Linking Artificial Models and Reality:
Cutting Through Misunderstandings

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Abstract

The recent introduction of computer simulation in social sciences in general and in management sciences in particular, means that it has yet to be accepted in the researcher's "toolbox." To guarantee computer simulation's early acceptance by the scientific community, its users have paid particular attention to the validity of their results. In particular, external validity, through comparison of real-world and simulated data, has been observed. However, this focus on reality has diverted attention from the most fertile issues regarding computer simulation, and created some misunderstandings. The aim of this paper is to clarify main misunderstandings, which are part of the reason that simulation methods are now well understood, in order to convince computer simulation non-users of the interest of this technique. After the misunderstanding clarifications, we provide and promote a new way, more useful, to use computer simulation for management researchers.

Keywords

Computer simulation; Models; Validity; Reality; Artificial data

Computer simulation has become a critical part of the social science researcher's analytical 'toolbox' (Axelrod, 1984; Gilbert & Troitzsch, 1999), including that of the management researcher (Dooley, 2002; Harrison, Li, Caroll & Carley, 2007). Computer simulation can be used to answer questions relating to organizations at different levels: intra-organizational level (Carley, 2002), organizational level (Einseinhardt & Bathia, 2002) and inter-organizational level (Sorenson, 2002). First simulation models used in management science are not recent (Cyert & March, 1963; March, Cohen & Olsen, 1972; Nelson & Winter, 1982). Moreover, academic journals regularly publish articles that use this method. McKelvey (1997) estimates that simulation will develop exponentially throughout the 21st century, until it accounts for nearly 25% of publications. However, even if the popularity of computer simulation in the management community increases (Dooley, 2002), this method is not yet completely accepted by the scientific community (Davis, Bingham & Einseinhardt, 2007). Computer simulation is absolutely not a new research method but there are only a few who regularly use it (Lomi & Larsen, 2001). Research using computational models remains too often limited to special issues (e.g., American Journal of Sociology in 2005), to specific books (e.g., Lomi and Larsen, 2001), to specialized conferences (e.g., North American Association for Computational Social and Organizational Sciences Conference) and to specialized academic journals (e.g., Computational and Mathematical Organization Theory). One possible reason for this exclusion is to be found in the recurring criticisms addressed to computer simulation (Chattoe, 1998; Fine & Elsbach, 2000): oversimplification, disconnection from reality and too conceptual nature. The ability of this method to produce knowledge is questioned. Cyert's point of view (1994, p. viii), that "social scientists, particularly economists, have a fatal attraction for working on theoretical propositions with mathematical models or simulation models and avoiding the real world" is widely shared by management researchers. The absence of direct links with reality raises many questions about the validity.

To avoid such criticism, computer simulation users rigorously assess both internal validity and external validity. Internal validity is considered as an inherent characteristic of the simulation model, but external validity represents its main weakness (Davis, Bingham & Einsenhardt, 2007). For that reason, authors have used validation procedures based on the confrontation between simulated data and real-world data (Carley, 1996; Davis et al., 2007; Knepell & Arangno, 1993). As a final stage in these procedures, the link between real-world data and simulated data is evaluated. Figure 1 presents the logic of computer simulation, as it is now generalized.

