An Agent-based Model to Support Measuring Drug Choice and Switch Between Drug Types in Rural Populations

Georgiy Bobashev
RTI International
Research Triangle Park, NC
Bobashev@rti.org

Eric Solano
RTI International
Research Triangle Park, NC
Solano@rti.org

Lee Hoffer
Case Western Reserve University
Cleveland, OH
lee.hoffer@case.edu

Abstract—**In rural areas availability, price, and legal consequences can force some drug users to switch between primary drugs of choice. For example, as a consequence of stricter law enforcement policy in rural Ohio we observed a shift from methamphetamine use to heroin and prescription opiate use. We propose a polydrug agent-based model that describes drug users interconnected in a network. Behavior rules are based on our ethnographic research. The drug selection mechanisms are dictated by drug liking, drug availability, drug cost, perception of health and other life consequences, perception of potential punishment and pressure from the peers. The model produces time series of users' choices of one or concurrent drugs. Modeling and ethnographic data collection are interlinked i.e. model results lead to the improvements in quantitative measurements, which in turn improve the model. Polydrug trends are of particular interest to policy makers because short-term interventions can lead to long-term adaptation.**

Keywords- decision making, drug use modeling, drug switch, agent-based model, model-based survey

I. INTRODUCTION

National and regional drug use patterns have been changing, reflecting changes in individual choices of drugs, for example, marijuana in the late 1960s and 1990s, heroin epidemic waves of the early 1950s and 1970s (1971–1977), the crack epidemic in the late 1980s, and the methamphetamine epidemic in late 2000s [1]. These trends are difficult to predict because they reflect several adaptive factors including individual choices, public policy, public acceptance, and the adaptation of the supply side of the market. Despite the "war on drugs," drug use patterns and trends surprisingly persist [2]. Individual choices and drug trajectories have been extensively described by a number of researchers [3,4,5]. On the other hand, market adaptation has been extensively studied from a cost-effectiveness point of view [6]. However, these two components are seldom put together with a few exceptions [7,8]. Understanding is a critical component in policy and decision making. By "understanding," here, we mean the identification of causal patterns and feedbacks that could predict qualitatively or quantitatively the response resulting from the actions taken. Such understanding is complicated by a lack of available data and a lack of experience in collecting the right data. In this sense, to develop the right understanding, modeling and data collection should complement each other in an iterative manner. Data collection about illegal and adaptive behavior could benefit from model-based suggestions about which aspects of behavior to include as data items, and conversely, the collected data should educate the model about unexplained events and possible adaptations. In our NIDA-funded study we employ this approach. Based on initial ethnographic information we have developed a behavioral model which is now providing suggestions about specific aspects of ethnographic information that needs to be collected to further develop the model. The model is theoretical, meaning that the goal is to formally reflect our qualitative "understanding" of rural drug use patterns. The model is not supposed to reproduce numerically the observed data but rather identify qualitative trajectories of individual and collective response to external interventions.

Our agent-based model describes individual drug choices under the conditions of drug availability, perceived risk of drug use, impact of social network, and drug use "burnout." Although there are a few models that describe the process of drug use and operation of drug markets [4,6,10,12], there was little focus on modeling the switch between drug use. We considered two models: a simplified model focused on the specific phenomenon of switching between methamphetamine and opiates and an extended model that considers a greater variety of drug choices as well as the evolution of the supply side of the market. In this paper we focus on the simplified model because it serves the specific purpose of the study and provides a basis for the extended model under development. In the next section we describe the model's assumptions and the basic rules that are followed by drug using and market agents. Then we present our preliminary results and discuss the implication for data collection, policy analysis, and future work.

II. METHODS

To provide suggestions about specific aspects of ethnographic information that needs to be collected for understanding switches between markets we developed a theoretical agent-based model that describes our understanding of market functioning. The model is built using the Overview Design concepts and Details (ODD) protocol that was introduced and standardized by Railsback and Grimm [9]. The ODD is designed to demystify ABMs and provide the reader with a clear description of the logic, structure, and components of the model. The rest of the section is structured according to this protocol.

A. Purpose

The purpose of this model is to describe the manifold drug use patterns leading to community response to drug use interventions. The model will help to understand how drug preference, drug-acquiring effort levels, drug use consequences, and drug-sticking factors in a networked population affect the decision to switch the use of one drug for another. Drug preference identifies how much an individual likes a specific drug at a specific time.

