

# Agent Frameworks for Discrete Event Social Simulations

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**ABSTRACT:** *Discrete event simulation (DES) provides a means of representing abstract concepts in a traceable and rigorous manner that is particularly useful for gaining insights into complex problems associated with human groups. Current problems facing public policy and military decision makers require a greater understanding of societies and their potential responses, both on group and individual actor levels, to a variety of potential policy decisions. Recent work from the military modeling and simulation communities has underscored the need for social simulations that can provide measures designed to inform decision makers of potential futures. Here we describe the application of concepts from DES to the problem of representing societies and provide a framework and overview of core components necessary for the creation and analysis of discrete event social simulations.*

## 1. Introduction

Discrete event simulations (DES) have found extensive use in a variety of applications in operations research and analytic communities across both industry and the government (Henderson et al., n.d.). The DES concept of the event list provides a means of abstracting a variety of concepts and situations into a manageable registry of events that are scheduled and cancelled based on the rules of the simulation (A. Buss, 2001). In social simulations such as the one described herein, this list contains events corresponding to the actions of entities in the model, such as observations, communications, and changes in the internal states (such as belief states) of actors.

Time	Agent ID	Action
1	Blue_1	Observes Political Advertising
2	Blue_1	Changes Political Beliefs
3	Blue_1	Communicates with Blue_2
4	Blue_2	Changes Political Beliefs
5	Blue_2	Communicates with Blue_3
6	Blue_2	Communicates with Blue_4

Table 1: Example of Social Simulation Events List

Crafting an authentic simulated society that is based on real social data, and delineating events such as these, provides a means of gaining insight into the

potential futures of populations and societies that can be applied to a variety of contexts germane to both public policy and military decision makers. DES concepts offer a well understood simulation framework (Schriber & Brunner, 2004) for use in the exploration of the complex behavioral and social systems that comprise a society. With the idea that applying DES to the social and behavioral domains is still under early development, we review DES concepts as applicable to social simulations, provide an overview of a general modeling approach to social simulation that embeds a multi-agent system within a DES framework, and propose several reusable agent patterns for use within these social simulations.

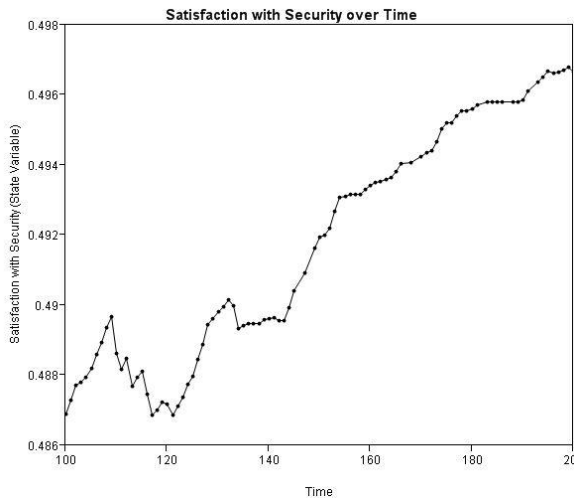
## 2. Discrete Event Social Simulation (DESS) Framework Overview

Discrete event social simulations (DESS) present a simple means of abstracting the complex interactions that exist in societies into model components useful for exploration with simulation experimentation. Below we review concepts from DES, the event graph representation of discrete event simulations, and introduce a specific DESS, the Cultural Geography (CG) model, as a discussion point to explore aspects of this type of framework.

### 2.1 Discrete Event Simulation Overview

DES models are distinguished from time stepped models by the manner in which time is treated in each paradigm. Specifically, in time-stepped models, all simulation events are considered at set intervals as time progresses in the simulation, whereas DES leverages the future events list (FEL) as a means of advancing time in the simulated world (Arnold Buss, 2009). Current events schedule future events to occur at specific times, and update the centrally-maintained FEL accordingly. For example, in Table 1 above, the event the agent’s observation of political advertising at time = 1 schedules the event the corresponding changes to the agent’s political beliefs at time = 2. As events occur, time is advanced in discrete steps from the scheduled execution time of the current event till the scheduled time of the next event on the list, such that the FEL effectively manages the execution of the entire simulation (Arnold Buss, 2009).

The minimum set of elements required for DES models consists of states, events, and scheduling relationships between events (Arnold Buss, 2009). The addition of parameters provides the flexibility to accommodate a broad variety of conceptual models.