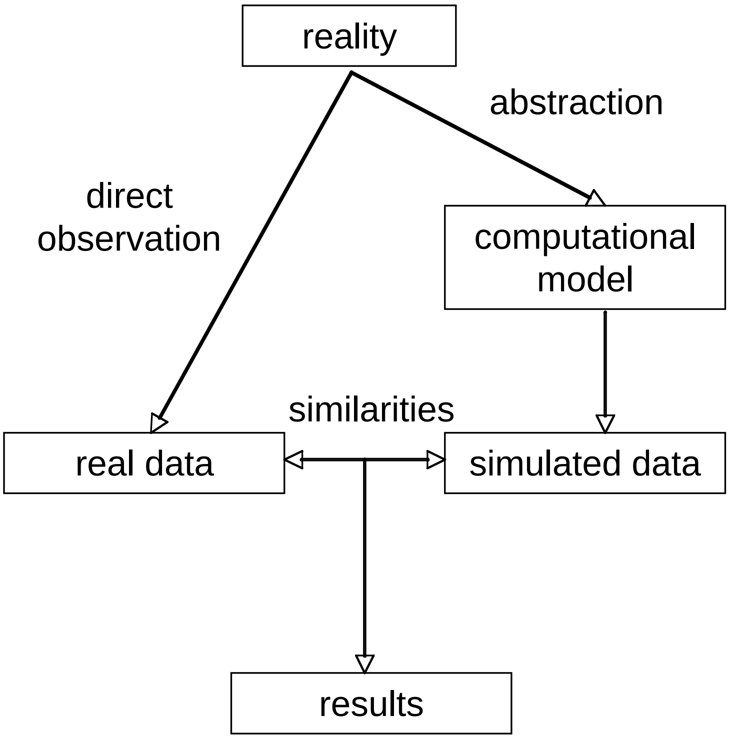

Figure1. Classical Logic of Computer Simulation

This continual search for a fit between real-world and artificial data leads to three main misunderstandings about the computer simulation: the aim of computer simulation is to reproduce accurately the reality (misunderstanding 1), to explain real complex phenomena, the more complex model is the best (misunderstanding 2), and real data and artificial data are the same things (misunderstanding 3). These misunderstandings are part of the reason that simulation methods are now not well understood. The aim of this paper is to cut through these misunderstandings in order to clarify the link between artificial models and reality. Through this clarification, we want to promote and to provide an overview of a new way to use artificial models. If the disconnection of simulation models from reality involves specific precautions that must be taken into account in assessing a piece of research, it also represents the main interest of the method.

In this article, an epistemological debate is avoided. As most of artificial modelers, a realist orientation is taken. Indeed, it is considered that there are some 'real' social processes or mechanisms existing that generate the observations that actors and research perceive (Azevedo, 1997; McKelvey, 1997; 2002). According to this epistemological view, the three misunderstandings are clarified in a first part. Secondly, a new approach for computer simulation, based on the misunderstanding analysis, is presented and discussed.

MISUNDERSTANDING #1. THE AIM OF COMPUTER SIMULATION IS TO REPRODUCE ACCURATELY THE REALITY

Without some degree of realism, computational models become a simple logical and/or numerical exercise. At the other extreme, total realism is not more useful. Progress in computing science and the evolution of computers have made it possible to consider the interaction of an increasing number of elements. Consequently, some researchers are tempted to make their models more complex, to represent reality more accurately by introducing a great number of elements in their artificial models. For example, it possible to read: "[w]e attempted to make our simulation as descriptive as possible […]” in Mezias and Glynn’s article (1993, p. 94). The idea is to model reality with most part of its details. This conception of computer simulation is widely represented through the germane works (Burton & Obell, 1995). Obviously, computational models need to be close to the real world and have external validity, but how close depends upon the research question (Burton, 2003). As Cohen and Cyert (1965, p. 306) note: “[…] even though the assumptions of a model may not literally be exact and complete representation of reality, if they are realistic enough for the purposes of our analysis, we may be able to draw conclusions which can be shown to apply to the world.”

A parallel can be drawn between management and literature. For realists, it is necessary to provide every detail, to be sure of avoiding any kind of idealism. In a famous passage in *The Red and the Black* (1830), Stendhal described the novel as a mirror being carried along a roadway. When building their computational models, some researchers adopt this realistic perspective. In this case, computational models are the mirror that is carried along a roadway near firms and the economic environment. Unfortunately, this perspective is naïve, because it is impossible to include in a model (as in a novel) every detail of reality. By complexifying the computational models to reproduce more precisely the behaviors of individuals or organizations, researchers provide an illusion of reality, not an interesting reproduction. In this case, computer simulation imitates the reality, but never represents it. Reproduction does not mean an accurate copy. As for painting, it is possible de give an interesting representation of the reality while moving away from this reality. Fauvism, pointillism or cubism offer representation of realty as interesting as the Dutch School for example.

Yet, the aim of computer simulation is to represent reality, not to imitate it. Computer simulation is rather a tool that highlights one or more elements of the reality by taking a particular view. Computer simulation is an intellectual representation of reality from which useless or accidental details of reality are filtered out. The aim of this simplification is to establish the essential being of the studied situation. Parsimony is a scientific principle, and it is necessary to apply it in computer simulations (Gauch, 2003). Sometimes a partial but simple model is more useful than a complete but complex one.

