Journal Club

Discussion on the paper :

Selecting a Dynamic Simulation Modeling Method for Health Care Delivery Research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force

Marshall et al.

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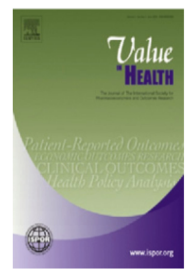


ISPOR TASK FORCE REPORTS

Selecting a Dynamic Simulation Modeling Method for Health Care Delivery Research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force

CrossMark

Deborah A. Marshall, PhD[1,], Lina Burgos-Liz, MSc, MPH, BSc Ind Eng[2], Maarten J. IJzerman, PhD[3], William Crown, PhD[4], William V. Padula, PhD, MS[5], Peter K. Wong, PhD, MS, MBA, RPh[6], Kalyan S. Pasupathy, PhD[7], Mitchell K. Higashi, PhD[8], Nathaniel D. Osgood, BS, MS, PhD[9,10], the ISPOR Emerging Good Practices Task Force*

Presenting by :

Dr. Mohammadreza Mobinizadeh

Associate Professor of Health Management and Economics, Tehran University of Medical Sciences

National Institute for Health Research of the Islamic Republic of Iran

Simulation Types

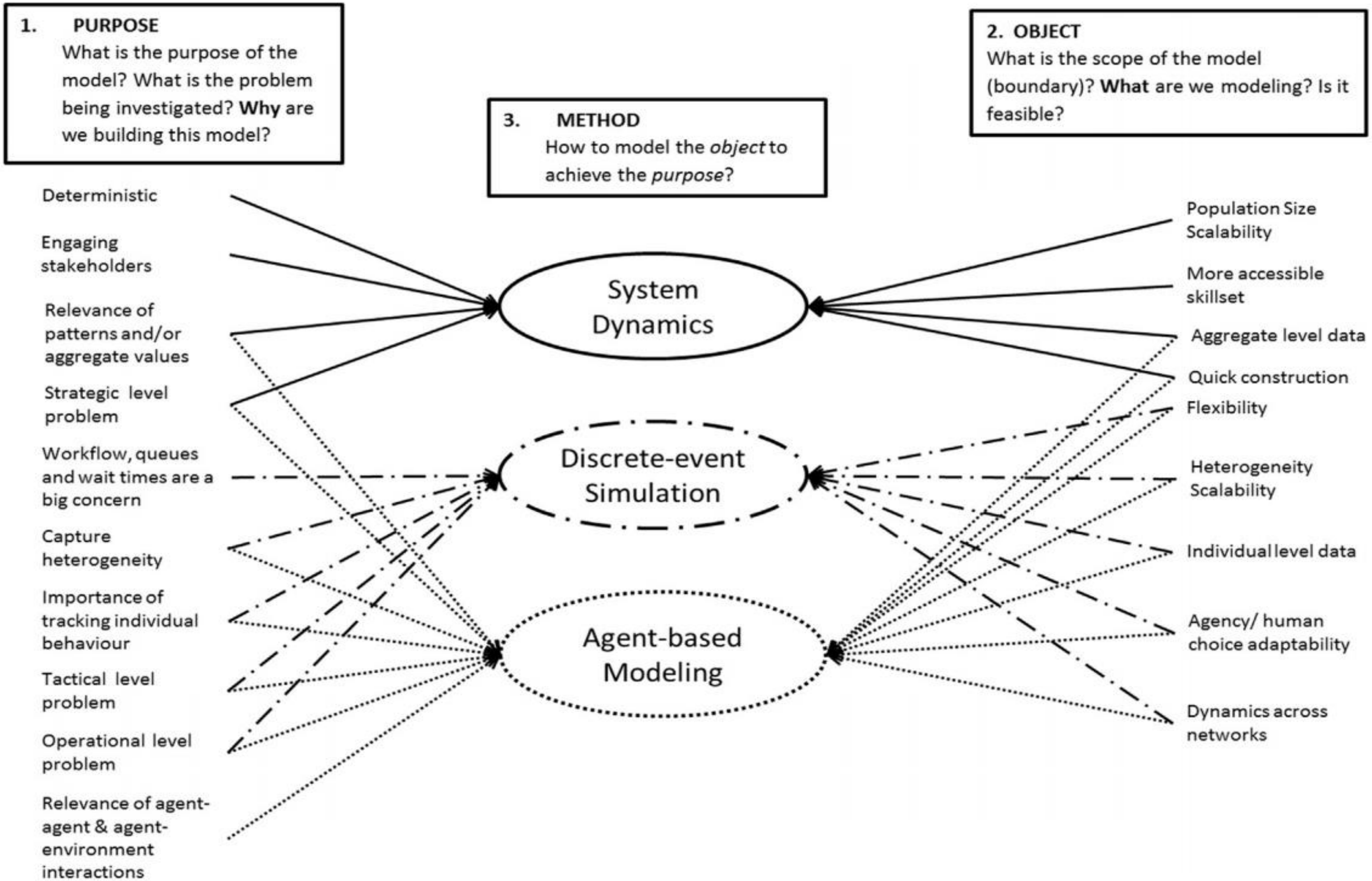
1) **Static Simulation :**

- Machine Learning

2) **Dynamic Simulation :**

- System Dynamics
- Discrete Event Simulation
- Agent-based Modeling

High-level summary of criteria for selecting a dynamic simulation modeling method



