DEVS-Based Framework for Modelling and Simulation of Propagation Phenomena in Social Networks: Application to the Information Spreading in a Multi-Layer Social Network

Article *in* SIMULATION: Transactions of The Society for Modeling and Simulation International · June 2018
DOI: 10.1177/0037549718776368

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PrePrint to Appear in Simulation
https://doi.dox.org/10.1177/0037549718776368

Discrete Event System Specification-based framework for modeling and simulation of propagation phenomena in social networks: application to the information spreading in a multi-layer social network

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Abstract
The diffusion of information is defined as the communication process by which an idea or information spreads within a social system and impacts the behavior of social actors (individuals). The social interaction plays an important role in studying the propagation of information and how it influences people. When an informational event occurs, it can either die out quickly or have significant impact on a population. The interactions could be supported by physical proximity contact, remote collaboration, any type of social meetings, and some forms of verbal or written communication, depending on the situations. Institutions and firms search to understand and predict the impact of information propagation on individuals. Agent-based modeling is a powerful approach for studying such a collective process. However, existing models oversimplify the cultural attributes, the different types of links, and information content, despite the evidence of their central role in the diffusion process.

In this context, great benefits could be derived from the exploitation of an individual's personality and cultural values in the diffusion models. In this paper, we describe a new architecture for an agent-based model using the DEVS (Discrete Event System Specification) framework and show how this architecture is flexible and can support the simulation of the dissemination process. In more detail, we define a set of models of individuals characterized by a set of state variables to represent the behavior of an individual and the individual's network within a multi-layer social network. Then, we start by introducing the platform architecture, specifically designed to simulate message propagation in a multi-layer network. Finally, a military scenario of message diffusion during a stabilization phase is used to test our DEVS models on the platform and the relevancy of the simulation results.

Keywords
Formal modeling, simulation, Discrete Event System Specification formalism, modeling and predicting information diffusion, information propagation, social network

1 Introduction

Nowadays, many researchers are interested in developing new and more efficient systems for social simulation. The issues explored include psychology, organizational behavior, sociology, political science, economics, anthropology, geography, engineering, archaeology, and linguistics.[1] For instance, armies have investigated simulation systems to support deep analysis of an individual's behavior. The communities in a real social network are affected by changes at the individuals' level. Tracking and understanding these changes play an effective role in areas such as sociology, anthropology, bioinformatics,[1] sociolinguistics, geography, information science, politics, marketing,[2] etc.[3] As an example, the evolution of informal

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groups within a large organization can provide insight into the organization's global decision-making behavior. Another example includes the tracking of the early stages of an epidemic disease in a specific subpopulation.[4]

Many real-world systems can be modeled as networks, that is, sets of interconnected entities. In some cases, the connections between these entities represent communication channels: they indicate that information items present at one of the entities can be transferred, or propagated, to some neighbor entities. At the individual level, an entity represents a person or a group of people, and connections represent the relationship between people. In most cases, these networks are dynamic. The factors leading to the dynamics can be the fact that a person meets new people, he changes attitude toward others, he switches job, he moves from one place to another, and so on. However, in fact, most research methods were suited for static networks cases. In this work, we aim to bridge this gap between simulation models in social science and real-world observations. The objective is to anticipate by simulation and to observe the impact of information over a population.

SICOMORES is a multi-agent system composed of many collaborating agents. It intends to generate a population model based on socio-demographic data and to simulate the effects of psychological and CIMIC (*Civil Military Co-operation*) military operations. In the information propagation process, the simulation of cognitive processes supporting message treatment involving agent features and the representation of a relevant socio-cultural context are the two most important elements taken into account.[5] In the context of this project, we developed a tool used to generate an artificial population (creating the nodes and the network) based on the actual socio-demographic data and depending on the study specification level.[6]

Modeling population needs understanding of the specific norms and ways the society organizes itself. As instance, an Eastern European society does not have the same features as an Asian, Western Europe, or African one. Moreover, inside each cited society, sub-categories can be defined.[6] The model of the population must respect the codes of the society to accurately simulate the information diffusion. Furthermore, the relationships between people are too complex to be modeled by one link. In general, most real and engineered systems include multiple subsystems and layers of connectivity. Then, it is important to take such features into account when trying to obtain the most complete understanding of the global behavior.

Social networks are generally based on only one relationship between people, or an aggregation of several relationships. They are part of networks that we call *multiplex* (or *multi-layer*). Multiplex networks are structured in layers and with connections between layers. The interconnections between two layers exist only between a node and its counterpart in the other layer.[7] Multi-layer social networks (MSNs) begin to emerge due to the importance of each relationship in the communication process.

Flattening a MSN into a one-dimensional social network does not allow one to consider each relation as a unique way to communicate with its own communication rules. It also does not allow representing the complexity of an individual social life. In this paper, a MSN is modeled with the idea that information disseminates differently according to the link through which the information propagates: people do not receive and transmit information in the same way, according to the person who gave them the information. Following this postulate, this paper presents the general framework of our MSN to generate a model of a population based on several relationships. Then, using social science research, some relationships representing a part of the human social life are described.

The aim of our works takes place between applied and theoretical modeling and simulation (M&S). It proposes a general framework to model a population based on its social structure rules and its cultural features and to simulate the diffusion phenomenon in networks. This framework is adaptable thanks to the MSN architecture that separates and distinguishes the relationships. It is then easy to add or delete a dimension and to set for each dimension its own features and diffusion rules. The use of a MSN allows us also to model the message acceptation and the transmission rules for each dimension.

2 Background and related works

In this section, we introduce the Discrete Event System Specification (DEVS) formalism, the concept of multi-layer networks, and the influence spread modeling within social networks.

2.1 DEVS formalism

DEVS[4] is a formalism to model Discrete Events Systems. The hierarchical and modular structure of DEVS allows the definition of multiple models that are coupled to work together in a single model by connecting their input and output through messages.[4] In the same way, the resulting model can also be coupled with other models defining multiple layers in the hierarchical structure. In DEVS, atomic models define the behavior of the system, and coupled models describe the structure of the system. The DEVS formalism supports an open approach to formalism extension, allowing the researcher to explore new extended or specialized formalism.[8] It is frequently adapted or specialized when it is placed in a specific context of application. These extensions facilitate the development of models for various applications in many different domains, such as biology, engineering, and sociology. For example, Barros[9] proposed the dynamic structure DEVS formalism (DS-DEVS), which allows the change of the model structure during execution. Chow and Zeigler[10] proposed parallel DEVS (P-DEVS) for parallel execution benefits. From a network modeling perspective, Uhrmacher et al.[11] proposed Multi-Level-DEVS (ml-DEVS), which supports an explicit description of the macro and the micro level and Wainer and Giambiasi[12] proposed the cell-DEVS formalism which is a combination of cellular automata and DEVS that allows the implementation of cellular models with timing delays.

There are many DEVS-based simulators. Each DEVS simulator has a certain peculiarity that makes it more suited to certain applications. In this study, the models are implemented using VLE (Virtual Laboratory Environment). VLE software[13] implements DEVS and supports multi-modeling, simulation, and analysis. It is based on an extension of DEVS, the Dynamic Structure Discrete Event formalism (DSDE).[9] The implementation of the DSDE abstract simulators gives to VLE the ability to simulate distributed models and to load and/or delete atomic and coupled models during runtime. It is also possible to perform statistical analysis of results thanks to a plug-in that allows communication between VLE software and R script.[13] We used VLE to instantiate a DEVS model from the description of a social network (represented by individual attributes and relationships).[14] This simulation is used to study the network dynamics in terms of propagation of information.

