Simulation in Sociology: A Review of the Literature

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January 1999

Abstract

Simulation has a long and chequered history in areas of substantive interest to sociology, from before Forrester's (1973) model of over-population to up-to-the-minute approaches based on complexity theory or Distributed Artificial Intelligence. While in some respects it has failed to live up to its inflated promise, it offers nonetheless a very useful paradigm. Moreover, advancing simulation technology offers some advantages, particularly the modelling of macro–micro linkages too complex to deal with linguistically or mathematically. This paper briefly reviews the history of simulation in sociology, and goes on to consider in more detail specific areas such as system dynamics, cellular automata, iterated game theory, distributed artificial intelligence, neural networks, multi-level simulation, simulation of social networks and organisations, and policy-oriented tax–benefit micro-simulation. It concludes with a consideration of the role of statistics in simulation, and the very good potential for expanded use of simulation in sociology.

1 Introduction

Computer simulation has played a significant, though secondary, role in sociology almost as long as sociologists have had access to computers. As a methodology it has offered, and continues to offer, a set of fruitful approaches: it is with justification that some claim it to represent a third domain, complementing both natural languange and mathematical/statistical sociology (Schnell, 1990; Hanneman, Collins and Mordt, 1995). However, simulation has waxed and waned in prominence and has always stood apart from the mainstream of sociology, which has not fully appreciated its contribution.

In this paper I review the role simulation has played in sociology, the sorts of contributions it is currently making, and its future potential. The scope of the review is the discipline of sociology, but because we are concerned with a set of methods in no sense specific to the discipline, it is not useful to impose hard territorial boundaries. Indeed, research using simulation tends not to respect conventional disciplinary or publishing 'geography'. Therefore the scope of the review is research on simulation of social processes, and social phenomena, in general. This includes research on economic processes, viewed socially (but excludes research clearly within an economics tradition),

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some aspects of social psychology, of organisation theory, aspects of demography, anthropology and archaeology and so on where the substance is of sociological interest. It includes a brief consideration of the tax–benefit micro-simulation tradition. However, because of work presented in parallel papers in this issue, research on innovation and diffusion (Windrum, 1999), on business processes (Paul, Gliaglis and Hlupic, 1999) and on pure political-science issues (Johnson, 1999) will not be covered.

2 A brief history

Computer simulation in sociology has a history that stretches back almost 40 years[1] and has gone through a number of phases of vigour and retrenchment. Its literature is peppered with papers and books summarising its influence, advocating its use and pulling together examples in order to demonstrate its utility (Guetzkow, 1962; Gremy, 1971; Guetzkow, Kotler and Schultz, 1972; Hummon, 1990a; Troitzsch, 1990; Schnell, 1990; Gilbert and Doran, 1994; Hanneman, 1995; Gilbert and Conte, 1995; Troitzsch, Mueller, Gilbert and Doran, 1996; Hanneman and Patrick, 1997).

There are two important traditions associated with the early days of simulation in the social sciences. The first, temporally, is simulation gaming, especially in the fields of international relations and organisation theory. This was an approach, with roots in social psychology, which attempted to model phenomena such as diverse as the outbreak of World War I (Hermann and Hermann, 1967) and the structure of organisations (*e.g.*, Guetzkow and Bowes, 1957). In due course it became clear that computers allowed more extensive, if less flexible, simulations to be carried out, and at less expense.[2] This tradition accounts for some of the popularity of simulation in cognitive and social psychology, and in political science and international relations.

The second tradition is known as the 'world dynamics' or system-dynamics approach: this grew out of work done at MIT and became quite well-known in the early 1970s when Jay W. Forrester published his model of world-wide growth, population and pollution (Forrester, 1973), and which was incorporated in the famous report to the Club of Rome, *The Limits to Growth* (Meadows, Meadows, Randers and Behrens, 1972). However, though these models were fascinating in their depiction of the complex interactions of the elements of the world system, they performed poorly due to extremely high levels of aggregation, some arbitrary assumptions and a weak empirical base. In some ways, the popularity of the systems dynamics approach in the early 1970s hindered as much as it helped the medium-term growth of simulation. Nonetheless, it is still an important mode of simulation: see section 3.1 below.

Though these two traditions were influential there was a lot going on elsewhere, as the potential of computers became evident. Coleman's early paper (1962) demonstrates how a simple simulation can answer some theoretical questions about reference group effects (and avoid the individualistic error of analysing 'not the social system, but the IBM cards': p. 61). One field that took up simulation enthusiastically was demography, where the relative simplicity of the underlying processes (birth rates, death rates, *etc.*) coupled with the relatively chaotic observed population dynamics made simulation an

[1]The earliest reference I can find is Guetzkow and Bowes (1957), exactly forty years old at time of writing, representing the tradition of simulation gaming (with role-playing participants rather than computers doing the work) the immediate predecessor of much computer simulation research. However, as early as 1962 Coleman was making programmatic statements about the importance of computer simulation (Coleman, 1962), and a year previously Orcutt, Greenberg, Korbel and Rivlin published their seminal work on socio-economic simulation.