Static Simulation

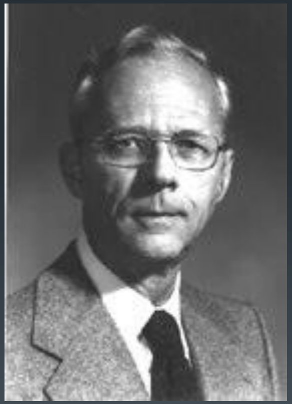
- A static model is trained offline. That is, we train the model exactly once and then use that trained model for a while.

- A static model can be thought of as providing a 'snapshot' of a system's response to a specified set of input conditions.

System Dynamics Simulation Model

- SD is a simulation modeling method used for representing the structure of complex systems and understanding their behavior over time (dynamic).

- It is rooted in “industrial dynamics” and was developed by Jay Forrester, Massachusetts Institute of Technology, in the 1950s.



(July 14, 1918 – November 16, 2016)

System Dynamics Simulation Model

- SD is based on the core assumption that the behavior of the system is a consequence of the system structure and not external forces or factors.
- The structure of the system can be understood as the feedback loop structure, and the structure of accumulations and rates, which generate the behaviors.

System Dynamics Simulation Model

- SD models traditionally aggregate the population in states and subpopulations rather than analyzing at the individual level.

- Therefore, SD models provide a deterministic cross-sectional view of a system by counting over time the number of people exhibiting particular combinations of characteristics or in particular (e.g., health) states.

- Variables can be one of three types—**stock**, **flow**, or **auxiliary**.

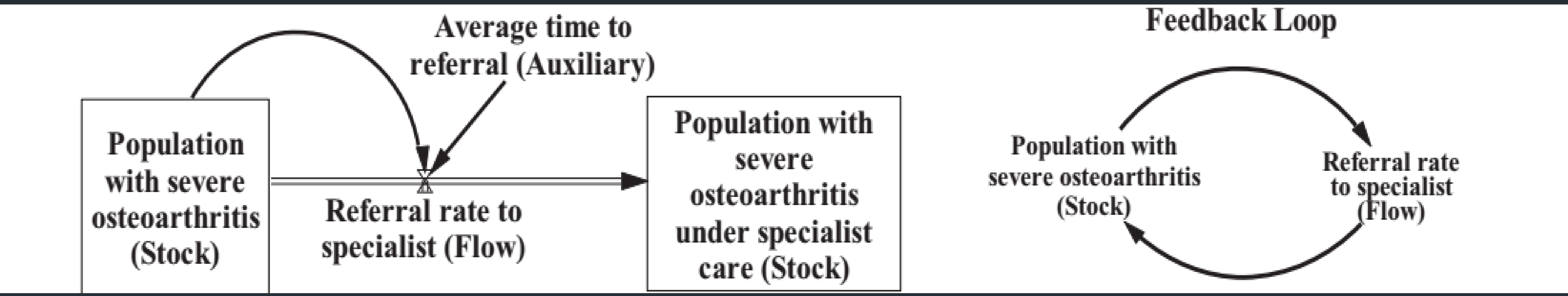
System Dynamics Simulation Model

- Stocks are accumulations or aggregations of something, for example, people, beds, or oxygen.

- The flow variables (also known as rates of change) change the accumulations of the stocks and control the rates of flow. Flows (rates) feed in and out of stocks and have the same units of stocks per time unit, for example, people per hour, beds per year, or oxygen per minute.

- The auxiliary variable are calculated values that can affect inflows and outflows or other auxiliary/constant variables.

System Dynamics Simulation Model



System Dynamics Simulation Model

SD can be used for policy analysis and design for problems in complex social, managerial, economic, and ecological systems. Any dynamic system is characterized by interdependence, mutual interaction, and feedback. Most applications can be categorized as

1) Recognition and identification of behavioral patterns in a system, for example, in an organization;

2) Gain insight into the processes of a system and the consequences of decisions;

3) Identification of leverage points and/or structures in the system to generate change and foster system redesign; and

4) Reproduction of a given behavior (reference mode).

System Dynamics Simulation Model

As an example, Milstein et al. used SD to study and evaluate the US health system reform that included three main strategies: coverage, care, and protection.