Thus, a computational model can be compared to a geographic map that represents the interactions between the sample of observed reality and the image produced by the observation tool (Hacking, 1981). Artificial models, such as geographical maps, simplify reality by extracting only the most important aspects. The aim is to build a map as a simplified representation of reality that will function as a guide for action (Azevedo, 1997). Unlike a photograph, a geographical map uses a filter and does not represent all the elements of reality that it is possible to observe. Similarly, artificial models do not describe a phenomenon completely, but highlight its most explicative parameters. By functioning like a geographical map, an artificial model extracts from the complex reality a restricted number of elements, but it always retains its explicative aspects. This search for simplicity should not be considered a limitation. As Lewis Carroll underlined, to seek a perfect correspondence between reality and a map is not relevant:

> Mein Herr looked so thoroughly bewildered that I thought it best to change the subject. ‘What a useful thing a pocket-map is!’ I remarked.
>
> - ‘That’s another thing we’ve learned from your Nation’, said Mein Herr, ‘map-making. But we’ve carried it much further than you. What do you consider the largest map that would be really useful?’
>
> - ‘About six inches to the mile.’
>
> - ‘Only six inches!” exclaimed Mein Herr. ‘We very soon got to six yards to the mile. Then we tried a hundred yards to the mile. And then came the grandest idea of all! We actually made a map of the country, on the scale of a mile to the mile!’
>
> - ‘Have you used it much?’ I enquired.
>
> - ‘It has never been spread out, yet,’ said Mein Herr: ‘the farmers objected: they said it would cover the whole country, and shut out the sunlight! So we now use the country itself, as its own map, and I assure you it does nearly as well’. (Caroll, 1973: 556-557)

By offering a more simplified version of reality than a photograph, a map is a more powerful tool. As Ziman (1978, p. 86) underlines, "paradoxically, a map often is a better representation of the territory … than a picture." By highlighting only the most visible aspects of a phenomenon, a map focuses on the most explanatory points and avoids sources of incomprehension. Indeed, a photograph contains symbolic and emotional elements not included in a map (Ziman, 1978).

For that reason, computer simulation models have to remain as simple as traditional models. Even though computer simulation offers more flexibility and increases the use of models, the basic principles of modeling remain the same. However, the use of computer simulation has sometimes generated a drift. It is easier to create complicated models than to establish robust results from their properties and their dynamics (Deffuant, Weisbuch, Amblard & Faure, 2003). For example, the firemen department of California initially used an extremely complete model. This computational model was very close to reality in order to predict fires. However, it was very quickly abandoned and replaced by a simpler one (Eklund, 2001) that used only a few variables (past fires, vegetation, ground orientation, crude oil stocks and road location). The most complete model was not more reliable, because it was impossible to collect all the data needed to calibrate it. For example, data about ground maintenance is not available.

Even if an artificial modeler never tries to reproduce exhaustively the reality with a first model, precision becomes an important aim for management scientists (use of computer simulation is often different in the other social sciences and engineering and applied sciences). A simulation research program may start with a simple model and then elaborate it. Artificial modelers increase complexity step by step (Harrison et al., 2007). Illustration of this point is given in the 'further research' sections included at the end of simulation articles in management journals. For example, it is possible to read in published academic articles:

> A possibility we do not model, worthy of future research, is that experience in a wide range of industries may help a manager to build and understand of what drives the relationship between choice and performance. (Gavetti, Levinthal & Rivkin, 2005, p. 709).

> A more comprehensive model would also need to take into account how the performances of firms within an industry are interdependent and linked over time. (Andersen, Denrell & Bettis, 2007, p. 423)

> We can also extend our models by introducing exogenous effects that are constant across time or people. (Franck & Fahrbach, 1999, p.270).

Adding elements by including new variables or by complexifying rules does not improve the model. Making the model more complex results in it becoming unintelligible, and it becomes impossible to analyze and discuss its results. As a consequence of their inability to capture all of the reality, researchers build models to focus their attention on particular elements. A model is “a simplified picture of a part of the real world” (Lave & March, 1975, p. 3). The model is a simplified reproduction of reality. Nevertheless, this simplified reproduction is accurate because the model “has some of the characteristics of the real world, but not all of them” (Lave & March, 1975, p. 3). It is important to note that a valid model for one purpose may not be a valid model for another (Burton, 2003). It is better to have different simple models for different research questions rather than a general model, which can fit with all the possible purposes or questions.

To work from a simplified version of reality using a map or a simulation model is consistent with the scientific method. As Gellner noted (1988, 196), “science is based on the assumption of an orderly, homogeneous, unified external system, accessible through its fragmented manifestations, and never directly approachable as a totality.” Moreover, working from a simplified representation of reality allows some advantages. By removing the nonessential aspects, the explanations of the accidental regularities are isolated. A double validation can also be used to validate the artificial model. Theoretical validation is ensured by the correspondence between the theory and the model. Instrumental validation is obtained from the correspondence between the model and the observation of reality.

