Computer Simulation in Sociology:

What Contribution?

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Computer simulation is spreading in the field of scientific research. In sociology, too, there are important applications. Some different techniques of simulation have developed: system dynamics, multiagent systems, cellular automata, and genetic algorithms. This article analyzes how each type of technique has been applied in sociology and how it is strictly linked to theoretical propositions that characterize each sociological approach. The introduction of computer simulation poses a question: Which contribution does it bring to the process of sociological research? This article aims to answer that question by examining the functions that simulation can carry out in the studies of sociologists.

Keywords: computer simulation, model, multiagent systems, cellular automata, genetic algorithms, complex systems, emergent properties

In the natural sciences, scientific laws are traditionally formulated through mathematical functions, and their effectiveness mainly stems from their simplicity rather than their ability to supply a model of the typical aspects of phenomena. Algorithms, expressed by means of computer programs, are now also able to formulate scientific laws. They can have an arbitrary form, provided that it is coherent. In a computer, physical objects and the structures of a system can be represented by symbols. We can write programs that are able to handle these symbols in conformity with the laws that regulate their behavior. This fact allows us to analyze complex systems that are impossible to study using traditional mathematical methods. The use of computer simulation is now considered an important addition to more traditional theoretical and experimental methodologies.

Mathematical formulation has had little success in expressing laws that regulate social phenomena. Computer simulation can therefore be used as a new tool for analysis and explanations that are impossible to formulate using mathematical functions only. The constant evolution of hardware and programming techniques has also contributed to the diffusion of computer simulation. In the field of scientific research, computer simulation has had an important role in the development of theories of nonlinear and dynamic systems, and the use of computer simulation has created a new interdisciplinary scientific area of study of complex systems.

In the field of sociology, the first pioneering work using computer simulation dates back to the 1960s. During the 1970s, new developments in hardware and software technologies and methodologies in other disciplines gave rise to ever more complex and sophisticated computational models. In this period, Forrester (1961, 1969, 1971) defined system dynamics, widely used to define computer simulations in the social sciences, as a model to analyze the variables of a global system. Recently the technologies derived from artificial intelli-

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gence and the theories of self-organizing adaptive systems have furnished new types of models such as cellular automata, multiagent systems, and genetic algorithms.

The aim of this article is to gain a better understanding of the contribution of computer simulation to sociology and to verify if it has had an important role in the development of sociological explanations.

SYSTEM DYNAMICS

The system dynamics model was introduced by Forrester (1961) to study industrial dynamics and the growth characteristics of urban areas (Forrester, 1969). Subsequently, he analyzed the stall effects of global economic growth on the environment and, consequently, on the course of growth itself (Forrester, 1971). This model has found a number of applications in engineering and the sciences.

Simulations of system dynamics developed in the field of social sciences are part of the group of theoretical perspectives that consider macrolevel phenomena, and, therefore, they focus on the global characteristics of social structures. According to the notion of Durkheim (1895), these models use a kind of variables-oriented explanation, which evaluates the general aspects of a system and considers the structure characterizing a society as "independent" from single components. This assumption allows us to define models in the social sciences in the way we do in the natural sciences.

System dynamics arose from cybernetic and systems theory and was first used to gain a better understanding of management (Coyle, 1977; Forrester, 1961; Roberts, 1980). Now, its applications have been extended to the field of social sciences systems, including global politics and international relationships (Forrester, 1971; Hanneman, Collins, & Mordt, 1995; Saeed, 1994; Wils, Kamiya, & Choucri, 1998). The aim of these types of simulation is to make decisions and predict social events.

The diffusion of system dynamics has also been fostered by the development of software that enables us to specify system dynamics models through a semimathematical but formalized language and that permits us to define computer simulation. In particular, some software, such as Stella and Vensim, provide a graphically oriented interface that helps us construct the model and understand its behavior. Richardson (1996) maintains that the graphical capabilities of software have made an important contribution to the diffusion of system dynamics, but these capabilities still need to be improved significantly. He hopes that in the future software will develop tools to help us understand connections between complex model structure and behavior. "In a sense, simplifying a complex structure while preserving a behavior of interest is one way of saying what we mean by understanding the connections between structure and behavior" (p. 143).