2.2 Network structure

A simple social network (i.e., a single-layer social network) can be represented by a graph.[15,16] A graph is a tuple $G = (V; E)$, where V is a set of nodes (vertices) representing social entities: humans, organizations, departments, etc., called also actors, agents, or instances, and $E \subseteq V \times V$ is a set of (ordered or unordered) edges (arcs, connections, or ties) that connects pair of nodes. Since social networks usually represent one kind of relationship, they are also called Single-layered Social Networks (SSNs).[17] Similarly, there is also a new type of social network that is called the MSN, in which actors are connected by multiple types of links[18–20]; for example, people in a society interact via their friendships, family relationships, and/or more formal work-related links.[20,21] A multi-layer network is a data structure made of multiple layers, where each layer is a single network. A multi-layered social network is a network extended to multiple edges between pairs of nodes/actors. It is defined as a tuple $< V, E, L >$ where:

- V is a set of actors (social entities);
- E is a set of tuples $< x,y,l >$, $l \in L$, $x \neq y$; $x,y \in V$ and for any two tuples $< x,y,l >$, $< x',y',l' > \subset E$ if $< x,y,l > \neq < x',y',l' >$, $x = x'$ and $y = y'$ then $l \neq l'$;

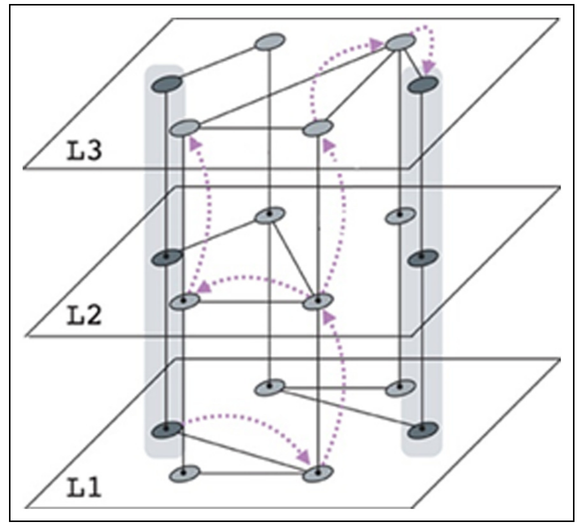

Figure 1. Example of multi-network with $M = 3$ layers (L1, L2 and L3) and $N = 6$ nodes. Nodes are the same in all the three layers. Intra-layers and inter-layer interactions are represented with solid lines, while dashed lines represent the propagation of an item. DEVS: Discrete Event System Specification.

- L is a set of distinct layers (types of relationships).

Each layer of the MSN corresponds to one type of relationships between people Figure 1). Different relationships can result from the character of connections and the type of communication channel. The examples of different relationships can be friendship, family, or work. The different communication channels that result from different types of connections are email exchange, Voice over Internet Protocol (VoIP) calls, instant messenger chats, etc. These networks can be defined as a sequence of graphs:

$$\{G\}_{\gamma}{}^{\delta} = \{(V_{\gamma}, E_{\gamma})\}_{\gamma}{}^{\delta} \tag{1}$$

where $E_{\gamma} \subseteq V_{\gamma} \times V_{\gamma}$ is the set of edges and γ indexes the graphs or the type of relationships. In our networks, the nodes (social actors) are the same across the different layers (i.e., $V_{\gamma} = V_{\delta} \forall \gamma, \delta$).

2.3 Modeling the spread of influence

Models of social influence and diffusion have been studied in several domains. For instance, they have been studied for the transmission of political opinions and news in political sciences[22]; the diffusion of innovations in management sciences[23]; the value of novel information in organizational behavior[24]; and the propagation of obesity and smoking behaviors in public healthcare.[25] Diffusion is the phenomena of propagation and dissemination of an item (e.g., information) within a social network. Social influence is the process by which nodes adapt or change their behavior as a result of social interactions within a social network. It is the ability of a node to manipulate the diffusion process by motivating other nodes to accept or reject the transmission. With the advent of sufficient storage and computational power, the propagation phenomena become essentially an emerging research area in computer science.[26] The strength of the social influence depends on many factors, such as the intensity of relationships between the nodes, the distance between the nodes, the temporal effects, and the characteristics of the networks and nodes.[27] Then, because of the combination of all these factors, the study of social diffusion and influence is complicated and relatively difficult to model. However, some research works shows that models exist that fit well with the reality under some assumptions. Most models proposed recently are extensions from the independent cascade (IC)[28] and the linear threshold (LT)[29] models. They characterize different aspects of social interaction.

The IC model focuses on individual (and independent) interaction and influence among friends in a social network. The IC models can also be identified with the so-called Susceptible/Infective /Recovered (SIR) model used for the spread of a disease in a network.[30] In this model, the process starts with a set of influenced nodes Ω. Each node v in the network has a probability $p_{v,w}$ to influence its neighbor w. If it fails, it will have no other chance. If it succeeds, w will become influenced in the next time step. The process ends where no more nodes can be influenced.

The LT model focuses on the threshold behavior in influence propagation; when enough of your friends have bought a new phone, played a new computer game, or used new online social networks, you may be converted to follow the same action: the LT model focuses on such situations. In this model, a node v is under influence of its influenced neighbors'w denoted as IN_v according to a weight $b_{v,w}$, such that $\sum_{w \in INv} bv, w \leqslant 1$. Each node v has a threshold $\theta_v \in [0, 1]$ and this threshold represents the level that must be met by the aggregated sum of v's neighbors' influence weights to influence the node v. So, the formal condition of influencing the node v is as follows:

$$\sum_{w \in INv} b_{v,w} \geqslant \theta_v \tag{2}$$

Similarly, for the IC model, the process runs until no more influences are possible.

2.4 Human behavior

Human behavior modeling (within groups of individuals or societies) concerns many fields of research, such as social science, economics, epidemiology, or military interventions (e.g., informational event diffusion) because it corresponds to many aspects of daily life. Scientific literature abounds in heterogeneous and highly specialized theoretically founded concepts of human cognition, emotion, and other behavior aspects.

For a formal social structure, macro-level characteristics can be explained by analyzing the global structure and organization of the system. This approach consists in analyzing the effects due to the nature of certain variables on the behavior of the entities composing the system without making hypotheses about the individuals.[31] For other societies (informal social structures), macroscopic characteristics and observations are explained on the basis of the aggregated effects of micro characteristics.[31] In many cases, particularly in propagation phenomena, the explanatory factors of the collective behavior reside at the individual level. If these social phenomena are modeled at the macroscopic level, it is impossible to represent these explanatory factors. According to Wickens,[32] ''aggregative models describe what the data looks like, but not where it comes from.'' The agent-based models (ABMs) have been introduced to address this problem, allowing them to work at both scales, describing the explanatory factors at the micro level and checking the dynamics emerging from the interactions at the macro level.

