

# Bottom-Up and Top-Down Approaches to Simulate Complex Social Phenomena

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## ABSTRACT

Social science research is concerned with the study of processes and phenomena in human societies, institutions and organizations. Social phenomena are complex due to many non-linear interactions between their elements. Social simulation represents a new paradigm for understanding social complexity with approaches that use advanced computational capabilities. The success of social simulation is largely due to its capability to test and validate hypotheses of social phenomena by the construction of virtual laboratories. This paper provides an introduction to social simulation and discusses approaches to model complex social phenomena.

## KEYWORDS

Agent-Based Modeling, Cellular Automata, Complex Systems, Dynamic Systems, Social Simulation

## INTRODUCTION

Social science research is concerned with the study of processes and phenomena in human societies, institutions and organizations. However, these processes and phenomena in human societies are complex due to many non-linear interactions between their elements (Gilbert, 2004). Social simulation can help to understand, test and validate hypotheses of social phenomena by the construction of virtual social laboratories. Social simulation is a research field emerging from the intersection of computer science, statistics and social sciences in which new computer and mathematical methods are used to answer societal questions (Sallach & Macal, 2001). The field is intrinsically collaborative: social scientists provide a vital context and insight into relevant research questions, data sources and methods of acquisition while statisticians and computer scientists provide expertise, in developing a mathematical model and computer tools. The use of computers in social sciences is almost as old as computers in general. This is partly due to the fact that some of the pioneers of computer science, such as John Van Newman who was among the founders of game theory, were at the time the pioneers in the formulation of social sciences (Von Neumann & Morgenstern, 1947). In addition, Herbert A. Simon, one of the pioneers in the formalization of social sciences, was among the first to adopt computer-assisted methods to construct social theories (Simon, 1959).

Social simulation is derived from the interests of psychologists, sociologists, anthropologists and some economists who are interested in the study of behavioral patterns and social phenomena (Axelrod, 1997b; Billari et al., 2008). It allows the analysis of structures and social organizations regrouping a set of actors (individuals, animals, etc.) in interaction. Simulation is described as the third way of “doing science”, complementary to the two standard methods in social sciences, induction and deduction (Axelrod, 1997a, Blaschke, 2008 and Ostrom, 1988). According to Gilbert and Troitzsch (Gilbert, 1999), the goal of simulation is to better understand a phenomenon or to predict the evolution

DOI: 10.4018/IJAEC.2018040101

of a system. Simulation also allows us to study quite finely dynamic processes that naturally take into account the temporal evolution. Researchers have often been interested in simulation as a method of developing and testing social theories. Hence, Nigel Gilbert and Doran (Gilbert & Doran, 1994) demonstrated that computer simulation is an appropriate methodology whenever a social phenomenon is not directly accessible.

Social simulation represents a new paradigm for understanding social complexity. It applies approaches that use advanced computational capabilities (Cioffi-Revilla, 2014). Social simulation refers to many computer-based tools (Suleiman, Troitzsch & Gilbert, 2012) ranging from information extraction, algorithms to computer simulation models, as well as concepts and theories. Social simulation also uses statistical and mathematical methods (De Marchi, 2005), and in some cases other methods such as geo-spatial methods (Crooks & Castle, 2012) visualization (Grignard & Drogoul, 2017) to understand social complexity. This new paradigm allows the study of dynamics of all sizes of social groups (Axelrod, 1997a; Billari et al., 2008; M'hamdi et al., 2017; Nemiche & Pla-Lopez, 2000; Nemiche & Pla-Lopez, 2003; Nowak & Lewenstein, 1996; Pla-López, 1989, Pla-Lopez, 2007; Turchin, Currie et al., 2013). Social simulation is a subfield of Computational Social Science (CSS) as well as Analysis of Social Networks and Complex Systems which are the most well-known research axes in CSS (Cioffi-Revilla, C, 2014). The role of CSS is to formalize theory in order to express, study, experiment, and develop our understanding of social complexity which is something inaccessible by the traditional methods of social sciences (Axelrod, 1997a; Cioffi-Revilla, 2014; Ostrom, 1988).

The motivations that encourage social scientists to use computational methods can be summarized in two points. The first point is the nonlinear dynamics of social processes that generally characterize social systems as complex systems (Axelrod, 1997a; Conte, Hegselmann and Terna, 2013; Edmonds & Meyer, 2015; Gilbert, 1999; Gilbert, 2007; Goldspink, 2000; Koch, 2016; Mason, Vaughan, & Wallach, 2014; Nemiche & Essaïdi, 2016; Ostrom, 1988; Simon, 1959; Troitzsch, 1997). The second point is the consequences of technological progress which have increased the amount of social data circulating on digital media and the capacity for computing which lead to the complexity of social systems (Rokach & Maimon, 2014; Wu et al., 2014).

Mathematics has sometimes been used as a means of formulation in the social sciences (De Marchi, 2005), but it has never been generalized except in some parts of econometrics. There are several reasons why simulation is more appropriate for formulating social science theories rather than mathematics (Taber & Timpone, 1996). First, programming languages are more expressive and less abstract than most mathematical techniques, at least those accessible to non-specialists. Second, programs treat parallel processes which are impossible with mathematical equations. Third, programs are (or can easily be) modular. So, major changes can be made in one part without changing other parts of the program. Mathematical models often lack this modularity. Finally, it is easy to build simulation systems that include heterogeneous agents. For example, to simulate people with different perspectives on their social reality, different knowledge bases, different abilities, makes it difficult to use mathematics (Gilbert, & Troitzsch, 2005).

The design cycle for simulation generally has three distinct phases as shown (Axelrod, 1997a; Bonabeau, 2002; Cioffi-Revilla, 2014; Epstein & Axtell, 1997; Gilbert & Terna, 2000): the modeling step, which is to constructing the model of the phenomenon to be studied. The experimentation step, which aims to submitting this model to a certain type of variation and the validation step, which consists in confronting the experimental data obtained with the model to the real-life data.

The construction of a model is always based on a theory that is, in classical simulation, an abstract description of certain aspects of the phenomenon. Each model will be a simplification - sometimes a drastic simplification - of the target to be modeled. The most difficult step in designing a model is to decide what should be left out and what to include (Cioffi-Revilla, 2014). In general, the accuracy (in terms of the number of data points and hypotheses integrated in the model) is important when the goal is prediction, whereas simplicity is an advantage if the goal is understood (Axelrod, 1997a).

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