime. The only way to increase the population is to implement reproduction mechanisms at the level of the agents. This is a largely used solution among agent-based modellers as it helps keep system dynamics partly under control. An open system allows the entry into and exit from the system of a given number of agents at any point in time. It becomes much more complicated to track back any single individual trajectory, but these systems suit much better bar-like problems (bar attendance, airport lounge flows, market place encounters).

We chose to implement an open system that sustains a constant number of *users*, *dealers*, and *wholesalers* (*constables* and *outreach workers* remain the same). At each time step, for a given number of users who die from overdose, or escape addiction through treatment, or finish in jail, the equivalent number of new users will be created at the next time step. Likewise, a given number of arrested dealers or wholesalers will be automatically replaced. This strong assumption is based on the fact that no evidence supports the eventual change of users' or dealers' population sizes in Melbourne, beyond limited fluctuations.

### User

Estimations for Melbourne give a range of 30,000 to 35,000 drug users considered as regular or dependent heroin users. These figures represent nearly 50% of the estimated Australian population of dependent heroin users. In order to keep computing time into reasonable limits, we have decided to create a 1/10<sup>th</sup> model of the reality: 3,000 *users* are created in SimDrug. They

are randomly located on the grid at the beginning of the simulation. At each time step, the **createUsers** method will add new *users* into the system. The following table summarises the list of attributes and their corresponding meaning.

**Table 4: User attributes, variable type and description**

Attribute	Type	Description
cash	integer	Available money
crimeIntention	boolean	Readiness to commit a crime
drugNeed	integer	Daily needs of drug (in g)
drugShortage	integer	Number of consecutive days without a fix
myDealerLocation	streetblock object	Address of the current dealer
overdose	boolean	Declared overdose
previousDrug	symbol	Memory of last drug type used
myLocation	streetblock object	Home cell of the user
regularIncome	integer	Money from CentreLink
readinessForTreatment	integer	Attitude towards treatment program
readyToSell	boolean	Capacity to become an active user-dealer
myDrug	drug object	Current drug type, quantity, and quality
treatmentType	symbol	Detox / Methadone / TC / none
treatmentDays	integer	Duration of undergone treatment

CentreLink-like payments provide a \$200 fortnightly **regularIncome** to the users. This amount represent between 50% and 80% of real payments and takes into account withdrawal for other primary needs. Individual **cash** is increased with the profit made from crimes (burglary, shoplifting) or drug dealing (triggered by the **readyToSell** attribute).

Individual **drugNeed** is a constant value that indicates the agent’s degree of addiction. An early version of the model included individual trajectories from light to severe addiction. But the expert panel agreed that there was not enough evidence of such linear trends and decided the creation of three initial cohorts of users (based on ethnographic survey):

- Light addiction: 0.02 g/day for 30% of users equivalent to 1 fix/day
- Moderate addiction: 0.04 or 0.06 g/day for 54% of users equivalent to 2-3 fix/day
- Severe addiction: 0.08 or 0.1 g/day for 16% of users equivalent to 4-5 fix/day

At this stage, a user can buy and use only one type of drug at a time from his/her dealer. Each user is affiliated to one dealer’s location and goes to the same hot spot as long as the dealer is selling drugs. As soon as the dealer disappears, all the affiliated users have to find another provider by walking around or contacting friends. Information regarding the drug bought is stored in the attribute **myDrug**. In this prototype, we consider a street market with only two drugs available: “heroin” and “other” (being a generic term for amphetamines, cocaine, etc...).

A user will have a 0.5% chance to declare an **overdose** when injecting heroin if one of the following conditions is fulfilled: (i) the previous drug injected was not heroin (**previousDrug**: other), or (ii) variation in quantity from previous injection > 0.02 g, or (iii) variation in purity

from previous injection > 15%. A user declaring an overdose has a 90% chance to be rescued if there is another user around to call for an ambulance. The two chance parameters are partially calibrated against global figures of fatal and non fatal overdoses in Melbourne during the pre-drought period (reference year: 1999).

The attitude of users towards treatment programs is summarised within the attribute called **readinessForTreatment**. The initial individual values are randomly picked between 10 and 50. A decrementing process – borrowed from literature on diffusion of innovation – slowly raises the motivation of the user each time he is targeted by an Outreach Worker (decrement: -1) or each time he witnesses or experiences an overdose (decrement: -1). The value of the attribute is reset at 20 each time a user comes out from an unsuccessful treatment period. The initial range of values is partially calibrated against the observed average chance for a real user to enter a treatment program over a one year period. When the value of **readinessForTreatment** has reached zero, the corresponding user has 20% chance to enter a detoxification program, 10% to enter a TC program, and 70% to enter a methadone program (**treatmentType**). The actual implementation depends on the *Treatment Centre's* capacity to undertake the treatment (see below). Detoxification and TC are residential treatments while methadone programs allow the user to continue to interact with others in the system. In the latter case, a user has a 7% chance at each time step to consume illicit drugs as well. This percentage is derived from clinical research outcome data (2 days / month).

### Dealer

The real number of dealers in Melbourne is a very well kept secret (!). Hence, the expert panel decided to adapt estimated figures coming from the USA where the population ratio between users and dealers range from 1:10 to 1:30. We decided for a 1:20 ratio which partly corroborates corresponding ratios coming from Australian Higher and Magistrate's Courts. Thus, 150 *dealers* are initially created. At each time step, the **createDealers** method will add new *dealers* into the system. The following table summarises the list of attributes and their corresponding meaning.

**Table 5: Dealer attributes, variable type and description**

Attribute	Type	Description
cash	integer	Available money
dealType	symbol	Hidden (apartment) / visible (street market)
readyToSell	Boolean	Capacity to enter a new deal
myDrug	drug object	Current drug type, quantity, and quality
myLocation	streetblock object	Usual dealing place
myWholesaler	wholesaler object	Address of current wholesaler

At this stage, dealers can buy only one type of drug at a time from their wholesaler (**buyDrugFromWholesaler**) and then sell it to users. Initial **cash** amounts range randomly from \$5000 to \$10000. The question of the different mark-ups between wholesaler, dealer, user-dealer, and user has embarrassed the expert panel for a while. Drawing from heterogeneous data and information, we have agreed on the following:

- Wholesaler's mark-up: x2.0
- Dealer's mark-up with user: x3.0
- Dealer's mark-up with user-dealer: x1.5
- User-Dealer's mark-up with user: x2.0

Hence, for an initial value of \$150/g of heroin on the market, a wholesaler will sell at \$300/g to the dealer. The dealer will sell at \$900/g to the usual users (taking less than 1g of drug at a time) and \$450/g to the user-dealer (taking at least 1g of drug at a time). A user-dealer will sell at \$900 to any other user. The same cascading mark-up system applies to the other drug on the market.

Initially dealers are assumed to deal on the street market only. But they are able to assess the risk created by the presence of constables in their surroundings (**assessRisk**). As a consequence, they can choose to freeze temporarily their activities (**readyToSell**: no) or eventually to change their **dealType** from street market to hidden sale, according to a 20% probability. This chance parameter has not been calibrated yet.

### Wholesaler

Reliable figures from Australian Higher and Magistrate’s Courts indicate a ratio of 1:48 between defendants considered as wholesalers or importers, and small dealers. We decided to apply a very conservative ratio of 1:15 in SimDrug in order to take into account the eventual under-representation of ‘big fish’ in the Court’s figures. Hence, we created 10 *wholesalers* in the system. The following table summarises the list of attributes and their corresponding meaning.

**Table 6: Wholesaler attributes, variable type and description**

Attribute	Type	Description
cash	integer	Available money
myDrug	drug object	Current drug types, quantities, and qualities
myLocation	streetblock object	Usual dealing place
myDealers	dealer object	List of current clients (dealers only)

Wholesalers are in charge of buying the two types of drug available on the market (heroin or other) and to supply the different dealers with one or the other. Initial **cash** amounts range from \$50 000 to \$100 000. They have to reset their stocks every 30 time steps (**updateSupply**) while dealers come to buy more whenever they need. The availability of one drug or the other is given by the ratio between both. This ratio is considered as an externality of the model (depending on successful importation) and it is filled in from an external data file containing daily values of quantities, market prices, and purities. Wholesalers keep track of their usual clients. Hence, when Police succeed in arresting one of them, all the corresponding dealers fall with him.

### Constable

Initially, 10 *constables* are created and located at the *Police Station*. They can move randomly around the grid or target a specific street in response to a protest from the *suburbs* (**missionType**: crackDealer). In this case, they are tracking down dealers and user-dealers. They have 10% chance to **arrest** a dealer, and 40% to arrest user-dealers in the neighbourhood. These figures are estimated from existing criminological studies.

**Table 7: Constable attributes, variable type and description**

Attribute	Type	Description
missionTarget	streetblock object	Address provided by Police Station
missionType	symbol	CrackDealer / crackWholesaler





The Police Station will send constables to a given location on a dealer chase if the average protest of the corresponding suburb reaches a value of 5. In the reality, operations against wholesalers are often initiated by special units (drug squads) and rely on external intelligence or insider's information. Hence, we decided that the Police Station has a 0.25% chance to get reliable information and to send constables to the corresponding address (**missionType**: crackWholesaler). As mentioned above, the dealers linked to an arrested wholesaler are also retrieved from the system.

### **Outreach Worker**

10 *outreach workers* are created and initially located at the *Treatment Centre*. Their aim is to convince users to undertake treatment programs. The Treatment Centre will send outreach workers to the street blocks displaying the highest overdose rates. As mentioned above, outreach workers have a purely mechanical effect: they decrease by 1 the value of the attribute **readinessForTreatment** for all the users located on the same street block.

## **UML structure**

Several authors mentioned in the first sections assert that research on illicit drug use needs a trans-disciplinary approach. Such an integrative approach itself requires a common language in order to first communicate, and then to build a consensual ontology. In the world of Complexity Theory – more specifically among the atomists – a common language is available. The Universal Modelling Language (UML) is developed around a series of visual paradigms (diagrams) that enable developers to share their knowledge with other experts and to encapsulate new knowledge into their project. Three main diagrams are usually used to describe the functionalities of a given model:

- The class diagram: it describes the entities of the modelled system (classes) with their internal characteristics (attributes and methods) and external links with other classes. It corresponds to the casting of the model.
- The sequence diagram: it describes the successive actions conducted independently by different classes or interactions between several classes. It corresponds to the storyboard of the model.
- The activity diagram: it describes the intimate actions embedded into a given method. The exhaustive list of all the activity diagrams corresponds to the script of the model.

## **Modelling sequence**

SimDrug is divided into six successive main stages:

- resetting and updating population;
- updating drug supply on the market;
- activating users decision making process;
- updating treatment centre performances;
- updating street blocks status;

- activating police station and constables crackdowns.

Stage (i) updates the population of agents, based on the changes triggered during the previous time step. All detainees are retrieved from the system and new users, dealers and wholesalers are created accordingly. Outreach workers are moved back to the treatment centre and dealers who were at their wholesaler's place go back to their street location. Stage (ii) entails the methods for wholesalers and dealer's interactions towards drug supply. Wholesalers are given the opportunity to refill their supply once a month while dealers can visit their wholesaler as soon as their drug stock is sold out. Stage (iii) focuses on the users' interactions with their environment and other agents. They start by assessing their need looking at their available cash and drug and decide whether they need to commit a crime. They, then, find their usual dealer (or alternatively a new dealer) and buy some drug. They use it at once and might declare an overdose. Stage (iv) allows the Treatment Centre to manage new users entering treatments and on-going treated users reaching the end of their treatment duration. Stage (v) consists in updating the street blocks risk and conductivity status and calculating the new suburbs' protest values accordingly. Finally, Stage (vi) allows the police station to adapt its strategy by reallocating constables on the grid and eventually performing successful crackdowns.