The model was designed to address questions around the impact of these strategies nationwide, individually and together. This is a typical example of a broad problem with system wide implications that requires a holistic perspective with attention to dynamic processes within the system and its structure.

System Dynamics Simulation Model

The modelers estimated the relative and combined effects of the three strategies from 2000 to 2010 and asked what might have happened had the United States taken decisive action in these three areas during that decade in terms of reducing avoidable deaths and lowering health care costs for Americans. Results and simulated scenarios show that all three strategies have the potential of saving millions of deaths while offering good economic value.

System Dynamics Simulation Model

COSTS, ISSUES & CONTROVERSIES

By Bobby Milstein, Jack Homer, Peter Briss, Deron Burton, and Terry Pechacek

Why Behavioral And Environmental Interventions Are Needed To Improve Health At Lower Cost

DOI: 10.1377/hlthaff.2010.1116
HEALTH AFFAIRS 30,
NO. 5 (2011): 823–832

ABSTRACT We used a dynamic simulation model of the US health system to test three proposed strategies to reduce deaths and improve the cost-effectiveness of interventions: expanding health insurance coverage, delivering better preventive and chronic care, and protecting health by enabling healthier behavior and improving environmental conditions. We found that each alone could save lives and provide good economic value, but they are likely to be more effective in combination. Although coverage and care save lives quickly, they tend to increase costs. The impact of protection grows more gradually, but it is a critical ingredient over time for lowering both the number of deaths and reducing costs. Only protection slows the growth in the prevalence of disease and injury and thereby alleviates rather than exacerbates demand on limited primary care capacity. When added to a simulated scenario with coverage and care, protection could save 90 percent more lives and reduce costs by 30 percent in year 10; by year 25, that same investment in protection could save about 140 percent more lives and reduce costs by 62 percent.

Bobby Milstein (bmilstein@cdc.gov) is the coordinator for the Syndemics Prevention Network at the Centers for Disease Control and Prevention, in Atlanta, Georgia.

Jack Homer is president of Homer Consulting, in Voorhees, New Jersey.

Peter Briss is the medical director of the National Center for Chronic Disease Prevention and Health Promotion, at the Centers for Disease Control and Prevention.

Deron Burton is a Commissioned Corps officer at the Center for Global Health, at the Centers for Disease Control and Prevention.

Terry Pechacek is the associate director for science of the Office on Smoking and Health, at the Centers for Disease Control and Prevention.

Americans are engaged in a long-standing quest to fundamentally improve the US health system. The Affordable Care Act of 2010 in-

health system as a whole, with attention to the dynamic processes that connect its distinct parts and produce changes over time.

We estimated the relative and combined health

Discrete-Event Simulation model

- DES is used to represent processes at an individual level where people may be subject to events, whether they be decisions or occurrences over time.

- DES is a simulation method that is used to characterize and analyze queuing processes and networks of queues where there is an emphasis in the utilization of resources.

- Core concepts in DES are events, entities, attributes, queues, and resources.

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Discrete-Event Simulation model

- Patients are individual entities with particular characteristics that flow through the processes of “triage and admission” and “consult and procedure”, both of which take a certain amount of time and require resources such as a triage nurse and a physician.

- Patients wait in queues for both processes, proceed through them, and are finally discharged.

Discrete-Event Simulation model

- An example of a problem that can be addressed with DES is to facilitate decision making for a health system to invest in expansion of ED and/or intensive care units (ICUs) based on variable patient flow.

- The flow of patients into a hospital is typically limited by ED capacity; ICUs also limit flow at times when admissions are high, or patient flow increases from other parts of the health system such as the ED, surgery, or decompensated patients in general medicine.

Discrete-Event Simulation model

- Thus, future patients requiring critical care are held in the ED for longer times, and those who may have had scheduled high-revenue appointments such as surgery have to be cancelled and rebooked.

- The lack of bed availability in the ED prohibits additional patients from being accepted at a facility. This classical case leaves many health systems constantly investigating whether to expand ED capacity, as well as downstream units such as the ICU, to enhance flow.

Discrete-Event Simulation model

ScienceDirect

Surgery
Volume 146, Issue 4, October 2009, Pages 608-620

Central Surgical Association

Using simulation to determine the need for ICU beds for surgery patients

Philip Marc Troy PhD, Lawrence Rosenberg MD, PhD

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https://doi.org/10.1016/j.surg.2009.05.021

Background

As the need for surgical ICU beds at the hospital increases, the mismatch between demand and supply for those beds has led to the need to understand the drivers of ICU performance.

Method

A Monte Carlo simulation study of ICU performance was performed using a discrete event model that captured the events, timing, and logic of ICU patient arrivals and bed stays.