**Figure 1.** Entity state transition over model run from CG model, a DESS.

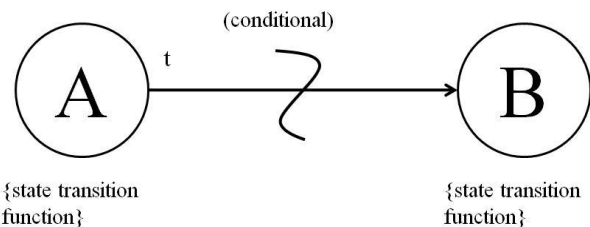
State variables, those DES elements that are able to change at some point during a simulation run, contain the information to provide a complete report on the status of the simulated world at any discrete point in time. State variables are piecewise constant changing instantaneously based on rules described in a state transition function. This approach places the focus on modeling the rules

governing state transitions, but does not restrict the representation of continuous trajectories (Arnold Buss, 2009). Events within DES cause transitions (changes) in state variables. Transitions for all possible cases to be modeled are encapsulated within events that state variables within the simulation. Events may also schedule the occurrence of future events, to include their own. Parameters, by contrast, do not change over the course of a simulation run, but each model instantiation provides a specification of a sequence used during the course of a model run (Arnold Buss, 2009). In the context of social simulations, example state variables include the an entities level of satisfaction on security or other important issues and can be thought of as the results of census polling.

The advance of time relies on the future event list, with time moving forward in non-regular intervals based not on predetermined set time intervals (as in time-stepped simulation), but the time to the occurrence of the next scheduled event on the central event list. All scheduled events are placed on the FEL, maintained, prioritized and canceled based on the rules of the simulation. This centralized management allows for full traceability of model outcomes. For a more complete examination of the implications of time in social simulations, see Alt & Lieberman (2010).

### 2.2 Event Graph Modeling

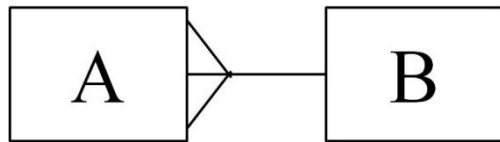
Event graph representations of DES are used to communicate the information described in 2.1 in a more intuitive visual manner. Nodes represent events while edges represent scheduling relationships between events. Conditional relationships can be communicated on the edges and the transition function for each state variable at each node can be fully expressed in associated psuedocode (A. Buss, 2002).



**Figure 2.** Basic event graph, depicting two events (A and B), a conditional scheduling edge, and a delay, t, the scheduling arc.

Event graphs of the specific model components, as shown above, can be combined through the concept of listener patterns in Simkit. This results in a higher level

component mapping described by Buss and Sanchez and referred to as Listener Event Graph Objects (A. H Buss & Sanchez, 2002). Simkit facilitates two listener patterns, the SimEventListener and the PropertyChangeListener. As the names suggest the former listens for the scheduling of events while the latter listens for changes in state variables (A. Buss, 2001). The concept of listeners enables the connection of disparate components maximizing the potential to reuse code objects and event graph components.



**Figure 3.** Graphical depiction of LEGO component model, B listens to events from A.

### 2.3 Cultural Geography Model

The Cultural Geography (CG) Model is an implementation of a DESS that uses an embedded multi-agent system to simulate changes in the beliefs, values, and interests (BVIs) of large social groups (Alt, Jackson, Hudak, & Steven Lieberman, 2010), such as a population<sup>1</sup>. The model, implemented in Simkit<sup>2</sup>, a DES development environment, represents the population in an area of interest as part of a conflict ecosystem (Kilcullen, 2006) that includes conflicting actors (such as government and insurgent forces), and recipients of actions (such as population segments). Scenario development is unique to the area and time period of interest (Alt, Jackson, & Stephen Lieberman, 2009), as well as the population and issues chosen for representation. It closely follows the counter-insurgency intelligence preparation of the battlefield (IPB) framework described by Mansoor (Mansoor, 2007). The key outputs of the model are changes to the BVIs of actors in the population (also called issues stances) on the issues chosen for representation within the simulation. The implementation builds on a conceptual framework grounded in both cognitive psychology and structural sociology (Sanborn, Mansinghka, & T. Griffiths, 2006). Correspondingly, two main modules within the framework are the entity cognition module, which manages the internal states of actors, and the social

structure module, which manages the interactions of agents. Together these modules form the conflict ecosystem within which the agents interact and change their stance on issues of importance.