**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**

**Figure 1: Class diagram**

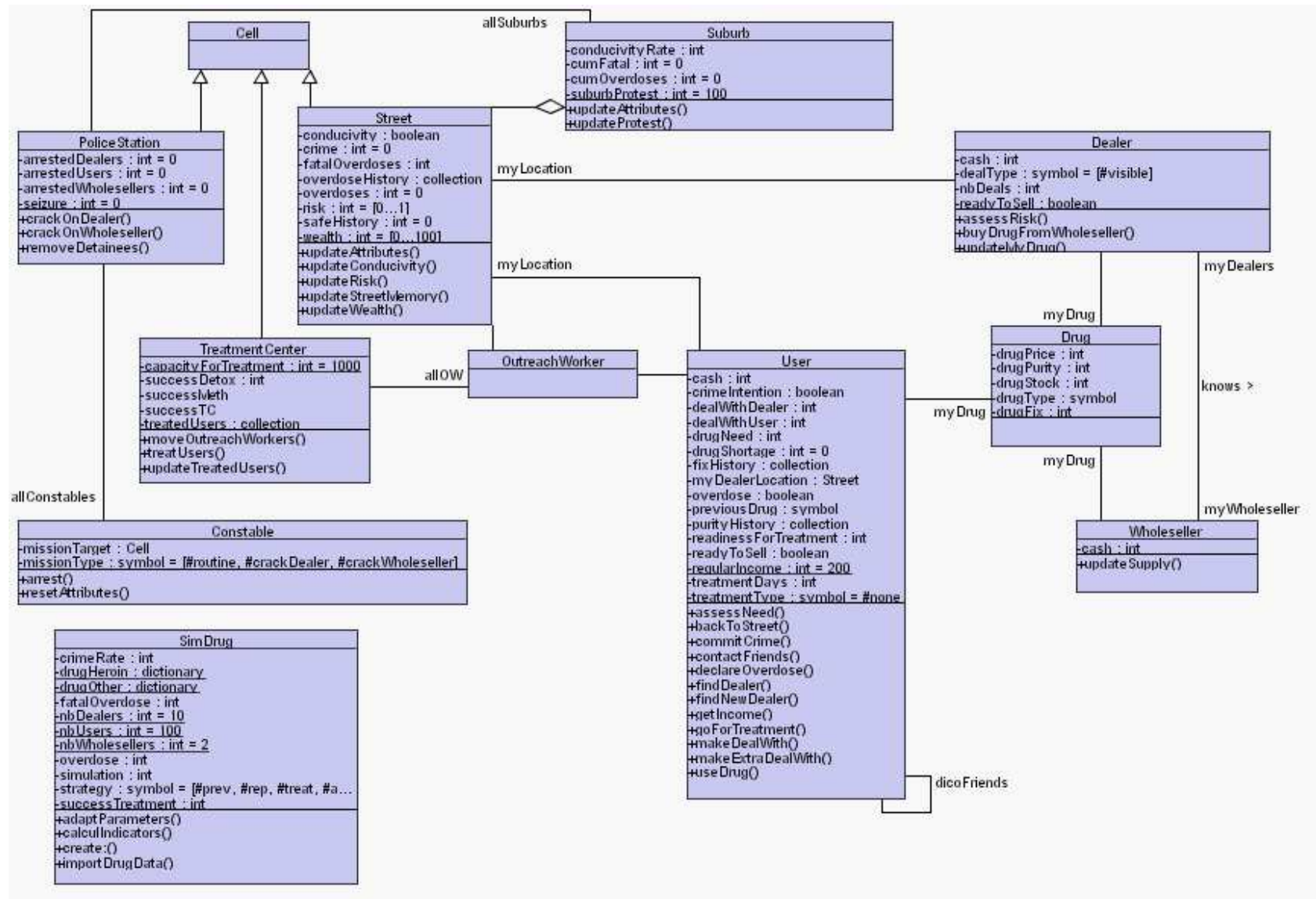
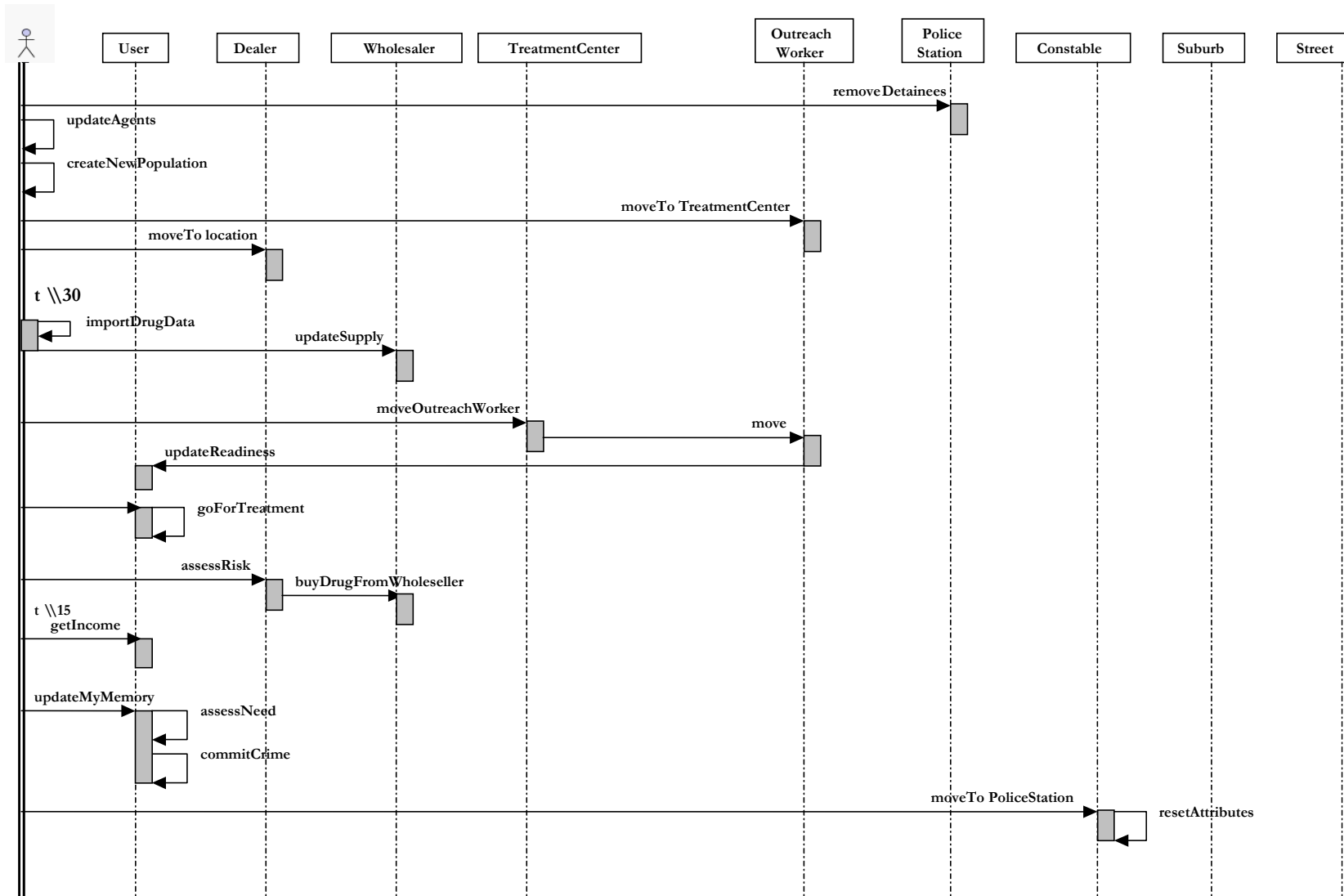
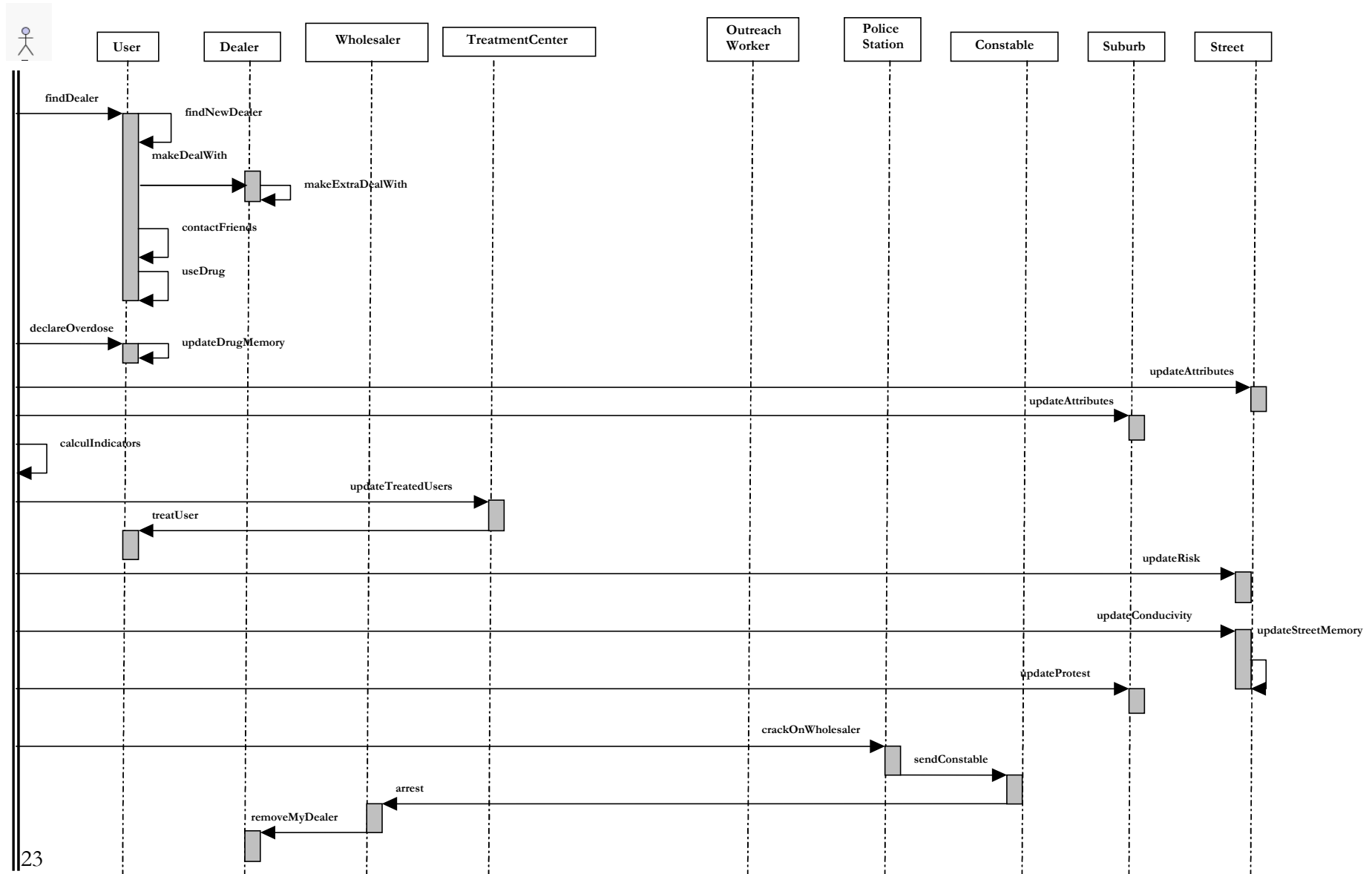