A few related works have provided DEVS models of human behavior that we use with slight modifications: Seck et al.[33] (33) present a DEVS-based framework for the M&S of human behavior with the influence of stress and fatigue; Faucher et al.[34] proposed a first approach using G-DEVS formalism for Civil–Military Cooperation actions and Psychological Operations (PsyOps), which are actions of influence processed before or after a combat-like stabilization phase. Silverman et al.[35] proposed a framework for integrating Performance Moderator Functions (PMFs) in behavior simulation models. His framework, named PMFserv, is a model of an agent's cognitive-affective state and reasoning abilities that is applied to profile the traits, cognitions, and reasoning of individual leaders, followers, and others. It is composed of various behavior moderators in different categories (physiology, stress, emotions, and decision) and allows the agent to adopt different coping modes depending on its internal state.

We note that human behavior modeling is evolving and tending to be more realistic in various fields. However, these models remain formalized in the shape of graphs or mathematical formulas and then directly implemented and coded using classical programming languages. The disadvantage of such an approach is that there cannot be a clear distinction between M&S. This is why the applications are specific and difficult to reuse in a different context.

3 Materials and methods

In this section, we present the specification of an agent using a low-level framework, the modeling of a network structure using DS-DEVS formalism, and the DEVS-based architecture for M&S of propagation phenomena in social networks.

3.1 Agent-based social network modeling

There are several methods to study the information propagation in social network, such as complex network analysis,[36] cellular automata,[37] and agent-based modeling.[38]

A social network is composed of a set of social actors (such as individuals, groups, or organizations in the society) and the interaction relations between them.[19,39] In general, there are three aspects considered while studying social networks: the structure-oriented aspect, the actor-oriented aspect, and the actor–structure crossing aspect. In the first view, researchers mainly focus on analyzing the network's topological structure and the characteristics of the interactions among social actors. In this view, the social actors are abstracted into uniform nodes in graphs, and their behavior characteristics are neglected. In the actor-oriented aspect, researchers mainly focus on analyzing the characteristics and effects of actors' behavior in social networks. In this type of view, the characteristics of the topological structures of the social networks are not reinforced.[19,40,41] In the actor–structure crossing view, both social actors and network structures are subjects of concern, and their crossing effects are explored.[42] In this type of view, researchers investigate both how social network structures influence the actors' behavior and how the actors' behavior forms the network structures.[43]

In this paper, we investigate social networks from the perspective of multi-agent systems. Both social networks and multi-agent systems are composed of interacting and self-organizing individuals and adopt an emergent behavior. Computational models and simulations, especially agent-based ones, have been widely used to study a variety of social, organizational, and natural phenomena. ABMs can simulate macro-level structures resulting from micro-level interactions of heterogeneous agents within complex systems.

3.1.1. Agent specification.

3.1.1. Agent specification. In the ABM, individuals or a group of individuals are represented as agents. Each agent is described by a set of attributes distinguished into two categories as follows.

- Static attributes: gender, social status, religion, age class, ethnicity, leadership, and language.
- Dynamic attributes (variables): opinion, interest, and un/satisfied-needs.

Static attributes are intrinsic or unchanged parameters, that is, time has no effect on them. Dynamic attributes evolve with time or events. For example, individuals can be reached or not by the information depending on their opinion and the social network configuration. To mimic the behavior of an agent receiving information, the agent is formalized as an atomic DEVS model with several states. Messages are exchanged between agents using discrete events. Values taken by the ports of the DEVS model match with values of exchanged messages between the different models of agents.

The perception is specified by the arrival of external events on the model ports. These events change the state of one or several models. The behavior of the model is driven by the internal transition functions. The action of an agent can be seen as the set of output functions. Finally, all the internal transition functions define the autonomous behavior of the agent.

Each agent A can be specified as an atomic component:

$$M_{agent} = \{X_{agent}, S_{agent}, Y_{agent}, \delta_{intagent}, \delta_{extagent}, \delta_{conagent}, \gamma_{agent}, ta_{agent}\}\delta \tag{3}$$

Figure 2 describes the message influence on the individual behavior and potentially its dissemination using the DEVSs. The first state is used to configure and initialize the agent attributes. Then, the state changes to "Idle." The component will remain in "idle" state until an event arrives at its input port, triggering an external transition. Then, if it receives an external event from another agent on port "In_1" (In ? Packet), the state changes to "phase_0." Here, the agent computes the Degree of Interest (DI) or motivation to process the message depending on the social pressure, similarity between it, and the sender (based on the religion, language, and age class), and its sensitivity to the message theme (see Section 3.3). If the DI is less than a threshold (to be identified during the calibration phase), the receiver rejects the message and the state changes to

```
X_agent = {"In_1"}

S_agent = {'Init', 'Idle', 'Phase_0', 'Phase_1', 'Phase_2',
'Phase_3', 'Phase_4'}

Y_agent = {"Out_1"}
δ_intagent: 'Init '→ 'Idle'
'Phase_0' → 'Phase_1'
'Phase_1' → 'Phase_2'
'Phase_2' → 'Phase_3'
'Phase_3' → 'Phase_4'
'Phase_4' → 'Idle'
δ_extagent:  ('Idle', "In_1") →'Phase_1'
δ_conagent:  δ_con(S,ϕ)  = δ_int(S)
γ_agent:  'Phase_4' → "Out_1"
ta_agent:  'Init' → θ
'Idle' → ∞
'Phase_0' → θ
'Phase_1' → θ
'Phase_2' → θ
'Phase_3' → θ
'Phase_4' → θ
```

Figure 2. Discrete Event System Specification inside agents.

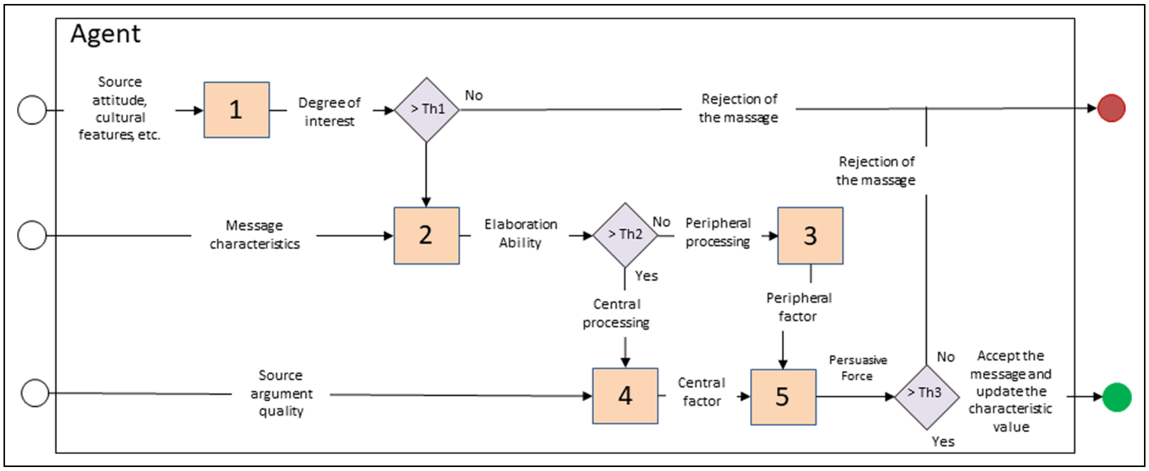

Figure 5. Block diagram of the diffusion process between agents.