[2]The journal *Simulation and Gaming* has to a significant extent come from this perspective.

attractive proposition. In particular, it became popular in anthropological and historical demography, where it allowed the reconstruction of processes that were only partially observed. Examples in conventional demography include Dyke and MacCluer (1975) and, more recently Pennec (1993). Roth (1981) and recently Whitmore (1991) focus on historical reconstruction of population change, and Doran (1970) and Wobst (1974) represent early use of simulation in archaeology. Anthropological demography (and anthropology in general) also provided interesting problems for simulation: the highly structured models of kinship relations, incest taboos, marriage relationships and so on that anthropologists developed, lent themselves readily to expression as computer programs (Kunstadter, Buhler, Stephen and Westoff, 1963; Gilbert and Hammel, 1966; MacCluer, Neel and Chagnon, 1971; McArthur, Saunders and Tweedie, 1976; Howell and Lehotay, 1978; Hammel, McDaniel and Wachter, 1979; Fix, 1981). Some use simulation to make unexpected links between aspests of the studied societies: for instance, Dombrowski (1993) uses a simulation to demonstrate that the practice of bridewealth, usually understood purely in terms of solidaristic inter-familial exchange, may well have the important and unexpected consequence of reducing the risk of cattle herds dying out, and thereby making economic the practice of small-scale cattle husbandry.

Computing became more accessible, cheaper and in many respects easier over the past few decades, and simulation has grown with it. In particular the development of high-level languages, from FORTRAN IV to object-oriented, platform-independent languages like Java, passing through more specialised ones like Lisp, Prolog and Smalltalk and workhorses like C and C++, has made it easier to write complex simulations. Special simulation languages like DYNAMO (for system dynamics), GPSS and SIMSCRIPT *inter alia* have removed the requirement that the simulator be competent in a programming language (as long as the type of simulation fits into the package's model).[3] Programmable statistical packages such as SAS (and more recently Stata), and spreadsheets, mean that many more people have the means to carry out simulations at their fingertips. Perhaps more importantly, a large body of technical knowledge about simulation (in all disciplines) has been built up and is becoming formalised (*e.g.*, Whicker and Sigelman, 1991; Davies and O'Keefe, 1988).

But some other developments in computer science and related areas have made for qualitative rather than quantitative advances in simulation:

- the object-oriented programming paradigm, mentioned above, is an approach which facilitates modelling reality both computationally and conceptually and is particularly suited to modelling, for instance, nested structures such as societies containing groups made up of individuals (see section 3.4 below);
- Connectivist or neural networks allow the creation of systems or agents with the ability to learn from their environment (section 3.3);
- The 'artificial life' tradition (sometimes associated with the Santa Fe Institute (Santa Fe Institute, n.d.)) has developed the 'cellular automata' model (section 3.2; this is a very useful paradigm for modelling individuals embedded in a spatial structure), and the 'distributed artificial intelligence' approach (DAI: see section 3.3) in which systems composed of artificially intelligent agents are set up and studied (also closely related are issues of chaos and complexity theory, and the 'evolutionary computing' paradigm).

[3]These packages can make simulations much more efficient to write: in Hanneman et al. (1995), for instance, a sophisticated, if stylised, theoretical model of imperialism (in terms of the relationship between internal factors promoting imperialism, the arms industry, the legitimacy of the state, the power of enemy states and so on), in the systems-dynamics tradition, can be written in a mere 34 lines of DYNAMO code.

3 Overview of existing research

The diversity of work in simulation in sociology (or of phenomena of sociological interest) is considerable, and raises a problem of presentation: whether to divide by substantive content, or by the sort of simulation used. Partly because sociological simulations which arise directly out of established substantive areas are less common, and partly because there is an association, though weak, between types of simulation and the issues they deal with, the following overview of current sociological simulation is organised according to simulation method rather than according to substantive or theoretical content.

3.1 System dynamics

System dynamics was for a time *the* simulation paradigm, and despite not living up to its initial perceived promise, it is still in widespread use and is still generating interesting results. The essence of system dynamics is that it models systems, where systems consist of a set of quantities or stocks or 'levels' which can grow or decline, and where the rates of growth and decline are affected by 'feedback loops' from each stock itself and other stocks, in potentially complex ways. Once a system permits feedback, its path becomes hard to predict in advance, making simulation a useful approach. Forrester's famous world model (Forrester, 1973) consisted of five such stocks:

1. population;
2. natural resources;
3. capital investment;
4. capital investment in agriculture; and
5. pollution.

