Deduction and abduction in computer simulation:

Comparing logics in theory development

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Abstract

The article presents a review of a sample of simulation studies in the management and organization body of literature. The proposed approach to the review hinges upon the analysis of the logic of inference that underpins the selected studies. In particular, I suggest that the two recurring type of inference that, deliberately or unintentionally, inform the use of simulation analysis are: deduction and abduction. In addition, the paper proposes an historical journey into process of diffusion of computer simulation studies within management and organisation literature. The presented review aims at two goals. First, the paper strives to contribute a point of view to help researchers to approach the design of a simulation-based study with increased awareness. Second, the reported analysis ought to help researchers who are not familiar with simulation to study to appreciate the possible contribution of simulation studies to theory development.

KEYWORDS: Computer Simulation; Research Methodology; Theory Development.

INTRODUCTION

With different fortunes and oscillating enthusiasm, computer simulation has supported theoretical investigation in managerial disciplines since the 60's. In the attempt to further corroborate the role of computer simulation in the repertoire of research strategies available to social scientists, the aim of the present essay is twofold.

First, I present an historical journey into a selection of contributions to portray the motivations that fostered the diffusion of computer simulation studies in management and organisation literature.

Second, differently from received approaches to the review of computer simulation studies, which mainly aggregate studies on the basis of the adopted simulation technique, my review of a sample of simulation studies proposes a more subtle point of view to bring forth different logics of inference that underpin the studies.

To begin with, it is important to set up in the front a definition for computer simulation. Computer simulation has to do with the manipulation of symbols using a computer code; more specifically, it uses algorithms to derive propositions from the assumptions that come together in a computer model. A computer model is a formal model in which '[…] the implications of the assumptions, that is, the conclusions, are derived by allowing an electronic digital computer to simulate the processes embodied in the assumptions' (Cohen and Cyert 1961: 115).

In this respect, computer models can be regarded as special cases of mathematical models (Cohen and Cyert 1961) in which conclusions are derived from assumptions by using a computer simulation rather than a process of analytical solution. On the other hand, however, computer models not necessarily have to be stated in mathematical and numerical form (Clarkson and Simon 1960) since they allow manipulation of symbols that can be words, phrases and sentences. Therefore, computer models make up the subset of mathematical models that are solved numerically rather than analytically but not all the computer models are stated in mathematical terms since they may incorporate not-mathematical symbols. In this respect, Troitzsch suggests that computer simulation is a third system beside natural language and mathematics (1998: 27).

In principle, computer simulation is just a technologically-aided process of deduction. Yet, the crude technology can vary strongly from different approaches and, more importantly, the difference in the adopted technology often unveils profound differences in the philosophy that lies beneath modelling.

For example, computer simulations based on systems of difference equations are inspired by a structuralist stance that sees the behaviour of the individuals that are embedded within a social system as determined by the feedback nature of the causal relationships that characterize the system (Forrester 1958, 1961). Agent-Based models or cellular automata, on the other hand, simulate actions and interactions of autonomous individual entities and build on the idea that the behaviour of social systems can be modelled and understood as evolving out of interacting autonomous learning agents (Epstein and Axtell 1996; Axelrod 1997). Thus, a crucial feature of these models is the emergence of ordered structures independently of top-down planning.

While Agent-Based models and cellular automata show how interaction among individual decision-making and learning may generate complex aggregate behaviour, differential equation modelling aims at reducing aggregate and often puzzling behaviours into underlying feedback causal structures. As a consequence, these latter models typically aggregate agents into a relatively small number of states, assuming their perfect mixing and homogeneity (Rahmandad and Sterman 2004) while cellular automata and, especially, Agent-Based models preserve heterogeneity and individual attributes thereby sacrificing parsimony. The reader looking for an overview of approaches and techniques may refer to the texts edited by, for example, Liebrand, Nowak and Troitzsch (1998) or Gilbert and Troitzsch (2005).