The theoretical groundwork for the cognitive module relies on Walter Fisher's narrative paradigm (Fisher, 1989) as the premise for the development of issue stances for population sub-groups based on their relevant BVIs. The narrative paradigm proposes that an individual possesses a collection of stories, a unique narrative identity, that encompass their BVIs and shape the way they view the world and interpret events. The narrative identity is implemented as a Bayesian network (Tenenbaum, T Griffiths, & Kemp, 2006).

The social structure module generates theoretically sound and precise patterns of agent interactions based on the internal characteristics of the agent population. A unique social structure exists for every simulated society at each discrete point in time as an expression of the instantaneous distribution of social factors within the society. The well-established idea of homophily, complementary to the narrative paradigm, states that the degree of social factor similarity for every pair of actors corresponds to the pair's likelihood of interaction (McPherson, Smith-Lovin, & Cook, 2001)(Blau & Schwartz, 1997). Social factors are taken to be any attribute that impacts an individual's association, including socio-economic, socio-demographic, and socio-cultural attributes, as well as BVIs. Thus, the more similar a pair in terms of their social factors, the more they interact and influence one another throughout the simulation.

## 3. Event Graph Description of Components for DESS

This section will provide event graph models for generic components used in DESS. These event graphs build on and extend those used in the CG model.

### 3.1 Population Agent

Population agents are modeled as simple reflex agents that interact with the environment, in this case the social network and infrastructure objects, based on a set of conditional statements provided at their instantiation.

Parameter:

- Demographic composition: age, sex, education, occupation.
- Consumption rate of commodities: energy, food.

<sup>1</sup> The CG Model is government-owned, open-source, and available free of charge at [https://soteria.nps.navy.mil/rucgwiki/index.php/Main\\_Page](https://soteria.nps.navy.mil/rucgwiki/index.php/Main_Page)

<sup>2</sup> SimKit is freely available at <http://diana.nps.edu/Simkit/>

- Communication rate.

State variable:

- Issue Stance, {0...1}: satisfaction with security, satisfaction with infrastructure.
- Location, {1...n}: discrete named locations.

Event Graph:

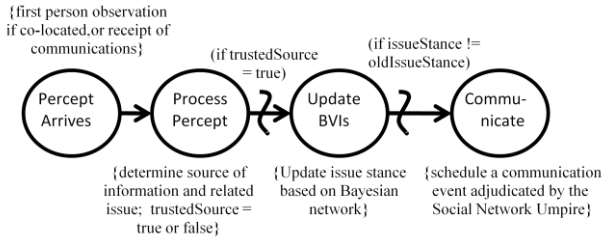


Figure 4. Event graph depicting a civilian entity component.

The state transition function used in the case of civilian entities in the CG model is implemented as a Bayesian belief network (BBN).

### 3.2 Threat Agent

Threat agents, gangs or violent extremist networks (VEN), are currently treated as single reflex agents within the model and not a true network of interacting entities. Work is ongoing to provide add more detail to this portion of the model as traceable data becomes available.

Parameter:

- Demographic composition: age, sex, education, occupation.
- Role: direct action, planner, etc.

State variable:

- Average Population Issue Stance, {0...1}.
- Location, {1...n}: discrete named locations.

Event Graph:

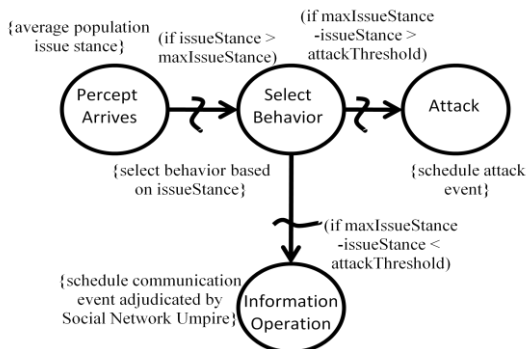


Figure 5. Event graph depicting threat agent component.

The state transition function used in the threat agent in this case based on statistics from the environment that are

accessible by the threat agent. Design decisions describing the level of access to knowledge of other entities aside, the calculation of this is a straightforward calculation of the mean issue stance on a given issue.

### 3.3 Media Agent

Media agents receive information and retransmit information from the simulation environment. They can also send out messages in a semi-autonomous manner, regardless of the incoming information from the simulation environment depending on design decisions made during scenario construction.

Parameter:

- Affiliation: political party, pro/anti government.