System dynamics has come to play a very important role in management, where only mathematical and restrictive models once existed. Moreover, it is very useful for exploring policies and making decisions.

> One builds a simulation model from policies that in turn make decisions. The model generates streams of decisions controlled by policies built into the model. . . . If the resulting behavior is undesirable, one searches for a better set of policies that yield improved results. (Forrester, 1998, p. 5)

It can be noted that simulation in the economic field has had more success than simulation in global politics and international relationships. I think that this disparity stems from two important problems linked with system dynamics. The first concerns the fact that a system dynamics model has a fixed dynamic structure, and it is not able to reproduce the process of moving from one structure to another. Cortes, Przeworski, and Sprague (1974) maintained that system dynamics furnish a set of tools for representing dynamic structures and investigating how such structures behave but that they can be applied only to "synchronic change" (change produced by a fixed dynamic structure) and not to "diachronic change" (change derived by a process of replacement of a structure by another). In some long-term simulations, the set of variables and the causal relationships can change over time. For example, in a model that describes population growth, such as Forrester's (1971) *World Dynamics*, a new unforeseen technological innovation could change the relationship between natural resources and population growth.

The second problem of system dynamics concerns the quantification of a model. Some models include soft variables that are difficult to translate in numerical values. "The justification for the inevitable uncertainties has always been that system dynamics concerns itself with behavior modes, dominance of modes and dominance transfer, not with precise numerical values" (Coyle, 1998, p. 356). Jacobsen and Bronson (1987) have tried to define some criteria to move from theoretical variables of the model to values of simulation. However, experience shows that system dynamics is more successful in an economic context, because it provides variables that can be easily operationalized and quantified in terms of monetary units (incomes, capitals, prices, etc.). These variables meet criteria of face validity and realism that are essential for a scientific simulation. When the concepts are not so simple, as in the case of behaviors or attitudes that can have a lot of interpretations, the process of quantification is quite intuitive. It is therefore very difficult to compare results from different simulations or to accumulate results and practice. I think that in the future the most important challenge in the field of system dynamics will be to define some standardized concepts typical of the social sciences and to establish their operationalization. Indeed, Richardson (1996) stated that "to advance in this area, the field requires both academic research and reflective, constructively self-critical practice" (p. 150).

MULTIAGENT SYSTEMS

Simulations based on multiagent systems originated from the evolution of distributed artificial intelligence. The aim of such simulations is to develop "autonomous agents"—such as computational systems working in complex, dynamic, and often unpredictable environments—that are able to learn and to adapt to the external world.

These types of simulation are closely linked to the concept of emergent property, because they allow us to define computational models that are able to create a set of global properties from all the characteristics of the elements of a system (Gilbert, 1995). We begin with a definition of the behavior of each component in response to interactions with other components or to particular environmental conditions so that we might discover, after several runs, which structures emerge at a global level and are not included in the initial programmed units. In the social sciences, it is just the same as having a theory about human behavior: From this theory, we can observe what happens if some specific conditions arise. What we can learn, through simulation, are the macro properties that the theory on social actors produces. Simulations of this type are conducted according to the sociological theories of social interaction to verify which regularities they cause in the global level of system.

It is clear that the point of departure in agent-based modeling is the individual. Therefore, the definition of a multiagent system includes a detailed list of rules of agents' behavior, that is, protocols of communication and decision-making procedures that consider environmental changes and all interactions with other agents in that system. This means that multiagent systems furnish a powerful tool for modeling social interaction. Until recently, most aspects of social interaction have been explained through interpretative analysis. Now, multiagent systems can contribute by providing new means for formalizing social roles (see Brent & Thompson, 1999).

Simulations of multiagent systems have also been applied in archaeology and anthropology. The simulations regarding archaeology (Doran, Palmer, Gilbert, & Mellars, 1994; Kohler, 1996) are based on the following principle of microeconomics: Individuals aim to collaborate with others when they are in a situation of economic variability, and collaboration allows them to survive. Starting from this rational individual behavior, these simulations observe how villages developed and how hierarchies formed into villages. In social anthropology, we find some applications based on the studies of the emergence of social norms (Bousquet, Cambier, Mullon, Morand, & Quensiere, 1994; Conte & Castelfranchi, 1995; Findler & Malyankar, 1995; Hutchins & Hazlehurst, 1995; Treuil, 1995). In these types of applications, the definition of agents is based on the concept of bounded rationality developed by Simon (1957). This notion is much weaker than standard economic rationality: The reasoning regarding goals is progressively refined by means of procedures that take into account the limited knowledge and abilities of the decision maker. The concept of bounded rationality provides us with a new perspective to construct sociological theories based on a methodological cognitivism (Viale, 1994). Methodological cognitivism involves different disciplines, including cognitive science, sociology, and computer science.

