# Case study and system dynamics research: Complementarities, pluralism and evolutionary theory development

G. Papachristos
Section of Management & Organisation Studies
Department of Mechanical Eng. & Aeronautics
University of Patras
26500 Greece

**Abstract**

This paper explores the complementary use of system dynamics and case study research methodology for process theory development. The rationale for this is provided on the grounds of the limitations of human cognition, particularly in understanding the evolution of complex non linear systems and processes in time. This poses difficulties when attempting to arrive at causal mechanisms for phenomena of interest with some confidence. Viewing research as an evolutionary process where better explanations are continuously sought, generated, selected and retained, simulation can be of use both in increasing the range of alternatives considered and serving as a concrete background against which the selection process takes place, thus facilitating the attainment of a satisfactory level of system understanding. Modelling and simulation has the added benefit of providing a documented artifact through which conclusions are reached and consequently it allows for replication or at least a thorough review.

## 1 Introduction

Research aims at the attainment of sufficient levels of knowledge, through which useful theory can be developed or falsified. The vast array of methods and approaches available reflects the multifaceted nature of phenomena that are investigated. For example, in organization theory (Hatch, 1997), these can be linear or non linear, static or dynamic and single or multi level. Accordingly, one or more methods are applied to their study. This usually takes place either in vivo (the real world) or in some controlled laboratory experiment (in vitro). In the context of organisation theory, the former rather than the latter is most often the case, considering the open ended nature of organizations as entities that exist in a social milieu. Observing a particular phenomenon in reality can only be done once. Once it is over, a repeat is highly unlikely. This is a core difference to the natural sciences where controlled experiments are possible far more often. Consequently this requires that more attention and energy be directed in observing phenomena and as many of their facets as possible, as they unfold. In order to achieve this, the application of a suitable array of methods and/or perspectives is required. In this regard, this paper focuses on two methods used widely in a variety of research areas: case study (Yin, 2003) and system dynamics (SD) modelling and simulation (Sterman, 2000). Adopting the view that models are autonomous and distinct from theory and the real world (Morgan and Morrison, 1999), it discusses the potential for their conjoint use, the advantages and potential complementarities that develop and places them along a three step process of theory development.

Section two discusses case study research methodology and section three explores some of the reasons for its limitations in studying complex system processes. Subsequently, section four looks at the nature of the research process and sets the scene for section five where the benefits that modelling and simulation can confer on case study research are discussed in an evolutionary research context. Section six consolidates some of the points made in section five and relates the characteristics of each methodology to the overall research process. Finally, section seven concludes the paper.

## 2 Case Study Research

Case study research focuses on understanding phenomena (in single or multiple cases), at different levels of analysis. Case studies are rich, empirical descriptions of particular instances of a phenomenon that are typically based on a variety of qualitative and quantitative data sources and perspectives. Yin (2003) provides a generally positivistic approach to case research, and defines it as an empirical enquiry that investigates a contemporary phenomenon within its real life context, where the boundaries between phenomenon and context are not clearly evident. It is also possible to consider a research design in which a generic hypothesis, dynamic or otherwise, is tested in several cases and contexts.

In contrast to experimental research designs that deliberately separate a phenomenon from its context, case studies examine a phenomenon in its real life setting and the influence that it might have. Because of this, case studies often begin without a strong consideration of a conceptual framework, and this provides some flexibility for modifying theoretical propositions, questions or activities as the analysis progresses. Case studies can be used to accomplish various aims: to provide description, test theory, or generate theory (Yin, 2003). For example, in inductive theory development, theory is developed by tracing relationships among postulated constructs and/or looking for the same relationships across cases (Eisenhardt and Graebner, 2007). Of course, there is always the possibility that such theories concern an idiosyncratic phenomenon and as a result further generalization is difficult or impossible. Such a theory can still be testable and valid but its reach will be rather narrow, unlike theories like resource based view, population ecology and behavioural economics (Eisenhardt, 1989).

The article focuses on explanatory case studies. These usually consist of: (i) an accurate rendition of the facts of the case, (ii) consideration of some alternative explanations for them, and (iii) conclusions based on the explanation that has been singled out as appearing to be most congruent with the evidence. In process theory development, the search for an explanation is a kind of pattern matching process between the event sequence as observed and documented in the narrative and that of the explanation considered (Yin, 1981; Abbott, 1990). This is required even for a single case study because the explanation should link all of the factors analysed and relate them in a rational way. In effect the researcher constructs and consolidates a chain of evidence as he conducts the case study and documents it. This chain can consist of particular pieces of evidence, from each stage of research as it shifts from data collection to within-case analysis and/or cross-case analysis and to overall findings and conclusions.