- *a''* component sends an event to A Server.
- A Server reads the event and can propagate the information to its networks, depending on its state (motivation) and rules. Thus, an event is sent to *a* and *a'* components.
- *a, a'*, and *a''* components read the event and, depending on their state and rules, can diffuse the information to their neighbors. In this case, *a''* has the information already and does nothing; *a'* sends an event to *b'* and *d'*, and *a* sends an event to *b*.
- *b, b'*, and *d'* components send an event to respectively *B* and *D* Servers and so on.

3.3 Message processing

The model of the message processing implemented in our framework is based on the persuasion model. To represent the range of processing activity available to message receivers, Petty and Caccioppo[44] introduced the concept of the ELM, which explains the information processing inside an individual. Elaboration Likelihood Theory (ELT)[44] is a conceptual model describing how an audience processes information obtained through media and its impact on attitude changes. ELT posits that an audience can follow one of two cognitive routes in responding to a media communication. In the first route, considered as the *central route*, a receiver chooses to consider carefully the arguments contained in the media presentation. The second or *peripheral route* offers an often-expedient mechanism for processing information that demands less cognitive effort and can often appeal to an audience that is poorly prepared to consider an elaborate argument. Figure 5 shows the agent model based on ELT. It reduces the complexity of the theoretical knowledge of the ELM to a comprehensible extent, and only the most important variables were used to generate the elaboration motivation and ability. We also summarized certain aspects in a more general construct. For instance, the variable ''message characteristics'' stands for source expertise, the number of arguments for a message, and further source credibility. Variables are represented as arrows, and blocks contain the transition functions in which the entry variables are computed to obtain the exit variables. The dimensions of all variables lie between 0 and 10.

Through a variety of situational and personal characteristics affecting elaboration likelihood, the motivation and the ability factors have received the most attention from ELM researchers.[5] We integrate the elaboration motivation aspect in our framework as a computation of the DI (Block 1 in Figure 5). It is determined by various variables detailed by Bergier and Faucher.[5] Here is only detailed the measure of the motivation to the message *theme* expressed by the receiver, by Involvement by Cultural Features (ICFs). Let q be the number of cultural features of $\{cf_1, \ldots, cf_n\}$ with a value above a certain threshold in Cultural value system (i) and $imp_i, \ldots, imp_n$ be their respective importance:

$$ICF(i,p) = \frac{1}{n}.(\sum_{i=1}^{n} imp_i) + \frac{q}{n}.(1 - (\frac{1}{n}.\sum_{i=1}^{n} imp_i)) \quad (6)$$

If the DI is less than a threshold, the receiver rejects the message (it does not feel concerned enough to process the message further). If not, the elaboration APM is computed. The elaboration ability is determined by the Clarity of Content Impact (CCI) (the aggregation of the clarity of the message and the intellectual level of the receiver) and the General Complexity (GC) of the message. Increasing the *GC* of the message reduces the APM (e.g., a text message sent to an illiterate receiver) (see Equation (7):

$$Elaborationability = \frac{1}{2}.(CCI + (10 - GC)) \quad (7)$$

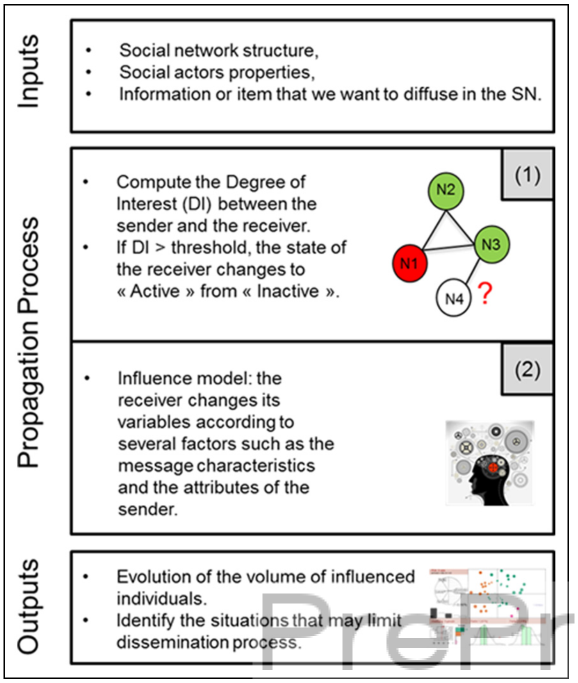

Figure 6. Description of the propagation process in social networks.

If elaboration ability is below a threshold, the receiver will follow a peripheral route to persuasion. In this case, only peripheral variables are considered for computation of the persuasive of the message, for example, the number of arguments, source expertise, and similarity between the sender and the receiver. Argument quality has no impact in this case. For the central processing of the message, the persuasion depends on the quality of arguments (e.g., strong arguments bring about attitude change in the intended direction, whereas weak arguments have a counterproductive effect). If the message targets a characteristic of the receiver, such as hit opinion toward an event, the characteristic value after persuasion results from the sum of the previously held characteristic and the change generated by the persuasion (e.g., the receiver of the message may shift its characteristic value some distance toward or away from that of the emitter's characteristic value).

In our case, we implemented the algorithm that compute the DI in the proxies and the server updates the agent's behavior (attitude change) if it receives a notification from the proxies (the proxy has an interest in the item). This architecture allows the integration of various diffusion models, taking the characteristics of the layer into account (type of relationship or the communication channel). This approach aims to enhance the reusability and the model representation, and thus eases the development. It is easy to add a new network: only the specific rules (if any) must be built in a new Proxy component. Individuals can be changed without changing the networks. Drawbacks are the increased number of nodes and links. Figure 6 illustrates the propagation process in a social network adopted in this work. The method we propose to model the propagation of a message has two components. The first one is a diffusion process based on the network structure for the interaction between each pair of social actors. The second part is based on the persuasive communication for message processing by receivers. This process makes possible the simulation and the study of the network dynamics, which is expressed by changes in the variables of the nodes.

3.4 Architecture

Formal methods, models, and tools for social data are largely limited to graph theoretical approaches for the form and fed by conceptual developments in relational sociology and methodological developments in social network analysis for the content. As far as we know, there are no integrated modeling approaches to social data across the conceptual, formal, and software realms. Our work addresses this problem by proposing an integrated modeling approach involving a conceptual model for social data, a formal model of the conceptual data based on set theory, and a schematic model of a software application fed by the conceptual and formal models.

In more detail, this approach can be divided into three modules, as shown Figure 7.

3.4.1 Pre-simulation. Before making a simulation, we build a new experiment by generating a network of population with socio-cultural attributes. An experiment includes one or several groups. A group includes many individuals. A network or graph represents all relations between individuals. The algorithms used to generate the population taking into account the socio-cultural characteristics and several type of links between individuals are discussed by Forestier et al.[6] We opt for the storage of information in a database so that each experiment is easily accessible and re-playable. The repository contains all the models available to execute the simulations, that is, all the servers and proxies that are used by the *Executive model* to produce the simulation model.