This type of simulation has made a very important contribution to resolving the conflict between the micro and macro approach. Proponents of the micro approach consider the macro social phenomena derived from the actions, motivations, and behaviors of single individuals. Supporters of the macro approach maintain that we can explain social phenomena only by analyzing the global structure of a social system. Multiagent simulation is based on a theory of individual behavior, but, at the end of the simulation, we may discover structures that have emerged at a macro level and are not included in the initial "programmed" units.

I think that the future of simulation in social sciences is closely linked to the evolution of multiagent systems. This type of system seems to have a lot of potential in the modeling of social interaction; future developments in this field should help define new models of explanation. In particular, I think that research in multiagent systems will go in the following directions.

1. Use of theories and models of rationality that are realistic, understandable, and can be applied in the case of limited knowledge. In particular, theories of rationality need to be extended to learning and adaptation.
2. Formalization of all the aspects of psychological theories (emotions, motivations, desire, intent, consciousness).
3. Formalization of knowledge. This aspect remains one of the principal challenges in the development of multiagent systems. We must determine if it is indeed possible to formalize all types of knowledge—for example, common sense knowledge—and, in this case, what would be the best formalization.

CELLULAR AUTOMATA

Cellular automata are interesting tools in the simulation of complex dynamics. Cellular automa were first defined by John von Neumann and Stanislaw Ulam at the end of the forties to make simulative models of biological evolution and self-reproduction (see Neumann, 1966). Thanks to the growing power of computer technologies, these tools were subsequently used in science and engineering. In some respects, it can be asserted that cellular automa are similar to multiagent systems, in the sense that cellular automa are a particular kind of multiagent system in which the agents have a specific and determined position in a lattice and are homogeneous in their behavior and in their modality of interaction.

One of the aims of simulation is to verify if a system tends to one point of stability where there are no longer state transitions. Another objective is to determine what kind of final state configuration emerges; those configurations originate some particular spatial structures that need to be interpreted, like the global phenomena of a system. Therefore, cellular automata are able to verify emerging properties of a social system. The type of interaction defined at the micro level can lead to a final organization of the system that is impossible to predict through an analysis of individual units alone. A simulation of this type of model allows us to verify which sort of order emerges from individual behavior, and, therefore, all possible self-organizations of social systems should be studied. In the social sciences, simulation models have also been used to study the emergence of public opinions (Nowak & Latané, 1994; Nowak & Lewenstein, 1996), the evolution of cooperation (Axelrod, 1984; Bruch, 1993; Hegselmann, 1996; Kirchkamp, 1994; Liebrand & Messick, 1996; Nowak & May, 1992), and the dynamics of international conflicts (Bremer & Mihalka, 1977).

An interesting and positive aspect of this method is its simplicity. In cellular automata, the behavior of each unit is formalized in a very simple way, and explanations for complex phenomena can be developed based on a few rules for the single components. Moreover, the results of a simulation can be easily understood because they are represented graphically. For example, in the study of the emergence of public opinions, at the end of a simulation, we can graphically see the aggregations of groups of opinion that derive from interactions at the micro level. Often, a visual inspection may reveal the global structures of the macro level. In some cases,

> visualization serves not only the role of a heuristic for discovery, but also a scientific proof. In other cases, however, once visual inspection discovers phenomena of interest, appropriate, more precise measures may be utilized to quantitatively characterize the phenomena of interest. (Nowak & Lewenstein, 1996, p. 257)

A limitation of cellular automata is the use of synchronous updating of states; we assume that there is a global clock according to which all cells are updated simultaneously. This assumption may not be found in real social processes, because individuals modify their attitudes and opinions at different moments. In physics and natural sciences, this assumption is considered very dangerous. Huberman and Glance (1993) proved that the results of the model of Nowak and May (1992), describing the evolution of cooperation using a cellular automata, depends strongly on synchronous updating. To resolve this problem, instead of applying transition rules simultaneously to all units, we can choose to modify only some units.