Results

The study found that functional ICU capacity, ie, the number of occupied ICU beds at which operative procedures were canceled if they were known to require an ICU stay, was the main determinant of the wait, the number performed, and the number of cancellations of operative procedures known to require an ICU stay. The study also found that actual and functional ICU capacity jointly explained ICU utilization and the mean number of patients that should have been in the ICU that were parked elsewhere.

Conclusion

The study demonstrated the necessity of considering actual and functional ICU capacity when analyzing surgical ICU bed requirements, and suggested the need for additional research on synchronizing demand with supply. The study also reinforced the authors' sense that simulation facilitates the evaluation of trade-offs between surgical management alternatives proposed by experts and the identification of unexpected drawbacks or opportunities of those proposals.

Discrete-Event Simulation Model

Agent-based Simulation Model

- ABM is a simulation method for modeling dynamic, adaptive, and autonomous systems. It is useful to discover patterns or emergence by using “deductive” and “inductive” reasoning.

- In contrast to SD or DES models, which begin with a “top-down” approach of mapping a system or process, ABM begins with a “bottom-up” approach.

- The foundation of an ABM model begins with individual objects and describes their local behavior with local rules.

- One of the earliest agent-based models in concept was Thomas Schelling's segregation model, which was discussed in his paper "Dynamic Models of Segregation" in 1971.

1921-2016

Agent-based Simulation Model

- At the core of an ABM model, these “autonomous” and “interacting” objects are called agents.

- Agents are social and interact with others, they live in an environment, and their next actions are based on the current state of the environment.

- In addition, an agent senses its environment and behaves accordingly on the basis of simple decision rules.

- The definition of agent behaviors uses a range of simple to complex mathematical logic operators.

Agent-based Simulation Model

The three core concepts that form the basis for ABM are **agency**, **dynamics**, and **structure**.

- **Agency** means that agents have goals and beliefs and can act. Examples of agents can include patients, providers, and administrative staff. These agents can move through space and time, interact with each other, learn, and disseminate new learnings to other agents in their social network.

- **Dynamics** means that both the agents and their environment can change, develop, or evolve over time.

- **Structure** is emergent from agent interaction.

For instance, how populations of people tend to aggregate in certain locations on the basis of predefined behaviors is an example of agent interaction.

Agent-based Simulation Model

An example of ABM is the study published by Macal et al. in which they model the community-associated methicillin-resistant Staphylococcus aureus (CA-MRSA) epidemiology in Chicago to identify target interventions to reduce transmission.

They developed an agent-based model to represent heterogeneity in population locations, behavior, and contact patterns, which are relevant for transmission and control.

Agent-based Simulation Model

The Chicago CA-MRSA ABM included places such as households, workplaces, schools, gymnasiums, nursing homes, hospitals, jails, and college dormitories. Each agent in the ABM has a “daily activity profile” that determines the times he or she occupies each location. Social contact between agents occurs when multiple agents occupy the same location at the same time.

Depending on age, for example, some agents are assigned to schools. Also, households are assigned visits to other households within the same census area and other areas.

Agent-based Simulation Model

Macal *et al. Journal of Translational Medicine* 2014, **12**:124
http://www.translational-medicine.com/content/12/1/124

JOURNAL OF TRANSLATIONAL MEDICINE

RESEARCH Open Access

Modeling the transmission of community-associated methicillin-resistant *Staphylococcus aureus*: a dynamic agent-based simulation

Charles M Macal[1,2*], Michael J North[1,2], Nicholson Collier[1], Vanja M Dukic[3], Duane T Wegener[4], Michael Z David[5,6], Robert S Daum[7], Philip Schumm[6], James A Evans[8], Jocelyn R Wilder[6], Loren G Miller[9], Samantha J Eells[9] and Diane S Lauderdale[6]

Abstract

Background: Methicillin-resistant *Staphylococcus aureus* (MRSA) has been a deadly pathogen in healthcare settings since the 1960s, but MRSA epidemiology changed since 1990 with new genetically distinct strain types circulating among previously healthy people outside healthcare settings. Community-associated (CA) MRSA strains primarily cause skin and soft tissue infections, but may also cause life-threatening invasive infections. First seen in Australia and the U.S., it is a growing problem around the world. The U.S. has had the most widespread CA-MRSA epidemic, with strain type USA300 causing the great majority of infections. Individuals with either asymptomatic colonization or infection may transmit CA-MRSA to others, largely by skin-to-skin contact. Control measures have focused on hospital transmission. Limited public health education has focused on care for skin infections.