Figure 2: Sequence diagram



# SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE



# SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE

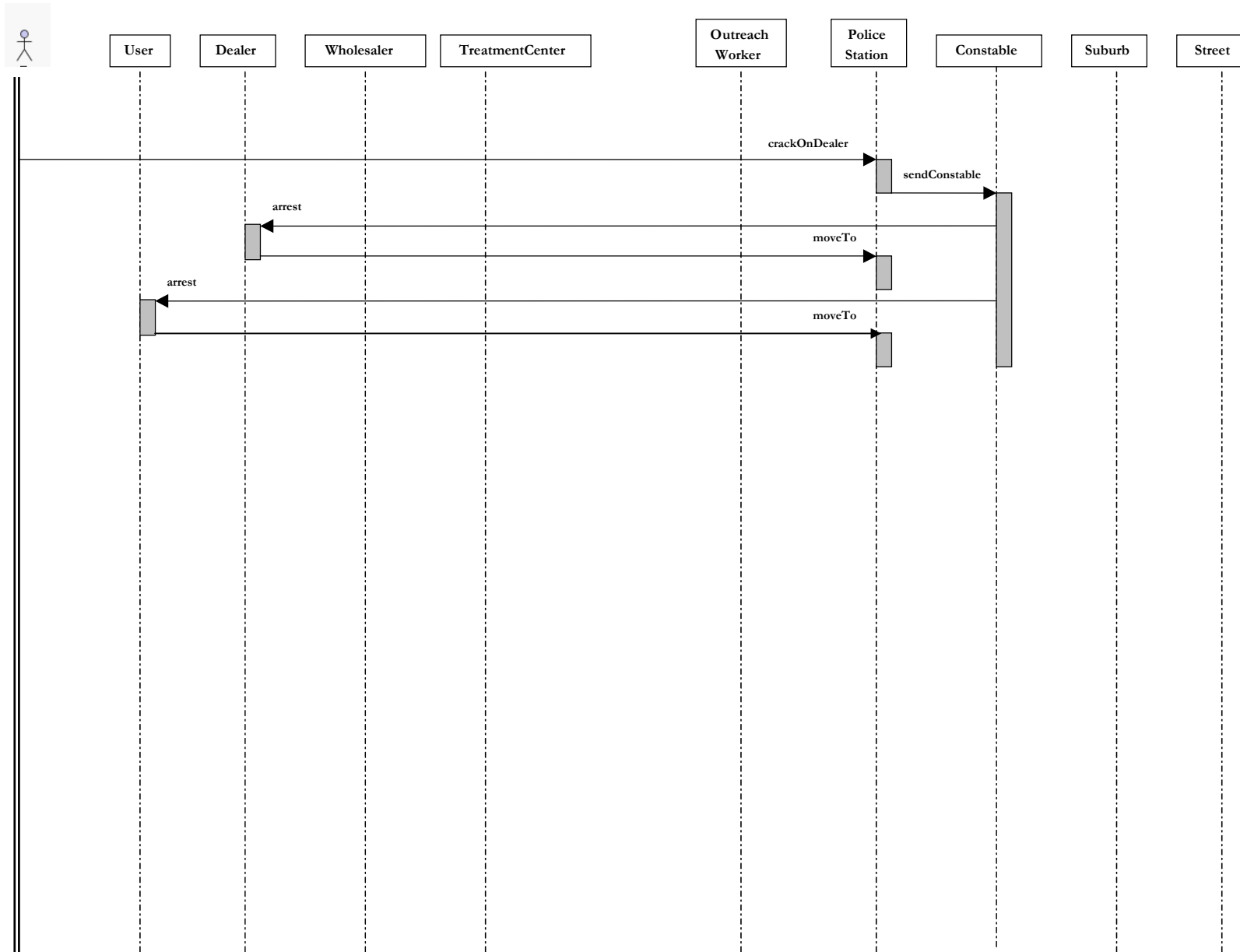
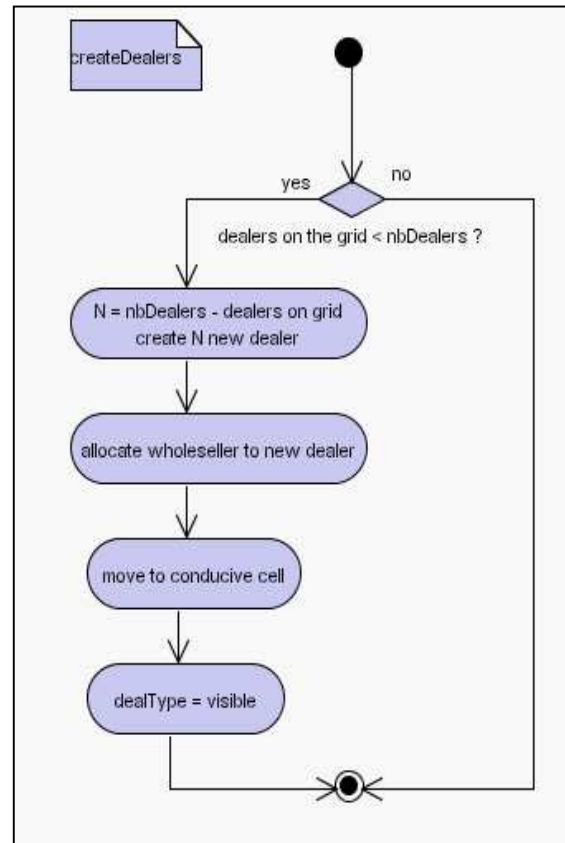
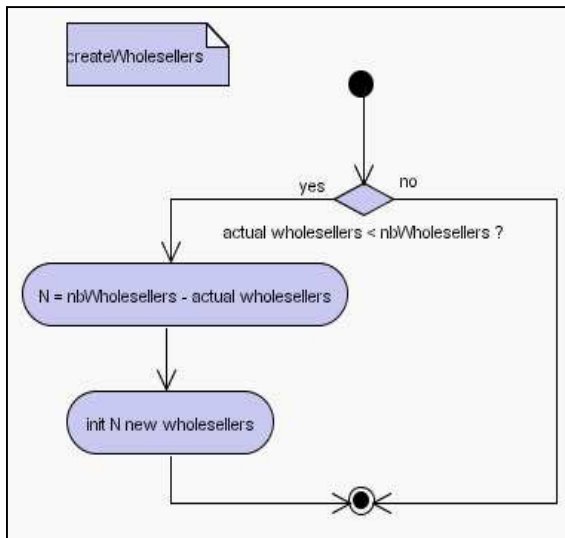
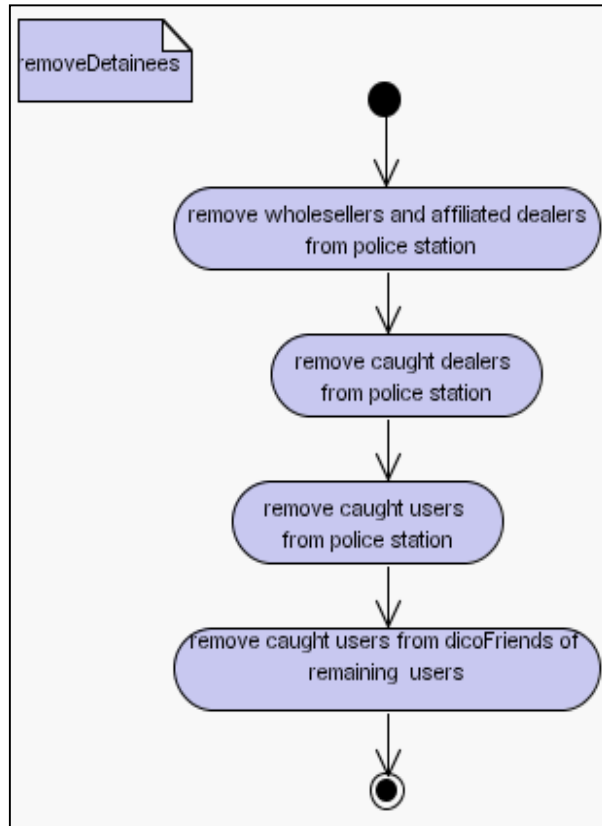
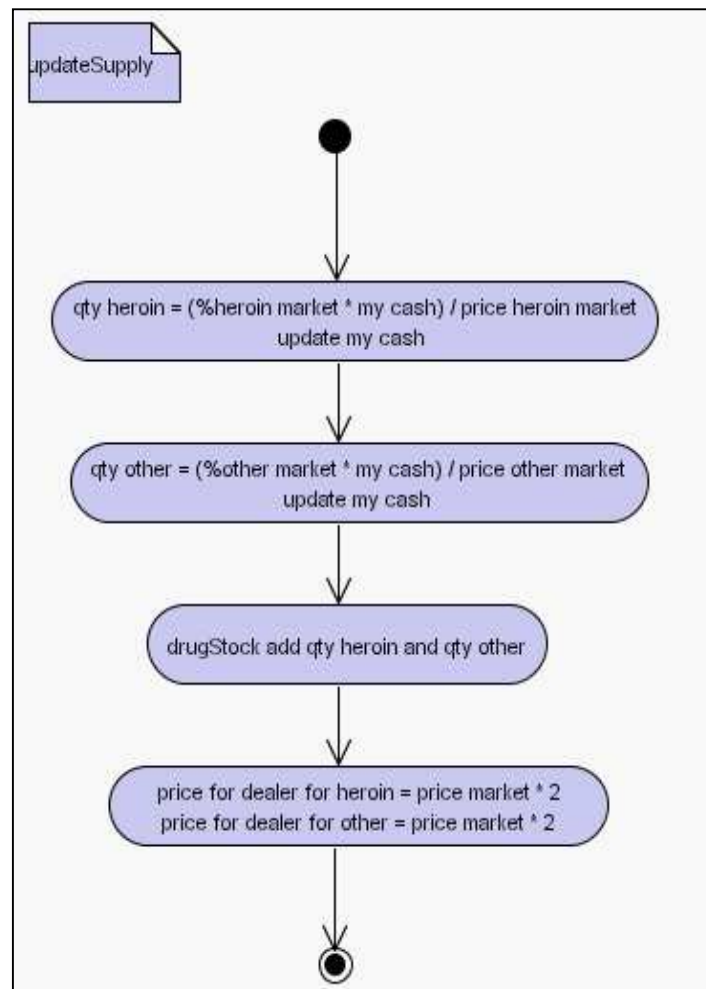
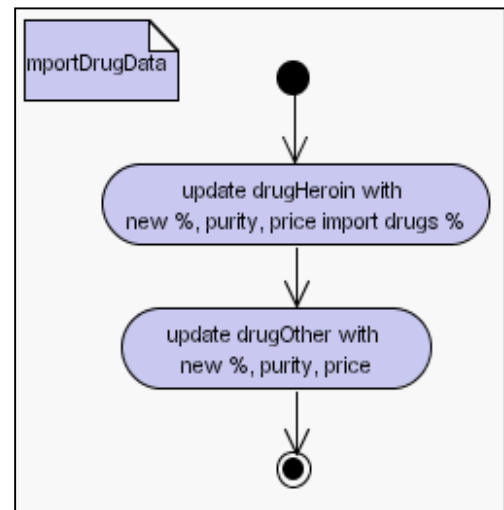
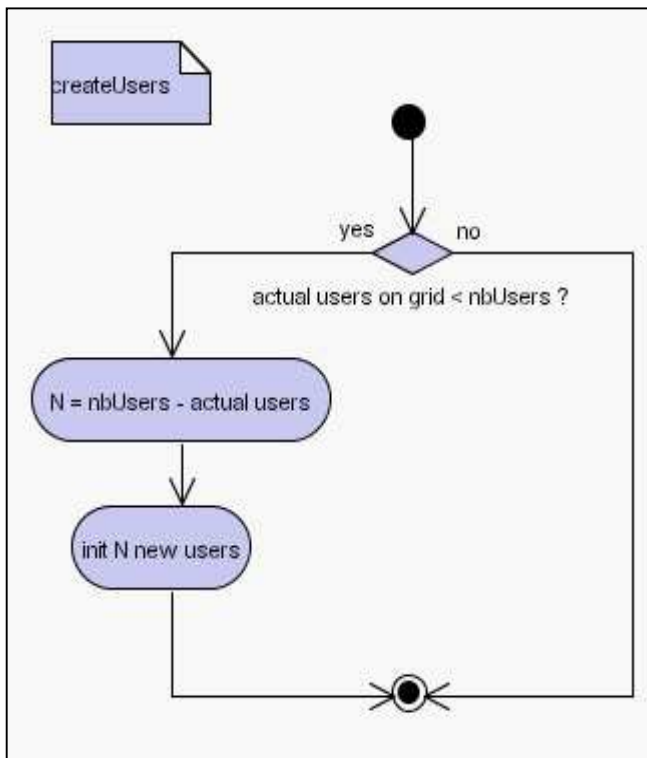


Figure 3: Activity diagrams

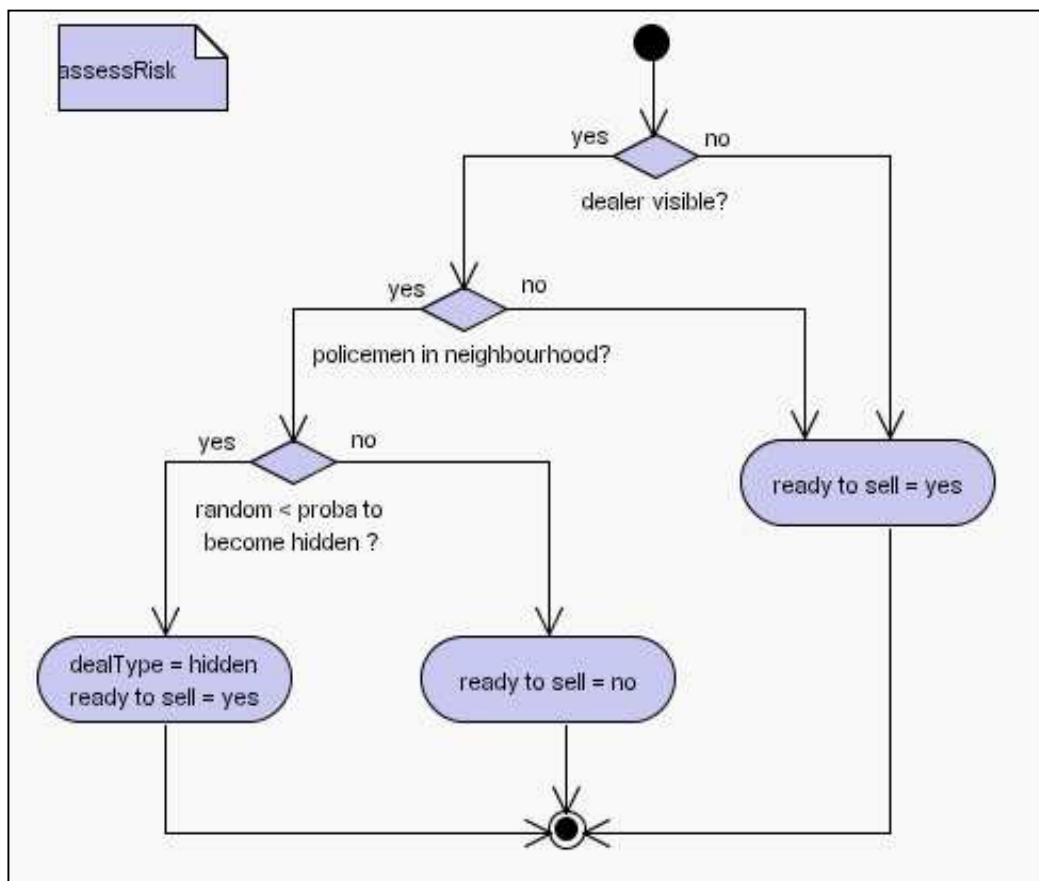
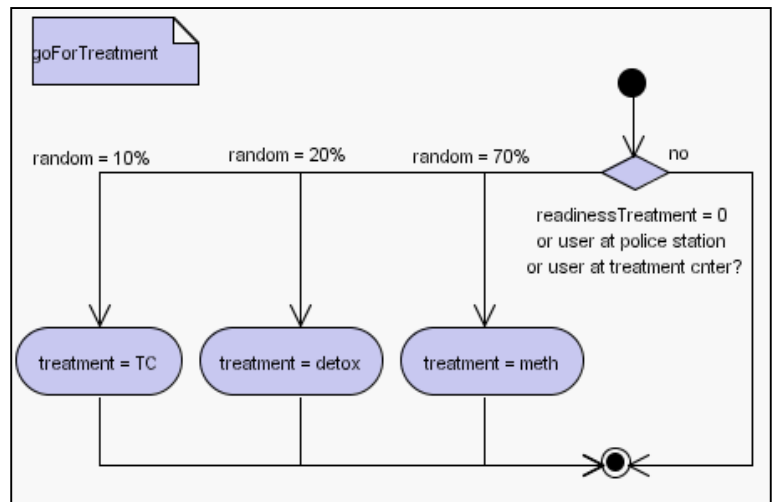
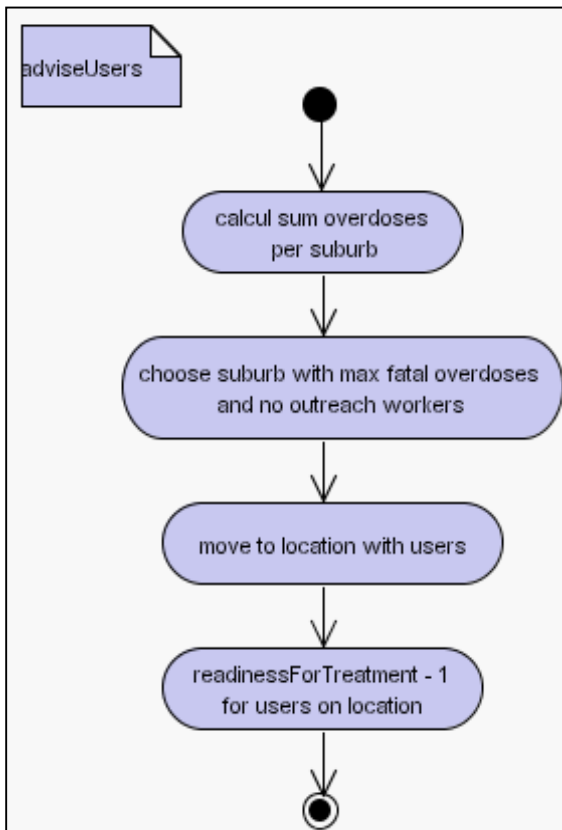