These are linked together by feedback loops: for instance, the death rate is affected by the level of population (crowding increases mortality), pollution, and material wellbeing (in turn a function of capital investment and the consumption of natural resources); both production and population increase pollution, and the rate of absorbtion of pollution is a declining function of the level of pollution, and so on (see Forrester, 1973, Fig. 2.1). Though it has only five 'stocks' there are many complex links between them, and a large number of parameters to specify, to say nothing of the functional form of the feedback loops. As a result it constitutes a system whose behaviour varies dramatically over time and as the parameters change. Moreover, it does so in an unpredictable way. With good data on parameters, well specified functional links, and properly specified stocks (for instance, without excessive aggregation: the birth rate is better considered not a function of the population, but of the population of women of child-bearing age, *etc.*) such a simulation model can be a successful and enlightening representation of reality. Unfortunately, Forrester's model was too aggregate and based on too many unfounded assumptions and was publicly seen to fail. As Schnell (1990) points out, subsequent modelling moved to a more regional focus, paid more attention to specifying economic processes well, and worked with a shorter time frame.[4] Nonetheless, the world-modelling paradigm as an instance of system dynamics is no longer significant. (In contrast, the tax–benefit micro-simulation paradigm has become increasingly important for forecasting and counter-factual analyses, but is entirely non-aggregate, usually working at the individual level: see section 3.6 below.)

[4] Schnell's paper contains a systematic overview of simulation in sociology and despite being slightly out of date is well worth reading.

3.1.1 The elaboration of theory

However, despite the failure of predictive models, the paradigm has been found to be useful for other purposes, notably the elaboration of macro-sociological theories. For instance, Hanneman et al. (1995) (see note 3 above) makes an extensive argument that natural language is inadequate for the formulation of complex theories, especially where there is a system of multiple causation involved, or where dynamics are important. Where possible a mathematical formulation is preferable, but often the mathematics is intractable or outside the skill of the researcher and then simulation provides a powerful alternative.[5] They present an example of the sort of theory-development they mean by taking ideas on imperialistic conflict from Simmel, Coser and Weber, and setting up a system-dynamics model with 'levels' including the legitimacy of the state (and therefore, relative to the desired level of legitimacy on the part of the state, the legitimacy deficit), the size of the arms industry, the size of the state-dependent economy, the amount of booty derived from imperial exploitation, *etc*. By starting with a very stylised model, and by careful manipulation of parameters, they are able to draw out certain interesting relationships, for instance between the size of the legitimacy deficit and the military power relative to enemy states and the system's temporal path in terms of conflict and stability. They are careful to note that these simulations do not represent reality: rather, they force the re-statement of theory in a rigorous symbolic form where more complex consequences of the theory may be drawn out.[6]

3.1.2 Theorising norms

Another example of macro-level theory development using system-dynamics is given by Jacobsen and Vanki (1996) (see also Jacobsen, Bronson and Vekstein, 1990). Here the substantive issue is change in norms bearing on the suitability of engineering as a career for women in Israel. The perspective on norms is drawn from fairly traditional streams in sociology, including structural functionalism (*e.g.*, Berger and Luckman, 1967; Merton, 1957), but simulation confers the advantage of a dynamic perspective to the usual staticness of functionalism.[7] The quantities in their model are such things as level of deterrence, the legitimacy of violation, the numbers of violators and so on. Because of the system perspective, they can deal with the circular (but nonetheless logical) relationship whereby the more complied with a norm is, the stronger it is, and correspondingly the more it is violated, the weaker it becomes. Their model allows them to assess the separate effects of internalisation of norms and of external social control, and they conclude that the slow rate of growth of female engineers is more due to the slow rate by which women are internalising positive views of the career than to informal social control.[8]

[5] They are perhaps tongue-in-cheek when they claim that the appeal of simulation should cross existing divisions in sociology: theorists will find it 'offensive to [their] antipositivist meta-theoretical tenets' while quantitative sociologists will consider it 'a defective form of empirical analysis carried out with imaginary data'.

[6] Elsewhere, Hanneman and Patrick (1997) make the same point more generally, and make reference to the fact that system-dynamics tend to suit macro-level theories (where the entities are macro-level 'variables') but that the general argument is also applicable to micro-simulation approaches (where the entities are 'individuals' such as persons, households, or firms). Schnell (1990) also makes a strong case for theory development through micro-simulation.

[7] Another simulation approach to the sociology of norms, but from an entirely different direction, can be seen in Conte and Castelfranchi (1995).

[8] The method they use to relate their simulation to real world data – attempting to recreate observed trends by running the simulation with different parameters – is potentially problematic. Indeed, the whole area of

3.2 Cellular Automata and Iterated Game Theory

While system-dynamics persists as a simulation tradition it is increasingly just one approach among many. Of the other popular approaches, two related methods are common, and of particular relevance to social processes and phenomena. Game theory is in itself a major tradition in social science, perhaps especially economics but also in sociology in association with the growth of rational choice theory, and in recent years has developed into the more complex and often more interesting direction of iterated games, where the players may develop long-term strategies based on knowledge or assumptions about the other participants. The Cellular Automata tradition is logically distinct from game theory but is often associated with it because it allows players to be situated in a pseudo-spatial structure.