Another important limitation regards the restrictions imposed by spatial structures, establishing that each individual interacts only with a subset of the whole population. This type of restriction may be acceptable, because it is impossible for a person to interact with all the individuals in a population. However, it is very difficult to define the neighborhood of a unit. In the real world, interactions can also take place among individuals who are not "physically" close to one another: For example, just consider the role of the media in a lot of social processes. Furthermore, the neighborhood can change over time. When we model cellular automata, we must consider these aspects if we want the model to be plausible.

GENETIC ALGORITHMS

Holland (1975) introduced genetic algorithms at the University of Michigan in the 1970s. They are based on Darwin's theory of evolution. According to this theory, a species evolves in relation to its own capacity to adapt to the natural and complex environment. Darwin's theory is based on the assumption that information, stored up by every species during its own evolutionary history, is contained in the chromosomes of each member and is passed on by parents to their offspring. Changes in chromosomes come about in two different ways: through the process of crossover and the process of mutation. These two mechanisms create the process of evolution. Crossover corresponds to the process of genetic mixing in sexual reproduction: The genes of the offspring contain some of the genes of both parents. Mutations cause changes in the genetic material that can introduce new characteristics, allowing animals to adapt better to their environments. Thus, the mechanism of natural selection aims to "choose" individuals that better adapt to the environment where they are living. Then, those individuals will reproduce, and the characteristics codified in their genes will be passed on to their offspring and propagated into new generations.

We can find two types of application of genetic algorithms to sociology: game theory and cultural evolution. Game theory deals with the rational behavior of individuals who aim to gain personal advantages: People prefer interacting with others only if this interaction can bring them some benefits. Evolution will then assure the survival of those types of interactions that yield the greatest benefit for all individuals. In particular, we find important simulations that analyze the emergence of cooperation, according to the prisoner's dilemma (Axelrod, 1987; Epstein, 1997; Riolo, 1997;). Indeed, in this case, it is very easy to use the model of genetic algorithms. In these simulations, there is, initially, a population of strategies that constitute the chromosomes of the algorithms. Moreover, there is also a function that evaluates the fitness of each strategy. Through crossover and mutations, it is possible, after some generations, to select the best strategy that constitutes the best solution to a specific problem.

There are also some studies that apply evolutionary theory to cultural transmission (Reynolds, 1994). They study "how cultures emerge and transform out of vast number of micro-interactions entailing the diffusion or disappearance of cultural fragments" (Lustick, 2000, paragraph 2.6). In these cases, the unit of analysis is a cultural fragment. Since the 1970s, there has been much debate over the relationship between genetic processes and cultural processes. In particular, sociobiology has focused on the application of the theory of natural selection to human behavior. Sociobiologists try to use new-Darwinian concepts to study the mechanisms of the evolution of cultural practices. Campbell (1975) considers human culture as a product of evolutionary selection. The human population was always reorganized in systems with different religions and customs. From this standpoint, a process of selective conservation of organizational structures and ideologies can exist. It is independent of individual fate, but it contributes to functionality of social systems (Campbell, 1975, p. 1106). Anthropology has turned its attention to the connections between survival and human reproduction on the one hand and social practices on the other hand. According to these concepts, it is possible that cultural practices spread according to their level of efficiency.

A number of different models based on Darwinian evolution theory are used to represent cultural components. This results from the fact that cultural information can be transmitted in a number of different ways. According to Cavalli-Sforza (1993), the biggest difference between biological and cultural evolution is that in biology the hereditary material is the gene, whereas in culture, the essential material that is passed down is knowledge, an impalpable material that does not seem to have a chemical structure (p. 305). Therefore, the genetic material that contains the cultural characteristics of each individual does not have a physical or chemical nature, but it has an informational nature, and it can be reproduced by a computer. Moreover, culture is not transmitted only vertically from generation to generation but also horizontally among individuals of the same generation (Boyd & Richerson, 1985; Cavalli-Sforza & Feldman, 1981).