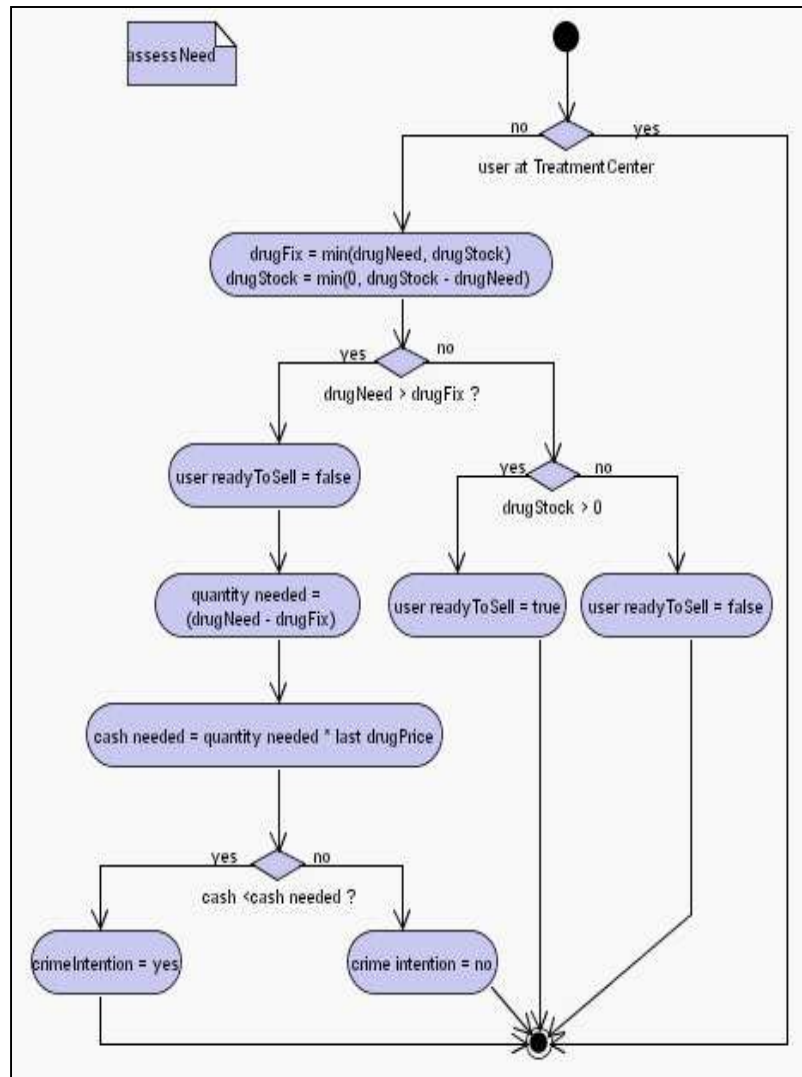
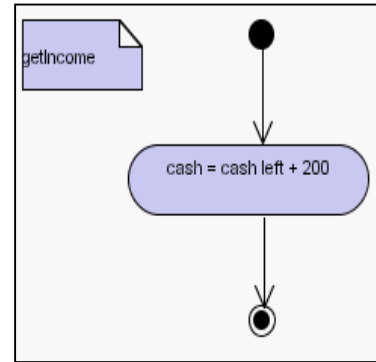
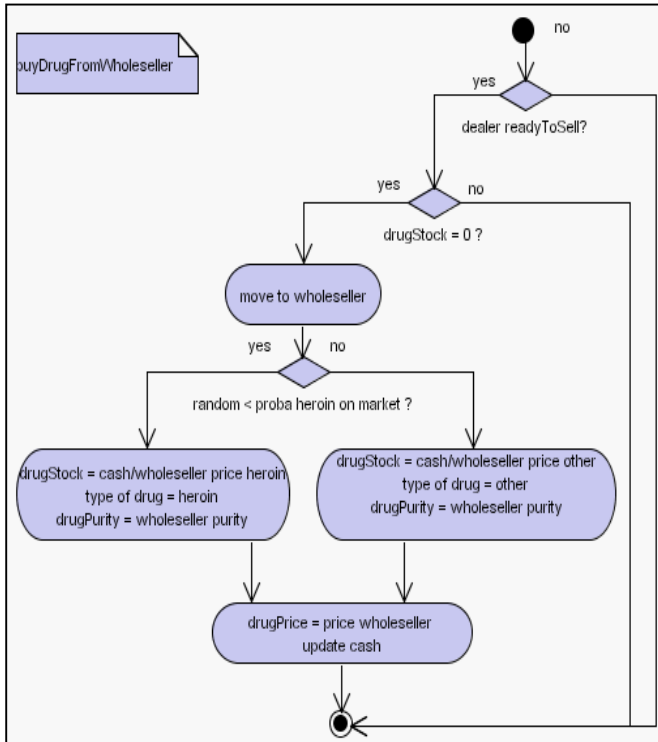
**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**

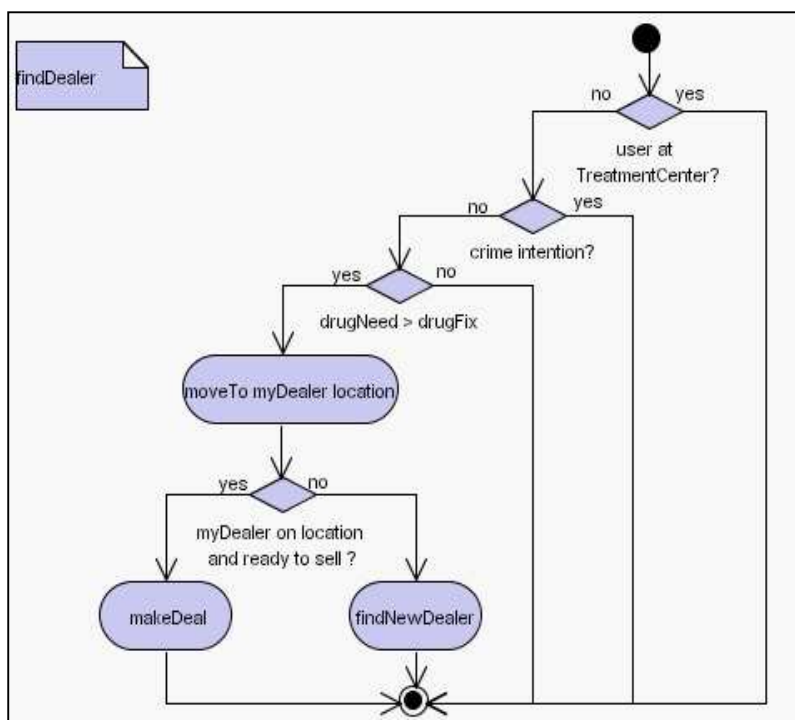
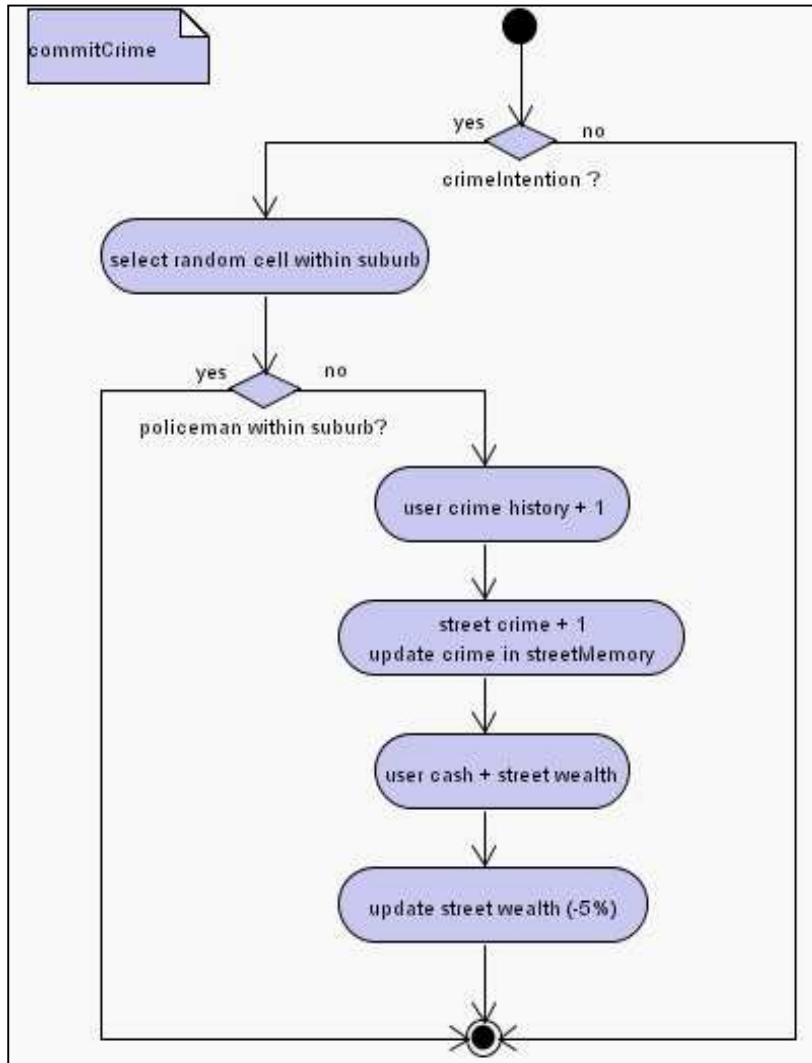


**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**

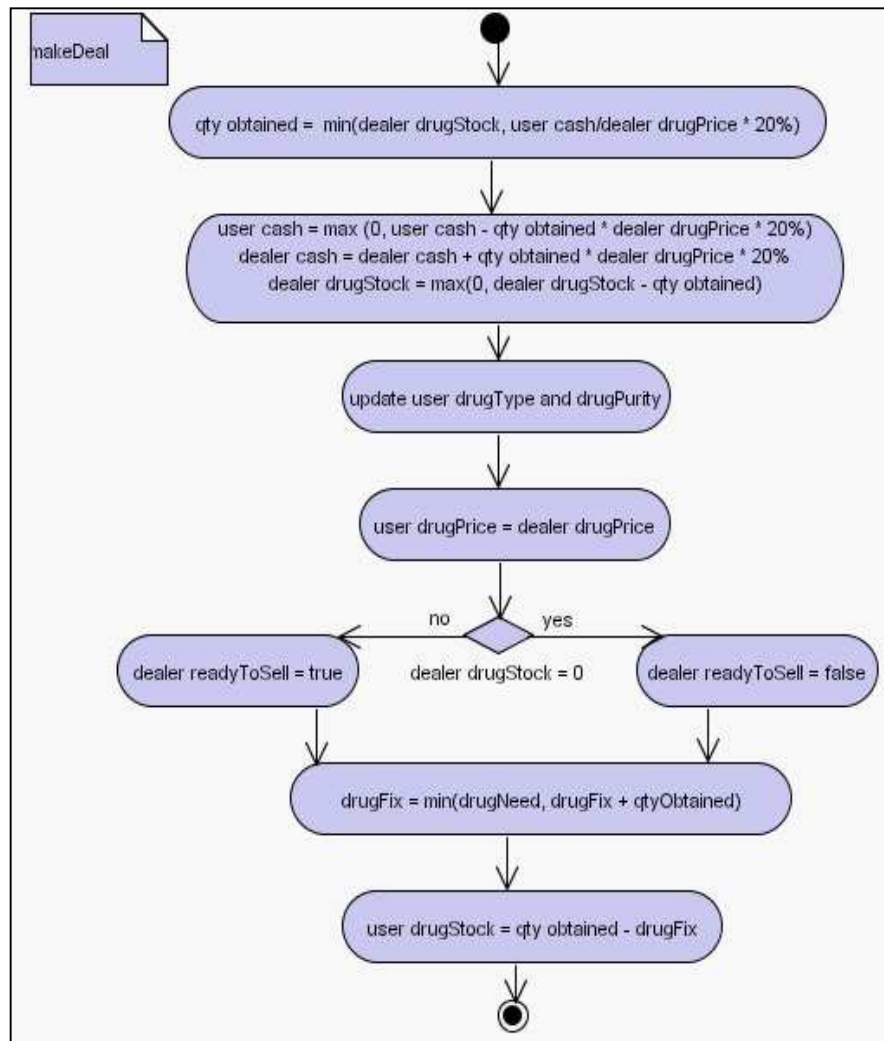
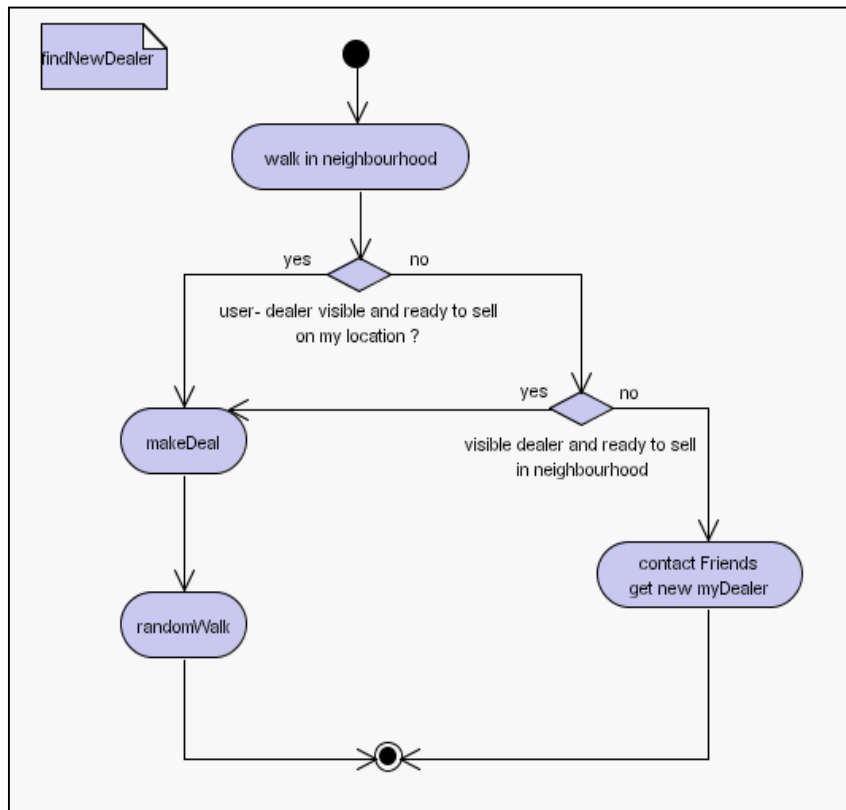