If there is limited theoretical knowledge about a phenomenon, then inductive theory development based on case study research can be a good starting point (Siggelkow, 2007). These can combine qualitative with quantitative evidence. Although the terms qualitative and case study are often used interchangeably (e.g., Yin, 1981), case study research can involve qualitative and quantitative data (Yin, 2003). Moreover, the combination of data types can be highly synergistic. Qualitative data can provide an understanding of the relationships and dynamics that are thought to be in place. This is instrumental in securing the internal validity of the explanation offered about the studied phenomenon. However, just as in hypothesis testing, an apparent relationship may simply be a spurious correlation or may reflect the influence of some exogenous variable on the other two. Therefore, it is important to discover and provide an answer on why the relationship exists. Quantitative evidence can indicate relationships which may be overlooked otherwise. It can also keep the researcher from being carried away by vivid, but erroneous, impressions in qualitative data, and/or it can bolster findings when it corroborates with them. In short, qualitative data can reveal different candidate relationships, or rationales for understanding a phenomenon of interest, or may lead directly to theory which can be strengthened by quantitative support (Jick, 1979).

Subsequently, having identified and described the phenomenon of interest, it is necessary to identify those processes which give rise to it at a level below that at which it is observed, in order to explain it. Thus, it is necessary to identify mechanisms which, given the properties of the constituent elements of the phenomenon and their interactions with the environment, give rise to it in time. In linear systems, this is straightforward and analysis sooner or later points to the phenomenon's source. Where non-linearity is present, such analysis will not suffice, as the mechanisms which give rise to the phenomena cannot be located in the individual constituents but rather are a property of the system elements as a whole. This does not imply, however, that it is impossible to come up with simple explanations of non linear phenomena (Goldspink, 2002).

An approach that integrates these two modes of analysis (multi level and temporal or processual) is said to be contextualist in character. The multi level aspect attends to the causal interdependences between higher or lower levels of analysis upon phenomena to be explained. The horizontal aspect refers to the temporal sequential interconnectedness among phenomena in historical, present and future time. There are a number of characteristics of contextualist analysis (Pettigrew, 1990): (i) the study of change in the context of interconnected levels of analysis, (ii) the importance of revealing temporal interconnectedness, (iii) the need to explore context and action, i.e. how context is a product of action and vice versa and (iv) the absence of linear, or singular causes of change. Indeed narrative approaches cannot be used to identify external singular causes (Abell, 2004; 2001). Thus there is no attempt to search for an overarching grand theory of change, or of how and why a single independent variable causes or even influences a dependent or outcome variable. An awareness of this necessitates the adoption of a critical perspective.

The search for an explanation in contextualist analysis, can be complicated by different temporal patterns that occur at different levels of the process (Lerner and Kaufman, 1985; Abbott, 1990). Time sets a frame of reference for perceiving kinds of changes and explaining them. For example, a firm may be changing more quickly or more slowly than the economic sectors of which it is a part. Thus, it may be difficult to detect the influence of changes of one level on another – a perennial problem for contextualist research. In other words, change and continuity are a matter of time, empirically and theoretically. Any adequate empirical inquiry into change has to be capable of revealing the temporal patterns, causes and movements from continuity to change and vice versa. This involves meeting certain challenges as discussed next.

**Case Study Research As A Decision Process**

Collecting and analysing comparative and longitudinal data on change processes is a complex, social and intellectual task and the resultant accumulation of details can be overwhelming. The process involves cycles of expanding complexity and simplification. Periods of increasing complexity and openness are necessary to gain appreciation of the richness of the subject matter being investigated. Periods of closure and simplification are also necessary for making sense of the data, for structuring them and identifying patterns in them. Subsequently further verification through more data collection can follow.

This alternation between complexity and simplification should provide the reflexive space to reveal the deep seated continuities of historical and social processes and their idiosyncratic untidiness. The end result of this process is a narrative that can include continuity and change, patterns and discontinuities, the actions of individuals and groups and the role of contexts and structures (Griffin, 1993). For the analyst interested in the theory and practice of changing, the task is to identify the variety and mixture of causes of change and to explore some of the conditions and contexts under which these mixtures occur in time (Pettigrew, 1990). Arguments over the true or single source of change, while interesting and even worthwhile in the sharpening of academic minds and egos are ultimately pointless.