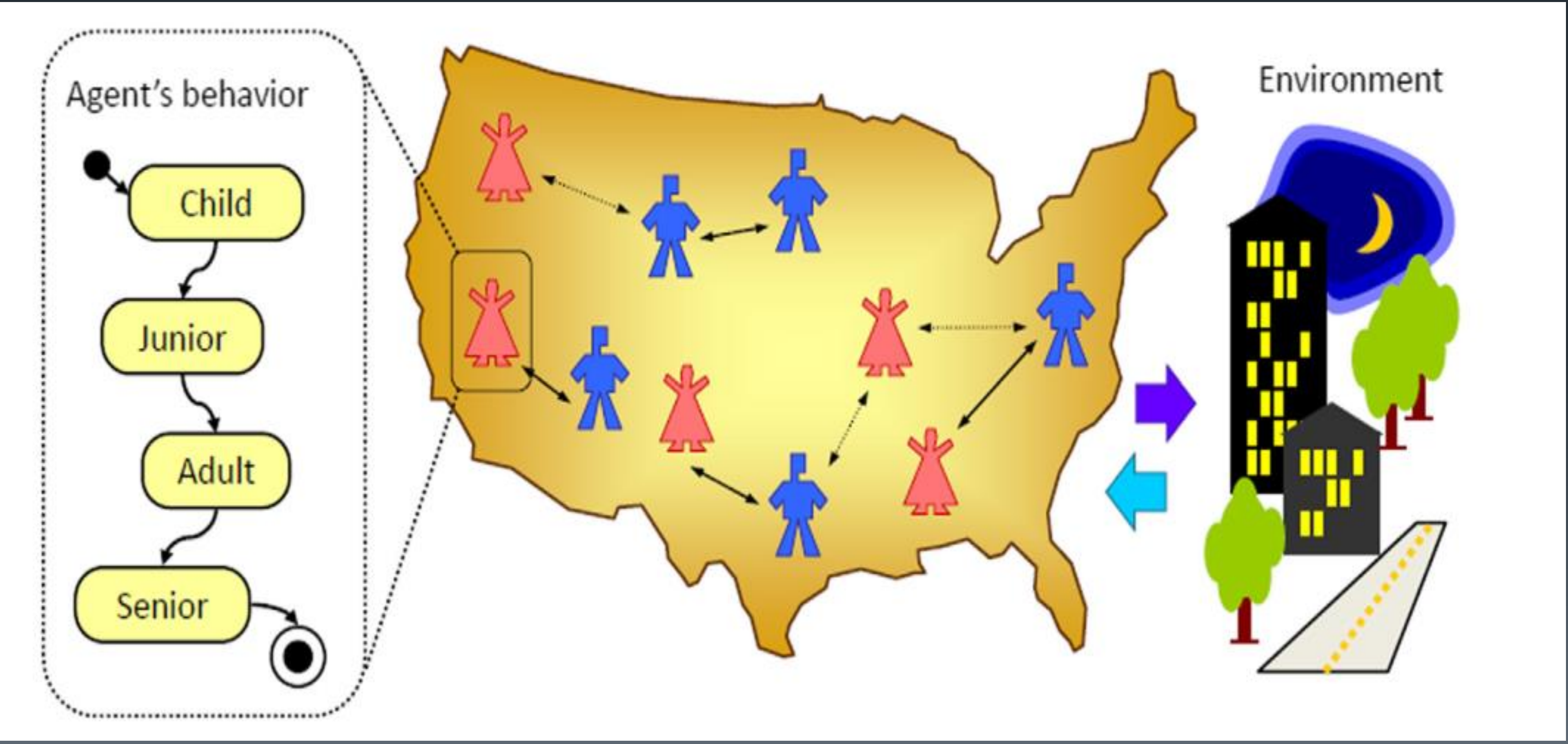
Methods: We developed a fine-grained agent-based model for Chicago to identify where to target interventions to reduce CA-MRSA transmission. An agent-based model allows us to represent heterogeneity in population behavior, locations and contact patterns that are highly relevant for CA-MRSA transmission and control. Drawing on nationally representative survey data, the model represents variation in sociodemographics, locations, behaviors, and physical contact patterns. Transmission probabilities are based on a comprehensive literature review.

Results: Over multiple 10-year runs with one-hour ticks, our model generates temporal and geographic trends in CA-MRSA incidence similar to Chicago from 2001 to 2010. On average, a majority of transmission events occurred in households, and colonized rather than infected agents were the source of the great majority (over 95%) of transmission events. The key findings are that infected people are not the primary source of spread. Rather, the far greater number of colonized individuals must be targeted to reduce transmission.

Conclusions: Our findings suggest that current paradigms in MRSA control in the United States cannot be very effective in reducing the incidence of CA-MRSA infections. Furthermore, the control measures that have focused on hospitals are unlikely to have much population-wide impact on CA-MRSA rates. New strategies need to be developed, as the incidence of CA-MRSA is likely to continue to grow around the world.