Another important aspect regards the difference between "biological mutation" and "cultural mutation." In the case of biological evolution, all mutations are random, and they determine the creation of species in living organisms. Cultural mutation, on the contrary, is essentially constituted by an innovation, which has a function similar to the function of biological mutation but is not random because it is motivated and constitutes an attempt to solve a problem. If this attempt is successful, it is more likely that the innovation will spread (Cavalli-Sforza, 1993, p. 314).

Can simulation with genetic algorithm models be considered a good tool for explaining the evolution of social processes? Do they furnish a realistic account of these types of phenomena? Undoubtedly genetic algorithms also provide another metaphor for us to use in our search for an understanding of social processes. However, we need to have a clear interpretation of the models and then a realistic representation of them. There are many types of evolutionary models: We should choose our models carefully. Chattoe (1998) attempted to define a correct interpretation in applying evolutionary algorithms to model social processes. The first step is to recognize the differences between social and biological evolution. In the social sciences, in addition to the Darwinian model, we can also apply the Lamarckian model. Another problem that we consider is the verification of which units are used to store and move information on social behaviors. Moreover, most evolutionary models have been developed with instrumental objectives in mind: For example, the use of fitness function must be used with care because it implicates the existence of an invisible hand that guides evolution.

In conclusion, we must realistically map the characteristics of social evolution in an evolutionary model. This process can often create confusion. For example, Chattoe (1998) has demonstrated that, in the economic field, there are some simulations that are characterized by the absence of distinction between genotype and phenotype, the ambiguity of selection operators, and the misinterpretation of crossover process. Therefore, genetic algorithms continue to be criticized or ignored by the majority of social scientists. We must discover the weaknesses and strengths of these models to recognize their many variants and to choose the most appropriate model for certain social phenomenon. Chattoe considers the problem of the development of the market and analyzes the relationship between some simulations that use evolutionary models and empirical reality. From this analysis, he deduces that we can obtain a better interpretation through the development of genetic algorithms like genetic programming, which are more flexible in their representation of the evolution of the mental decision process. However, other types of evolutionary algorithms, such as classifier systems, and their combination with the neural network should also be explored to determine if they furnish more powerful tools with which to represent social processes.

THE ROLE OF COMPUTER SIMULATION IN SOCIOLOGY

We have seen that new techniques have been developed to define models of simulation. In the field of sociology, even though computer models are not as widely used as in the natural sciences, more and more scientists are employing them. This fact raises some questions: How are sociologists using simulation? What is its position in the research process? To better understand the role of simulation in sociology, we analyze its functions in the work of social scientists, as well as its applications.

A Language for Expressing Theories

To construct theories, we need a "language" able to express them. Ostrom (1988) maintained that there are three types of language to choose from: natural language, mathematical language, and computational language. The first can deal with uncertainty and fuzziness, but it is ambiguous. Mathematical language offers analytical techniques for producing derivations, but we cannot use it to explain nonlinear phenomena. Computational models provide a type of language that is halfway between natural and mathematical language. They allow for a careful and unambiguous formalization of a specific phenomenon. However, they are useful in some situations where processes cannot be represented using mathematical models.

In the field of system dynamics, Hanneman et al. (1995) have explicitly translated concepts expressed previously by Weber, Simmel, and Coser regarding some aspects of conflict theory. Hanneman et al. maintained that verbally formulated theories are too limited because we cannot explore nonobvious implications. On the other hand, mathematics allows for a careful and unambiguous formalization of a specific phenomenon. However, there are some situations where processes cannot be represented by mathematical models. In these cases, simulation can be a valid alternative. It works at a lower level of generality: "Instead of deriving, for example, an abstract function showing how the relationship between conflict and legitimacy is conditioned by other variables, we obtain a series of experiments limited to particular scenarios" (p. 8). Through the exploration of these scenarios and the comparison of all results, it is possible to determine what initial conditions and parameters of a model determine certain consequences.

Moreover, Forrester (1971) considered the system dynamics model as a tool able to render mental models explicit. In our minds, we have concepts and relationships that we use to represent the social reality that surrounds us. Using the language of system dynamics, a mental representation becomes a "concrete representation." Vazquez, Liz, and Aracil (1996) argued that "system dynamics could be considered as a 'language'. With the help of this 'language', we see and describe reality" (p. 33). If we have a scientific theory regarding a certain social phenomenon, the mental model, and therefore the system dynamics model, can be considered like an instance of this theory.