The model translates ethnographic observations and narratives into formal causal rules and parameter values. The model can then be used to generate simpler aggregate system dynamics and statistical models that in turn could be calibrated and validated to "hard" survey data.

B. Entities, State Variables, and Scales

The model includes individuals who are drug users. There is a constant population of drug users during the entire simulation.

The simpler model contains only three reinforcers: Heroin, Opiates, and Other. Note that "Other" could include other drugs such as alcohol and marijuana, but also non-drug reinforcers such as sporting activities. For simplicity we separate methamphetamine and opiates from the other reinforcers.

The agents in the model use one, two, or all three reinforcers. We do not distinguish between occasional and regular use; however, we distinguish between never use, first use, and use of the reinforcer. The reason for such distinction is that the effect of the drug on individual perception of liking can change after first use and then after consequent use. Thus, in relation to each of the drugs an agent could be in one of the following non-overlapping states: Never used, tried it, use it, and used in the past. The extended version of the model also considers occasional and regular use (Figure 1).

Each individual can be in the community or institutionalized (incarcerated or in treatment). Each drug state is characterized by attitudes toward the drug (i.e., drug liking) and a number of external factors. The transition between the stages is additionally governed by external factors such as peer pressure.
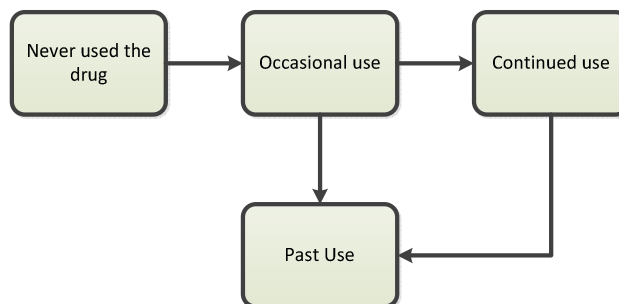
Figure 1. State chart for an agent in the multiple drug user model

The population of drug users is interconnected. Drug users are linked to a number of other drug users during the simulation. The linkage between two drug users is maintained during the entire simulation.

C. Process Overview and Scheduling

This model proceeds in monthly time steps. Within each month or time step, four phases are processed in the following order: drug selection probability calculations, selected drugs identification, drug use state update, and drug preference update.

At each time step an individual considers a number of competing priorities, and evaluates them according a combination of six drug factors:
- Drug liking
- Drug availability
- Drug cost
- Perception of health and other life consequences
- Perception of potential punishment
- Pressure from peers

These factors can change in time according to external or internal factors. For example, external influences can be related to drug availability, activities of drug cartels, or the perception of punishment, which could increase due to formation of a police task force to fight a specific drug. Internal influences are associated with the increase of "drug liking" after prolonged use. We also consider that in time some drugs could lead to "burnout" and decrease in liking. Although we use the term "drug liking" for the description of both positive and negative reinforcement, we implicitly distinguish between them by assuming that occasional use is a result of positive reinforcement and dependence is a result of negative reinforcement. The resource can be stable over time or get reduced because of loss of a job caused by addiction. Thus, a number of complex feedback loops impact the formation and development of individual and community drug use patterns in the drug market environment.

Agents can get institutionalized depending on perceived punishment. Although the punishment perception should follow the severity of the punishment we assume that these factors are immediately correlated and controlled externally by an observer or external input.

Timeline. We are more focused on long-term changes rather on daily behavior. The time horizon in the simulation is 10 years. The time steps are of 1-month duration.

Scheduling. At each timestep each agent first evaluates the external and internal factors and then makes a decision about which drugs to use for the next timestep. Among external factors we consider the prevalence of drug use among agents' peers. In a simplest implementation we assume that the community is closed and everyone is connected to everyone, so rather than considering a complex social network we average the drug use in the community to create the "peer pressure" factor. In a more realistic setting we consider two overlapping networks: heroin and methamphetamine. The assessment of the network is done before any individual state changes.

D. Design Concepts

The model design assumes that each person is interconnected with a number of people in the population. The model hypotheses are that changes of use from one type of drug to another depends on drug preference, drug-acquiring efforts levels, drug use consequences, and drug-sticking factors.

The model design assumes that drug supply is a commodity that is always available. Drug suppliers are different for different drugs. Drug preference changes over time for each type of drug. If a person has null preference for a drug, the only way to change it to a positive preference is through social pressure exerted by the person's network.