3.4.2 Simulation. The ABM is used to simulate the process of item diffusion within the network generated during the first step. The simulation starts with the experiment to simulate, as well as servers and proxies to use. In this way, for the same experiment, we can test different behavior algorithms. The *GraphLoader* model, which conforms to the DS-DEVS, connects to the database to retrieve all the information from the experience to execute. It transforms the dataset stored in the database (node properties and different relationships) into a DEVS coupled model

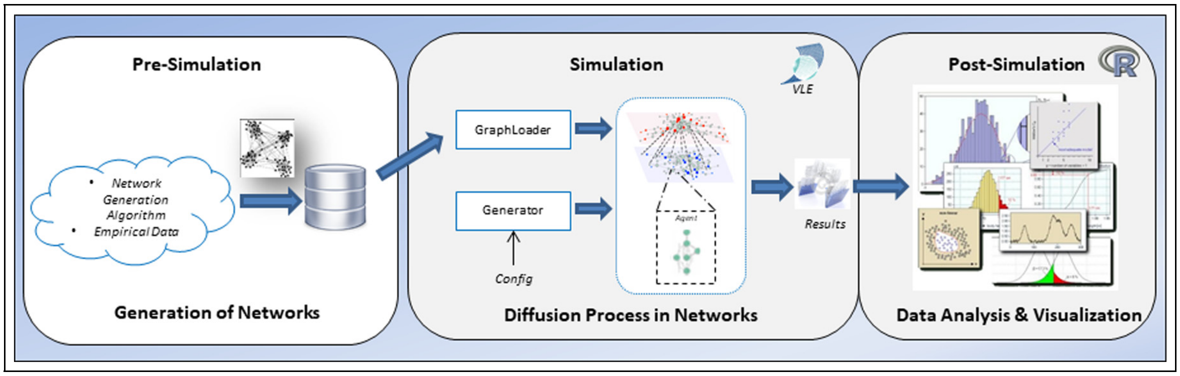

Figure 7. Agent-based simulation framework.

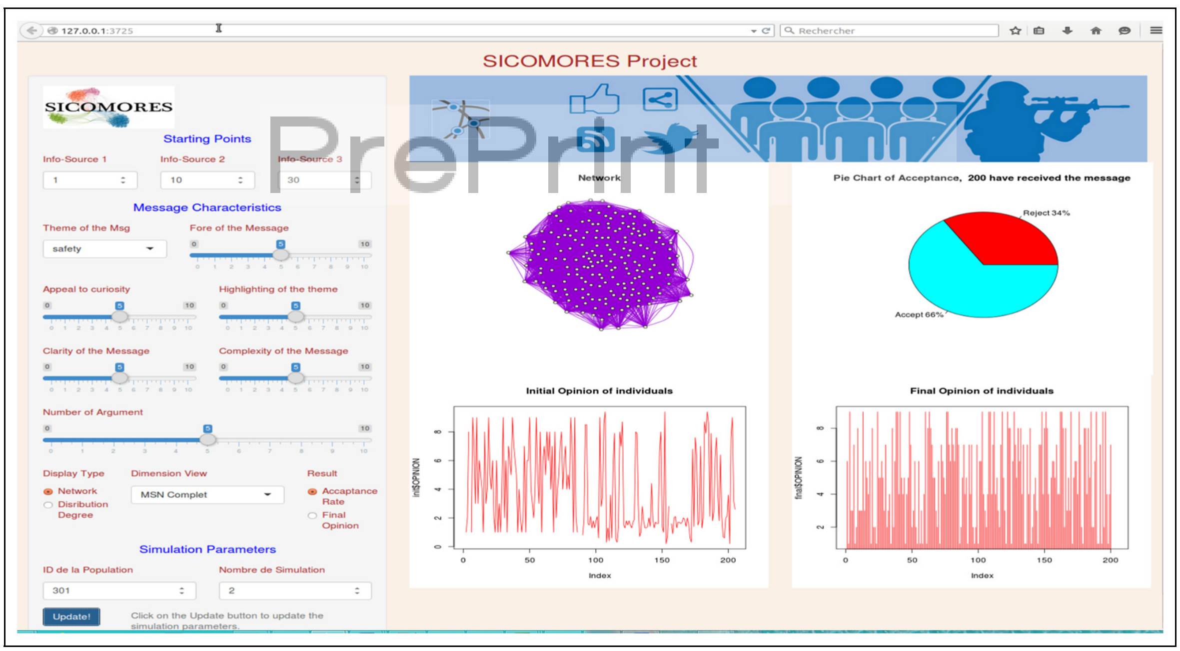

Figure 8. A snapshot of the user interface for the SICOMORES system.

called a "DEVS network." Another DEVS atomic model, the *Generator*, is used to prepare the information item to be spread through the network and sends it to info-sources at time beginning of the simulation. This part is developed within the framework of the VLE application. Within the cycle of M&S, the implementation task aims at writing a source code starting from DEVS formal specifications. Within the VLE framework, the implementation of a DEVS model is achieved by an inheritance of the DEVS atomic model class, a DS-DEVS executive model class, or another DEVS extension (e.g., cell-DEVS) of the VLE framework.

3.4.3 Post-simulation. The R[45] script post-processes the simulation result. The result file is used to visualize the course of the simulation and to provide an analysis and conclusion. The analysis can lead to a new simulation, that is, to run a new pre-simulation, simulation, and post-simulation cycle. We have developed a user interface using the Shiny package in R to visualize the network, which allows users to directly examine the visual patterns of the network being created. The network analysis result displays as well as an in- and out-degree histogram and a degree correlation plot, which includes a general network statistic measure report. These results are automatically calculated and visualized when the network is modified. It provides the user instantly with the summary characteristics of the generated networks (Figure 8).

4 Experiment

4.1 Model description

The following experiment is based on sociological studies of sub-Saharan African societies. These societies have

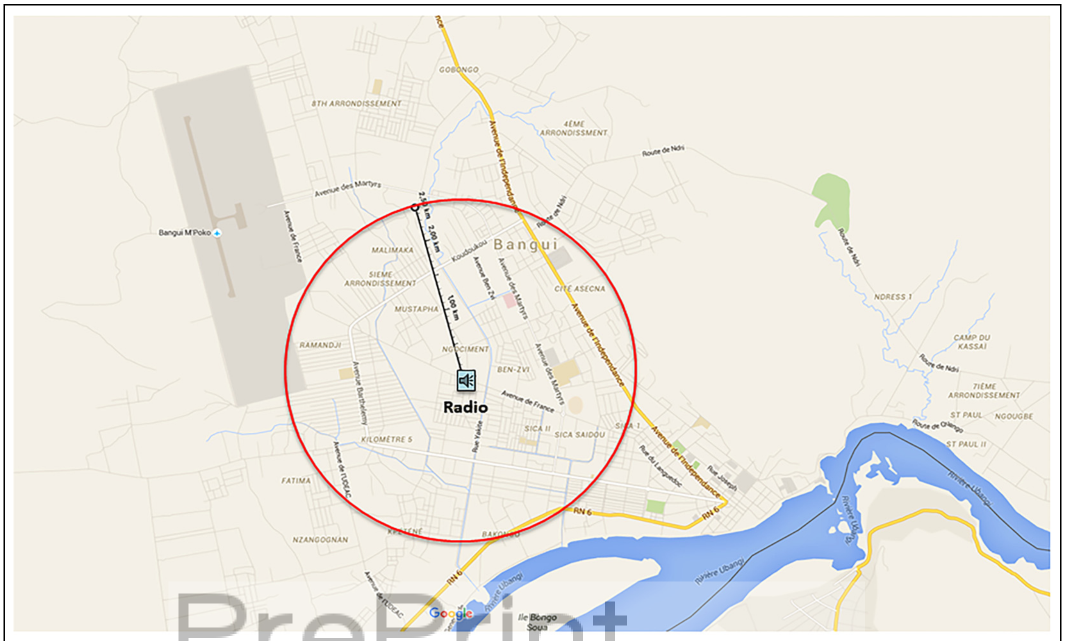

Figure 9. Radio station location in the conflict zone.