Obviously, computer simulation users never have in mind to generate a perfect representation of reality. But, the continual search for a more complete model is now a reality and a general pattern. Contrary to other methodologies, artificial modelers tend to quickly forgot oldest and most fundamental scientific principles (Thanks to Willian of Ockham, *lex parsimoniae* principle is well known since the 14th century). Structural equations, for example, are coupled with parsimony fit statistics which penalize large models with many estimated parameters and few leftover degrees of freedom (Bollen & Long, 1993). It could be interesting to couple this kind of parameters to computational models. Axtell et al. (1997) try to determinate if a set results in a simple model of cultural transmission built by Robert Axelrod (1997) could also be obtained by a more complex one (the Sugarscape model designed by Epstein and Axtell in 1996). This comparison is very challenging because, as underlined by authors,

> the two models are […] clear examples of different approaches to computational modeling: Sugarscape is designed to study the interaction of many different plausible social mechanisms. It is a kind of 'artificial world'. In contrast, the Axelrod Cultural Model (ACM) was built to implement a single mechanism for a single process, with the aim of carrying out extensive experiments varying the parameters of that mechanism. It much more resembles the spirit of traditional mathematical theorizing in its commitment to extreme simplicity and complete analysis of each model parameter. (Axtell et al., 2007).

However, the two models obtain very similar results on some dimensions and for some purposes event though the model complexity levels differ dramatically. Then, simplicity of assumptions is important and it requires adhering to the KISS principle, which stands for the army slogan "keep it simple, stupid" (Axelrod, 1997). The KISS principle is vital because it is very helpful to be confident that we can understand everything that went into the model when a surprising result occurs.

MISUNDERSTANDING #2. MORE THE REAL PHENOMENON TO REPRODUCE IS COMPLEX, MORE COMPLEX THE COMPUTATIONAL MODEL HAS TO BE

As other social sciences, organizational processes are complex by nature (Harrison et al., 2007; Lomi & Larsen, 2001). A lot of researchers have the intuition that creating complexity requires models that are themselves complex. Whenever a phenomenon is encountered that seems complex it is taken almost for granted that the phenomenon has to be the result of some underlying complex mechanisms. But that assumption is sometimes wrong. Simple models can produce great complexity. Although the topic being investigated may be complex, the assumptions underlying the computer simulation should be simple. The complexity of computer simulation should be in the simulated results, not in the assumptions of the model (Axelrod, 1997). Wolfram (2002, p. 2) noted it, "even some of the very simplest programs that I looked at had behavior that was as complex as anything I had ever seen". This misunderstanding may appear from a more general misunderstanding about the term ‘complexity’. Indeed, it is necessary to distinguish informational complexity and computational complexity in producing explanation. The complex character of a social phenomenon is often not due to the number of elements in interactions, or to the number of parameters taken into account (informational complexity) but to the non-linear character of the relations between elements (computational complexity). These non-linear relations lead to the emergence of a complex phenomenon, impossible to predict while, at the same time, the behaviors of the individuals are extremely simple. The emergent behavior cannot be globally predicted even if individuals have simple rules locally. Simple rules at the micro level can lead to the emergence of a complex behavior at the macro level. So, when simplicity is searched, it is about informational simplicity.

Emergence is part of the theories of complexity. These theories try to understand simple models like clouds of birds or fish bench movements impossible to model through the classical mathematical tools. But they also make it possible to model social phenomena which are particularly complex by nature (Eptstein & Axtell, 1996). Like any complex phenomena, the social phenomena are macro phenomena, which emerge through simple local behaviors.

The ‘game of life’ or ‘life’ is one of the simplest model of emergent complexity created by the mathematician John Conway in 1970 (Gardner, 1970). This model is a classical study of how elaborate patterns and behaviors can emerge from very simple rules. The ‘game of life’ is played on a grid of square cells but extending infinitely in every direction. A cell can be alive or dead. Each cell in the grid has a neighborhood consisting of the eight cells in every direction. To apply one step of the rules, the number of living neighbors for each cell was counted. What happens next depends on this number. A dead cell with exactly three live neighbors becomes a live cell (birth). A living cell with two or three live neighbors stays alive (survival). In all other cases, a cell dies or remains dead (overcrowding or loneliness). Conway chooses the rules carefully after trying many other possibilities, some of which caused the cells to die too fast and others, which caused too many cells to be born. The ‘game of life’ balances these tendencies, making it hard to tell whether a pattern will die out completely, form a stable population, or grow forever. A model as simple as the ‘game of life’ helps us to understand some complex social phenomena which can be model starting from simple rules. Indeed, any human behavior can be reduced to some simple rules (Wolfram, 2002).