However, independently of the approach adopted and the inspiring philosophy, research employing computer simulation has frequently been regarded, in social sciences, as influenced by an autonomous logic in respect to mainstream research. Simulation studies, however, have a long tradition in organizational research. Going back to seminal work in the area of the behavioural theory of the firm and organizational decision theory, some of the most important theoretical pieces are based on a simulation approach. This is true, for example, for the well known Garbage Can model (Cohen, March and Olsen, 1972) and for the work leading to the development of The Behavioral Theory of the Firm (Cyert, Feigenbaum and March 1959; Cyert and March 1963). Recent organisation science, as well, has used computer simulation to advance theory development (Carley and Prietula, 1994; Prietula, Carley and Gasser, 1998).

In recent times, computer simulations, gradually and regularly, have recuperated terrain in mainstream management and organization journals (Lant and Mezias, 1990; Harrison and Carroll, 1991; Carley, 1992; Mezias and Glynn, 1993; Carroll and Harrison, 1994, 1998; Lomi and Larsen, 1996; Sastry, 1997; Adner, 2002; Zott, 2003; Gary, 2005; Lomi, Larsen and Wezel, 2010; Aggarwal, Siggelkow and Singh, 2010).

To push further legitimization of computer simulation in the strategy and organization research, this essay aims at capturing logical underpinnings of successful simulation work.

The paper is organized as follows; in the next section I briefly pinpoint key milestones in the history of computer simulation applied to strategy and organization research and, in the following section, the reasons that motivated early adopters to use computer simulation are summarized. In section fourth, I consider a sample of recent works that use simulation and I muse on the differences in the underlying logic of enquiry. In the last section of the chapter I draw some conclusions.

COMPUTER SIMULATION AND THEORY BUILDING

An increasing number of scholars in social sciences propose that computer simulation proves useful in supporting theory building.

First, in general, computer simulation may generate inputs in the form of time-series. This may result of some help when time-series can be compared directly with real-world quantitative figures, for example demographic data. In this case, the availability of real and simulated time series that are accessible in a similar quantitative format facilitates pattern-matching thereby allowing researchers to visually assess resemblance between simulated series, which follows from the quantitative simulation of a theoretical hypothesis, and an empirically observed behavior. In this respect, it is possible to generate measures of how simulated events match empirical instances of those events (Sterman 1984). This is a not trivial opportunity to facilitate dialogue between micro and aggregate data: in a computer model simulated aggregated data are rigorously consistent with assumptions describing microbehavior (Bergmann, 1990) and, as a consequence, they become hypothetical explanations of really observed aggregate time series.

Second, computer simulation allows for a rigorous longitudinal articulation of theorical behaviors. In other words, the computer-aided process of deduction goes far beyond the human capability to appreciate the long-term features of the behavior of selected variables. Thus, computer simulation can support researcher to find plausible sufficient conditions for complex patterns of behavior to happen such as peaks and lowest point, oscillations with different characteristics and changes in rates of growth or decline.

Third, researchers, by simulating a formal model, can articulate their predictions by contemporaneously producing behavior of different variables and the interactions of these latter. In particular, researchers can simulate the interaction of independent and dependent variables in each time step, along a given time horizon. This cross-sectional articulation of patterns of behavior increases the points of contacts between a set of behavioral hypotheses and the empirical context of a case study. As Kaplan suggests ‘What counts in the validation of a theory, so far as fitting the facts are concerned, is the convergence of the data brought to bear upon it […]’ (1964: 314). Thus, a computer simulation expands the terrain where comparison between theory and empirical setting takes place by generating a rich longitudinal and cross-sectional articulation of behavior under study. In this light, the convergence of data and the concatenation of events that is necessary to obtain to use a case study to confirm a theory is increasing demanding.

In this respect, computer simulation aids researchers to design field studies to produce difficult experiments where the falsifiability of a theory is easier because fitting the facts becomes increasingly hard. Of course, on the other hand, had empirically collected facts to fit, at least qualitatively, into a complex web of interweaved simulated behaviors, the experiment would lead to stronger evidence to confirm propositions contained in the theory.

Having a detailed (often formalized) description of a causal structure, thus, and a description of a repertoire of plausible histories, a field researcher will have a variety of points in which the theoretical hypothesis, which crystallized in to the model, can be falsified (Bell and Bell,1980).