A cellular automaton is a cell in a grid (of usually two dimensions, but sometimes one or more than two) which obeys a set of rules, based on the states of its neighbours, and which operates in discrete time. The classic example of CA is Conway's 'game of life', where each cell could be alive or dead, depending on the states of its neighbours in the previous period: too many live neighbours and it 'dies' of overcrowding, too few it dies of loneliness; if the appropriate number of life cells surround a dead cell it springs into life.[9] The result of these simple rules operating on automata in a two-dimensional lattice leads to the emergence of unexpectedly complex mobile and sometimes persistent patterns. This concept of 'emergence' has special significance in the 'artificial life' and complexity theory world, and the game of life is often invoked as a example of the emergence of complexity at a higher level (*i.e.*, the grid) from simple rules at a lower level (*i.e.*, the cells). Sociologically, emergence has major significance for approaches which wish to explain macro-level phenomena in terms of the outcome of the behaviour of micro-level actors.

It is not immediately clear that the game of life serves as a useful paradigm for sociological work, but there are many more relevant examples. An early case (which does not identify itself as CA, but which Hegselmann (1996) shows to fall within the bounds) is Sakoda's 'checkerboard' model of group interaction (Sakoda, 1971), where he shows that a negative attitude to members of another group is sufficient to explain the development of spatial group clustering (*i.e.*, without there being a positive attitude to members of same group). CA has been used many times to deal with group segregation, often with the issue of racial residential segregation in the US as the implicit or explicit referent (Hegselmann also quotes Schelling, 1969).

The connection between iterated game theory and CA arises because the players in a game can be considered automata, and it becomes very useful in iterated games involving choice of partners at each cycle to have the option of imposing locality constraints (*i.e.*, that the automaton chooses not from the entire population of players, but only those in its immediate neighborhood). There are many instances of iterated prisoner's dilemma games played out in CAs (*e.g.*, Lomborg, 1996; Kirchkamp, 1996). Hegselmann (1996) develops an example using a 'support' game (which under certain conditions reduces to a form of prisoner's dilemma; at random, automata become in need of support, which is very beneficial if they get it and which costs the helper a relatively small amount but more than refusing to help does), in a CA which allows migration, and where there are several distinct classes of automata, with different probabilities of requiring support. Migration allows a sorting of the automata: every-

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the validation of simulation with respect to empirical data is problematic, and needs work: see section 3.7.

[9] The Game of Life is well known in computer science, and many examples exist on the World Wide Web, for instance at `http://alife.fusebox.com/cb/alife.html`.

one prefers to be near low-risk rather than high-risk automata, and as a result there is clustering, with members of the same risk groups clustering together. However, he can also develop more useful results: for instance, non-identical risk classes may be content to remain adjacent as long as they are not too different, and the importance of this difference is markedly less for mid-range risk classes than either extreme.

Hegselmann goes on to make some more general arguments about the utility of CA simulations in social science, among which is the issue of locality (*i.e.*, that the automata have locations and interact with others in their neighborhood, which, especially once migration is allowed, is very like social interaction). Other arguments include the insight the model gives over the emergence of macro-phenomena, and especially (almost echoing Weber) the way in which unintended consequences of behaviour can lead to unexpected outcomes. Another relatively formal advocation of CA for social research can be read in Leydesdorff (1995). Both Hegselmann and Leydesdorff, among others, are working on systematic analysis of cellular automata systems: more formalisation of such analysis has the potential to add significantly to the leverage of these models.

3.2.1 Related models

Apparently outside the domain of CA, though (as Hegselmann points out) fitting within it in principle lies some of the work of Axelrod.[10] In work reported in Axelrod (1995) and elsewhere he describes a model of political actors (in this case, states) residing in a one-dimensional space and relating to their neighbours conflictually (they can fight, exact tribute and form associations according to simple rules). His interest is in the issue of how supra-national entities may emerge from rational micro-level action. In repeat runs of the model, many interesting features emerge: clusters of commitment, surrounding one strong state, often emerge, and occasionally these strong states may dramatically collapse, as they get embroiled in disputes involving client states (Axelrod dubs this ‘imperial overstretch’).

While this model has obviously interesting implications for political science and the sociology of states and their international relations, it is perhaps most interesting in the present context for its contrast with Hanneman et al. (1995). First, the usually valid association of CA with micro-level analysis and system-dynamics with macro level is present but in an odd way: in each case the unit of analysis, the state, is the same. In the systems dynamics model the system is the state and we look to its internal functioning to understand outcomes (and, as the authors are aware, ignore the detail of its environment which consists of other states), whereas in the CA model we take the internal functioning of the states as given and look at the dynamics of their interaction.

3.3 DAI and neural networks

A great deal of work in simulation is driven by developments in computer science. In this section I briefly consider two separate approaches which have related implications for simulation: Distributed Artificial Intelligence, and neural or connectivist networks. Each area holds special promise for social research, in that they allow the modelling of ‘societies’ of more or less complex agents, which can learn from and react to their environments.