One of the first attempts to apply computer modeling to social science are Thomas Schelling’s segregation model (1969; 1971a; 1971b; 1978). Schelling placed pennies and dimes on a chess board and moved them around according to various rules. The board can be interpreted as a city, with each square of the board representing a house or a lot. Pennies and dimes are agents representing two groups in society (blue or red people, male and female, smokers and non-smokers, etc.). The neighborhood of an agent occupying any location on the board consisted of the squares adjacent to this location. According to his neighborhood, rules determine whether a particular agent was happy in its current location. If it was unhappy, it would try to move to another location on the board, or possibly just exit the board entirely. As can be expected, Schelling found that the board quickly evolved into a strongly segregated location pattern if the agents' 'happiness rules' heavily favored segregation. Surprisingly, he also found that initially integrated boards tipped into full segregation even if the agents' 'happiness rules' expressed only a mild preference for having neighbors of their own type.

Like the segregation phenomenon, it is possible to model and to study management problems thought simple models like the 'game of life' because complex strategy processes can be reduced to simple rules (Einsenhardt & Sull, 2001). In a seminal paper, Lomi and Larsen (1996) study the firms' location strategy according to the competitor location through a computational model similar to the 'game of life'. Initially, firms are randomly distributed on a grid where each cell represents a potential niche that a single organization can occupy. When a firm is located, it interrelates with the other firms in its neighborhood. A simple set of rules governs the dynamics of the simulated population. Two forces determine the birth and death of firms. On one side, firms need neighbors because they cooperate in order to generate positive agglomeration effects. When a firm is not surrounded enough geographically, it dies of solitude. On the other side, firms are in competition for scare resources. When too many competitors encircle the niche, firms die from overcrowding. These simple rules make it possible to simulate a complex dynamics. The Lomi and Larsen's main result is similar to that of Schelling (1969), the global space configuration depends on the local rules of location.

Lomi and Larsen (1996) model is just one of numerous examples of the power of simple models in management science. Since classical models (cf. Cyert & March, 1963; Cohen, March & Olsen, 1972) to more recent ones, it is possible to find relatively simple models which model complex realities and which offer stimulating new insights. NK models (Levinthal, 1991; 1997), VDT project models (Levitt & Jin, 1996), cultural models (Harrison and Carroll, 1998; 2007), search and reliability models (Carley & Lin, 1997) or learning models (March, 1991; Levinthal & March, 1993) are a short list of example of classical simple but useful models. Understanding these models does not require knowledge in computer science. Computer simulation does not complicate them. It merely facilitates the study of complex phenomena. In cases like this, simple models lead to very interesting results, raise new questions and improve theoretical developments in many fields.

In the first part of the article, parsimony was highlighted in order to use simple and intelligible models. In this case, models are useful maps, which give a specific representation of the reality. But, sometimes, reality is very simple and it possible to represent it very accurately through a simple model at the informational level. Parsimony and complexity are not opposed.

MISUNDERSTANDING #3. REAL DATA AND ARTIFICIAL DATA ARE SIMILAR

Analysis of the correspondence between data resulting from computer simulation and data resulting from an empirical study is the main criterion by which to judge the validity of a computational model (Carley, 1996; Davis et al., 2007; Gilbert & Troitzsch, 1999). Article quotations published in academic journals illustrate this point.

> In contrast to many other System Dynamics studies, an attempt was made to base the model on statistically treated empirical data. (Hall, 1976, p. 191).
> Results of computer simulations are consistent with empirical observations. (Bruderer and Singh, 1996, p. 1322).
>
> […] we wanted to compare the statistical estimates obtained for artificial populations with those reported by empirical studies of actual organizational populations. (Lomi and Larsen, 1996, p. 1304).
>
> I tested the predictions derived from the simulations on the radio station data used in earlier work on aspiration-level updating. (Greve, 1998, p. 10).
>
> […] the model makes several other testable predictions. To examine these predictions, simulated data from the model are compared with a large empirical study of 45 industries during 1991-2000. The predictions of the model are consistent with the empirical data. (Andersen, Denrell & Bettis, 2007, p. 407).

Following this analysis, simulation results can be used to test assumptions and to confirm theories, using deductive logic, or to build a theory, using inductive logic. More, if a correspondence between these two kinds of data can be established, then artificial data and real-world data can be used in a substitutable way.

However, the nature of artificial data is radically different from that of real-world data. The idea of prediction underlies the confrontation between real-world and simulated data. If a model is able to reproduce past behaviors, it is also able to predict future ones. However, computer simulation is not, by itself, a prediction tool. Statistical models are better adapted to reach this goal, and remain the best method of achieving it. If a statistical correspondence between real-world data and simulated data can be established, the results stemming from the simulation can always be disputed, as a result of the specific way in which data were produced.