Inevitably, at some point in time the results of research must be documented and disseminated – published. A time for this comes when an adequate level of understanding has been built up about a system or a phenomenon, and there is considerable confidence about the conclusions of the research. Whether this point has been reached or not, is a judgement made initially by the researcher. Subsequently, when this work is documented, it is usually subjected to the judgement of peers as well. The iterative nature of research usually entails facing this decision numerous times (Morgan, 1983). A negative decision is reached on the grounds that the work can be improved and provide a better explanation, or more confidence/support, in what is being proposed. This decision is influenced by scientific judgements about the quality and quantity of evidence and theoretical interpretation and it is also bounded by pragmatic considerations about the sequencing of work and the requirements of funding bodies (Pettigrew, 1990). There is no ideal time to write up research.

For example, the issue of concluding data collection and analysis is closely linked to the problem of evaluating the outcome of a change process (Pettigrew, 1990). Change is what the researcher defines it to be in his theoretical framework. Thus it is left to him to explicitly define what is perceived as change, and explain it by research. It is also left to them to stop the ensuing data cycle of increasing complexity and simplification.

**Narrative – Quantification Continuum**

The scientific endeavour oscillates in this continuum, in cycles of data collection and simplification, which can include the quantification and categorization of concepts and findings. The narrative and quantification strategies lie at the two ends of a continuum that opposes empirical accuracy and theoretical parsimony. While the narrative approach leads to theoretical accuracy (Weick, 1989), quantification leads more easily to parsimonious theoretical conceptualizations (simplicity). This is because it abstracts from the original data and replaces the ambiguous, rich and context specific description with precise, and more general indicators-categories with clear boundaries. Accuracy thus is not necessarily the strong point of such theories, even though the gap between the data and the emerging model may be defensible. The advantage of generality needs to be handled with care and having a study properly documented improves its transparency and thus facilitates the validation or falsification of the conclusions of the study.

At the narrative end of the continuum, the challenge is to consolidate the wealth of information of the case in generating insights and answering research questions, while avoiding details that are idiosyncratic to the data. It makes sense for researchers that go into great lengths to collect and compile rich qualitative data and descriptions of processes, to pay more attention to them before transforming this data into a smaller and manageable data set so that the specific is not lost in extracting the general. At the other end of the spectrum, relying solely on quantification strategies, may lose critical elements of process understanding in abstractions so general, that the results obtained may be clear and unambiguous but fairly trite. Thus the quantification strategy gains credibility when some of the context or narrative is retained, that enables interpretation and confirmation of the mechanics of the model. One of the quantification techniques is dynamic simulation (Langley, 1999). It is mainly used for examining the dynamic relationships between events and verifying dynamic theories that involve feedback loops.

The following sections do not focus on the issue of whether models (linear or complex) can represent the true causes of phenomena (natural or social) in the real world. This issue has been explored in depth elsewhere (for example see McKelvey, 1999a; 2002, Goldspink, 2002, Richardson, 2001; 2004; 2005). The issue dealt with in the following section is the ability of humans to infer the causes of the phenomena observed in complex systems by conducting case study research alone, and the value of simulation in relation to that.

## 3 Humans & Complex Systems

Research, consists in defining a system of interest and investigating it. The researcher develops some understanding of its dynamics, its behaviour and what influences it. In the process he develops his own mental model about the system, its modes of change and the problems it faces. This task requires knowledge of the empirical domain, theoretical sensitivity and creativity on the part of the analyst, in order to identify patterns and causal mechanisms. It could be straightforward and thus accomplished in a linear manner were it not for the complexity of the studied systems and their dynamic change processes, and the limitations placed upon their study by the human mind. In other words, in the complex systems view where everything can be considered as endogenous and part of a single overarching system (Richardson, 2005) it is impossible to know the system completely.

Distinctions made between subject and object, outside and inside, exogenous and endogenous, define the boundary of the system and make a difference to the kind of knowledge that can be attained about it (Maturana and Varela, 1980). This is because systems are incompressible i.e. it is impossible to have an account, that is less complex than the system itself without losing some information about it (Cilliers, 1998). This is an important aspect of complex systems for the development of any analytical methodology, or epistemology. Incompressibility essentially means that any system description through a perspective, paradigm, framework, etc. is incomplete. Consequently, any learning and progress in problem solving achieved through a system description is finite and partial. The choice of a particular perspective is dictated by the needs of the analysis – problem, rather than some permanent characteristic of the system itself. It is also dictated by the need to simplify in order to study it because of human limitations on cognition and attention. Therefore, since no single perspective can capture the intricacies of complex systems, analysing problems in them requires two things: (i) the application of a number of perspectives, and (ii) the application of perspectives that are complementary in nature, in recognition of the fact that human cognition is limited.