The described avenues through which computer simulations aid theory building, however, prove effective if they are informed by a rigorous logic of inference. How simulation experiments are designed and described seems often the result of lucky intuitions and ex-post justification more than the product of a rigorous ex-ante articulation of a research strategy.

THE LOGIC UNDERPINNING THE USE OF COMPUTER SIMULATION

As Cohen and Cyert suggest (1961), computer models are of two types: synthetic and analytic. In synthetic models, the modeller knows with a high degree of accuracy the behaviour of the component units of the phenomenon under scrutiny. On the other hand, in analytic models, the behaviour of the phenomenon is known and the problem is to capture the mechanisms that produce the behaviour. In this classification, synthetic and analytic models reveal different underpinning logics of enquiry. While synthetic computer models are informed by a pure deductive logic, analytic models are characterized by an inductive logic (Cohen 1961).

To start with, however, a word has to be said to better define what we mean by inductive or deductive inferences. More specifically, the associations synthetic/deductive and analytic/induction may sound not necessarily intuitive.

Deductive process has been acknowledged as a key component of scientific reasoning since Aristotle. A deductive inference moves from general assumptions to specific consequences; in this respect, consequences drawn from assumptions have an inferior degree of universality than their premises. Deductive inferences have two properties; first, the information embodied in the deducted consequences is more or less explicitly, included in the assumptions; second, deducted consequences originate necessarily from assumptions. In other words, if assumptions are correct, deducted consequences must be correct as well.

On the other hand, inductive processes move from particular instances to general conclusions. In this respect, in inductive inferences, derived conclusions are not entirely included in the premises. In other words, the information content in inducted conclusions is greater than the one crystallized into the premises. Thus, inductive inferences say something new, or different, in respect to premises; thus, they add information. This property conceals an hazard because correctness of premises does not necessarily imply that conclusions are correct as well.

As for the distinction between *analytic* and *synthetic*, starting from Kant's Critique of Pure Reason (firstly published in 1781), an analytic statement is purely explanatory of an existing concept and it does not add more information than that already contained into the concept itself. A classic example reported by Kant regards the statement that affirms that an entity of matter is extended in the space. The fact that an entity of matter is extended in the space is already implicit in the definition of entity of matter. It does not add information regarding the concept *entity of matter*; rather it provides an extension, or further explanation, of the concept. On the contrary, a synthetic statement is *extensive* because it adds more information than that contained originally in a concept. For example, the fact that an entity of matter has a weight, explains Kant, is not included necessarily in the concept of entity of matter (it suffices to think of a state of absence of gravity) and rather it stems from a synthesis between an original concept and a quality external to the concept.

Given this distinction between synthetic and analytic statements, Peirce, for example, put forward a dichotomy between deductive/analytic and inductive/synthetic inferences (Harshorne and Weiss 1931/1935).

Thus, we have to be very careful in interpreting the distinction proposed by Cohen and Cyert between analytic/inductive and synthetic/deductive, since in their framework the concept of synthesis pertains to the use of simulation to aggregate local, or partial, components of a phenomenon, into a global emerging behaviour. On the other, analysis concerns the dissection of behaviour of interest into its components, or determinants.

In addition, to capture the logic underpinning the use of simulation, another type of inference can be very useful: the *abduction*.

Abduction, or *retroduction*, is an inference that goes from the observation of a fact to the hypothesis of a principle that explains the observed fact (Burks, 1964; Fann, 1970). As Peirce himself explains (1955), the form of this inference proceeds as follows: "The surprising fact, C, is observed; But if A were true, C would be a matter of course, Hence, there is reason to suspect that A is true" (1955: 151).

Suppose that what Peirce calls A is a model. In other words, we have a model as a candidate theory. This model produces simulated behaviour similar to those empirically observed. Then, had the world crystallized into the theory to be true, observed patterns of behaviors would be the reasonable result of an underpinning structure that is isomorphic to the model's structure.

In this perspective, the comparison between an empirical phenomenon and model-generated behaviours triggers an abductive inference that contributes to the development of an hypothesis to explain the observed phenomenon.