[10] Axelrod is of course very well known in the world of game theory (*e.g.*, Axelrod, 1984)

3.3.1 Distributed Artifical Intelligence

Distributed artificial intelligence refers to systems consisting of several 'artificially intelligent' agents which can interact with one another and their environment (they are 'distributed' because they may, but need not, reside on different computers). They have many applications, not least in robotics and related complex control systems, but are also being aplied interestingly to social phenomena. For instance, the EOS project (Doran, Palmer, Gilbert and Mellars, 1994; Doran and Palmer, 1995) uses a DAI testbed consisting of artificially intelligent agents which can forage and form groups to examine competing theories of stone-age social change in south-western France. Also using DAI techniques (but with more of a knowledge-representation flavour) Findler and Malyankar (1995) investigate the emergence of more properly social groupings with shared normative systems. Along with Conte and Castelfranchi (1995) (a work which to some degree forms a bridge between CA/game theory and DAI), it is interesting to contrast this approach with that of Jacobsen and Vanki (1996) discussed in section 3.1.2.

In terms of emergence of complexity, this approach offers two advantages: one, more interesting (or realistic) phenomena may emerge from more complex building blocks, and two, it may be easier to account for the emergence of 'meso' level phenenomena, such as groups within societies.

3.3.2 Networks

Neural networks have excited a lot of interest since they were first demonstrated, partly due to a misdirected enthusiasm that by using the building-blocks of the brain we could soon develop truly intelligent computers. Their actual uses are more mundane but they are nevertheless of real use. Their real benefit in sociological simulation is that their behaviour includes learning, the ability to classify based on experience. This mimics human behaviour well enough for neural networks to be interesting in a variety of simulations (*e.g.*, Bainbridge, 1995a; Bainbridge, 1995b; Duong and Reilly, 1995; Parisi, Cecconi and Cerini, 1995). In Parisi et al., for instance, the networks are the individuals in a population which reproduces across the generations, and patterns of altruism between kin emerge and strengthen over the generations (this is, of course, an evolutionary system with direct biological analogies).

In a work with some fascinating implications for the emergence of socio-cultural structures, and which is thus profoundly sociological despite originating in cognitive psychology, Hutchins and Hazlehurst (1995) take a particular type of neural network which learns to classify inputs (by converting them into an internal representation which is then converted into a representation to be compared with the input; this is done with an initially random set of parameters, or 'connection weights' which are adjusted in response to success and failure), and make their internal representations 'visible' to other members of the society. The internal representations thus become inter-personal symbols, initially random and devoid of meaning, but in the course of the simulation as the individual networks learn to distinguish the inputs, and see others doing so, the internal representations become standardised, and analogous to symbols. If a new network (*i.e.*, with random weights) is exposed to the inputs and the symbol system it learns to discriminate between the inputs much more quickly. This is an extremely simple model of the emergence of language, but it may serve as a starting point for research on the emergence of truly socio-structural phenomena (rather than just emergent complexity).

3.4 Multi-level models: MIMOSE *et al*.

Another approach that has the potential for providing a handle on more complex emergence of social structures is the multi-level modelling approach (analogous to, but distinct from the statistical approach of the same name: see section 3.7). This approach builds into the simulation a recognition of a layered structure to societies, such as students within classes within schools within a school system, or individuals within groups within societies. It is associated with the MIMOSE simulation language (Möhring, 1996), but can be implemented elsewhere also (*e.g.*, Gilbert (n.d.) presents a Lisp-Stat implementation that is surprisingly small: like MIMOSE it relies heavily on object orientation). One of the important features of the approach is that processes at all levels, individual, intermediate and macro, can bear on the development of the model, and thus it offers the potential to improve both on the system-dynamics style macro orientation, and the bottom-up micro orientation seen in CA and DAI approaches. Saam (1996) uses MIMOSE to explore theories of military intervention in Thai, using individuals, groups (such as the military) and time-series information about Thailand, and can explain the sequence of coups d'état. Moreover, the nature of the model allows her to apply a systematic and formal sensitivity analysis, something which is likely to be an increasingly important requirement of simulation research.

3.5 Network and organisations

This section deviates from the organisation of the paper in terms of modes of simulation rather than sociological substance or theory, and considers the use of simulation in two specialised, related, areas where it has arisen with its own dynamic. These are social network analysis and 'computational' organisation theory. In both cases, simulation offers a way of dealing with the high level of complexity that these sub-disciplines encounter, and both cases represent important exceptions to the usual paucity of simulations arising from pre-existing sociological concerns.

Social network analysis is an increasingly important part of sociology, as researchers increasingly realise that many important phenomena are strongly conditioned by their being embedded in networks. However, it brings with it a complex methodology because of the inherent complexity of networks. Thus it is a field characterised by relatively complex mathematics (or mathematical problems), and by sophisticated statistical models (see below, section 3.7, for discussion of Greve, Strang and Tuma, 1995). Thus it is hardly surprising that social network simulations are becoming common (*e.g.*, Hummon, 1990b; Hummon and Fararo, 1995a; Hummon and Fararo, 1995b; Abrahamson and Rosenkopf, 1997).