State variable:

- Publication rate.
- Location, {1...n}: discrete named locations.

Event Graph:

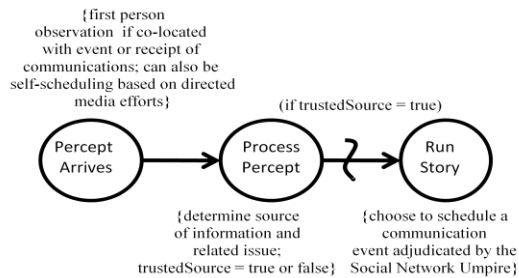


Figure 6. Event graph depicting media entity component.

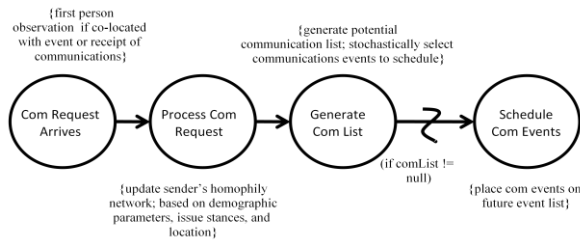
### 3.4 Representing the Social Network through Referees

The central component that allows for and facilitates the interaction of agents is the social network referee. This component adjudicates and schedules communications throughout the artificial society. The entity itself does not contain state variables, but instead a set of rules in the form of parameters are used to determine the recipients of communications that are scheduled by the other entities within the simulation.

Parameter:

- Social distance equation.
- Relationship threshold.
- Communications rate.

**Event Graph:**



**Figure 7.** Event graph depicting social network umpire component.

The social distance equation used in the artificial society is a realization of the concept of homophily as explained above. Each agent occupies a position in multidimensional space based on their internal attributes. This space is a hyperrectangle where the length of each edge is determined by the range of values of the corresponding social attribute. Each dimension of this space represents a social factor, that is, an internal attribute that influences the interactions of the agent. The likelihood that a pair of agents will interact is directly proportional to their distance in this space where more similarity (shorter distance) indicates increased likelihood of interaction. Thus, social distance is calculated simply as the Euclidean distance between any two agents occupying positions in this hyperrectangle.

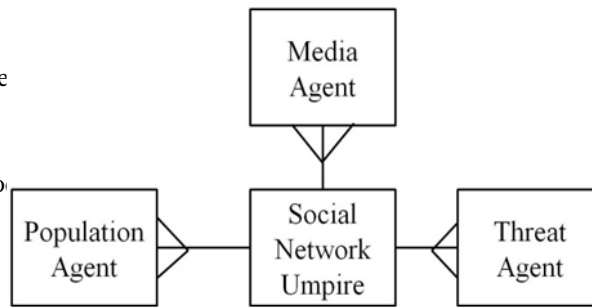
While every agent is connected in the society (i.e., it is possible for all agents to interact), there is a practical bound or threshold on the distance. Since agents are more likely to communicate with those in proximate space, we can understand the social structure of the artificial society by thresholding relationships between agents (i.e., for visualization) where agent-pairs that surpass a certain social distance are understood to *not* be connected with one another.

The social distance directly controls *which* other agents will be targeted for communication by an agent. The communication rate, likewise, specifies the time it takes for that communication to be initiated and completed. Similarly to the intrinsic relationship threshold, there is an inherent limit to the number of communications that an agent can engage in over a set period of time. This parameter is controlled directly for the agent population with a communications rate specification. This controls both the maximum number of other agents engaged, and the maximum number of messages that can be passed, over a certain period of time.

**4. Component Level Architecture**

The use of component level architectures flows naturally from the event graph. A single event graph depiction of even the simple components described in section 3 would rapidly become confusing and unreadable. The use of component level diagrams allow the communication of complex models in an efficient manner and facilitate the rapid re-use of previously developed and functional code.

Each component represents a fully complete instance of the event graph model. In the case of social simulation the components are linked using an event listener pattern. In the diagram below, the SocialNetworkUmpire component listens for the scheduling of communications events and attack events.



**Figure 8.** Component level architecture for discrete event social simulation with SimEventListener pattern.

**5. Conclusions and Future Work**

The use of DES for social simulation presents opportunities to develop emergent societies and behavior in a fully traceable manner. The use of these techniques have implications for the validation of this class of models for use in a variety of settings in support of decision makers. The use of modular frameworks supported by DES facilitates the re-use of code and the implementation of competing theoretical concepts for experimentation.

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