Emergence. We do not consider explicit emergent behavior, but rather expect that emergent behavior could form on its own from existing rules. We might expect to see that the impact in one limiting parameter such as increase in punishment for a single drug without providing alternative reinforcement option for "no use" could lead to the increase in other drugs becoming dominating depending on the punishment and availability of the new drug. Thus, with the delay in response we might expect long-term waves in drug use that have been historically observed in the United States and worldwide.

Agent objectives. Agents have their resources and are willing to spend them depending on the current assessment of the situation. They do not have any long-term objectives, but rather make a choice according to the criteria based on a combination of expected effect and risks.

In real life individuals have resources such as time and funds that they spend on their priorities. The resources act as limiting factors that control the mix of drugs an individual can use. By considering other reinforcers we cover the entire space of choice possibilities that compete for these resources. Rather than have an explicit set of resources we consider a relative score which is defined as a scaled absolute score and the agent makes choices based on the values of that relative score. For each choice we define an absolute score Xi as follows:

$$X_i = \frac{Liking * Availability * PeerInfluence}{(1+Price)(1+HealthProb)(1+Punishment)}, \quad (1)$$

where each of the components is defined on a scale from 0 to 100. The relative score is defined as $S_i = \frac{X_i}{\sum_i X_i}$. We also provide the rule for making the choice to try and to use the drug. If for a specific drug the score $S_i > T1$, where $T1$ is an upper threshold, then the individual will become a user of

that choice. If the relative score is between *T1* and *T2*, where *T2* is a lower threshold, then the user will try the reinforcer, and if the score is less than *T2* then the user will not be using that drug. The natural low limit for *T2* is 1/3 given that we have 3 choices of reinforcers. This will guarantee that at least one choice will be made. The example of the relative score is presented in Figure 2.

Adaptation. Agents assess their social network and include the assessment in the objective function.

Learning. Agents' learning ability is represented in the form of drug-liking dynamics. The more an agent uses the drug the more it "likes" the drug. We use the term "liking" as a surrogate of the actual liking and dependence. Although one of the characteristics of drug addiction is negative reinforcement (i.e., an individual uses a drug to reduce discomfort) we consider that limited to the dynamics of the drug-liking function (i.e., they can move from occasional to regular users). Future model versions will have the affinity to their drug using group as a part of generating "comfort" as an additional factor impacting the choice of drug.
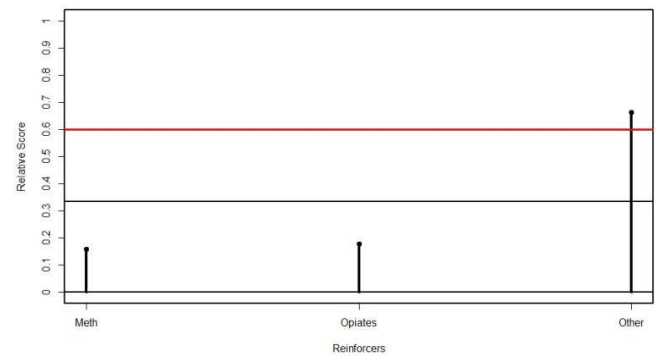
Figure 2. Example of the relative score diagram. "Other" reinforcement shows the highest score thus this agent will choose the "Other" reinforcement.

We distinguish growth in drug use liking after first use and tempering out with time reflecting the "burn out" in drug use. This is done by multiplying the liking by the burnout function which has a logistic shape with characteristic time. The functional form for the growth and burnout in liking is represented with a function with interpretable coefficients:

$$L_i = \frac{at^b}{(1+at^b)} \frac{1}{(1+ce^{(d(t-t'))})}, \quad (2)$$

where t is the time since the first try, a, b, c, d and t' are scaling parameters with a corresponding to the speed of initial growth and is used to distinguish between occasional and regular use. Parameter b is characteristic of different drugs, parameter c corresponds to the end point for the liking, d corresponds to the speed at which the liking is reduced, and t' to the timing of the decline in liking. The largest possible liking corresponds to the value of 100.
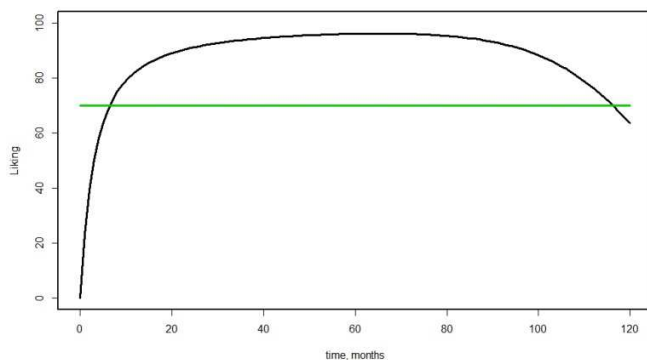
Figure 3. Liking function for heroin.