Computational organisation theory is the preferred label for the growing body of work simulating the operation and development of organisations. To an extent it overlaps with social network simulation, not least because organisations can usefully be considered as networks, but also because of an overlap of the individual sociologists involved (*e.g.*, Hummon, 1990b). In a useful overview of the field Carley (1994) notes that it draws heavily from sociology, psychology, existing organisation theory and, perhaps most importantly in terms of the simulation element, DAI.

3.6 Micro-simulation: tax and welfare benefits

While micro-simulation is properly defined as simulation based on populations of 'low-level' units such as individuals, in the broader context of social policy research (both social and economic) the term is usually understood to refer to data-driven tax–benefit micro-simulation models. These models are designed for forecasting and pseudo-experimentation on the tax and welfare system, and usually exploit survey or census information to create simulated populations with characteristics modelling those of the real population. This is combined with extensive expert knowledge of the tax and welfare systems, and theoretically and empirically derived transition rates within state spaces (such as employment status, family and fertility status, *etc.*). A typical use of a tax–benefit micro-simulation (TBMS) model is to assess the aggregate and distributional effects of a change to a tax or welfare benefit: what would be the expected effect on revenue (or expenditure), and who would gain or lose out. Static TBMSs are relatively simple in structure, and assess what net income each individual would, counterfactually, have had under the new system; dynamic TBMSs are more complex in that time has a role: individuals age and stochastically undergo transitions, as well as being subject to modified (or unmodified) fiscal regimes. The dynamic case can thus compare the expected outcome over a number of years under a no-change scenario with that under a modified tax or welfare system.

Such policy oriented micro-simulations can trace their history back to the early 1960s (Orcutt, Greenberg, Korbel and Rivlin, 1961), but have developed extensively since the 1980s (Orcutt, Merz and Quinke, 1986; Citro and Hanushek, 1991). Examples include LIFEMOD and its derivatives, developed at the LSE and Cambridge (Falkingham and Lessof, 1991; Hills and Lessof, 1993; Cambridge Microsimulation Unit, n.d.), the Darmstadt Pseudo-micro Simulator and Micro–macro simulator (Heike, Beckmann, Kaufmann, Ritz and Sauerbier, 1996) and a set of models of the Australian system developed at Canberra (a very useful introduction to these models and to tax–benefit micro-simulation in general is available at the website of the Australian National Centre for Social and Economic Modelling (n.d.); Merz (1996) also provides a useful overview of the field.) Work is also underway to integrate models of most European Union countries (Callan and Sutherland, 1997).

These models are undoubtedly useful from a policy point of view in that they assess quite well the overall short-term effects of policy change, but their ability to forecast in the mid and longer range is less convincing. And from the point of view of sociology in general their interest is limited, in that they focus very explicitly on the bounded domain of government transfer policy. That is, they do not speak to wider issues, and embody more technical knowledge than theory. Nevertheless, they answer some real questions, and furthermore are developing a methodology which is applicable to other issues of interest to sociologists: the dynamic simulated population can be used to forecast outcomes in other domains (*e.g.*, fertility, residential mobility, labour market trends) under different regimes, and they can serve as a testbed for comparing competing theories about social processes, where verisimilitude to historical population distributions is a relevant criterion. However, there is as yet little work in this direction.

3.7 Statistics and simulation

There is a long tradition of simulation in statistics that, at least by its existence, has some bearing on simulation in sociology. However, statistical simulation typically has the purpose of investigating properties of new statistical methods, in many cases estimating empirical distributions, where the mathematical solution is intractable, to construct confidence intervals around parameter estimates. This is the 'Monte Carlo' method, where results are generated for large numbers of randomly distributed input data, and is clearly not sociological.[11] However, there are three respects in which statistics is relevant for simulation in sociology:

1. statistical models of data are in an important sense a case of simulation;
2. simulations require statistical analysis for interpretation;
3. and perhaps most importantly, the boundary between 'pure' statistics and statistically formulated sociological theories is not sharp.

Statistics is by its nature a form of simulation, but rather different from that currently under discussion. That is, a statistical model of a set of data is a simulation of that data generated according to clearly defined rules embodied in the model, and the adequacy of the simulation is to be judged (in the first instance) by the difference between the simulated and the real data, using clearly defined rules and calculations in turn backed up by a clearly defined theory of probability and distributions. However, there are different ways in which the 'rules' of the model relate to the data and the processes generating it: very often the analyst simply believes there are *associations* between some of the measured variables and applies a model 'off the shelf' which will pick up the associations if they are there, but which is blind to the nature of the association (*e.g.*, whether the association is as a result of a causal relationship or a selection process) and the form it may take (*e.g.*, using a linear form for simplicity of estimation and interpretation when the true form may not be linear). But in other cases the model will address the processes creating the data set in meticulous detail, incorporating theories about the phenomenon of interest as well as 'nuisance' information about the effect of factors considered uninteresting, and about the process of collection of the data (issues of sampling and differential probability of observation, measurement error and so on). The latter case involves much more hard work and is often more satisfactory; the former, while occasionally a mark of bad statistics, can be very useful but is less akin to simulation.