We suspect that the appropriate logic to address the review of computer modelling in management and organisation theory would probably focus on the distinction between computer simulations that adopt a deductive or an abductive logic of inference (Barton and Haslett, 2006). Within this framework, deductive computer models focus on the specification of a set of mechanisms or processes and explore unfolding consequences of such specifications whereas abductive computer models move from the definition of an aggregate behaviour and use simulation to test whether candidate mechanisms or processes are able to determine *in vitro*, and thus explain, the aggregate behaviour.

We agree, however, that simulation studies show a much broader variety of approaches that blend elements of deduction and abduction. In addition, in computer simulations abduction and deduction are intertwined in a cyclical process of theoretical investigation. Abduction works when we introduce in a model a casual mechanism that we deem possibly responsible for an observed behaviour. In this case, we run history backward to reproduce the conditions for the behaviour under study to emerge.

On the other hand, when we run a sensitivity analysis, we may be interested in the relationship between the causal mechanism, or a class of similar causal mechanisms, and a class of behavioural phenomena. In this case, when we run a computer model and we observe simulated consequences of changes in parameters' calibration or amendments in the model's structure, we are embarking into a deductive inference. Thus, deduction and abduction are often tightly interlaced in a research design based on computer simulation. We thus expect differences among simulation studies to be detected in the degree of accuracy of the description of the elements that compose an aggregate phenomenon or of the features that characterize the aggregate phenomenon itself.

Simulation studies in which a deductive logic of inference prevails will move from the accurate modelling of those components that are candidate *generative mechanisms* of behaviours of interest while simulation studies informed by an abductive logic will set forth from a rich and detailed description of an aggregate *emerging behaviour*.

Nonetheless, maintaining two idealtypes of computer models, deductive and abductive, seems a good strategy, or at least a safe point of departure, to sketch a set of guidelines to analyze and conceive of a simulation study. An idealtype crystallises what is essential about a phenomenon (Swedberg, 2005: 119). It helps to interpret hybrid and unclear empirically observed instances by gauging the relative distance of the observations from the pure form (Thorton, Ocasio and Lounsbury, 2012: 53). Our approach is justified by the fact that, differently from other typical, qualitative and quantitative, research strategies that are more legitimized and disciplined, simulation-based research has been structured in a variety of different guises.

Only recently, Davis, Eisenhardt and Bingham (2007), by developing a roadmap for rigorous simulation-based research, have convincingly positioned simulation studies among other methods of enquiry within strategy and organization research. Yet, the field still looks like a rather heterogeneous collection of studies categorised more on the basis of the technique adopted (System Dynamics or Agent-Based Model, for example) than in respect to underpinning logic.

Thus, to carry on our avenue, we apply the two idealtypes to capture the often subtle differences in the logic underlying simulation studies. In the following, we explain how a study may be classified in one of the two idealtypes. Table 1 reports the qualifying differences among the studies analyzed.

TABLE 1 - HERE

Computer simulation and deductive inference

To address typical features of deductive inference in simulation studies, we begin from the classic Cohen, March and Olsen's *Garbage Can* simulation model (1972). The authors do not specify in details a reference mode of behaviour to be explained, beyond the broad idea that they want to address the way in which *organized anarchies*[2] undertake decision-making activity. Rather, the emphasis is on the modelling of the structural features of decision-making processes in specific types of organizations. The aim is to develop 'a behavioral theory of organized anarchy' (1977: 2). To do so, the authors developed a model that describes decision making within organized anarchies and examine '…the impact of some aspects of organizational structure on the process of choice…' (1972: 2). The structure of the research design encompasses the modelling of organizational decision-making processes and the analysis of the behavioural consequences of such modelling.

More specifically, the authors adopted a view of an organization as a *garbage can* in which are collected '…choices looking for problems, issues and feelings looking for decision situations in which they might be aired, solutions looking for issues to which they might be the answer, and decision makers looking for work.' (1972: 2). Along these lines, they modelled problems that require a specific amount of energy devoted by members of the organization to be solved and depicted two matrix structures that describe organizational features. The first matrix defines the *access structure* that associates choices to problems by determining what choice is accessible to what problem. The second matrix represents the *decision structure* and associates decision-makers to choices by establishing what decision maker is eligible to make what choice.