Keywords: MRSA, Agent-based model, Infectious disease model

Agent-based Simulation Model



Dynamic Simulation Models :Comparative Format

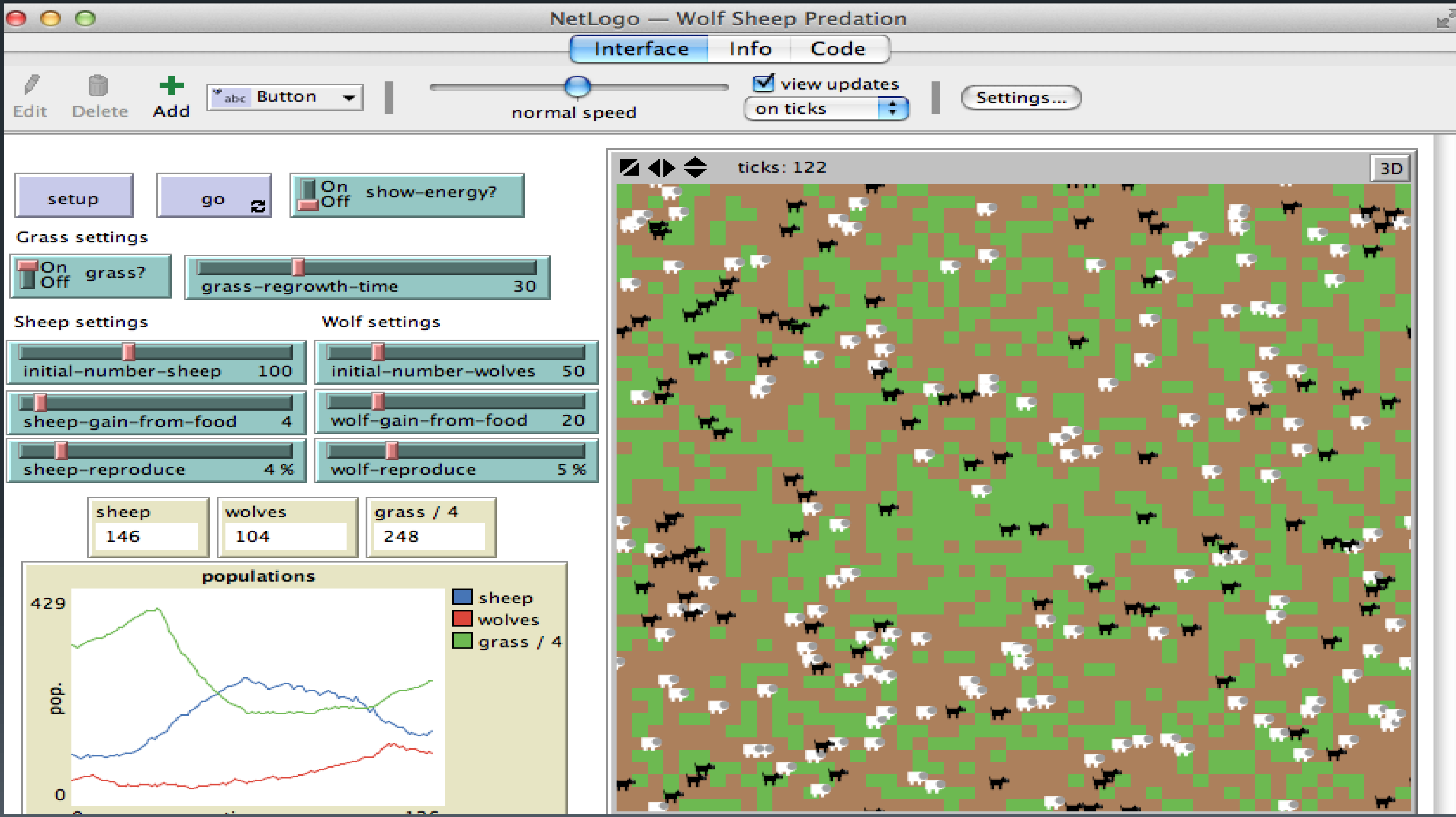
	Method		
Aspect	**System dynamics**	**Discrete-event simulation**	**Agent-based modeling**
Type of problems	Strategic, operational	Operational, tactical	Strategic, operational, tactical
Perspective	System-oriented, emphasis on dynamic complexity (top–down)	Process-oriented, emphasis on detail complexity (top–down)	Individual-oriented, dynamic and detail complexity (bottom–up)
Resolution	Homogeneous entities, continuous policy pressures and emergent behavior	Individual heterogeneous *passive* entities, attributes, and events	Individual heterogeneous *active* agents, decision rules
Origin of dynamics	Deterministic endogenous fixed structure	Stochastic endogenous fixed processes	Agent–agent, agent–environment interactions and adaptive behavior of agents
Handling of time	Continuous	Discrete	Discrete
Approach	Exploratory and explanatory	Explanatory	Exploratory and explanatory
Basic building blocks	Feedback loops, stocks, and flows	Entities, events, queues	Autonomous agents, decision rules
Data sources	Broadly drawn: qualitative and quantitative	Numerical with some judgmental elements	Broadly drawn: qualitative and quantitative
Unit of analysis	Feedback loops and stocks' dynamics	Queues, events	Decision rules, emergent behavior
Mathematical formulation	Differential equations	Mathematically described with logic operators	Mathematically described with logic operators and decision rules
Outputs	Understanding of structural source of behavior modes, patterns, trends, relevant structures, aggregate key indicators	Point predictions, performance measures	Detailed and aggregate key indicators, understanding of emergence due to individual behavior, point predictions
Model maintenance	Upkeep may require large structure modifications, global	Upkeep may require process modifications, global. Allows for local modifications regarding individual heterogeneity	Upkeep may require simple local modifications
Development time	Dependent on the problem, purpose, and scope of the model; these models may require less time to be developed	These models are more data intensive. This requires more time regarding obtaining data and data analysis to prepare model inputs. Programming and calibration are usually very time consuming	These models can be data intensive, which requires data analysis and time to obtain the data. Programming and calibration are usually very time consuming
Cost	In general, SD is less costly than are DES and ABM. This involves data requirements, and skill sets needed	Because of costs associated with data and skill sets required, these methods tend to be more costly than is SD	If the model is data intensive or requires primary data collection, costs may increase. Skill sets required may also increase the costs