Futhermore, to the degree that simulations attempt to replicate historical or real world data, it becomes harder to distinguish conceptually between them and statistical analysis.

The second point: simulations require statistics. This is perhaps obvious but worth stressing. Not only do simulations generate large amounts of data which need to be interpreted as well as possible, but they also expose social scientists to the unfamiliar territory of the experimental method. Taking the latter point first, the typical quantitative sociologist is used to applying regression-like techniques to survey data sets, and is usually unfamiliar with issues of experimental design and the large body of statistical methods evolved to deal with experimental data. Efficient testing of a simulation model is facilitated by proper design and integration with suitable statistical methods. The former point is in a way a generalisation of the latter: the data that simulations generate is potentially very rich, and to get its full benefit it is necessary to analyse it using tools that take its nature into account, and can answer the required questions. Here, because the analyst knows the generative processes (having written them) it is perhaps even more important that appropriate statistical methods be used. Longitudinal data may call for hazard rate models, or Markov models; the emerging paradigm of multilevel simulations (see section 3.4) seems to be extremely well suited to exploiting statistical multilevel models (Plewis, 1994; Goldstein, 1987), independently developed but with considerable conceptual overlap.

[11] As a method it long predates computers, with tables of random numbers being used instead of computer pseudo-random number generators.

The third point: in practice the boundary between statistical and substantive theory is not always clear. Certain specialised statistical models embody a great deal of substantive theory, and certain theoretical models are expressed in terms of the sorts of outcomes a data analyst could measure (or, at least, there is a systematic interplay between theory and statistical analysis of data). One area of sociology that is widely perceived to be quantitative and technical in its general orientation is social mobility research. Over the past twenty years research on inter-generational mobility has utilised and developed a battery of techniques for the analysis of categorical data, and in particular for analysis of the square origin–destination (traditionally 'father–son') mobility table (Hauser, 1978; Goldthorpe, 1980; Hout, 1989; Erikson and Goldthorpe, 1992). This simple cross-tabulation of class of family of origin by individual's adult class, is treated as an outcome measure of the society's processes of social mobility and some relatively complex models are constructed to relate the structural outcome to the sorts of processes and relations between social locations that might explain it. In particular loglinear 'topological' or 'levels' models (Hauser, 1978; Erikson, Goldthorpe and Portocarero, 1979; Goldthorpe, 1980) have been used with some success. These allow the sociologist to build up, from a set of statements about the characteristic of the various class locations in relation to one another (the barriers between them, the sorts of resources they typically imply and how these may be passed across generations, the affinity between locations and so on), a model to explain the association between the categories and thus the structure of the table. In other words, in a large part of the last two decades' social mobility literature, the theories that are applied to the data are embodied in and constrained by the statistical techniques used.

Because of this closeness, statistical simulations relating to the loglinear model of the mobility table take on a theoretical complexion they would not otherwise have. Thus Logan (1996) uses simulations to address Hauser (1978), and in particular his requirement 'to separate "rules of access" to social positions from "the interplay of supply and demand"'. His simulations suggest that a different statistical model should be used, because loglinear models cannot adequately separate these two aspects. Jones, Wilson and Pittelkow (1990) address a related issue by means of simulation: when using the loglinear model of the origin–destination table, many differently specified models can achieve similar goodness of fit by conventional criteria, and it becomes difficult to justify one over another. They present a method, based on Monte-Carlo generation of simulated tables from the fitted models, paying particular attention to the distribution of residuals, which enables them to avoid both under-fitting and over-fitting the data.

Another statistical simulation with theoretical relevance is reported in Greve et al. (1995). They address a set of statistical models of diffusion in networks[12] in terms of their ability to discriminate between conceptually distinct aspects of diffusion such as individual susceptibility and social proximity. They generate simulated temporal data representing diffusion according to different types of process and use this to test the robustness and discriminating power of the models they propose.

These examples are addressed directly to statistical issues but because of the interpenetration of statistics and theory in these particular fields they also have real sociological content. This interface between statistics, simulation and sociological theory is critically important for the development of a sociology that is both theoretically sound and empirically founded, particularly when it comes to deal with issues which are inherently complex.

[12] See section 3.5 on network analysis, and Windrum (1999) for discussion of diffusion of innovation.

4 Discussion: Prospects for simulation in sociology

This overview of simulation research of sociological relevance has been very superficial, necessarily so because of the breadth of the field. Certain threads have been overlooked entirely[13] and others only sketchily represented. However, a number of important features relevant to simulation in sociology have become apparent. Among these are the benefits of formal statement and manipulation of theory that simulation allows, and the way in which simulation work rapidly comes up against (and to some extent, offers solutions or new approaches to) central problems of sociology such as the agency–structure duality, and the relationship between macro and micro levels.