In their experimental design, they portrayed different kind of organizations with different energy distribution, different problem loads and different organizational structures. Through simulation experiments, the authors derived emerging decision-making behaviours with typical features. For example, they observed that, depending of the different assumptions crystallized into the initial calibration of the model, organizations may show different styles in decision-making and problem-solving.

We define this type of work deductive since the curiosity that triggers the effort of researchers regards the deduction of typical emerging patterns of organizational behaviour given the detailed description of organizational structures and decision-making processes.

Similarly, in their simulation study of entrepreneurial strategies, Lant and Mezias (1990) formalized an organizational learning model by which firms collect performances, set aspiration levels, search alternatives and change organizational features. They designed an experimental setting with a population of 150 firms, to each firm one out of sixteen different organizational features was assigned, one out of three entrepreneurial strategies, and one out of two levels of entrepreneurial activity. The research design involves the generation of a number of different simulations to explore what kind of firm would successfully survive. Through the simulation experiments, the authors derived longitudinal implications on firms' performances, growth and survival and generated theoretical hypotheses on the relationship between entrepreneurial strategies, levels of entrepreneurial activity and firm performances. In this case, again, the research design moves off from the description of firms' decision-making processes and investigates the consequences of these latter in terms of unfolding behaviours. The study, thus, maintains a deductive attitude in its interest for the dynamic consequences of a set of assumptions concerning entrepreneurial strategies as these are built in the specification of the simulation model. As the authors explain, the data generated '…represent implications for organizational performance, growth, and survival of the different entrepreneurial strategies and two levels of entrepreneurship' (1990: 152).

On similar veins, Gavetti and Levinthal (2000) examined the role and interaction between search processes that are forward-looking, and are based on a cognitive choice, and those that are backward-looking, and are the consequence of experiential learning. Gavetti and Levinthal represented the environment as a fitness landscape and modelled two decision-making processes that are alternatively informed by a backward-looking experiential learning mechanism or a forward-looking cognitive mechanism. Experimental design devises a set of simulations in which performances of the two mechanisms are compared. The experiments allowed the authors to ascertain that the two mechanisms may productively interact, with the cognitive mechanism that seeds the experiential learning mechanism. More precisely, Gavetti and Levinthal explored the role of the two mechanisms in different experimental conditions. For example, they found that the more complex the environment, the more accentuated is the role of the cognitive mechanism in supporting decision-making. In this study, as well as in those before mentioned, a computer model serves as a virtual laboratory where researchers deduct consequences from different initial calibrations. The trait that is shared among these studies is that the value added from simulation is to elicit complex implications that are already hidden into a set of assumptions. In this respect, the term *deductive* maintains its attitude to describe an inference process in which consequences are already contained in the premises. However, this inference process is far from being an unimaginative or infertile process; on the contrary, researchers, by connecting premises with their often counterintuitive or surprising consequences, discover plausible causal relationships among variables that may contribute to theory development. This active role that simulation can play in theory building motivated Mezias and Glynn to say that '[…] simulation results do not simply reflect suppositions built in the model, but yield knowledge that adds value beyond its explicit assumptions' (1993: 95).

Computer simulation and abductive inference

As we assumed in this work, researchers adopt an abductive inference when they proceed from an aggregate phenomenon, more specifically, from the description of a behaviour that unfolds longitudinally over time, and use computer simulation to select plausible determinants of the phenomenon among alternative causal mechanisms.

For example, Adner (2002) studied the emergence of disruptive technologies and set up his research design by stating at the front the description of the characteristics of the phenomenon he wanted to investigate. After clarifying that his contribution is to explain the emergence of disruptive technologies, Adner modelled consumers' individual preferences and firm technological strategy to obtain mechanisms that are sufficient to produce the previously described phenomenon.

A similar logic inspires the work of Lee, Lee and Rho (2002) that conceived of their research design with the aim at explaining the emergence of strategic groups. They developed a number of theoretical hypotheses that define causal relationships among four explanatory mechanisms and strategic groups' emergence, persistence and differential performances. They modelled a population of 50 firms and a pay-off function with two peaks (a global maximum and local maximum). Adopting an evolutionary framework, they built a genetic algorithm that mimics a process of variation (innovation in strategy), a process of selection (payoff received) and a process of retention (imitation of successful strategies by new entrants). They run experiments varying each of the four mechanisms at time and examined under what conditions strategic groups are likely to emerge and persist.