been selected to highlight some cultural features to be generated inside the populations. For example, the notion of neighborhood is truly important in sub-Saharan social life. In this mission, we focus on tactical PsyOps using radio transmissions to support military leaders during a conflict to impact the behavior of the civilian population. In the case of radio transmission, the scope corresponds to the maximum distance between the transmitting station and the receiver. Figure 9 shows the location of the radio transmission station in the designated area and its scope.

The study has generated a population of 1200 individual considering five types of links. Formally, we create a network with five layers (family relationships, friendships, neighbor links, religious links, and political links). All agents start in a state equal to 0 (they do not receive the message yet). When an agent receives the message, its state changes to 1 if it has an interest in the message. The state changes to 2 if the agent receives the message but it has no interest in the message. The agents in state 2 block the spreading process and they do not update their behavior. Conversely, agents in state 1 update their behavior and their parameters. In this case, the update of the agent's opinion is based on the concept of opinion change described by Fredkin and Johnson.[46] Social influence occurs when a message emitter and a message receiver get in contact. The message emitter attempts to communicate its position about an opinion to the receiver. As result of this conversation, the receiver of the message may shift its opinion some distance toward or away from that of the emitter's opinion. This opinion is characterized by the opinion range and the opinion confidence bounds. The study proposes to distinguish two categories of population: extremist and moderate people. The first category is located at the ends of the distribution of opinion (their uncertainty is lower, they block the messages). Figure 10 shows the graph network of the community with different links.

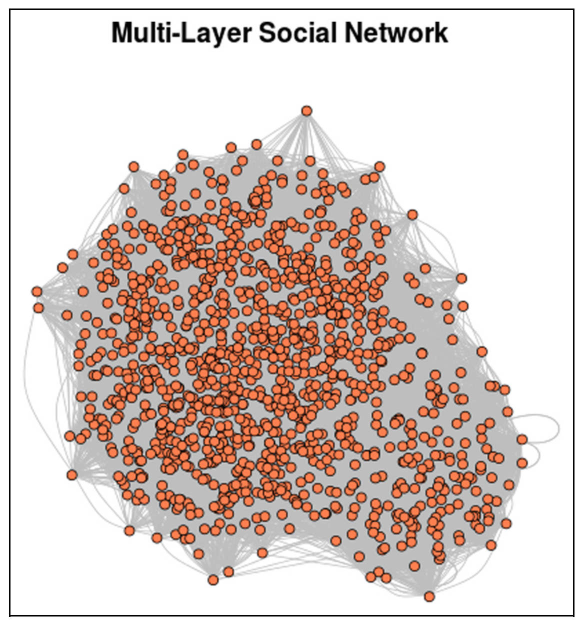

Figure 10. Graph network of the community.

The first step of the simulation is to generate the community to be simulated. There are several parameters that need to be setup: the number of persons, the religions proportions, the percentage of alone persons, the average number of friends, and so on. In this step, the community generated is stored in the database with different features. More details about the generation algorithms are presented by Forestier et al.[6]

- **Human terrain and message characteristics**

Each agent is described by a set of attributes and variables that lie between 0 and 10.

- Social characteristics: gender, age, socio-professional level, religion, political opinion, leader status,.
- Cultural characteristics: {cultural feature and their importance}.
- Reachability features: language(s), literacy, reachable by {radio, television, text message}.
- Psychological characteristics: opinion about the presence of the force in the area.

The political opinion indicates the belonging to one of the political factions represented on the political layer. Some agents have a specific role, such as head of the family or political or religious leader. To be consistent to the dissemination process presented previously, the algorithms need some inputs, such as the proportion of each type of family. People can also speak several languages, but in this version, agents speak only one language, that is, the language the most commonly spoken and understood.

The objective of this experiment is to simulate the propagation of a PsyOp between the individuals of a civilian population during a stabilization phase. In our system, a PsyOp action is treated as a discrete event and is composed of several variables, such as content clarity, content complexity, source credibility, highlighting of the theme, argument quality, and the legibility of message support.

The dimension of all variables lies between 0 and 10. Certain variables have a point of indifference at 5 (e.g., no attitude toward a certain issue), whereas 10 and 0 represent an extremely positive and extremely negative value, respectively. The values of other variables are minimal at 0 and maximal at 10 (Table 1).

The info-targets (agents that the PsyOp aims at being reached and affected in the theater) are determined by the chosen medium, which can have a broad scope, in our experiment a radio broadcast, making the desired info-targets a subgroup of the direct info-targets. This important distinction allows the simulation of the attitude of the untargeted agents, which can nonetheless receive and process the message.

The following treatment describes the transition functions of the model for an agent (i) reached by a PsyOp product (p). The DI is determined by the Involvement by Cultural Features (ICFs; see Equation (1)), the Similarity between the Receiver and the Sender (SRS), the category of the message (e.g., a message with a professional nature sent in a familial network) and the highlighting of the theme (Equation (8)):

$$\begin{aligned} DI(i,p) = \frac{1}{4}.(&\text{Highlighting of the theme}(p) \\ &+ SRS(i,p) + ICF(i,p) \\ &+ (10 \times (\text{category of message}(p) = \\ &= \text{type of relationship}))) \end{aligned} \tag{8}$$

If the DI is below a certain threshold (fixed at 7 in this experiment), the receiver rejects the message. If not, then the model changes its state and calculates the ability of the receiver to process the message. The elaboration ability is determined by Socio-Cultural Level (SCL), Complexity of the message (CM), Message Support Technical Noise ($MSTN$), Clarity of Content (CC), and the Number of Arguments (NA) (Equation (9)).

$$\begin{aligned} \text{Elaborationability} = \frac{1}{5}&(CC(i,p) + SCL(i) + NA(p) \\ &+ (10 - MSTN(p)) + (10 - CM(p))) \end{aligned} \tag{9}$$

If the elaboration ability degree is less than 5, the receiver will follow a peripheral route to process the message. If not, the receiver will follow a central route to process the message. In the peripheral processing, the persuasive force of the message depends on the Number of Arguments (NA), the degree of Similarity between the Receiver (SRS) and the sender, the Source Credibility (SC), and the Weight of Peripheral Factors (WPF). Argument quality has no influence in this case (Equation (10)).