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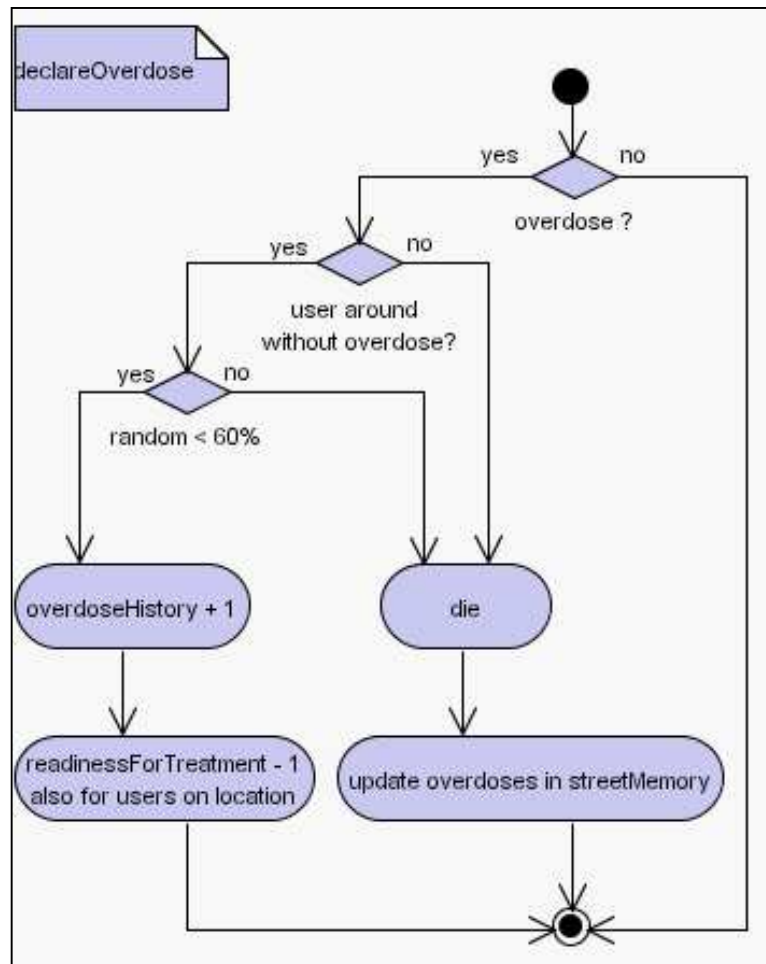
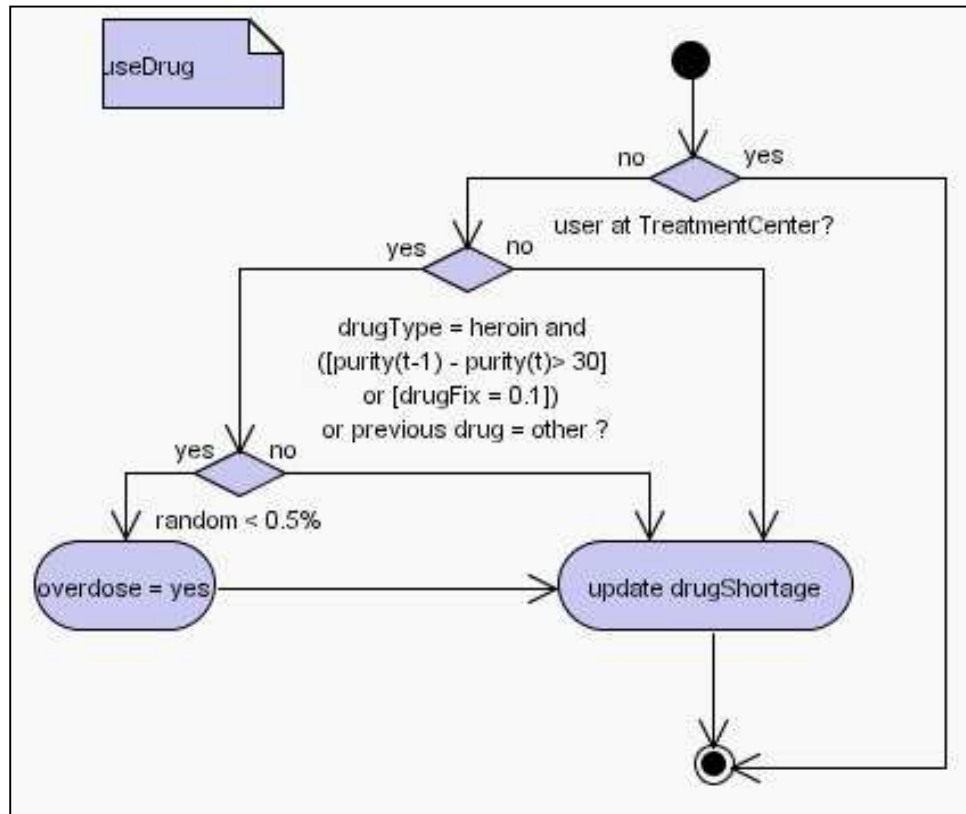


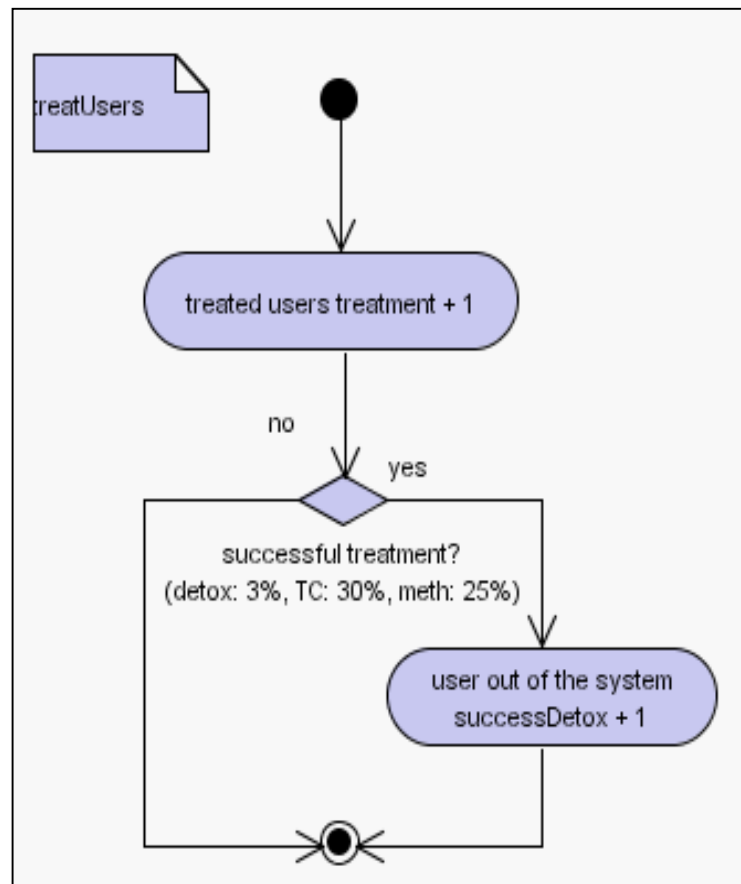
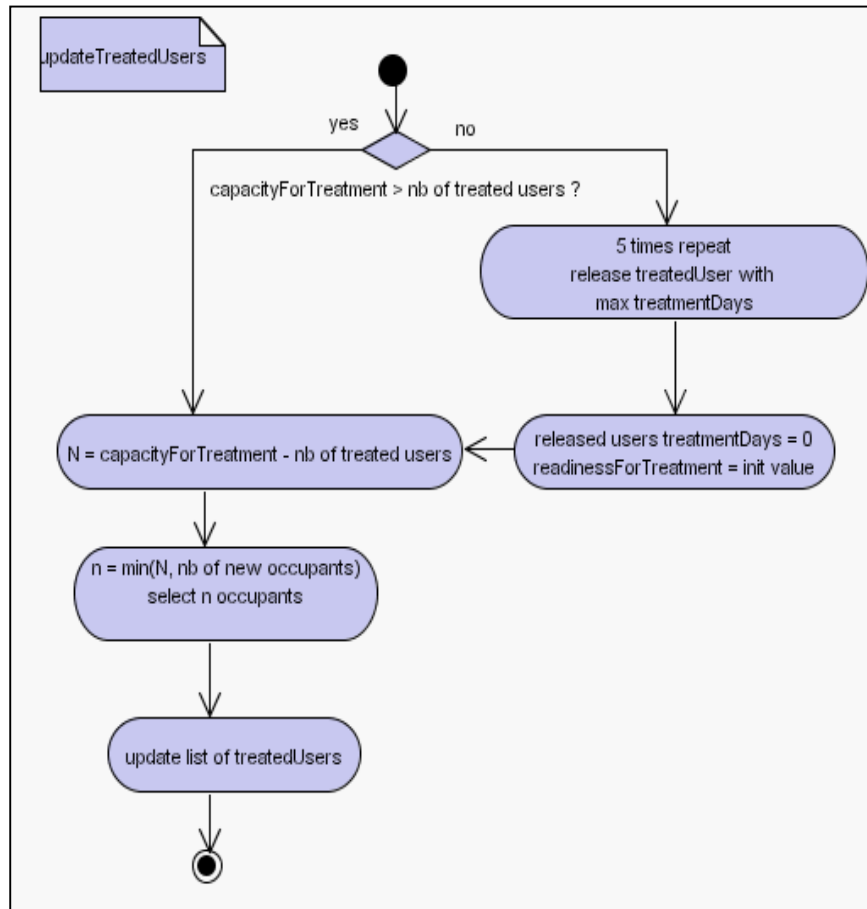