This pluralistic attitude towards system study is even more necessary in social science research as systems are in continuous flux and boundary definition is even more a subjective matter than in natural science. It presents researchers with problems for research design and theory testing (Goldspink, 2002). Thus the exploration of different perspectives is imperative for the same reasons of system complexity and human cognition limitations. The latter is widely referred to as bounded rationality. The view of humans as boundedly rational individuals has been put forward by Simon (1979, 1982; 2000) and specific aspects of it have been studied, such as the misperception of feedback (Sterman, 1994) and the stock and flow failure (Cronin et al., 2009) i.e. the innate limitation of humans to appreciate processes of accumulation.

**Misperception Of Feedback**

People systematically misperceive feedback among system elements, because the mental constructs that guide their decisions are dynamically deficient (Sterman, 1989a; 1989b). People adopt an "event based open loop view of causality" (Diehl and Sterman, 1995, p198), do not appreciate system delays and feedback processes, and the possibility that the intensity of feedback loops in the system may change. The misperception of feedback hypothesis is supported by studies in experimental economics, psychology and management (Smith, Suchanek and Williams, 1988; Funke, 1991; Brehmer, 1992). The same difficulties in learning have also been studied at the organizational level (Rivkin, 2000).

**Stock And Flow Failure**

Research on the stock and flow failure has shown that people, including those with a background in science, technology, engineering, mathematics or quantitative social sciences, have a poor understanding of how stocks and flows result in accumulation or depletion. Evidence for this is provided in articles that investigate the stock and flow understanding of people (Sterman and Sweeney, 2007; Pala and Vennix, 2005) and the management of common pool resources (Moxnes, 2000). The correct response to stock and flow problems is often counterintuitive, and it eludes even highly educated people with strong mathematics and calculus backgrounds (Cronin and Gonzalez, 2007; Sterman and Sweeney, 2002). People cannot correctly infer that a stock rises (or falls) when its inflows are higher (or less than) its outflows. Instead, people often use some correlation heuristic, concluding that a system's output is positively correlated with its inputs (Cronin et al., 2009).

Despite the fact that accumulation is a ubiquitous process that is present in most temporal, spatial and organizational scales, people perform poorly even in simple dynamic systems with no feedback processes, time delays, or nonlinearities, including systems consisting of a single stock with one inflow and one outflow (Sweeney and Sterman, 2000; Cronin and Gonzalez, 2007). The level of human performance is not a result of limits on working memory, capability of mental computation, ability to read graphs, time constrains, or subject motivation. It is also not related to the attribute of the task, or the context or volume of data. Data presentation in numbers, text, tables, or graphical displays (bars or graph lines) does not alter the results. The stock–flow failure is a robust phenomenon that results from a failure to apply the basic principles of accumulation.

Instead of these a range of inappropriate heuristics is employed. Research in human dynamic decision making shows that people have great difficulty in understanding and managing dynamically complex systems i.e. systems with multiple feedback processes, time delays, non-linearities, and accumulation processes (Sterman, 2002). Furthermore, learning in dynamic systems that would lead to improved performance is often slow and weak, even with repeated trials, unlimited time, and performance incentives (Kleinmuntz and Schkade, 1993; Sterman, 1989a; 1989b). Bounded rationality places a limit to human cognitive maps and the extent to which these can be used to correctly infer the behaviour of a system. Inevitably these insights are of limited value. In order to achieve effective learning both of these limits must be overcome (Sterman, 1994). Even in the case that a correct understanding of the system could be achieved relatively fast, it would be difficult for people to transfer the lessons learned from one domain to another, even in the case where the structure of the task structure is isomorphic (Sterman, 2010).

The implications of this phenomenon are significant since accumulation processes are ubiquitous. Failure to appreciate its dynamics can result in erroneous inferences about the causes of system behaviour, or their timing. This could lead the research endeavour to an early conclusion, or produce an insufficient set of causes for the systems behaviour. In either case the learning about the problematic situation will have been compromised. Effective approaches to learning about complex dynamic systems require (Sterman, 1994): (i) tools to describe and frame issues, extract knowledge and beliefs from relevant actors in order to create maps of the feedback structure of the issue, (ii) formal models and simulation methods to explore and evaluate the dynamics of these maps and test intervention policies, and (iii) methods to sharpen scientific reasoning skills, improve group processes, and overcome defensive routines for individuals and teams. These requirements must be satisfied in order to enhance the capability of individuals to learn and operate effectively in systems, or improve their design.

