# Computational Simulation

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# computational simulation

**Definition**
A computational simulation is a dynamic, process-oriented model instantiated on a computer. These can range from traditional economic models (expressed as equations) to more abstract constructs and processes (expressed as objects, agents, operators and algorithms).

**Abstract**
A significant and growing set of approaches in strategic management research are centred on the use of computational models realized as simulations. We provide a characterization of what constitutes a computational simulation and enumerate the possible roles computational simulations can play in strategic management research. By exploring the broad fundamentals and issues underlying the use and contribution of computational modelling, we hope to help facilitate the use of simulation in providing insight into key issues of strategic management. We provide a brief examination of the history, benefits, uses and forms of computational simulations, and explicate the concerns and issues that lie at the core of any simulation development effort.

A significant and growing suite of tools and approaches in strategic management research are centred on the use of computational models realized as simulations. However, as the study of strategic management itself is a moving target, it is important to understand the broad fundamentals and issues underlying the computational simulation approaches in order to intelligently discern how they can contribute to strategic management research.

## Brief historical overview

The computer has been an adjunct for research in strategic management for decades – consider the early work of Jay Forrester, incorporating systems dynamics simulations as mechanisms to improve a firm's strategic decisions (Forrester, 1958). In fact, by 1965 'simulation had become a widely used methodology' in the social sciences (Dutton and Starbuck, 1971: 3), including such publications as *Industrial Dynamics* (Forrester, 1961), *Simulation in Social Science* (Guetzkow, 1962) and *A Behavioral Theory of the Firm* (Cyert and March, 1963). The garbage can model (Cohen, March and Olsen, 1972), models of adaptive search (Levinthal and March, 1981), models of cooperation (Axelrod, 1984) and the exploration-exploitation model (March, 1991) all followed. Movements towards the consideration of the micro-phenomenon underlying macro-behaviour (e.g., Schelling, 1978) afforded legitimacy to reductionism in examining strategic constructs, but the use of simulation methods in mainstream management journals remained infrequent (Berends and Romme, 1999). Over time, interdisciplinary organizations emerged to accommodate intellectual exchanges (e.g., the World Congress on Social Simulation), the National Science Foundation provided support for research and summer schools educating Ph.D. students and faculty, and key conferences such as that held by the Academy of Management offered pre-meeting professional development workshops and support for computational simulations topics on management and strategy. Thus, the past several years have witnessed a distinct increase in the use and sophistication of computational simulations in management research. In other disciplines, computational simulation has become a 'third branch' of science (Pool, 1992), with that trend growing in studies of organization science (Carley, 2002) and economics (LeBaron and Tesfatsion, 2008; Tesfatsion and Judd, 2006). This trend is now gaining strength in the study of strategic management, which often bridges both disciplines. Furthermore, the exact nature of what type of simulation to engage depends on the particular investigative or theoretical context – for example, is it 'the strategy' (economic, macro-organizational) or the 'the strategist' (cognitive science, micro-organizational)? Accordingly, it is important to understand what constitutes a computational simulation and the possible roles computational simulations can play in strategic management research.

## What is a computational simulation?

For our purposes a computational simulation is simply a dynamic, process-oriented model instantiated on a computer. These can range from traditional economic models expressed as equations (e.g., Berry and Pakes, 1993; Werden, Joskow and Johnson, 1991) to models representing individual agents to societies (e.g., North and Macal, 2007; Zacharias, MacMillan and Van Hemel, 2008). In actuality, this is quite a powerful statement given the broad nature of the *types* and *extent* of models that can be realized on computer, and the fundamental robustness of computational formalisms as suggested by the Church–Turing thesis (Harel, 1987). Consequently, as one moves away from a more standard form (e.g., a system of linear equations, an LP model) to more flexible ones (e.g., using an agent-based package, programming your own model), it is essential that the assumptions, both explicit and implicit, are known and articulated. As these assumptions are embedded in any model that is created, they must be understood in order to appreciate their contribution to the analysis of model behaviour. For example, Davis, Eisenhardt and Bingham (2007) provide a comparison of five approaches to simulation, focusing on several dimensions: focus, common research question, key assumptions, theoretical logic and common experiments. Following that lead, we focus on computational simulations and examine the benefits and uses of simulation for strategic management research.

## Some benefits of computational simulation

As computational simulations are dynamic instantiations of models, incorporating incremental and causal changes in parameters over a precedent-temporal (i.e., event-driven or continuous) interval, they embody specification of processes. The value of this resides in the ability to specify the model at multiple and varying levels of complexity and formality, and to include the complex dynamics inherent in business, market or sector activity unfolding over time (Prietula, 2011). Consider four general benefits of computational simulations for strategic management research.