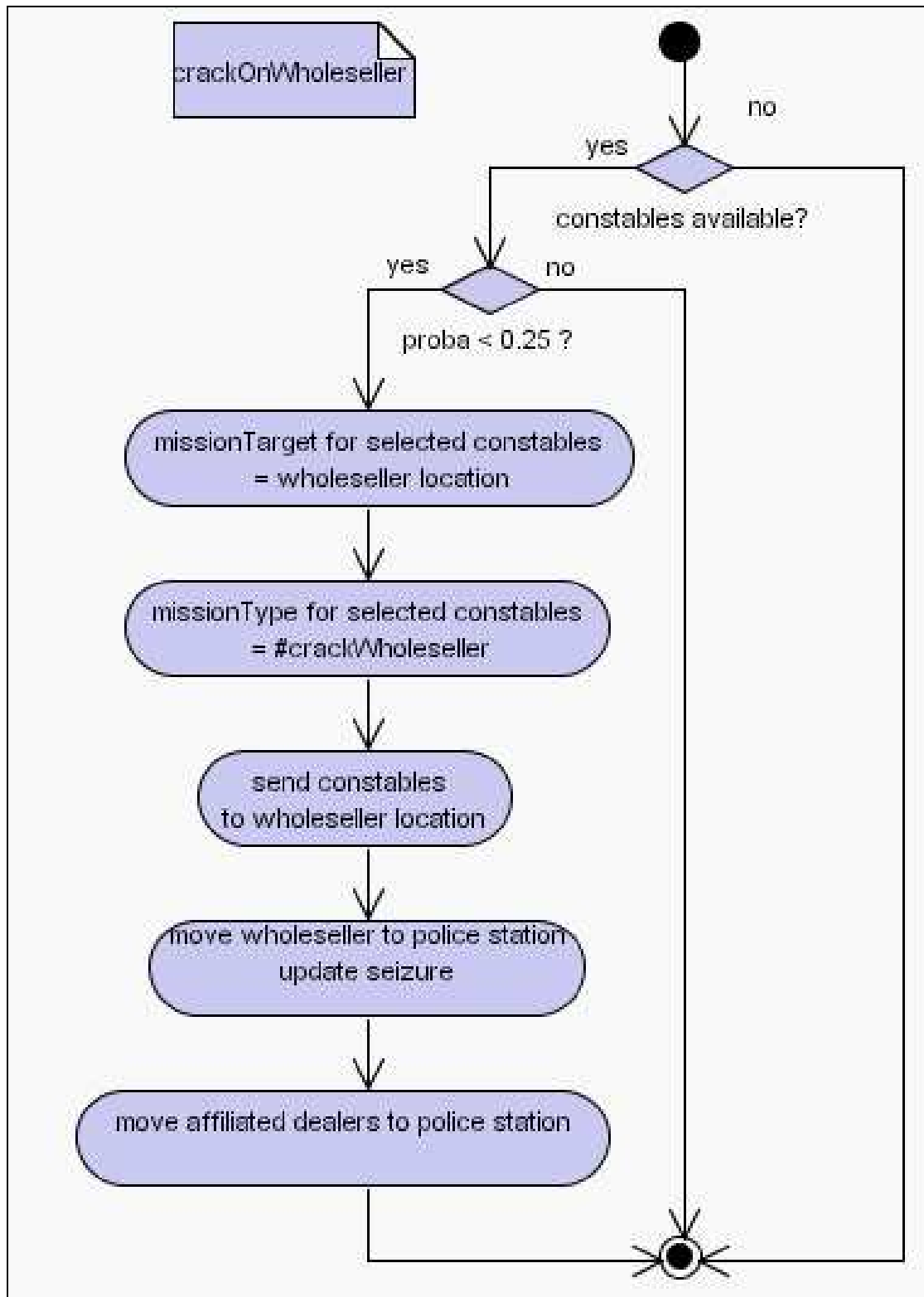
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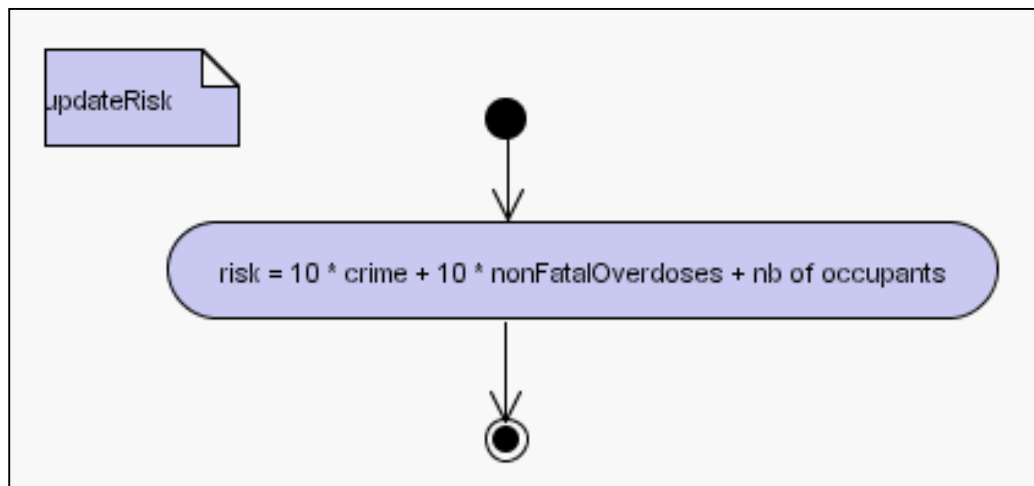
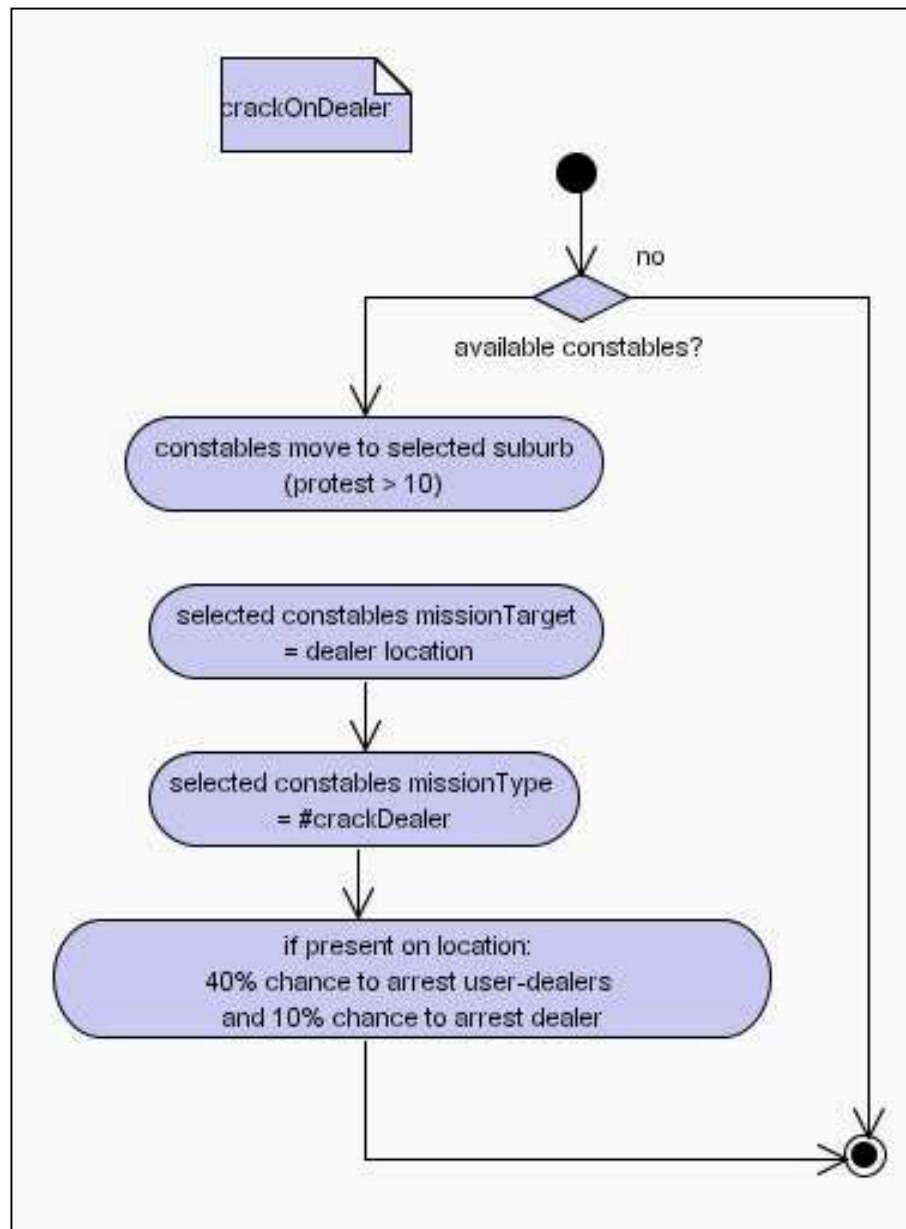
**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**



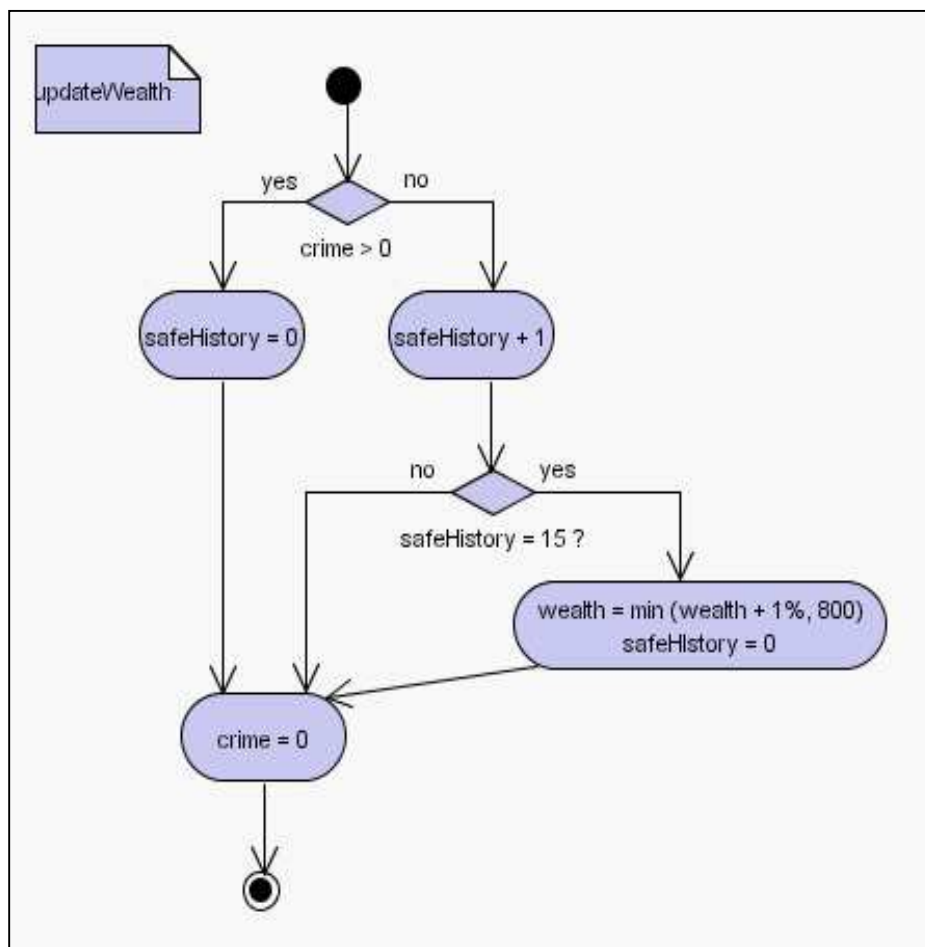
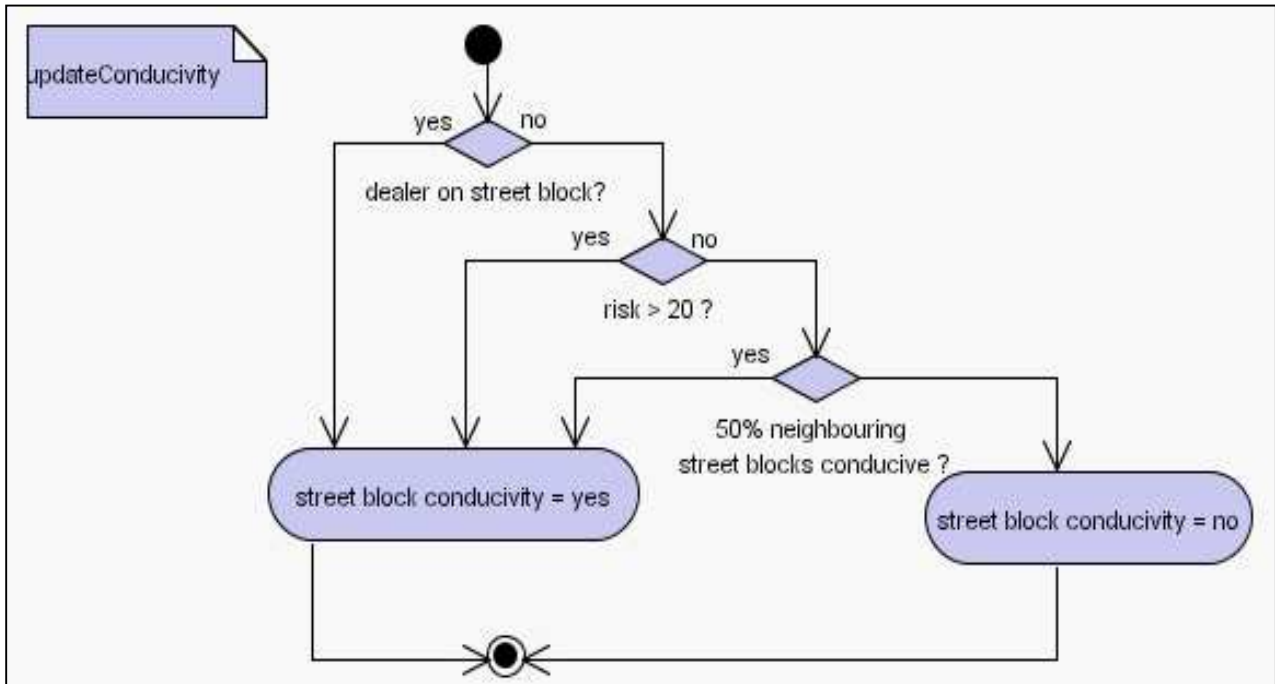








**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**



## SimDrug – Preliminary results

The Cormas platform encapsulates sensitivity analysis tools and provides output data directly into Excel format files. Each scenario is run 10 times and the recorded output variables (called “probes”) are given in the following table.

**Table 8: Output variables (‘probes’)**

<b>Probes (variables)</b>	<b>Description</b>
crimeRate	Total number of crimes per time step
dealer_CashMax	Highest available cash amongst dealers per time step
dealer_CashMin	Smallest available cash amongst dealers
fatalOverdose	Cumulative number of fatal overdoses
overdose	Cumulative number of overdoses (non-fatal and fatal)
popDrugHeroin	Number of users under heroin at each time step
popDrugOther	Number of users under other at each time step
popNoDrug	Number of users not consuming any drug per time step
popShortage	Number of users not scoring enough to satisfy their need per time step
popTreatedDetox	Number of users under detox treatment per time step
popTreatedMeth	Number of users under methadone treatment per time step
popTreatedMethAndHero	Number of users under methadone and scoring heroin per time step
popTreatedTC	Number of users under TC treatment per time step
arrestedDealers	Cumulative number of arrested dealers per time step
arrestedUsers	Cumulative number of arrested users per time step
arrestedWholesalers	Cumulative number of arrested wholesalers per time step
seizure	Heroin seized when a wholesaler + affiliated dealers are arrested
successDetox	Cumulative number of successful detox treatment
successMeth	Cumulative number of successful meth treatment
successTC	Cumulative number of successful TC treatment
totDealWithDealer	Number of deals between users and dealers per time step
totDealWithUser	Number of deals between users and user-dealers per time step
userDealer	Number of user-dealers per time step

The base scenario has been set up with the parameters and values described in the previous section. It contains 3000 Users, 150 Dealers and 10 Wholesalers. These figures are not subject to sensitivity analysis so far and remain unchanged for all the scenarios. The base scenario is used as a reference to derive sensitivity analysis on a chosen set of parameters summarised below:

- nb of Constables: **10**
- nb of Outreach Workers: **10**
- chance for a user to declare an OD: **0.5%**
- chance for a user declaring an OD to be rescued: **90%**
- wealth decreased by **5%** when a crime is committed on a given street block
- wealth increased by **3%** after a 10-day period with no crime
- crack on dealers occurs for suburbs with a protest value **> 5**
- chance for a user-dealer to be arrested during a “crack on dealer” mission: **40%**
- chance for a dealer to be arrested during a “crack on dealer” mission: **10%**
- chance for the police station to arrest a wholesaler at each time step: **0.25%**
- treatment capacity at the Treatment Centre: **1000**

As for the input data featuring drugs' characteristics, we have agreed on a very simplified set of values. Both drugs, "heroin" and "other", are equally available on the market. Hence, wholesalers spend half of their money on heroin and the other half on "other". Both drugs have the same purity (30%) which remains constant through the simulation. Wholesalers buy heroin for \$150/g and "other" for \$125/g. Hence, for the base scenario, we have decided to discard the impact of drug availability, quality and price in order to calibrate and analyse the remaining parameters.