In the field of multiagent systems, as well as cellular automata, the model aims to formalize the individual behavior of agents. In this case, we have at our disposal a language for translating some aspects of a theory of human behavior and social interaction in a clear and unambiguous form. Multiagent systems are modeled using tools developed in the field of artificial intelligence, such as heuristics, production rules, logic, frames, and semantic nets. The most famous is SWARM, developed at the Santa Fe Institute. The essential peculiarity of this toolkit is its ability to manage a set of autonomous entities that interact among themselves and with their environment without a centralized unit ruling their behavior. Each entity makes decisions on the basis of its personal evaluation of the world, its own internal state, and communication with other agents. SWARM is an object-oriented system where the basic unit is a swarm, a collection of agents executing a list of actions. Each agent is modeled through rules that determine its actions according to some stimuli. Beside agents, SWARM makes it possible to define some lists of discrete events that represent all processes happening in a system. During each simulation, the events of all the lists are executed; these events cause messages to be sent to agents.

The language of cellular automata is strictly related to spatial dimension. The majority of the components of a cellular automata model are graphical (lattice space, neighborhood, states of units). Therefore, we have a computational language where the visual element is very important.

To model with a genetic algorithm, we must represent the "genetic material." We have previously seen that we substantially have two cases: In the rational choice theory, the chromosomes are the strategies of single individuals; in the cultural evolution case, the chromosomes are cultural fragments. For each of these cases, we must choose a language able to codify information. Currently, this operation is not standardized, and each application uses a different modality of codification depending on the type of phenomenon or preferences of researchers. There are no software tools that help define a genetic algorithm model. Perhaps this is because genetic algorithms are in an explorative phase. Indeed, we are witnessing an ongoing definition of new variants of this model.

A Tool for Studying Complex Systems

This functionality is inherited from natural sciences. The impossibility of studying analytically and empirically certain phenomena has given a strong impulse to the use of the technique of computer simulation. Indeed, in some cases, it is the only possible tool for studying natural phenomena.

The study of complex systems does not permit a careful prediction of their evolution, but it allows us to determine the specific conditions that cause a meaningful change in the behavior of a system. In short, what emerges is that, in a number of cases, scientists can see the external world only through a "window" (Nicolis & Prigogine, 1987). Therefore, they should not seek a total understanding of phenomena.

The introduction of conceptions relevant to complex systems has led to the rapid spread of the simulation method. Most propositions constituting the theory of chaos and complexity derive from exercises of computer simulation. Indeed, simulation looks like the most suitable tool for exploring the evolution of nonlinear processes. In these systems, we are not able to identify universal laws, because chaotic behavior does not permit generalizable explanations. All that we can do is to reach local, but no less important, solutions to a problem.

In the field of system dynamics, we cannot know the behavior of a system in every situation; we can only explore what happens in a specific situation. What we can do is to execute a simulation with a set of initial conditions and parameters. Essentially, we determine the consequences relative to a vector of values. We can therefore determine when a system undergoes a meaningful modification in its behavior: for example, when it moves from a state of equilibrium to a chaotic situation. The problem is to find the critical points and the variables that determine a drastic change in the behavior of that system. Furthermore, though a simulation is not able to describe in a deterministic and detailed way the behavior of all components, it does allow us to observe what conditions cause drastic changes.

In the field of multiagent systems, cellular automata, and genetic algorithms, the concept of complexity is linked to the concept of emergent property. It is not easy to define an emergent property. Reflections on this topic have led to contrasting opinions. The central idea is that very complex systems survive and reproduce because they are able to adapt to environmental pressures gradually and spontaneously and reach different types and levels of self-organization. During this process, a system necessarily develops collective properties that transcend individual units. Hayek (1942) had already posed the problem of this phenomenon: "The conscious action of many men produces undesigned results, in so far as regularities are observed which are not the result of anybody's design. [This question poses a problem that] demands a theoretical explanation" (p. 288).