$$\begin{aligned} &\text{Persuasive force of the message for Peripheral Processing} \\ &= \frac{1}{3}.(NA(p) + SRS(i,p) + SC(p)) \times WPF(i,p) \end{aligned} \tag{10}$$

where the Weight of Peripheral Factors (WPF) and Weight of Central Factors (WCF) are determined by the ability and the DI of the receiver:

$$WCP(i,p) = \frac{1}{2}.\left(\frac{DI(i,p)}{10} + \frac{\text{ElaborationAbility}(i,p)}{10}\right) \tag{11}$$

$$WPF(i,p) = 1 - WCP(i,p) \tag{12}$$

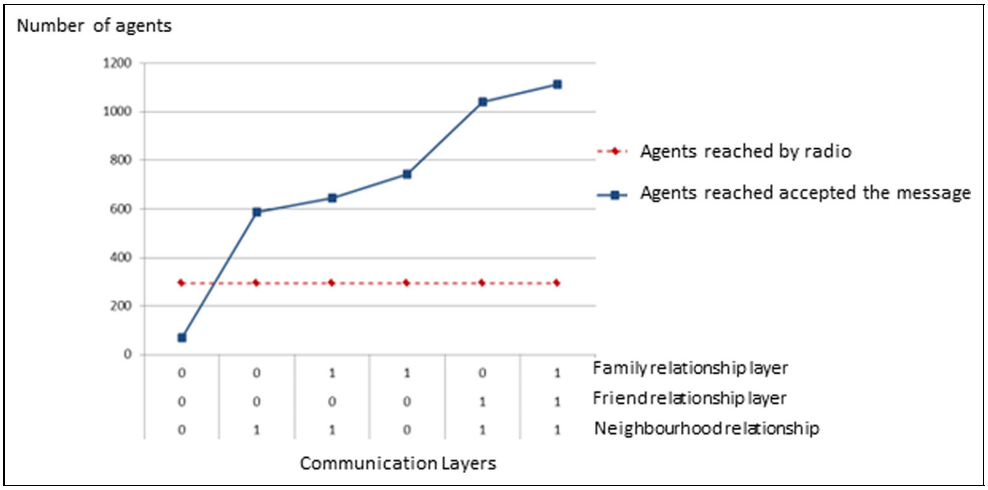

Figure 11. The number of agents interested or impacted by the message in terms of interactions between them.

In the case of central treatment of the message, the persuasive force depends on the Number of Arguments (*NA*), the degree of Similarity between the Receiver (*SRS*) and the sender, the Source Credibility (*SC*), Argument Quality (*AQ*), Socio-Cultural Level (*SCL*), and the Weight of Central Factors (*WCF*):

$$\text{Persuasive force of the message for Peripheral Processing} = \frac{1}{5}.(NA(p) + SRS(i,p) + SC(p) + AQ(p) + SCL(i)) \times WCF(i,p) \tag{13}$$

If the Persuasive Force is above 7, the receiver accepts the message and updates its opinion; if below, the message is rejected. The receiver's opinion toward the presence of the military force in the area after persuasion results from the sum of the previously held (or initial) opinion and a factor (*WPF* or *WCF*) increasing or reducing the opinion degree depending on the sender's opinion:

$$Opiniondegree = Opinion_{t-1} + \Omega \times (sender' opinion_{t-1} - Opinion_{t-1}) \tag{14}$$

where Ω is determined by the Weight of Peripheral or Central Factors.

The simulation result refers to a list of indicators related to the scenario purposes. Some indicators are within a micro level, which may be linked to agent attributes or calculated at a macro level by specific mechanisms.

4.2 Simulation

The specification of the experimental frame is given by the zip file (with VPZ file extension). It describes the entire setup of the system: the graph of coupled models, how models are initialized, and the way to observe them. In the following example, we use *GraphLoader*, which allows the automatic generation of lattice models (where a node is a coupled DEVS model).

In persuasive communication theory, a message has to catch the motivation of the receiver in order to be processed, with a high cognitive activity or not.[47] Then, we introduce such a step in our framework for the computation of the DI. We first compute the similarity between the receiver and the sender. Then we compute the social pressure measured from the number of active neighbors. We also calculate the receiver's sensibility to the theme of the message.

- **Impact of sociability on the number of individuals affected by the PsyOp product**

This scenario consists of simulating a PsyOp mission (PsyOp product) with different configurations in terms of interaction links between agents. This test allows one to verify the impact of sociability on the number of individuals reached by the product and on simulation time (number of time steps). Figure 11 illustrates the results of the experiment. It indicates the number of agents interested in the message during each iteration. For each iteration, the configuration of the activation of the layers has been modified in a random manner. This figure shows significant or negligible effects. On the one hand, combinations do not reach 50% of the population. On the other hand, combinations have a deep impact on the number of agents interested in the message. The reason for success/failure may depend on the direct neighbors (ego-network) of the info-sources or the rejection of messages by the receivers throughout the broadcast process chain. The conclusion of this experiment is that the topology or structure of a network is very important for the diffusion phenomena and,

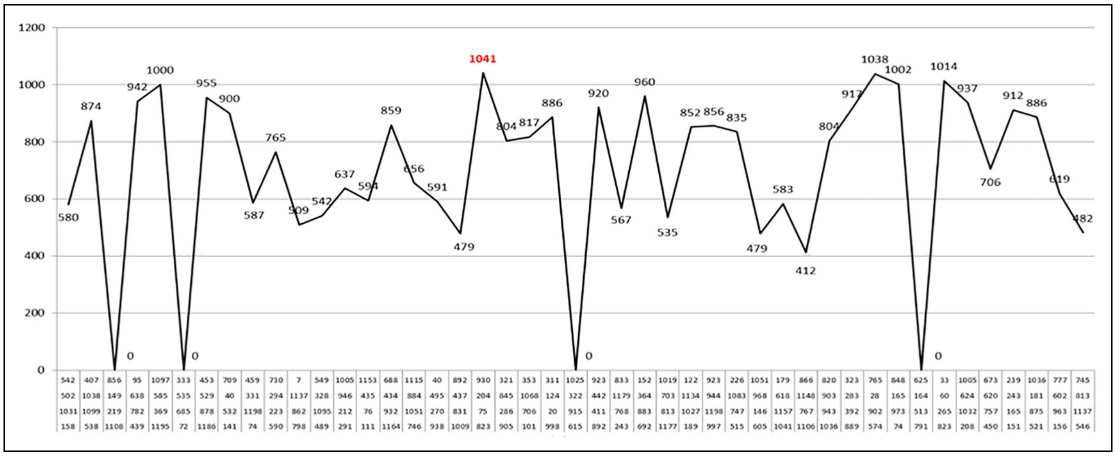

Figure 12. The number of agents concerned according to the information sources.

even if the node has a good centrality, the performance of the actions can be insignificant (Figure 11).

- **Impact of info-sources on the dissemination process**

In this experiment, we set all the parameters of the model, including the network structure, the parameters of the agent, and the characteristics of the PsyOp product. Only the source info is changed. We assume that there is direct contact between the forces and the civilian population. For this, we deactivate the medium Radio as a mean of transmission. Before starting the simulation, we connect the generator of the simulation platform with four different agents (info-sources). At each iteration, we define the info-sources in a random manner (they can be group leaders or civilian agents without any influence on others). At the end of the simulation, we store the result of 50 iterations in a file. After that, we analyze the variation and evolution of the number of agents reached as well as their opinion according to the different combinations of starting points. In this scenario, the population consists of 1200 agents. Figure 12 illustrates the results of the experiment. It indicates the number of agents interested in the message during each iteration. For each iteration, four starting points have been modified in a random way. This figure shows significant or negligible effects. On the one hand, several combinations do not trigger a propagation process. On the other hand, combinations have a profound effect on the population. Through this experiment, we observe that some starting points that are not identified as key agents (such as those that are not leaders or sometimes not well interconnected) can be revealed by simulation as a key or critical path to maximize the influence of information.