## Results from Base Scenario

### Overdoses

The proposed rules to declare an overdose are consistent with real data regarding overdoses and fatal overdoses. On an average, 1100 overdoses occur over a 4-year period, amongst which 150 are fatal. On an average, these figures correspond to a 9.2% p.a. rate of non-fatal overdose, and a 1.2% p.a. rate of fatal overdose over the entire population of users. Statistics for Victoria in 1999-1998 provide an estimated 10% and 1% for the observed values.

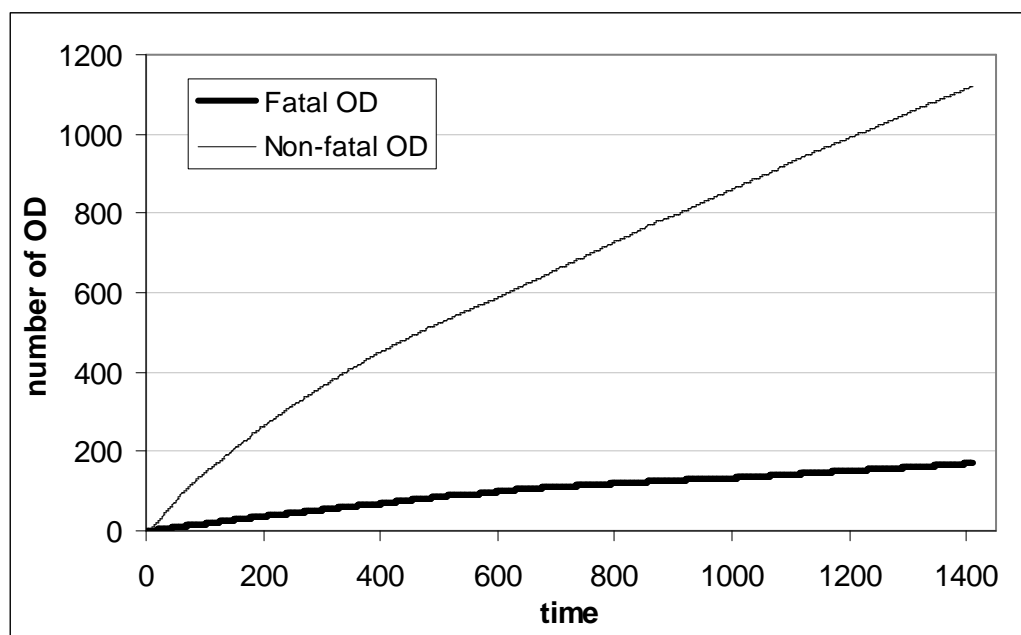


Figure 4: Cumulative number of fatal and non-fatal heroin overdoses over time in SimDrug

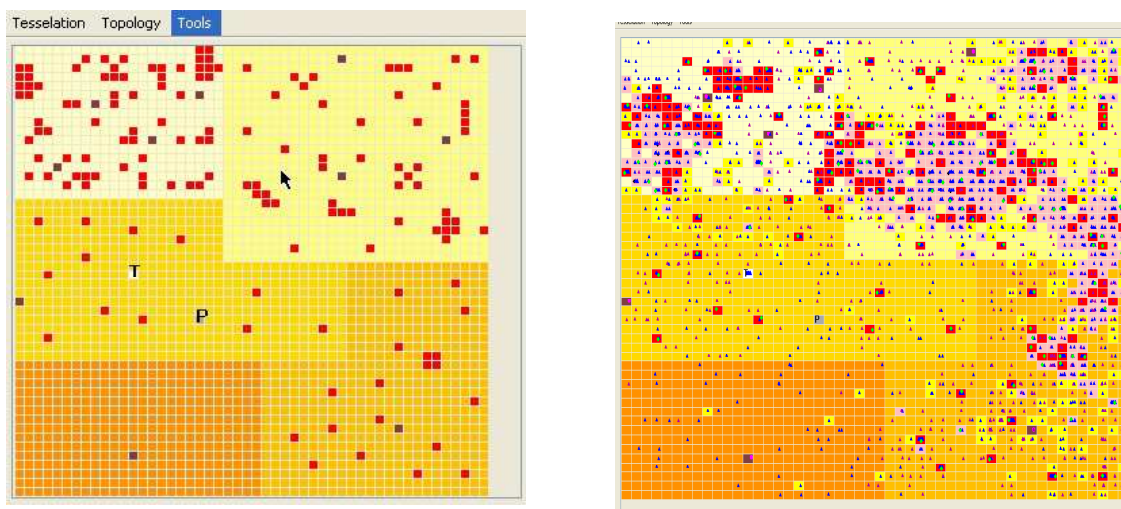
### Treatment

After 3 years, there are on average 800 users in treatment at any given time step: 750 are in methadone treatment (amongst which 50 also inject heroin), 40 are in TC and 10 are in detoxification. Statistics from treatment programs in Victoria indicate that 70% of real users are going through one program or another over a period of 12 months. Our 26% rate is much lower but constrained by the way users update their individual readiness for treatment. At the end of the simulation, 1000 users have been successfully treated (800 thanks to methadone, 170 thanks

to TC and 30 thanks to detoxification). Methadone treatment happens to be, by far, the most efficient way to deal with heroin addiction.

### **Crime and hot spots**

Crime rate follows a 15-day periodic pattern driven by the CentreLink-like payment periodicity. Crime rate increases as users' available cash decreases over the fortnight period and falls again when users receive their next payment. On an average, 800 crimes are committed per time step. This outcome needs to be discussed and validated against real data. In terms of spatial changes, locations of hot spots on the grid evolve over time as a result of the constables patrolling the grid in response to suburbs' protests. This spatial mobility of hot spots can be viewed as an emerging property of the system as no rules have been set up at the local level (street blocks) to define hot spots' patterns. The pictures below show the position of hot spots at the beginning of the simulation (left) and the extension and displacement and of hot spots at the end of the simulation (right).



**Figure 5: Hot spot positions at beginning of simulation (left) and end of simulation (right)**

### **Dealer's cash**

At the end of the simulation, dealer cash ranges between \$40,000 and \$800,000. On an average, one dealer earns \$2,400/week. These figures are close enough to the ones coming from police records (\$3,500 to \$4,000 / week) if we take into account that a significant number of new dealers in the model 'fail' to establish a profitable business.

### **User-dealer**

At the end of the simulation, 300 users are also user-dealers, which corresponds to 10% of the population of users. This result is consistent with current estimates provided by the expert panel.

## **Sensitivity analysis**

For each parameter, several scenarios have been run in order to test the impact of a change in value on the system. Thus, each scenario corresponds to a change in only one parameter in order to avoid overlapping effects. Tested values are displayed in the following table.

**Table 9: Sensitivity analyses: parameters, base scenarios and tested values**

<b>Parameters</b>	<b>Base scenarios</b>	<b>Tested values</b>			
nb of constables	10	1	50	100	
nb of outreach workers	10	1	20	50	100
proba overdose	0.5%	0.1%	1%		
proba rescue OD	90%	60%	80%		
decrease wealth	5%	1%	10%		
increase wealth	3%	0%	5%		
suburb protest	5	3	7		
arrest user-dealer	40%	10%	25%		
arrest dealer	10%	5%	20%		
arrest wholesaler	0.25%	0.1%	0.5%		
treatment capacity	1000	600	800		

The table on the following page summarises the effect of tested parameters on the output variables.

**SIMDRUG – EXPLORING THE COMPLEXITY OF HEROIN USE IN MELBOURNE**

**Table 10: Effect of tested parameters on output variables (crime, dealers’ cash, overdose, heroin use, treatment, arrest rate, fix with dealer/user, number of dealer-users, seizures)**

<b>Variables</b> <b>Parameters</b>	Crime rate	Dealer cash max	OD	Fatal OD	Pop heroin	Pop other	Pop no drug	Pop shortage	Pop treatment	Arrest dealer	Arrest user	Arrest wholesaler	Success treatment	Fix with dealer	Fix with user	Nb of user-dealers	Seizures
outreach workers [1 – 10 – 20 – 50 – 100]	-	-	+++	++	++	+	+++	+	+++	+	++	-	+++	+	+	+	-
constables [1 – 10 – 50 – 100]	+	+++	-	-	-	-	-	++	-	+++	+++	-	-	++	-	+++	-
update wealth [0 – 3% – 5%]	++	+	-	-	+	++	+++	++	+++	-	+++	-	+++	++	++	+++	-
arrest UD [10% – 25% – 40%]	-	-	-	-	-	-	-	-	-	-	++	-	-	++	++	++	-
arrest D [5% – 10% – 20%]	+	+	+	+	-	-	-	-	+	++	-	-	-	-	-	-	-
arrest wholesaler [0.1% – 0.25% – 0.5%]	-	-	+	++	-	-	-	-	-	-	+	+	-	-	-	-	++
suburb protest [3 – 5 – 7]	+	++	-	-	-	++	-	-	-	+++	+++	-	+	-	+	++	-
treatment capacity [600 – 800 – 1000]	-	-	-	-	-	-	++	++	+++	-	-	-	++	-	-	-	-

(-) means that there is no correlation (ie. no effect) between a parameter (for example, the number of outreach workers) and an output variable (number of crimes).

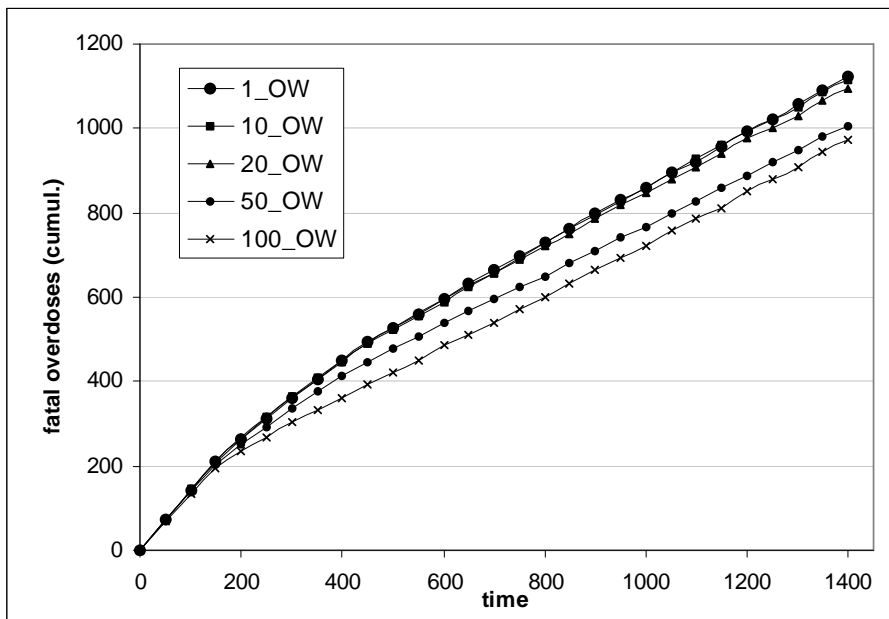
(+) means that there is a small effect or impact (either positive or negative) on a given variable

(++) and (+++) means that there is a strong correlation (again, can have a positive or negative meaning). For example, the more outreach workers, the less ODs, the more constables, the more arrested dealers.

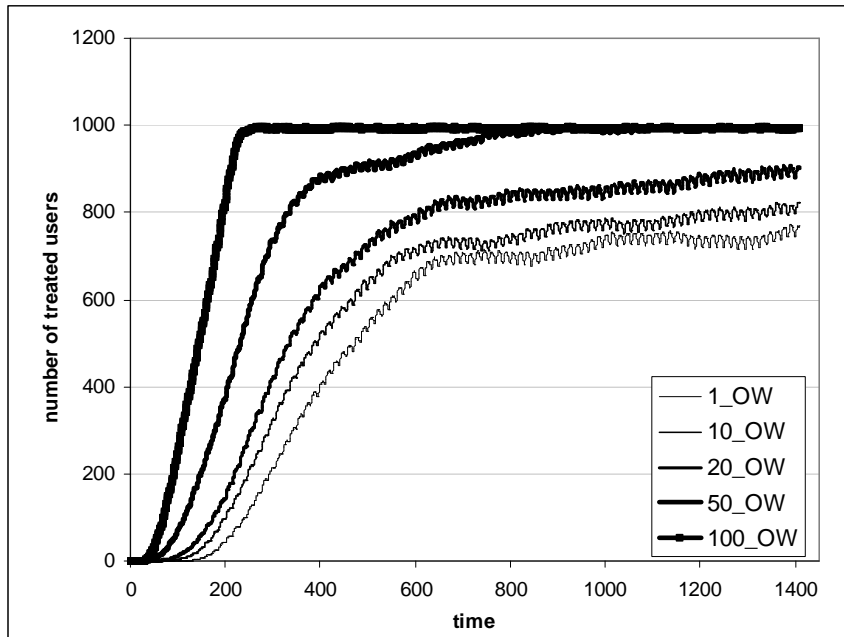


**Outreach workers**

The number of outreach workers influences strongly the overdose rates and the number of users undergoing treatment programs. This influence seems to take off beyond 20 agents located on the grid. This impact on the amount of treated users is a direct consequence of the ability of the OW agents to modify individual readiness for treatment. The clear impact on overdose rates is more interesting as any user quitting an unsuccessful treatment increases his/her chances of overdose due to the withdrawal period (reduced tolerance). Clearly, non-linearity between tested values and variables would open a window of opportunity to run cost-efficiency analysis amongst mixed strategies.