Generally, we define *emergent property* as a property of an object that is impossible to deduce through the complete knowledge of its individual components and their relationships. By working on complex systems, we note that

> it should not be possible to derive analytically the global emergent behavior solely from consideration of the properties of agents. In other words, emergent behavior is that which cannot be predicted from knowledge of the properties of the agents, except as a result of simulation. (Gilbert, 1995, p. 150)

The concept of emergent property seems to be closely linked to temporal dimension, because, in a sense, it defines a phenomenon developing over time. Moreover, emergence is often associated with the concept of the adaptability of a system, and it is considered a positive effect of self-organization. This aspect refers to the conception of "function" theorized by Parsons (1951). Indeed, emergence is deemed a mechanism that is responsible for the preservation of the equilibrium of a system. In the field of complex systems, the presence of emergent properties is based on the existence of attractors of a dynamic system. An attractor corresponds with a structure that self-organizes itself following an instable situation that arises from a sudden change of some conditions. The process of self-organization gives rise to some collective properties in the system that do not depend directly on individual properties. Through this process, a system reaches a certain order arising from processes of interaction that occur at the micro level, without supervision or higher level structure. The concept of self-organization can resolve the problem of complexity because it is thought of as coming about through a series of interactions that can be described simply. In this sense, a simulation simply discovers that complexity evolves from simplicity.

A Tool for Experimenting on Theory

Simulation can help scientists to explore some situations that cannot be investigated through experiments. An example of this impossibility in the field of physics is the study of the formation of galaxies. Many scientists consider computer simulation a kind of experimentation on models. In the natural sciences, the experiment has always been the main method for conducting scientific research. We can assert that the experimental method has been the fundamental part of the growth the natural sciences.

We know that experimentation has not been very successful in the social sciences. This has led social scientists to search for alternative tools, both analytical and observational. In one sense, simulation is considered a substitute for experimentation. It differs from experimentation in that it does not study reality directly but only its representations. In short, because it is very difficult to study a real social phenomenon, we define a model of it, which is more accessible.

Generally, this type of experimentation consists of defining different scenarios and controlling the consequences of each elaboration. In the case of system dynamics, we can conduct experiments by exploring different scenarios deriving from different values of parameters. We can also compare the behavior of different models. In a cellular automata model, we can verify the result of different initial configurations, different definitions of the neighborhood, or different transition rules. For example, in the case of dynamic social impact, researchers have studied, heuristically, what the necessary and sufficient conditions are that cause the clustering and the polarization of opinions (Latané, 1996; Nowak & Lewestein, 1996). A multiagent system model can be explored by changing the initial configuration of the environment or some functions or rules that define the behavior of each agent. In Doran et al. (1994), the simulative experiments make it possible to discover the circumstances that influence the formation of hierarchies in a social group. Finally, in a simulation with genetic algorithms, we can observe the results derived from different types of codification or different rules of crossover and mutation. Reynolds' (1994) application, which studied the emergence of cooperation in a population of Peruvian herders, is quite interesting. Comparing some experiments, he concluded that the process of cooperation evolves only if it is supported by a belief system.

A simulation is nothing but the formulation of a model in a special set of established circumstances; if we change some values of certain variables each time, then we can obtain simulations exploring different scenarios. Moreover, simulative experiments can examine counterfactual situations by associating to a variable some constant values different from the ones usually observed. In short, this kind of experimentation allows us to theoretically analyze some regions in a parameter space that are not open to normal empirical experiments. Therefore, it gives rise to a "new kind of scientific method, intermediate in kind between empirical experimentation and analytic theory" (Humphreys, 1994, p. 103). The possibility of distorting reality for certain theoretical purposes can be considered an important opportunity.

Simulation allows us to analyze a model and experiment on it rather than experimenting on the real world. Naturally, this type of procedure gives rise to new problems regarding the selection of aspects of a phenomenon, the validity of models, and so on. As a model of "plausible" representation similar to the observed reality, it becomes a new autonomous entity. The experiments on models do not produce results pertaining to empirical reality, as in the case of the classical experiments carried out in a laboratory. The outcomes of a simulation depend on the theoretical assumptions of the definition of a model. A simulation works following a "what if" kind of reasoning: What happens if we execute a simulation with some specific values of variables? A social scientist has at his or her disposal a new method for formulating experiments in the field of pure theory. In this sense, simulation can be considered a heuristic tool able to discover and test theories:

> Simulations play an important role in the process of developing hypotheses, models or even new theories. Analyzing the results of very many runs of a simulation model with different parameters may suggest new and simple regularities that would not have been extracted from the model assumptions otherwise. (Hartmann, 1996, p. 88)