**System Design & Interventions**

Simulation is important for another reason as well. Humans learn through feedback generated by their actions. In natural sciences this is accomplished through experimentation. But in social systems real world experiments for policy making are impossible in many cases or are quite costly. In addition the effects of the implemented decisions may take considerable time to manifest. Therefore simulation should be considered as a means to discover how complex systems work and where high leverage points for intervention may lie (Meadows, 2008). However, there are no methodological short cuts to the task of searching for good candidate theories and explanations. There is very little value, if any, in drawing insights from simulations of poorly understood systems. What should be sought after is a model along with a plausible explanation of why it displays a behaviour similar to that observed in reality (Lane, 2008). The inevitable cyclicality in this statement should not be discouraging since in this paper it is not argued that either understanding or simulation unilaterally drives the other.

The understanding of change phenomena and particularly change towards sustainability, is even more important when it comes to policy making (Sterman, 2002). This is where recognizing the limits of our knowledge, and the ''inevitable a priori'' assumptions that lie at its roots can make a difference when acting based on our mental models (Meadows, 1980). If people are to become willing to adopt a new perspective, and change their assumptions about the world and their deeply entrenched behaviours, they must first see the constrains of their current beliefs. In this respect the value of simulation lies in improving human intuition about system behaviour and finding ways of overcoming policy resistance.

**Effective Learning And Simulation**

Following on from this it is obvious that effective learning involves two challenges: (i) constructing meaningful system representations from which the dynamics of a system can be inferred, and (ii) deciding when a satisfactory level of learning about a system or a phenomenon has been achieved in order to draw insights and document conclusions. Deciding on when a level of effective learning has been reached is a subjective judgement by the researcher (or those concerned), a human, that uses mental constructs and processes to analyse a system. The research effort stops when the level of understanding of the phenomenon or system, is judged as sufficient in order to generate with confidence, an adequate and satisfactory explanation of the phenomenon under investigation. However, this faces serious limitations: all individuals enact them in their cognitive processes. It is logical to extent this to research and hypothesize that it is equally difficult for researchers to learn about larger complex systems that involve human interactions.

Even if researchers could learn perfectly from their environment, they can learn only as fast as events unfold. Subsequently they have to reflect upon them and update their mental models about the world. There are two limitations to this: (i) humans observe only one modality of the behaviour of systems at a time, the one that actually manifests, and (ii) when it comes to processes that unfold on different time scales (several decades), it is almost impossible to update mental models in any meaningful way, simply because it is impossible to observe how the whole process unfolds. Even when it is possible to attain such a level of knowledge, it would be available only after the process itself, by which time it would be rather late to apply it meaningfully because, as said colloquially, experience is something acquired only after it is needed.

Consequently, for useful learning to occur, individuals have to close the loop from their mental models to reality and back (with all the limitations discussed), relatively quickly to the rate at which actual events and processes unfold in reality (Figure 1). Yet, in the real world, particularly the world of social action, closing this feedback loop can be a long and ineffective process (Sterman, 1994). This is inevitable when observing path dependent systems far from equilibrium. It is hard to control for certain variables in order to discern cause and effect (causal ambiguity). Thus learning is slow and less is learned going each time around the loop. Sometimes it is just not meaningful to set up experimental settings or isolate the effect of the variable of interest. "Systems happen all at once" (Meadows, 2008, p5) therefore it is necessary to study the system as a whole. This is where simulation has an advantage as the creation of experimental settings of greater inclusiveness in silico can be advantageous to conducting experiments in vitro or in vivo. This comes at the expense of attending to detail but for studying a system's behaviour, inclusiveness of causes takes precedence over detail (Sterman, 2000).