The simulation allows results to be obtained at the level of individuals. The analysis of these results makes possible the classification of the agents according to their opinion, the modifications and improvements of the mission (for example, change of the means of transmission, increase of the frequency of product distribution, modification of arguments, etc.), and then the determination of the causes of the operation failure. However, we are interested in aggregated indicators at the population level (macroscopic level). It is also possible to visualize with R the results on a Google Maps-type geographic information system (GIS data) (Figure 13).

In the context of the SICOMORES project, we met several military experts to submit our modeling choices and compare our results with their expertise. However, the project delays did not allow us to carry out a full validation of our models. However, this work has already been confronted by two kinds of experts of the field in several conferences with a civilian and military reading committee.

5 Conclusions and future work

We introduced a DEVS-based architecture of a multidimensional social network for modeling relationships between agents. The framework is based on ABM, DEVS, and Network Theory to simulate the information transmission in a MSN, considering the behavior of the nodes in the network, the network configuration, and the different transmission mechanisms. The simulation allows the observation of the impact of the network structure in the message diffusion process. In addition, statistical computing and graphics are provided to enhance the simulation results to analyze graphically the dynamics of nodes of the network.

This new architecture is fully dedicated to simulate, as transparently as possible, the propagation of information within a population network. In detail, the mechanisms implemented in the models are simple, but they are easily

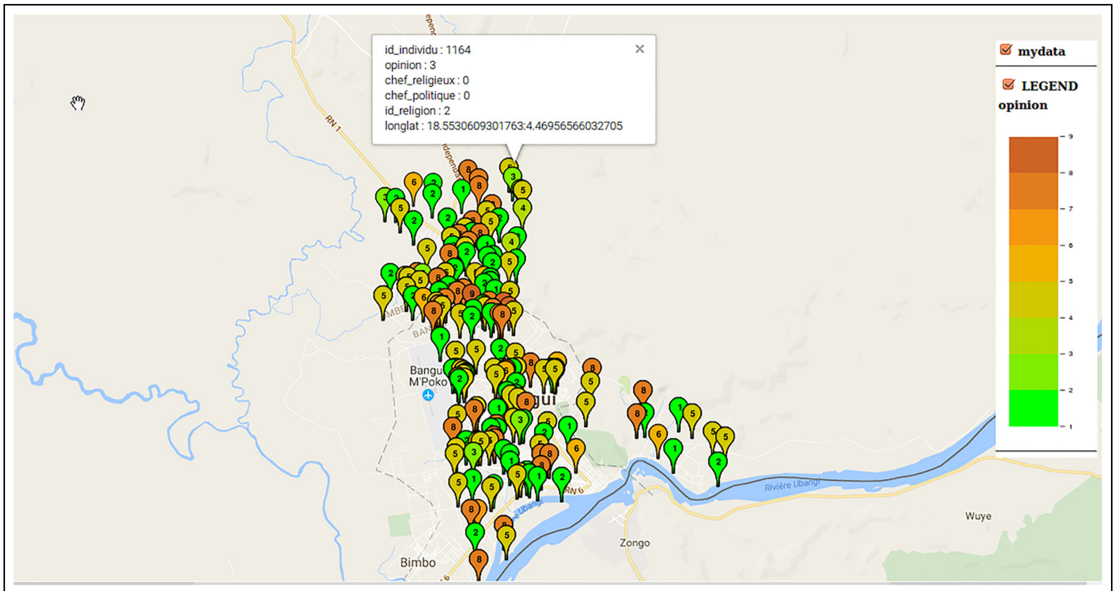

Figure 13. Visualization of social actors on a geographical map.

Table 1. Scaling of independent and dependent variables used in this study.

	Scale				
LABEL OF THE VARIABLE	0	1234	5	6789	10
OPINION	Negative				Positive
THE IMPORTANCE OF CULTURAL FEATURES	None				Maximum
DEGREE OF INTEREST	None				Maximum
ELABORATION ABILITY	None				Maximum
INVOLVEMENT BY CULTURAL FEATURES (ICF)	None				Maximum
SOURCE CREDIBILITY	None				Maximum
SIMILARITY BETWEEN THE RECEIVER AND THE SENDER	None				Maximum
HIGHLIGHTING THE THEME	None				Maximum
MESSAGE SUPPORT TECHNICAL NOISE	None				Maximum
CONTENT OF COMPLEXITY	None				Maximum
CONTENT CLARITY	None				Maximum
SOCIO-CULTURAL LEVEL	None				Maximum
ARGUMENTS QUALITY	Low		Medium		High

upgradeable by modelers. In addition, we assumed that relationships between people are too complex to be modeled by a unique network. Furthermore, information diffusion is dependent on the category of relationships between the persons who communicate. So, the DEVS-based agent framework with the Server/Proxy architecture has been proposed to separate individual behavior in the Server and perception of the environment in the Proxy. This solution is flexible and sensitive enough to take environment changes into account. In the last section, we present two experiments: The first one shows the impact of sociability on the number of individuals affected by the PsyOp product and the second one the impact of info-sources on the dissemination process. We are aware that, even if the different techniques employed were previously validated in their respective domain, the models and simulation results proposed in the paper need to be more validated. Nevertheless, we already presented the first results to experts in the domain and will continue in that way.

The use of the Proxy/Server architecture allows the easy addition or deletion of a dimension in respect of the population features. This framework can be used to solve the problem of influence maximization; that is, find a set of β initially activated nodes (info-sources) with the maximum number of activated nodes after the time step t by launching several simulations with different nodes. Then, we will compare the final results to select the nodes that maximally influence or spread the information.

For future research, we would like to configure and calibrate the simulation configuration by a comparison of the simulation model with reality (data collected from media networks), so that this simulation can be used for more experiments on other propagation issues. One possible way to validate the model is to compare the simulation results to the various elaboration processes of the ELM, since the model is based on a theory of social psychology that has been validated. Another way is to analyze empirical data for information diffusion in large-scale MSNs. In this research, we are limited by the amount of data we can collect through traditional data collection methods (surveys and interviews) used to generate a community (social network). Thus, we need to consider more effective methods to collect more data, especially data that characterize agents' attitudes and needs. To improve the simulation, we would like to introduce more heterogeneity among agents. For instance, during the generation of the population, we can assign different factors values to agents.

Moreover, this research has studied the dynamics of information transmission in multiplex networks considering that the propagation rules are different in different layers. This approach opens many possibilities for various application domains. Generating a population with cultural features can be used in marketing to simulate the adoption of a new product, in social science to observe dynamically the diffusion of information or the way an opinion changes, and in management to study the impact of informal communication inside an organization.

Declaration of conflicting interest

The authors declare that there is no conflict of interest.

Funding

This work was partially supported by the SICOMORES Project N° 132936073 funded by the French DGA (Direction Générale de l'Armement). It involves the following partners: IMS University of Bordeaux, LSIS University of Marseille, and MASA Group.

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