According to Latané (1996), simulation "is as a derivation machine, a way to discover the consequences of a theory" (p. 290). If it works, it can confirm what we know about a society or lead to the discovery of new theoretical propositions. Generally, it provides a new tool for testing gaps and fallacies. If we change some conditions systematically, we can determine which aspects of a theory are necessary for a particular result and which ones cause only a few variations. Rather than define the validity of a theory according to the correspondence of its results with data from the real world, it is interesting to consider simulation to extend this theory, "by adding complexity and recursion," to determine "whether the theory is robust with respect to variations in stochastic and other theoretically uninteresting variations," and to verify "which elements of the theory are critical to the resulting dynamics" (p. 295).

If we start from a simple model or a model formulated in a generic way, it is possible to explore possible regularities that did not emerge from an initial intuitive analysis. This type of procedure is quite common in the natural sciences. When we do not know the causal connections among elements of a complex process well enough, we can try to reproduce this process through a simulation to learn more about these relationships. In this sense, a computational model can help in the development of theory (Schultz & Sullivan, 1972). For example, Guetzkow (1962) applied the method of simulation to study international relationships with a view to producing a tool for developing certain theories heuristically.

CONCLUSION

Computer simulation techniques provide new opportunities to develop social research. The most important aspect is their capacity to include the dynamics of social phenomena.

The system dynamics of Forrester clearly derive from some concepts expressed by cybernetics, such as the concept of feedback. According to this discipline, the behaviors of a system retrace on themselves cyclically. It is clear that, above all, these models aim to formalize the dynamic aspects of a system. Feedback can be analyzed only if we carry out a study that considers the changes that take place in a system over time. This characteristic is closely linked to the concept of sequentiality typical of computers. Therefore, an analysis of this type can almost always be developed using simulations.

In the case of multiagent systems, the relationship with cognitivism allows us to define models of behavior that could be very useful, for example, for the description of the concept of role, so important in sociology.

On the contrary, a weakness of computer simulation remains: its connection with the empirical word. A simulation experiments on a model of a virtual world quite different, in the sense of "material components," from the real world to which it refers. Generally, each verified behavior is a mere deduction of the theory from which the model derives. The validity of a simulation can be determined above all from the validity of the theory that the model is based on and from the validity of the computational tools making its definition possible. Its main function is to determine the consequences regarding the changes of some variables or assumptions, but it cannot value if the model represents reality. The model does not tell us anything about the connection between theory and empirical data; it can be verified in another way. Nagel (1961) maintained that, if the models and the theory have an important role in a scientific inquiry, they do not substitute for the rules of correspondence between theory and empirical data.

Therefore, defining the validity of a simulative model becomes a very difficult undertaking. We can use an extension of the "Turing Test" (see Taber & Timpone, 1996): If we cannot distinguish the behavior of a model from the behavior of its real referent, that model can be considered valid. Then, also supposing that the model would be different from the reality, if the input and output of a simulation are equal to the correspondent data of an empirical phenomenon, it can be accepted. Now we have the problem of comparing "artificial data" with real data, but the variables of a model generally derive from a simplification and abstraction of a phenomenon; they are defined, above all, according to theoretical concepts on the basis of the model rather than empirical reality. For example, when we define a variable that represents the prestige of a political community we can decide that it should assume a real value between 0 and 1. How can we interpret the values assigned to this variable during the simulation? What does a prestige value of .4 mean, in a dynamic system?

Finally, in the social sciences, there are some problems regarding measurement. In the case of the natural sciences, generally, to define the relationship between empirical data and computational data, we need to transform the data derived from a particular tool of measurement (radar, modem, sensor, etc.) into a digital format interpretable by a computer. This procedure involves the introduction of further models; we then have a situation where the data used for validating a type of model are a product themselves of other models. In the social sciences, we often do not have standardized and consolidated tools of measurement at our disposal. Sometimes, therefore, the process of measurement is based on the personal intuition of researchers. This means that in the social sciences, the level of acceptability of a computational model is inevitably lower.

In conclusion, I think that the most important challenge of simulation in the social sciences will be the search for tools able to define the connection between the virtual world and the empirical world. With the proper tools, we can attempt to resolve the current problem of validation.

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