Another study with similar features is Abrahamson and Rosenkopf's analysis of the emergence of bandwagon in innovation adoption (1993). They defined the phenomenon of interest and used computer simulation to find sufficient conditions for bandwagon to emerge and for innovations to be retained by adopters after bandwagons have displayed their effects. More precisely, they modelled bandwagons and derived behaviour with simulation to understand how causal structures of the model, and the processes that the causal structures represent, contributed to produce the dynamic behaviour observed in the simulation experiments. Grounding on the observed cause-effect relationship, they derived propositions about bandwagon occurrence, extent, persistence.

Similar logic of enquiry informs Lant and Mezias' speculation on modes of organizational change (1992). They set off their research design from the definition of a dynamic behaviour of interest: Tushman and Romanelli theory of punctuated model of organizational change (1985). Afterward, they scrutinized candidate causal mechanisms to ferret out determinants of the behaviour of interest. In particular, they formalized an organizational learning model by which firms collect performances, set aspiration levels, search alternatives and change organizational features. Then, they used computer simulation to build a population of firms whose activities are governed by this process of experiential learning and demonstrated that an organizational change process that is informed by this learning mechanism can unfold displaying the typical pattern of punctuated change. Using computer simulation, they theorized that the same deep theoretical structure, in this case a learning mechanism, underpins both convergence and reorientation processes.

The explanation of the punctuated model of organizational change is at the core of Sastry's simulation study as well (1997). Sastry analyzed Tushman and Romanelli's verbal theory of punctuated change to demonstrate that the verbal theory does not contain the necessary causal mechanisms to explain the described behaviour. Sastry conducted a textual analysis of the verbal theory and used qualitative descriptions to produce a formal model that encapsulates the theory. She identified constructs and causal relationships that provided the basis of the formal model.

Once a computer model that formalized key traits of the theory was built, Sastry simulated the model and compared simulated behaviour with the one crystallized into the theory. The discrepancy between theoretical and simulated behaviours guided Sastry to introduce two new mechanisms that were not originally included into the verbal theory but that proved necessary to produce the behaviour purported in the theory.

The two mechanisms are, respectively, a routine for monitoring organization-environment consistency and a heuristic that suspends change for a trial period following each reorientation. The work of Sastry provides the opportunity to speculate further on the features of abductive simulation research. As we said in the foregoing, typically, abductive inferences bring about additional information that is not necessarily crystallized into the premises.

The abductive nature of the study of Sastry emerges when we appreciate that in the original premises of the study, which are captured in Tushman and Romanelli's verbal theory, there was not mention or any sort of indication that pointed at the causal mechanisms that Sastry included into the theory ex-post.

To clarify the position taken in this essay, however, when I suggest that abductive simulations bring in a study information content that is not included in the stated premises, I am suggesting that, given a set of initial premises, a simulation study has an abductive nature when it facilitates the enlargement or the modification of this set of premises.

In this vein, Malerba, Nelson, Orsenigo and Winter (1999) propose a class of computer models that they define *history friendly* because of the adherence of these latter to the empirical realm that is the object of exploration. In their simulation study, they focused on an appreciative theory that describes the pattern of evolution of the computer industry and developed a formal representation of that theory. Through simulation, they checked the consistency between the appreciative and the formal version of the theory by examining whether the formal version is able to reproduce the same stylized facts as described in the appreciative theory.

The empirically observed behaviour is the pedestal to build the computer model and the contribution of the simulation study is one of generating a repertoire of plausible causal mechanisms that might explain behaviours as observed in the real world.

What about induction?

In this vein, another example of abduction is provided by the study of Lomi and Larsen (1996) on population ecology. They focused on the typical model of density-dependent founding and mortality rates and addressed the micro-processes that take place at the level of individual organizations. The authors modelled micro-processes of local interaction and simulated emerging competitive dynamics of organizational populations. They designed a protocol of simulation experiments through which they tested different specifications of local micro-processes. For example, they varied the strength of the link between founding decision and local density. Then, they used data generated by the simulations to estimate a model of organizational founding and compared simulated estimates with existing population-level empirical estimates. They demonstrated the ecological model of density-dependent founding rates to be consistent with a number of micro-assumptions about the patterns and the range of local interaction among individual organizations. Again, in this case, the study maintains an abductive flavour in its using computer simulation to include plausible premises, a set of behavioural micro-assumptions, to the repertoire of possible explanations of observed aggregate behaviours.