First, computational simulations focus on organizational phenomena that go together in a theoretically meaningful way. A set of constructs are defined that operate dynamically, evidencing individual and collective behaviour over time, possibly addressing multiple levels of abstraction. For example, Lant and Mezias (1990) define and manipulate levels of entrepreneurial activity, as well as types of entrepreneurial strategy, under a learning model in order to examine the consequences (as performance, resources and bankruptcies) over extended time periods. Aggarwal, Siggelkow and Singh (2011) developed an agent-based model to examine the performance impacts of governance modes used to make decisions in inter-organizational alliances. Their model showcased the interactions between different governance structures, patterns of interdependencies and levels of organizational search capabilities.

Second, computational simulations describe both the process and the product of behaviour. That is, they allow a reductionist argument and permit traces of behaviour over time that can be associated with theoretical constructs in the model. There is a specific distinction between behaviour and performance. The oligopoly model described in Cyert and March (1963) included many process components. Prietula and Watson (2000, 2008) replicated that model and examined how the model component processes contributed to outcome product, but also demonstrated how its routines account for economic behaviour. By incorporating changes in risk preference at extremes of performance and alternative reference group strategies, Hu, Blettner and Bettis (2011) extend the prior process descriptive simulations of adaptive aspirations by March (1988) and March and Shapira (1987, 1992). Miller, Fabian and Lin (2009) used a simulation model to study participation by incorporating a new risk preference function and examining alternative strategies for setting reference groups of organizations in online communities as a means to use social learning processes to shape demand for products. The authors model product demand as a function of interpersonal communication and firm strategy, and find key contingencies that can inform firm strategies in this context. Markle (2011) uses experimental data and setting from a gift exchange game published in a prior study as a basis for a computer simulation to examine the judgement of firms regarding employee reciprocity. The simulation supports the dysfunctional learning process suggested in prior theory by demonstrating systematic bias towards an overemphasis on employee self-interest, and subsequent wage choice inefficiencies.

Third, computational simulations enforce both the formalism and uniformity describing organizational phenomena. Unlike verbal or 'pictographic' articulations of theory, computational simulations are more demanding of exact specifications of objects and processes of the model. If it is asserted in the model, it is represented in the code (at some level of abstraction), and the implications of the code are unambiguous in execution. But not all the components of the simulation embody components of the model, as ancillary elements may be needed to hold together and enable components of the model so that it can be realized in the simulation. One solution to this is to provide the code itself (Cohen, March and Olsen, 1972; Cyert and March, 1963; Levinthal and






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March, 1981). Nevertheless, as models become more complex the visibility of the constructs and their dynamics becomes somewhat obscured, thus obfuscating the model itself. Therefore, model complexity and ancillary elements (which may invade the definitions and behaviours of the model constructs) can lead to model obfuscation. Two basic methods to mitigate obfuscation risk are model assembly and code assembly.

*Model assembly* refers to borrowing components that are well defined in another model and manipulating them to fit the context of interest. For example, Gavetti, Levinthal and Rivkin (2005), Siggelkow and Levinthal (2005), Levinthal and Posen (2007), Ethiraj, Levinthal and Roy (2008), and Aggarwal, Siggelkow and Singh (2011) all construct strategic simulations based on modifying the NK model developed in the context of biology and borrowed from physics (Kauffman, 1993), while Carley and Svoboda (1996) incorporate an optimization procedure (simulated annealing) to model organizational adaptation. Systems dynamics has been well represented in model assembly approaches. Repenning (2002) examined the dynamics of implementation using systems dynamics, Black et al. (2004) developed a model grounded in ethnographic data from a prior study, and in his classic textbook Sterman (2000) has a rich set of examples. Other popular model assemblies one may encounter include genetic algorithms (e.g., Goldberg, 1989) for evolutionary contexts (e.g., Lee, Lee and Rho, 2002) and cellular automata (Wolfram, 2002). *Code assembly* refers to the use of an existing computational model or modelling environment (see subsequent section on **Forms of computational simulations**). Code assembly includes not only elements of a model (static and dynamic components) but the underlying mechanisms of running it directly. As noted, it is important to be aware of the assumptions and underlying mechanisms of model and code assembly, and how those relate to the model under construction.

Finally, another benefit of computational simulations is that postulated constructs can be manipulated explicitly. In the real world it may be difficult to find cases that give sufficient coverage of a parameter space to test hypotheses or theories. Accordingly, computational simulation can instantiate a theoretical model and examine its behaviour under varying conditions. For example, Gary (2005) manipulated seven diversification strategies in a computational simulation, which led to insights and refinements to extant theoretical descriptions.