In Figure 3 we present the shapes of the liking function for a drug such as heroin as it progresses in time. It takes a short period of use to get addicted but after a long period of use the liking is lowered because of the detraining health and lifestyle effects. The characteristic times of the liking dynamics could be defined as times when the liking reaches 70 of the maximum value. In Figure 3 these times will correspond to points where the liking function crosses the horizontal (green) line.

Prediction. The agents do not make any prediction. All prediction is described by an immediate assessment of health and punishment risks.

Sensing. Agents sense the state of the members of their network (currently everyone).

Interaction. Agents do not directly interact with each other, they only sense the state of network members.

Stochasticity. In the current version agents are deterministic by choosing the "best" combination of drugs; however, there is an option to randomly make the stochastic choice with probability of choosing being proportional to the relative score of the drug choice. The stochastic component is introduced at the level of creating connections in a social network. The potential usage of a drug is a binary variable that depends on the individual's social index. The social index is computed as a function of the individual's previous drug use and the previous drug use of the individual's peers. The potential use is then computed using a Bernoulli distribution with social index as the parameter. Initial drug preference values and initial drug use states are randomly selected from a set of four possible states, each with a given probability.

Collectives. Collectives are defined according to the type of reinforcer they use. Thus, an individual could be in more than one collective at a time.

Observation. The observer has options to impact drug availability and perceived drug punishment. At each step we record the individual's drugs of use which are recorded in the output file and then can be analyzed.

Initialization. A randomly linked network is initially created and used for each simulation. Each drug user is initialized by assigning a random number of linked people and the values of drug preferences and drug characteristics. A number of other structured networks has been considered, e.g. scale-free and a small world, but actual validation of the

network structure is not feasible at this point, thus we use the simplest random arrangement.

III. MODEL APPLICATIONS

The model was developed as a standalone Java application as well as a NetLogo model. The models were verified through a system of sequential tests: (1) a collection of individual users, no market agent (drug characteristics do not change), no networks; (2) addition of networks, no market agent; and (3) network and agents. Althought the direct validation of the model has not been feasible becase of the lack of direct measurements in the real world setting, the face validity of the resutls were discussed with the ethmographers and law enforcement respresentatives.

The main application of this model resulted in the design of a set of six questions aimed to calibrate the model. These questions corresponded to the items in the score and were defined at a 10-scale level. This questionnaire was included into a longer ongoing ethnographic survey of drug users. Upon the completion of the study the data will be used for model calibration and validation on historic data.

Here we present the results of a hypothetical scenario. After the market locally stabilizes, the action of law enforcement leads to the increase in consequences of the local methamphetamine market, which in turn leads to the reduction in meth use and increase in other reinforcements available in the social network. Because heroin has a higher addictive potential than "other" reinforces it eventually wins over the community with a temporary dominance of other reinforcements. Figure 4 shows the results of running the simulation for 2 years.
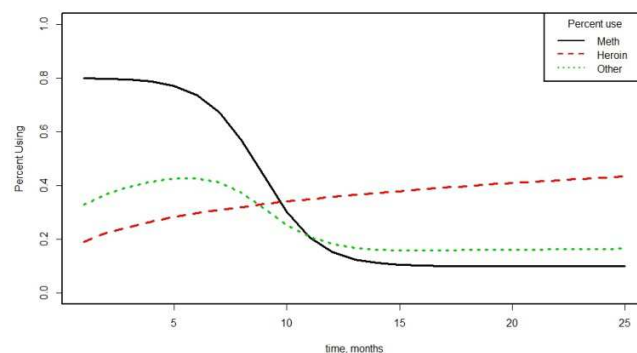
Figure 4. Drug use trends corresponding to the scenario where law enforcement activities led to the reduction in methamphetamine use and the increase in heroin use.

After users try heroin they get quickly addicted and by the time methamphetamine is reintroduced to the community many former meth users are on heroin. Addition of methamphetamine increases the chance of using both.