The interplay of abduction and deduction in simulation studies

A consideration is fundamental in order not to misinterpret the distinction between deductive and abductive simulation studies. In most of the simulation studies in social sciences, abductive and deductive inferences are intertwined. However, we cannot avoid noting that the logic by which they are inspired often differs not marginally. It is in this light that is justified our strategy of adopting idealtypes as analytical abstractions.

For example, in the mentioned study of Sastry, the logic of enquiry is clearly stated and hinges upon two elements. First, the author has a clear imagine of the dynamic features of the behaviour she wants to explain. Second, she uses the comparison between theoretical and simulated behaviour as a trigger to import in her modelling candidate causal mechanisms.

On the other hand, at the other extreme, consider, for example, Cohen, March and Olsen's *Garbage Can* simulation model. The authors described how problems, choices and people met within an organization but they start their enquiry without a precise idea about the aggregate decision-making behaviour that follows from the premises they designed. The curiosity was exactly to understand what the consequences are of representing an organization as an organized anarchy and the contribution of the study is indeed to suggest that organized anarchies maintain a peculiar style in their decision making behaviour. Many simulation studies, however, blend the two components.

For example, in his study on the emergence of disruptive technologies (2002), Adner proceeded from the description of the phenomenon of the emergence of disruptive technologies. He investigated how the phenomenon had been analyzed before in the literature and noticed that previous explanations had focused on the limits of incumbent technologies. Taking a different angle, Adner focused on the impact of market demand on development strategies. This choice directed his attention on the modelling of the structure of market demand and, more importantly, led him to introduce two new constructs, preference overlap and preference symmetry, to capture features of market demand that are connected to the behaviour of interest. In addition, however, the deduction, through simulation, of the consequences of modelled premises led him to produce a repertoire of plausible behaviours depending on changes applied to the calibration of the simulation model. Through this exercise of deduction the author provided an articulated portray of the phenomenon under study, eliciting different modes of competition among technologies. In this case, abductive inference, starting from a defined behaviour, aided the elicitation of sufficient causal mechanisms to observe the behaviour whereas deductive inference expanded knowledge of the behaviour by producing various simulated scenarios.

Beside cases in which the abductive or deductive approaches clearly come into view, many studies incorporate both approaches. A simulation study may incorporate a loosely defined idea of the features of the behaviour it is aimed to explain and this idea guides the modelling of the premises. The deduction of consequences from premises through computer simulation aids the refinement of the description of the behaviour of interest. On the other hand, the materialisation of surprising or counterintuitive behaviours induces the search for alternative causal mechanisms to modify the original set of premises.

Deduction generates repertoires of patterns of behaviour that represent near-histories that proceed from a common deep causal structure (March, Sproull and Tamuz 1991). This exercise contributes to theory building by making available ex-ante falsifiable hypotheses that connect casual mechanisms to behaviours. Deduction may also create counterintuitive and surprising behaviours that bring about marginal amendments in the modelling of the premises or may trigger revisions of modelled premises. In this case, the discrepancy between expected and simulated behaviour is the incentive to refine, or deeply modify, the modelled set of premises by introducing in the model new causal mechanisms.

For example, in their study on population ecology and competition among structurally different populations of organizations, Carroll and Harrison (1994) built a mathematical model, designed a structurally superior population and simulated competition between two populations (one inferior and one superior). Through the simulation study, they demonstrated, *in vitro*, that the dominance of structurally superior populations may not emerge depending on their timing of entry in the industry. The contribution of this theoretical falsification is to delineate the hypothesis of *historical inefficiency*, according to which the explanation of an observed behaviour is history-dependent and the time in which events happens modify their expected consequences.

In this case, given the modelled premises, the deduction of a behaviour that is incongruous with the expected one, facilitates an abductive inference leading to the engendering of the concept of *historical inefficiency*.