Thus, computer simulation is not a method of predicting social phenomena, but rather of understanding and analyzing them (Gilbert & Troitzsch, 1999). Computational models contribute by raising new questions, by highlighting previously unobserved phenomena or by developing counterintuitive reasoning. What must be judged is not the proximity of artificial data to reality, but their interest for research. Indeed, computer simulation generates ideas and new research questions. Axelrod (1997, p. 3-4) underlines that, in the case of one simulation technique, multi-agent models, “whereas the purpose of induction is to find patterns in data and that of deduction is to find consequences of assumptions, the purpose of agent-based modeling is to aid intuition”.

The purpose of computer simulation is not the same so artificial data cannot have the same status than real-world data. Consequently, it is not necessary to take so extensive precautions to preserve the validity of the research. Even if these data are not statistically representative of reality, they remain very interesting for the researcher. Historians are regularly confronted with this kind of problem. To deal with a large amount of data, they can represent the reality by examining the most frequent and represented events. They can also focus on specific cases. In this second case, generalization is not possible, but the aim is to raise new questions. For example, Foucault (2001) explains that, when he wrote the history of insanity (1965), he did not want to study the entire reality, but only some cases chosen according to his own criteria. “The choice that one will find there did not have any more important rule than my taste, my pleasure, an emotion, a burst of laughing, a surprise, a certain fear or some other feeling” (Foucault, 2001, 237). Because of the non-representativeness of his sample, Foucault knew that historians would not consider his work a research book (Foucault, 2001, 237). In fact, it can be considered a simple subjective book. However, the selected stories raised interesting questions and helped to improve knowledge of madness. Thus, even if simulated data are not totally representative of reality, like stories chosen without systematic criteria, they may be very useful, and present a great opportunity to improve knowledge.

Furthermore, through its ability to abstract, computer simulation can have the same purposes as metaphors, tales or myths that are used in social sciences to create knowledge. Philosophy very often uses these artifices to raise and illustrate deep philosophical questions (Boyd, 1979). In this light, few stories have been as instrumental for organizational theorists as the adventures of a Hungarian military detachment in the Alps. Weick related the facts:

> Planning isn't nearly as crucial for productive action as people think it is. I can illustrate this point most clearly by recounting an incident that happened to a small Hungarian detachment on military maneuvers in the Alps. Their young lieutenant sent a reconnaissance unit out into the icy wilderness just as it began to snow. It snowed for two days, and the unit did not return. The lieutenant feared that he had dispatched his people to their deaths, but the third day the unit came back. Where had they been? How had they made their way? Yes, they said, we considered ourselves lost and waited for the end, but then one of us found a map in his pocket. That calmed us down. We pitched camp, lasted out the snowstorm, and then with the map we found our bearings. And here we are. The lieutenant took a good look at this map and discovered to his astonishment that it was not a map of the Alps, but of the Pyrenees. (Weick, 1983, p. 48-49)

However, the reality of this story is not guaranteed. It was reported for the first time by the Czech poet Miroslav Holub, in a poem entitled “Brief thoughts on maps,” published on February 4, 1977 in the *Times Literary Supplement*. Publication made it possible to discuss the reality of this story. Although this story was written by a poet, not a management researcher, and although it was probably invented, it nevertheless led to improve knowledge in management science. Does its fictitious character reduce its interest?

Even if the historical veracity of this scene cannot be established (given the lack of historical sources), readers do not discuss is authenticity because the explanatory power of this story is so important. Who could worry about veracity when faced with such an illustrative story that enables us to understand instantaneously the concepts of enactment and sense-making? Later theoretical constructions of these concepts are only more detailed developments of the central idea presented in this military anecdote (Weick, 2001).

The results of this story are so illuminating that it was used and re-used many times, especially by Weick himself (Weick, 1987; 1990; 1995; 2001). In management it is considered a traditional story. This example demonstrates that data, even when disconnected from reality, may be of interest to the management researcher. It is also possible to consider the data resulting from computer simulation in this way, rather than as data to be used systematically, like real data. These artificial elements help intuition, and allow rich and useful intellectual developments. An artificial model can be a tool to discover implications that are not intuitively obvious (Repenning, 2002) where “the results of simulation should be viewed as implications of the assumptions of the theoretical model, not as empirical results” (Lant & Mezias, 1990, p. 154-155). Using computer simulation in such ways effectively disarms critics.

GOING FURTHER: ARTIFICIAL DATA AS METAPHORS

The aim of this paper is not to question the intentions of researchers who use computer simulation. Their willingness to establish a link between artificial data and reality have not been discussed. This article is focused on the necessity of this link. Instead of reducing criticism, the use of real-world data increases it. So, the question of the best use of the computer simulation remains. Figure 1 presents the logic of computer simulation, as it is now generalized. Starting from the reality, two different ways are used to obtain data. After the collection, similarities between real data and simulated data are examined. Research results come from this confrontation between the real and the artificial world.