ABM, agent-based modeling; DES, discrete-event simulation; SD, system dynamics.

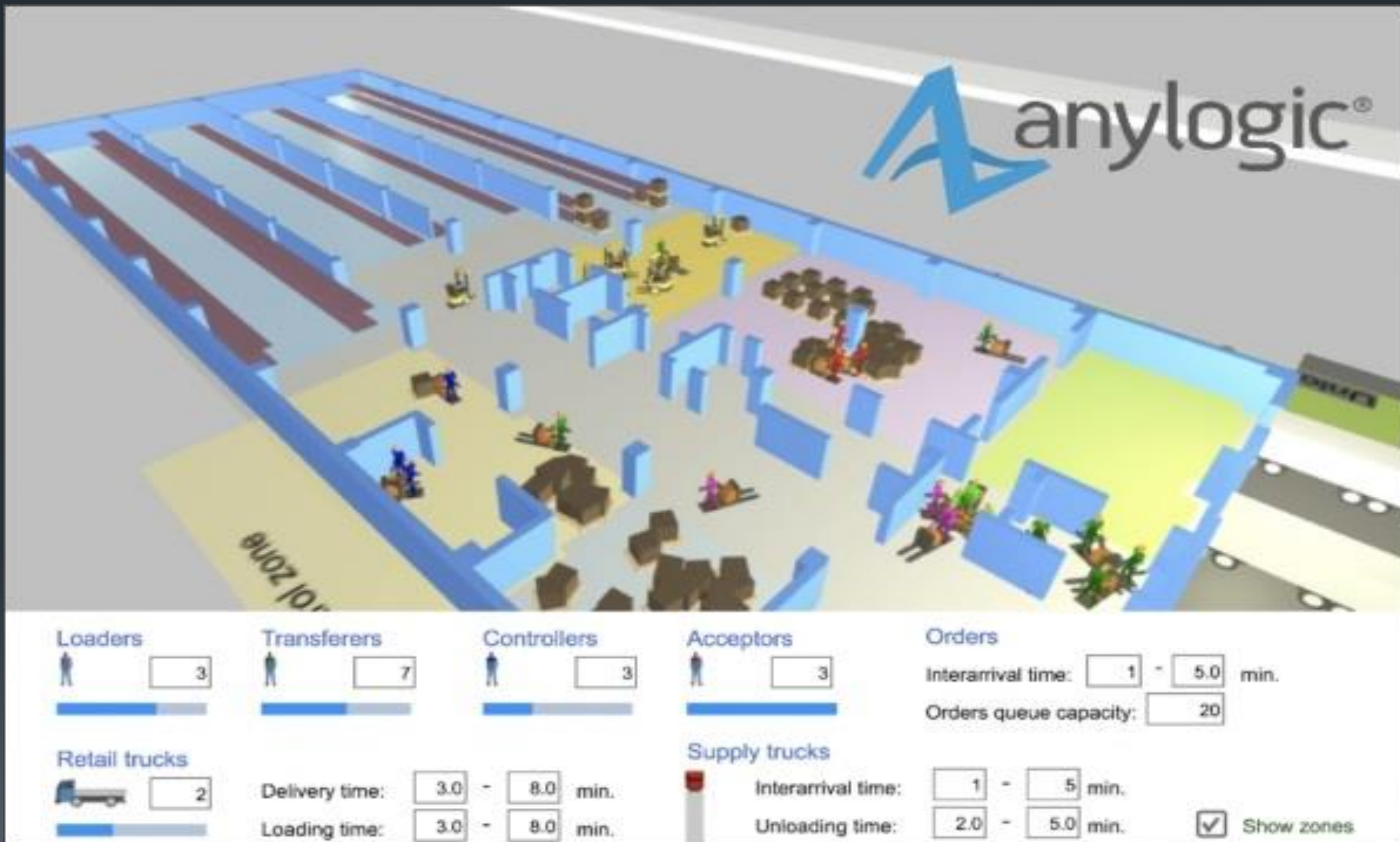
Dynamic Simulation Modeling Software

- System Dynamics : Vensim, Anylogic, Netlogo,….
- Discrete Event Simulation : Anylogic, Arena, …