IV. DISCUSSION

We present a model that describes individual priorities in the choice of drug and the relationship between the individual choices, drug supply adaptation and the impact of community and law enforcement which sometimes leads to

short time success followed by long-term resistance and opposite results. Our model provides a possible explanation on why law enforcement strategies often fail. When the law enforcement attempts don't consider long-term market adaptation and with limited resources the success is quickly diminished by the adaptation in a different dimension. These adaptations sometimes make drug markets more efficient as in [10] or dominated by a more addicted drug as in the case of Summit County considered in this paper. Historical precedents support the need for a systems approach. For example, the increase in border control between the United States and Mexico in 1969 (Operation Intercept) led to an increase in the use of other drugs (76% of students and 84% percent of patients reported that they increased their consumption of one or more other drugs (including alcohol) because of the unavailability of marijuana) [11]. Additionally, smugglers have found more efficient ways to smuggle the drug into the United States and domestic marijuana growth has increased, which made the illegal market more efficient [11].

Although our paper presents a simple theoretical model, ethnographic research can play a key role in a realistic understanding of feedback processes and consequences of interventions. Ethnographic research allows one to collect data on the actual reasoning and causal relationships that are often hidden from standardized surveys. Although limited to a smaller number of individuals, ethnographic data provide the basis for the development of theoretical mental models. The process of building ABMs allows one to convert these mental models into formal rules and parameters. By simulating trajectories from these ABMs one can obtain understanding of the main consequences and adaptations one can expect from the interventions. Although more difficult to calibrate and validate microsimulation have an advantage of capturing non-linearities that occur due to complex decision making and networks structures. As shown in [13] a simplification of an ABM by aggregating over the population agents and time requires careful analysis, otherwise a simplified aggregated model will not adequately represent the dynamics of the full model. After selecting the best theoretical scenarios ABMs can provide the basis for population-based data collection through more reliable means such as representative surveys. The advantage of such an approach is that now the surveys are grounded in realistic causal pathways and thus their predictive validity becomes much more prominent.

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REFERENCES

[1] Hunt, D., S. Kuck, and L. Truitt, (2006) Methamphetamine Use: Lessons Learned, final report to the National Institute of Justice, (NCJ 209730), available at www.ncjrs.gov/pdffiles1/nij/grants/209730.pdf.

[2] Global commission on War on drugs National report June 02 2011. Available online at: http://www.scribd.com/doc/56924096/Global-Commission-Report

[3] Anglin, M.D., et al., (2001). Drug treatment careers: Conceptual overview and clinical, research, and policy applications. In: F. Tims, C. Leukefeld, and J. Platt (Eds.), Relapse and Recovery in Addictions. New Haven, CT: Yale University Press, pp. 18-39.

[4] Agar M. (2005) Agents in Living Color: Towards Emic Agent-Based Models. *Journal of Artificial Societies and Social Simulation* vol. 8, no. 1

[5] Anderson T. (1998) A cultural-identity theory of drug abuse. Sociology of Crime, Law, and Deviance, Volume 1, pp 233-262.

[6] Caulkins, J P. and MacCoun R. (2005), Analyzing Illicit Drug Markets When Dealers Act with Limited Rationality. In Francesco Parisi and Vernon L. Smith (eds.) The Law and Economics of Irrational Behavior, Standard University Press, Stanford, CA, pp.315-338.

[7] Perez P., Dray A., Moore D., Dietze P., Bammer G., Jenkinson R., Siokou C., Green R, Hudson S.L., Maher L., (2011) SimAmph: an agent-based simulation model for exploring the use of psychostimulants and related harm amongst young Australians. The International journal on drug policy. 06/2011; 23(1):62-71

[8] Hoffer, L. (2006) Junkie Business: The Evolution and Operation of a Heroin Dealing Network, Belmont, CA: Thompson Wadsworth.

[9] Steven F. Railsback & Volker Grimm (2012) Agent-Based and Individual-Based Modeling: A Practical Introduction Princton University Press.

[10] Hoffer, L. D., Bobashev, G. V., & Morris, R. J. (2011). Simulating patterns of heroin addiction within the social context of a local heroin market. *In Computational neuroscience of drug addiction* (pp. 313–331). New York: Springer.

[11] McGlothlin W., K. Jamison, and S. Rosenblatt, (1970) Marijuana and the Use of Other Drugs, *Nature* 228: 1227-1229

[12] Lamy F., Bossomaier T., PerezP., SimUse: modeling recreational polydrug use through an agent-based model *Proceedings of the 12th International Conference on Modeling and Applied Simulation*, Athens, Greece 2013: 61-69

[13] Heard D., Morris J., Bobashev G.V., (2014) Reducing the Complexity of an Agent-Based Local Heroin Market Model, *PLoS One.* DOI: 10.1371/journal.pone.0102263