### How computational simulations are used

The previous section discussed some of the key advantages of computational simulations, but it is also important to consider what role these simulations may play from a researcher's perspective. Consider a sampling of purposes for computational simulations in social science relevant to strategic management research (Burton and Obel, 1980; Carley and Prietula, 1994; Axtell et al., 1996; Axelrod, 1997; Carley, 1999; Davis, Eisenhardt and Bingham, 2007; Harrison et al., 2007):

- Prediction (e.g., of consequences of alternative policy decisions)
- Proof (e.g., existence or sufficiency to demonstrate or account for phenomena)
- Discovery (e.g., of new effects of hypothesized mechanisms)
- Replication (e.g., of other theoretical or computational models to test reproducibility of results)
- Explanation (e.g., of what processes underlie the presence of a phenomena)
- Critique (e.g., to seek more parsimonious explanations for hypothesized phenomena)
- Prescription (e.g., for generating evidence to select a better policy, organizational design or strategy)
- Empirical guidance (e.g., suggesting further research areas to pursue)
- Theory development (e.g., refine and modify theoretical constructs or the conditions under which they apply)
- Hypothesis generation (e.g., run a series of simulations from a theoretical model to produce derivative hypotheses to be tested)
- Hypothesis testing (e.g., run a series of simulations to test hypotheses proposed by a theory)
- Instantiation (e.g., move from a verbal theory to a computational form)
- Docking or alignment (e.g., determining how/if two or more models that embody distinctively different mechanisms are equivalent or one can be subsumed within the other in explaining or predicting similar phenomena).

### Forms of computational simulations

It is important to understand that the model, per se, is not the focus; rather, it is what the model *represents* – that is, the theoretical justification and specification







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of the constructs and form selected for the simulation. The substance of the theoretical rhetoric and reasoning cannot be lost in the implementation. In any such model, one must be able to easily and unambiguously identify not only the theoretically relevant components, but how these components contribute to process behaviours.

Several general software options are available in helping to construct a computational simulation (recall previous discussion on *code assembly*), and each has its particular benefits and risks. These can be classified into three general (not necessarily independent) categories: free code, mathematical software and pre-structured environments. *Freecode* involves building a model from a general purpose programming language such as Basic, C++ or Java (including some statistical packages that allow general programming). The notion is that this approach is free of any bias towards particular organizational assumptions or design constraints. *Mathematical* software packages, such as Matlab, Maple, Magma, Mathematica and Sage, afford more constrained approaches that exploit underlying representations of mathematical objects and process. Finally, *pre-structured environments* are those that impose some type of design constraint on the specifications of the model, and reflect a broad range of environments. At lower levels of detail, Java packages and C++ libraries are available as pre-written components of simulations that may be reused. This makes the components transparent, but sufficient understanding of those languages is required in order for them to be exploited to the full. At higher levels of detail, programming environments dedicated to general types of computational and representational perspectives are available, including various systems dynamics environments or versions of agent-based frameworks as in MASON, Netlogo, Swarm, Ascape or RePast. Researchers also offer simulations that are more specific as to their underlying assumptions and approaches to representing organizations (Carley, 2002; Ren, Carley and Argote, 2006), types of markets (Somani and Tesfatsion, 2008) or societies (Epstein, 2006).

## Concerns and issues

In general, computational simulations require both *validation* (Did you build the *correct* model?) and *verification* (Did you build the model *correctly*?), which are issues at the core of any simulation development effort (e.g., Conway, 1963; Kleindorfer, O'Neill and Ganeshan, 1998; Naylor and Finger, 1967; Van Horn, 1971). Most concerns regarding computational simulation can be stated in these terms. In strategic management simulations the issue of validation has tended to receive much more attention. Verification is problematic in any software endeavour but in computational simulations it is mostly absent, except through exogenous review by releasing code, algorithms, or appealing to trusted sources (e.g., pre-structured environments). On the other hand, validation is where discussions specific to computational simulations in management have emerged (e.g., Burton, 2003; Burton and Obel, 1995; Miller, 1998; Thomsen et al., 1999). Transparency is lost as the complexity of the model increases. Once constructed, there is a fundamental difference between the following two questions (which must always be asked): What in the *model* is accounting for these phenomena? What in the *simulation* is accounting for these phenomena? For example, there are many alternative ways to *implement* NK, genetic algorithm and agent-based models that can result in subtle, but substantial, variations in behaviour.

Another issue centres on the plasticity of the computational environment, where models may simply be 'mere' *Gedenken* (thought) experiments. In fact, both science and philosophy have a rich history of thought experiments and their contributions (Horowitz and Massey, 1991; Sorensen, 1992). In fact, once a simulation is realized it ceases to be a thought experiment and becomes instead a substantive artefact of – and for – research. The thoughts are in the code. In such a context it may be more appropriate to consider the philosophical concerns of computational social science in general (e.g., Henrickson and McKelvey, 2002).

Perhaps a good place to begin in understanding the role of computational simulations and what they can contribute to strategic management research (and researchers) is John Sterman's Jay Wright Forrester Prize Lecture (2002), in which he notes that bounded rationality limits our ability to understand even the simplest dynamical systems. Through simulations, the complexity of our own theories may be explicated by creating and witnessing and sharing the behaviours of our creations.

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## See also

BEHAVIOURAL THEORY OF THE FIRM; CARNEGIE SCHOOL; LOCAL SEARCH; SIMULATION MODELING AND BUSINESS STRATEGY RESEARCH

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