Data describe the observed empirical forms and theory explains why these data are observed (Kaplan, 1964). Up to now, management researchers consider that artificial data, as any kind of data, have to describe empirical forms, which they try to observe. However, it is possible to consider that the first aim of artificial data is to explain reality rather than to represent it. Computer simulation may be used to create and to develop theories. Strauss (1987) summarizes his approach to obtain adequate theories through three concepts: induction, deduction and verification. Until now, artificial data are used primarily during the stage of verification, i.e. during the procedures that evaluate whether the assumptions should be rejected or accepted. In this case, it makes sense to investigate the correspondence between artificial and real data. But it is much more interesting to use artificial models during the induction phase, i.e. when the researcher takes actions that lead to the discovery of a hypothesis. In this case, computer simulation is a wonderful tool to generate ideas, to turn it into hypothesis and to determine whether they can operate temporarily. By using them in that way, artificial data do not have to fit exactly with reality. Consequently, a comparison with real data is not necessary here. In the most extreme case, simulations can be used to explore the consequences of processes totally theoretical even if the outcomes cannot be assessed empirically (Harrison et al., 2007). In this case, artificial model and empirical evidences are totally disconnected. A purely theoretical model is absolutely not a weakest model. On the contrary, theoretical simulation “is still a legitimate scientific endeavor with the potential to make important contributions to management theory” (Harrison et al., 2007, p. 1242).

In some way, artificial data act like metaphors. According to Cornelissen et al. (2008, p. 8) “metaphors guide our perceptions and interpretations of reality and help us formulate our visions and goals”. It is possible to use artificial models in that way. A computational model can be a useful guide for a management researcher. By acting as metaphors, simple artificial models facilitate and further our understanding of the world. But, even if they are ways of seeing, thinking, and learning (Ortony, 1975) and even if they have implication for sight, for thought and for action (Schon, 1979; Yanow, 1992; Miller, 1985), including the designing of research (Hatch & Yanow, 2008), metaphors are not the reality. They are inspired from reality but they remain a particular view of it. Indeed, researchers can establish similarities between the simulated model and reality, and work from artificial data. However, researchers have to ensure that they do not confuse analogy and identity. Analogies have a suggestive role but cannot be demonstrative. For example, Schelling’s (1978) segregation model employed an analogy between a cellular automata model and the American society. Even though this extremely simplified representation shares only some common features with reality, it raised new questions about the constitution of ghettos. However, Schelling (1978) never attempted to confront it directly with the real population, in order to observe any similarities between figures, charts and numbers. The role of Schelling’s model is not to provide proof. In parallel, Weick did not definitively establish his theoretical developments using the Hungarian detachment story alone. The role of metaphors is not only to provide an illustrative heuristic, but also to build theory (Boyd, 1979). Metaphors can be instrumental in formulating theoretical assertions for which no theoretical description yet exists. The same function have to be applied to computer simulation.

When, thanks to computer simulation, new problems and new questions are raised, researchers must go further. The second step may be the collection of empirical data to confront the theoretical model, built thanks to theory and artificial model, to the reality. Thanks to his artificial model, Schelling (1978) explains how segregationist residential structures may occur spontaneously, even if people are not segregationist. The artificial model is part of general background of the segregation phenomenon. Per se, the Schelling's artificial model is not a result. But, thanks to this model, it became possible to orientate researches about segregation in a new and unusual way, impossible to discover just with a theoretical background. After this step, sociologists went further by studying real segregation phenomena in specific cities. In order to provide recommendations for a best practice, a new logic of computer simulation use as it should be is presented (figure 2). Rather than to use it in an alternative way, we consider that the computational model has to be included at the beginning of the classical research process.

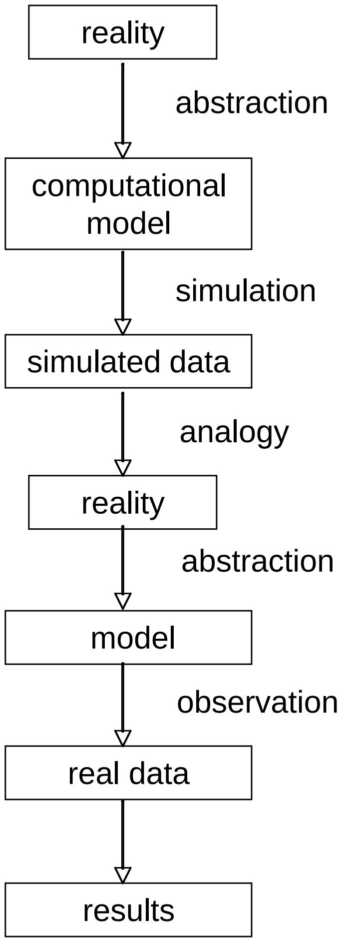

Figure 2. New Logic of Computer Simulation

To determine under what conditions will cooperation emerge in world of egoists without central authority, Axelrod (1984) applied this research logic (figure 3).