Schnell (1990) and Hanneman et al. (1995), among others, argue that simulation brings benefits by way of formalisation of theory. The act of translating a theory into a simulation requires making everything explicit, and quickly exposes internal inconsistencies and gaps. Translating it into a formal symbol system that can be manipulated (as validly mathematics as simulation) allows us to see consequences of the theory not visible in its natural language formulation: this allows us to take dynamics into account more easily, to see the unintended consequences of individual action, of 'emergence' of complexity from simpler components. In many cases simulation is more effective than mathematical formulation, where the mathematical problem is intractable, or less accessible to practitioners.

However, there is a downside to the power of formalisation: researchers can get seduced by ever more abstract, complex simulations whose relation to reality or theoretical interests is less and less. Something similar is sometimes seen in mathematical economics, where some research is done simply because a mathematical solution is tractable, and not because the problem is interesting. (There is also a downside to the tractability of simulation, in the danger of spending a lot of effort demonstrating a relationship easily derivable by mathematics.)

What is more exciting about simulation's potential for sociology is the way in which it comes up against core issues in the discipline, and maps onto existing polarisations within it. While it is not necessary for a tool to have features that are uniquely sociological for it to be of use to sociology (*i.e.*, a lot of sociologically useful simulation will have no relevance to the ideas in this paragraph), some simulation work has a very special bearing on central issues in sociological theory. First, we see a partial mapping between types of simulation and broad approaches to sociology: as noted, system-dynamics is often used by people with roots in structural functionalism and related traditions (the method maps well to the conceptual framework, given the common focus on system; the method may also protect against excessive functionalism by allowing more exploration of dynamics). Alternatively, many of the 'bottom-up' approaches that start with 'individuals', be they automata or artificially intelligent, relate to more methodologically individualist traditions (Gilbert, 1995). More interesting is the prospect that simulation can aid theorists and researchers to bridge the gap between these two perspectives (both are extremes: there is a lot of sociology that stands between the system theory of the Parsonian tradition, with its complete loss of the voluntaristic individual, and the extreme methodological, or indeed ontological individualism which seems to regard macro-phenomena as epi-phenomena, of certain forms of rational choice theory, for instance).

That is to say, while it is an entirely valid exercise to construct theories at either

[13] For instance, the French tradition in the sociology of education has recently branched into simulation (Bulle, 1996), drawing strongly on the non-simulation but mathematically formulated work of Boudon (1974; 1981).

a macro or a micro level, it is also necessary to bridge the two levels. This is a central preoccupation of sociology, going back at least to Marx and Weber, and finding contemporary statement in work such as that of Habermas or Giddens. The latter's structuration theory (Giddens, 1984) is probably the best known recent treatment of the phenomenon (at least in the anglophone world): '. . . neither subject (human agent) nor object ("society", or social institutions) should be regarded as having primacy. *Each is constituted in and through recurrent practices*.' (Giddens, 1982, p. 8, his emphasis.) What makes simulation exciting is its ability, not only to generate macro-phenomena from micro-level units in the sense of 'emerging' complexity – which runs the risk that the macro-level phenomena become considered as epi-phenomena, though also making explicit the causal relationship – nor to manipulate system-level phenomena, but its ability to model 'everything' simultaneously in a way that is impossible in natural language theorising. Multilevel simulations (section 3.4) are particularly interesting in this respect, as they allow the modeller to focus on micro-, meso- and macro-level processes at the same time. However, they are not a panacea: they require input at all levels in the form of data on how each level is supposed to operate, rather than generating behaviour at all levels from a single set of instructions. That is, they allow researchers to bring together different levels of phenomena without a providing theoretical framework to integrate them.

Other approaches bear very centrally on these issues: for instance, Hutchins and Hazlehurst (1995) (cited above, section 3.3.2), describe a process that is almost a direct representation of the process of structuration as in Giddens' quote above. The population of networks generates a phenomenon that stands outside each individual (a lexicon of representations of the inputs they are exposed to, a proto-language) by means of an iterated process of interaction between the individuals and their environment, and between individuals. The phenomenon exists only because of the individuals' interaction but exists outside them and has a real effect on them. Of course, in terms of the complexity and subtlety of human society this model is utterly simplistic, but it does present a means to investigate the genesis of social structure, a problem that is much less tractable in natural language.

However, for simulation to add to the development of sociology and the resolution of core theoretical problems, we need more than interesting techniques, or exciting modelling systems: we need sociologically informed researchers to use them. This is not meant as a negative remark on the sociological quality of the work reported above, but a reflection that it tends to be written by simulation specialists, and that relatively little of it comes from core sociology. A lot is to be gained if mainstream sociologists, qualitative, quantitative and theoretical, were to engage with simulation as a method.

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