**Figure 6: Relationship between number of outreach workers and cumulative fatal overdose rate (every 50<sup>th</sup> point displayed for graph clarity)**



**Figure 7: Relationship between number of outreach workers and cumulative number of treated users**

### **Constables**

Increasing from 10 to 100 the number of constables has a clear and expected positive influence on the number of arrested dealers. However, looking at dealers' maximum income, it is more surprising to notice the lack of major impact when comparing the scenarios with 50 and 100 constables. A plausible explanation lies in the ratio between constables and dealers that does not generate great difference for ratios above 1 constable for 3 dealers. But again, cost-efficiency needs to be assessed for such large ratios that would probably stretch law enforcement capacities beyond limits.

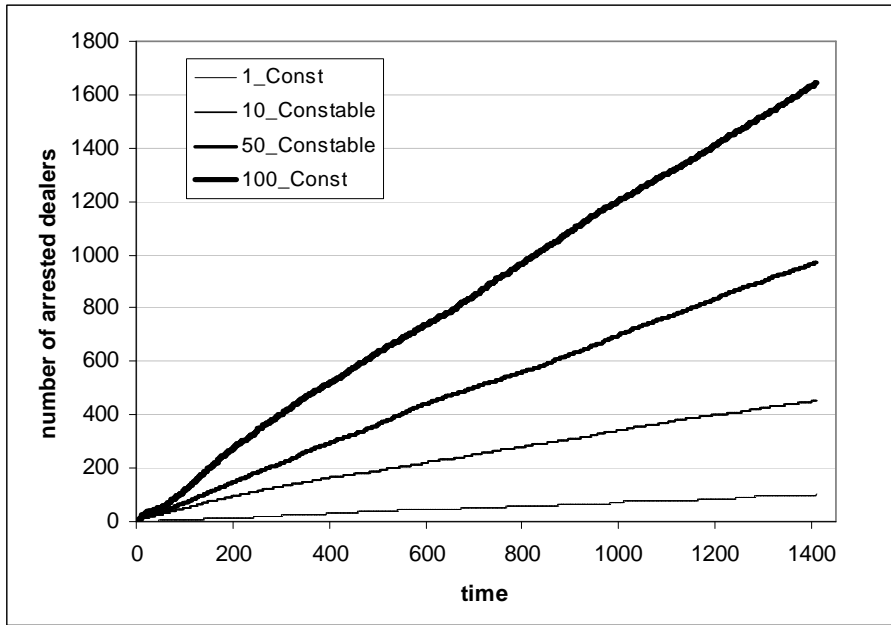


Figure 8: Relationship between number of constables and cumulative dealer arrest rate

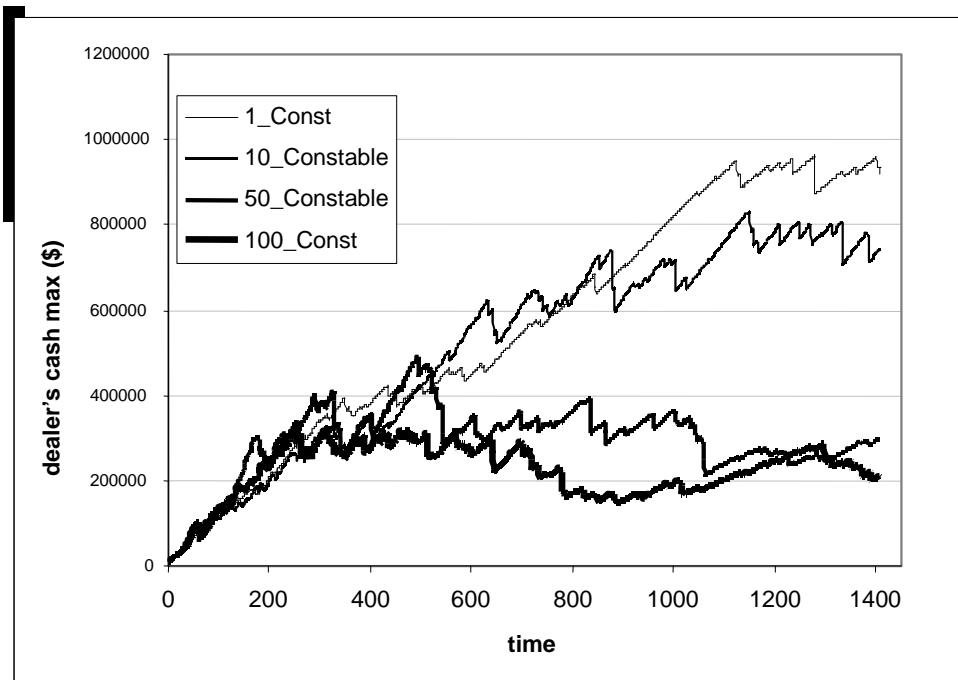
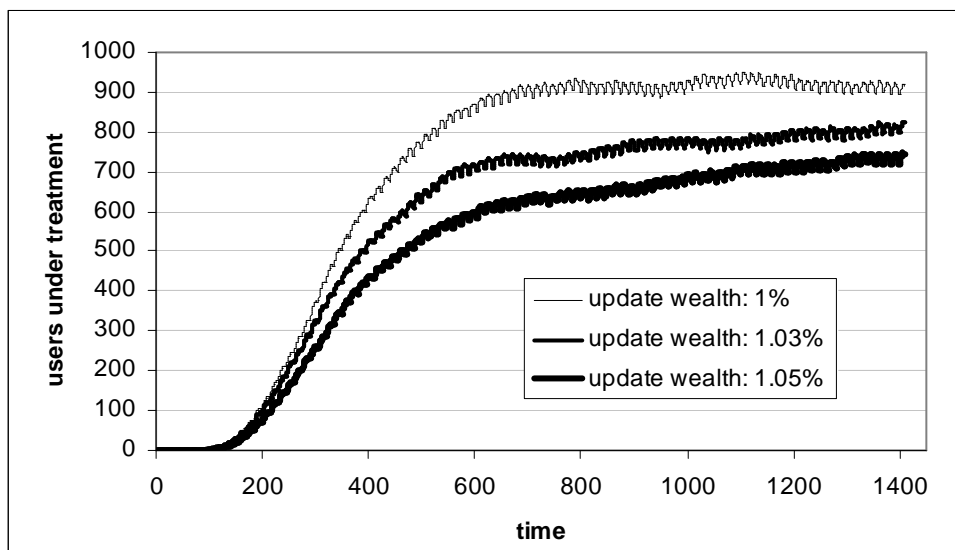


Figure 9: Relationship between number of constables and maximum dealer's cash

### Non drug-related variables

Interestingly, the way *wealth* attributes of the *StreetBlocks* are updated influences significantly most of the output variables. Obviously, the amount of wealth available on *StreetBlocks* drives users' revenues from crimes. It constrains the possibility to fulfil one's drug needs, and it impacts on the number of user-dealers. Consequently the number of arrested users is also affected. Beside, it affects the number of treated users by reducing the chance for users to reach the required stage of readiness without being caught by the constables beforehand (Figure 8). This outcome seems to validate some experts' claims about the necessity to better take into account *non-drug-related* environmental factors in order to understand these markets.



**Figure 10: Number of users in treatment according to increasing values for wealth updating rate**

### Simulating the heroin drought

The striking figures linked with the so-called 'heroin drought' concern the number of fatal and non-fatal overdoses reported in Victoria at that time. Within a few months, fatalities fell from an average 300 p.a. to an equivalent of 40 p.a. during the drought peak, resulting in a 52% permanent decrease in the number of casualties from the drought onset (Dietze et al., 2003). Despite all our efforts, it was impossible to set up a scenario for SimDrug to display such a dramatic response without pushing some parameters to highly unrealistic values. Hence, the expert panel analysed our initial assumptions again. It was decided to successively modify two essential features:

- Transforming SimDrug into a closed system rather than an open one. Thus, removed agents are not replaced in the system.

- Modifying the input data files in order to take into account the observed availability of heroin during the simulated period.

A closed system design succeeded indeed in creating a sharp fall in the number of overdoses, due to the simple fact that a decreasing number of users populated the system. But the system never recovers after the simulated *drought*, the market simply collapses. Beside, there is no evidence so far that the overall population of injecting users in Victoria significantly changed between 1998 and 2002. Nevertheless, it is probable that pre-drought conditions influencing individual decision to inject heroin had some effect. Hence, SimDrug's degree of openness should be reviewed in light of the pioneering work by Agar (2005).

Given the fact that modelling an illicit drug market based on two equally available drugs does not depict the reality of the heroin trade in Melbourne, we have decided to use heroin's purity, quantity, and price data derived from Dietze et al. (2003). The 'other' drug's availability was calculated in order to secure a constant overall availability of drugs on the market. The authors acknowledge that this first-pass assumption needs to be validated against further evidence. Figure 9 compares simulated fatal overdoses from this new scenario with the ones coming from the base scenario. While the base scenario – assuming that heroin covers 50% of the market at any time – provides a nearly steady rate of 35 casualties p.a.; the new scenario shows a sharp decrease - around time step 800 - which corresponds to the heroin drought period, from 60 casualties p.a. before the drought onset, to a mere 30 casualties p.a. afterwards. Though this 50% decrease is consistent with findings from Dietze and colleagues (2003), it has to be noticed that if our 1/10<sup>th</sup> scale were to be correct, the pre-drought simulated figures double the ones reported in reality. The same analysis and conclusions can be derived from results on total overdoses.

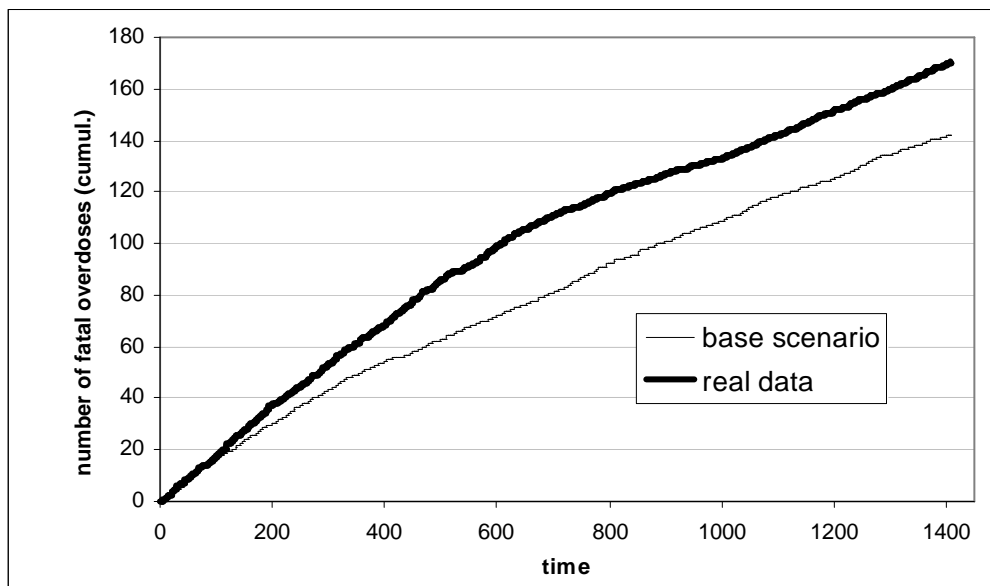


Figure 11: Number of fatal overdoses derived from the base-scenario and from real data

## **CONCLUSION**

This report presents our attempt to build a first agent-based model dedicated to study the illegal drug market in Melbourne during the ‘heroin drought’ period. As described by Gorman and colleagues (Gorman et al., 2004), drug use-related problems are heterogeneously distributed with respect to population and geography and consideration of local interactions. SimDrug has been conceptualised and implemented in order to capture the primary community structures and relationships that support drug use and related outcomes. Geography and local interactions are embedded within the structure of the spatial grid divided into 5 archetypal suburbs. Using the propriety of the cellular-automata, SimDrug allows for diffusion processes –such as hot spots displacement – to occur. Interactions amongst agents could be increased by creating converging sites where massive connections arise such as shopping malls or central rail stations. Moreover, as argued by Gorman et al.:

*“Models that capture the behaviour of [...] complicated community systems and control strategies that modify them must, therefore, combine available data, statistics, and spatiotemporal dynamics”.*

One of the main advantages of SimDrug is its ability to gather and blend, within the same tool, data (second-hand mainly) coming from very diverse sources. The structure is already flexible enough to integrate more information, as the prototype will evolve. The next stage will focus on transforming this data-collecting oriented platform into a discussion-oriented tool by improving the economical components. Integrating cost-efficiency analysis will help to explore combined strategies by adjusting the allocated resources between harm reduction (outreach workers), treatment (treatment centre) and repression (police station and constables). Using multi-agent systems to explore illicit drug market complexity appears to be cutting-edge domain. SimDrug encompasses great expectations to be used as a tool to confront and generate discussions amongst stakeholders and policy-makers. However, as pointed out by Gorman et. al, such approach will never provide an optimal solution but rather numerous possible context-specific solutions with potential outcomes being highly uncertain. In fact, the best global solution may be a collection of local solutions tailored to local circumstances and needs. Obviously, such an approach needs to be carefully explained and tools need to be genuinely tailored in order to appeal to policymakers, who would normally favour large scale standardised interventions that promise to deliver assured, definite, and extensive outcomes.

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