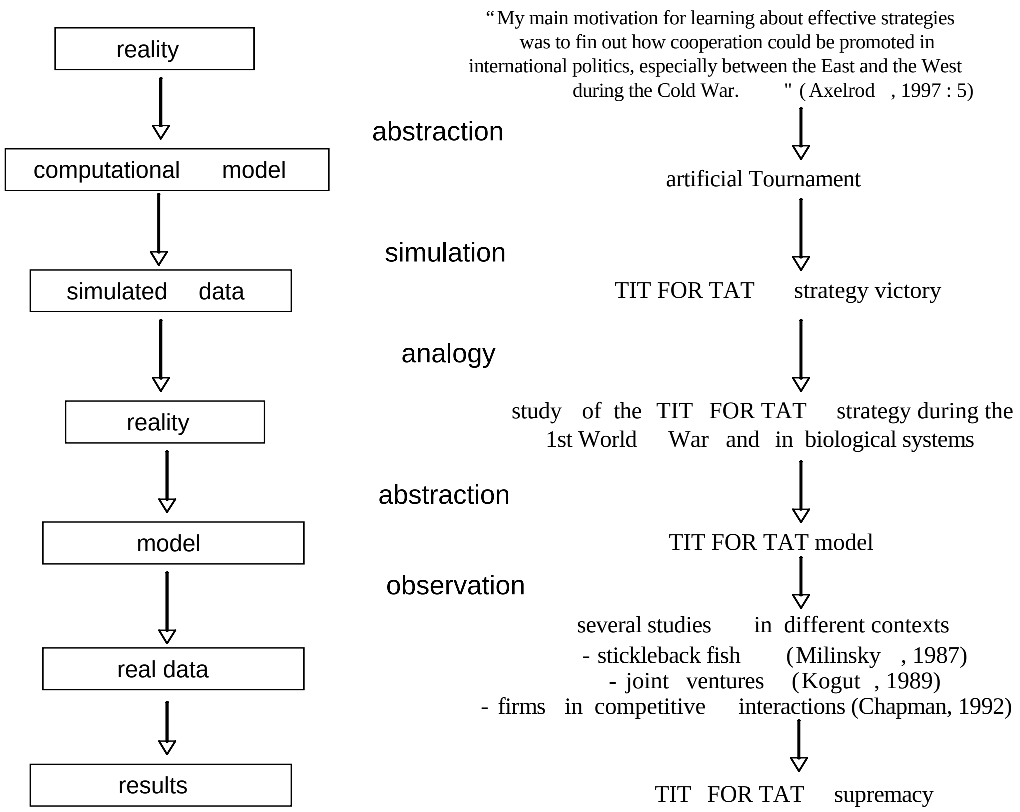

Figure 3. Investigating the TIT FOR TAT Strategy Through a Different Research Process

During his career, Axelrod was motivated for learning about cooperation by observing the behavior of countries during the Cold War. In 1980, Axelrod held a tournament of various strategies for the prisoner's dilemma. He invited a number of well-known game theorists to submit strategies to be run by computers. In the tournament, programs played games against each other and themselves repeatedly. Surprisingly, the winner of the tournament was the model using the TIT FOR TAT strategy, the simplest one. This first part of the research was very important because, thanks to the tournament, a particular strategy emerged as the most powerful. More, this first result was counter-intuitive. Traditionally, it was admitted that it is necessary to develop a very complex strategy to solve the prisoner dilemma. A second round was then held. Participants to the second round were all given the results and a detailed analysis of the first round. There also were many more participants in the second round, 62 entrants from six countries. TIT FOR TAT won the second round also. After this first step, Axelrod looked for analogies between the artificial strategy and real contexts. So, he studied the TIT FOR TAT strategy during the First World War and inside biological systems. After a first artificial study and two real cases, Axelrod proposed a theoretical model for the cooperation study. Finally, the model was applied to real data in order to obtain results in researches, which followed in diverse fields (Chapman, 1992; Kogut, 1989; Milinsky, 1987).

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