CONCLUSION

The proposed review suggests that simulation studies are gaining legitimization in management and organization literature. Nevertheless, few are the reviews that address the role played by this research approach in the mentioned disciplinary fields. More importantly, these reviews are often focused on the technical differences that characterize alternative simulation approaches. Times are mature to propose new theoretical lenses to review the field. Of course, I am aware that different simulation techniques are differently capable to tackling specific problems. In this respect, I am not downsizing the importance of reviews that portray the repertoire of available simulation techniques. Yet, I am convinced that an intriguing perspective to appreciate the variety of contributions and to guide future research is to capture the often subtle difference in the logic of inference that underpin simulation studies.

In so doing, I focused on two forms of inference: deduction and abduction.

These two forms of inference, it is advocated in the paper, are those more frequently used to structure a simulation study. I expect, however, that it is unlikely that authors build their research strategy by consciously making reference to a specific form of inference. More often the reference is made retrospectively.

Moreover, often, deductive and abductive inferences are so tightly interlaced as to make it an arduous endeavour to disentangle the two processes at work.

More frustrating, the profound interplay between the two kind of inferences may push scholars to dismiss the attempt to separate the working of the two mechanisms as an unnecessary subtlety.

I maintain, however, that the ability to discern the difference between deductive and abductive inferences scores two important goals.

First, by having in sight the difference between the two logics of inference, researchers more deliberately can design the structure of their simulation studies. Second, endowed with a sophisticated point of view, colleagues may more consciously read and appreciate the contribution that is brought about by computer simulation thereby discriminating between studies grounded upon a solid logic and work in which the aims and the purpose of using computer simulation remains obscure.

Technically speaking, a computer simulation cannot be anything different than a computer-aided process of deduction. This deduction process both unveils not necessarily intuitive cause-effect relationships that are implicitly hidden in the premises and assists rigorous articulation of appreciative theories. This facilitates researchers in producing testable hypotheses. On the other hand, when deducted behaviours do not match with expectations, this mismatch activates an abductive inference that amends the original set of premises.

Of course, this article shows a limit in its considering only a portion of the simulation studies that populate the management and organization literature. The selection from a rich repertoire of pieces of work was guided by the intention of highlighting the gradual acceptance of simulation studies in mainstream journals. Thus, I preferred articles written on these latter rather than those written on journals more prone to accept simulation studies. Also, this kind of articles, given their need to legitimize their publication on mainstream journals, generally devote more space and effort to clarify their methodology.

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NOTES

(1) Dorfman (1960: 603) recommends that computer simulation is particularly useful in the area of general systems analysis and in problems that involve inventory and queuing management. In particular, Dorfman explains that the operation researcher tries to simplify ' …his problems as much as he dares (sometimes more than he should dare), applies the most powerful analytic tools at his command and, with luck, just squeaks through. But what if all established methods fail, either because the problem cannot be forced into one of the standard types or because, after all acceptable simplifications, it is

still so large or complicated that the equations describing it cannot be solved? When he finds himself in this fix, the operations analyst falls back on "simulation" or "gaming."'.

(2) In Cohen, March and Olsen's Garbage Can model, *organized anarchies* are characterized by three general properties: problematic preferences (inconsistent and ill-defined set of preferences), unclear technology and fluid participation.

TABLE 1

	Generative mechanisms	**Emerging behavior**
Cohen, March & Olsen, 1972	Organized Anarchy *Problematic preferences* *Unclear technology* *Fluid participation*	Aggregate behavioral *implications*
Lant & Mezias, 1990	Entrepreneurial strategies	Firms' performances, growth & survival
Gavetti & Levinthal, 2000	Backward-looking experiential learning Forward-looking cognitive	Survival in different fitness landscapes
Adner, 2002	1) Preference overlap 2) Preference asymmetry	Technology adoption
Lee, Lee & Rho, 2002	1) Mobility barriers 2) Strategic interactions 3) Rivalry across firms 4) Dynamic capabilities	Emergence and persistence of strategic groups
Sastry, 1997	1) Monitoring Routine 2) Trial Period suspending heuristic	Punctuated change