- Agent-based Modeling : Anylogic, Netlogo

Dynamic Simulation Modeling Software



Dynamic Simulation Modeling Software



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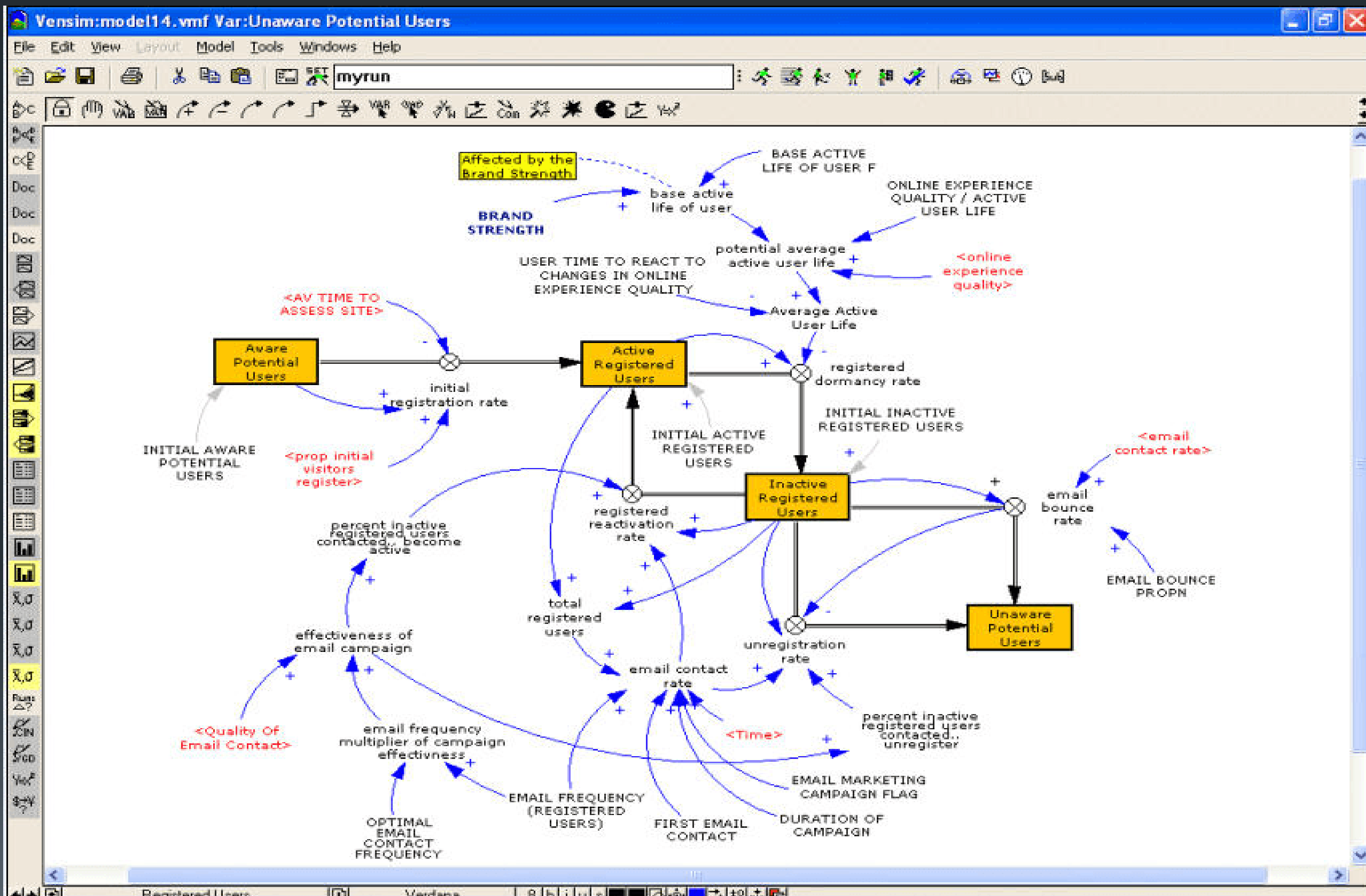


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