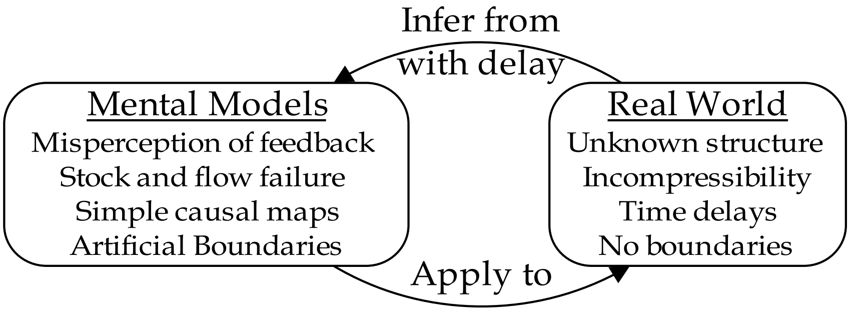


Figure 1. Feedback between reality and mental models (adapted from Sterman, 2000)

In summary, case studies offer a rich description of real world phenomena and the context in which they occur. However, when it comes to understanding and learning about nonlinear and complex processes, conducting case studies based on human cognition alone is insufficient. This is where modelling and simulation can contribute, by isolating the phenomenon from its context and abstracting the causal mechanisms, in effect creating a laboratory experiment for learning and changing the mental models of humans. Taken together with a roadmap of how computational modelling can be applied for theory development (Davis et al., 2007) they provide a conceptual outline of how to develop a good computational laboratory.

There is a range of models with which different social phenomena can be studied. For example, organizational learning, decision making rules, search, innovation and imitation processes and organizational design (Burton and Obel, 2011; Carley, 2009). Hence, empirical data gathering and field or laboratory case studies can be utilised to construct an initial range of alternative explanations for a process or phenomenon. Subsequently, computational models can be used to corroborate this evidence, and expand the mental models of researchers by offering a means to articulate more elaborate explanations, explore system boundaries and in effect venture beyond that which can be learned otherwise (Goldspink, 2002).

Since case study and modelling and simulation capture different aspects of the phenomenon under study, the results of both methods can be juxtaposed to deepen the insights and broaden the understanding of the system (Mingers and Brocklesby, 1991). The effectiveness of the complementary use of case study and simulation is based on the assumption that the strengths of each method counter the weaknesses in the other and that these differ between methods (Jick, 1979). It is also suggested by the discussion so far that only convergent inferences about the same problem from different methods really constitute knowledge, the basis for formulating and refining theory (McGrath et al., 1982).

## 4 Theory Development & Disciplined Imagination

Theory development takes place by an individual researcher (or group), and it may concern phenomena at spatial and temporal scales smaller or larger than the human scale. In conducting research, the researcher learns something about the system of interest. This involves the development (or alteration) of his mental model as he progressively comes to grips with its behaviour. The end result is an understanding of the system and explanation of its modes of behaviour under given conditions with a certain degree of confidence i.e. a theory about the behaviour of the system.

In creating useful theory a number of choices and simplifications with regard to the phenomena of study has to be made (Siggelkow, 2007). Starting from different assumptions a range of different explanatory attempts are usually made. Then the researcher evaluates their plausibility by looking in depth at the available evidence, and creating a convincing narrative in order to illustrate the rational behind each proposed theoretical mechanism for the phenomenon under study. Consequently, theory development involves the design, trial and interpretation of thought experiments in which explanations under different perspectives are tried out. This in essence, is an evolutionary process of generation and selection among a variety of different explanations at the level of the researcher. It has an artificial dimension as the theorist intentionally selects or rejects them. It can be driven by abstract mental activity (thought experiments) or peer review. There is also a natural selection dimension to it through empirical tests and application in the real world. Finally, that which survives the selection process is retained provisionally as a plausible theory. It is assumed that through this process, the explanatory strength of theory is increased. In this conceptualization of research process, learning and theorizing are construed as the outcome of a cumulative process where a number of theoretical schemes and/or mechanisms that have some correspondence to their assumed ontological referents, goes through a selection process (Weick, 1989). Through this, the researcher aspires to reach a level of understanding about the system so that he is in a position to make an inference about the behaviour of the system under certain conditions.

However, if inferences about systems at human spatial and temporal scales are erroneous as discussed, then it can be safely assumed that it also holds for making inferences in any other scale. The implication is that the research effort is fraught with difficulties as: “the theorist is overloaded by demands to run a miniature evolutionary system in a head that suffers from bounded rationality. That load reaffirms the value of working toward theories of the middle range.” (Weick, 1989, p529). The demands of theory development from a rationally bounded individual, necessitates the exploration of the use of simulation and thus the adoption of different perspectives in developing a range of possible explanations to phenomena.

Theory development, as a selectionist evolutionary process at an aggregate level has been treated elsewhere, therefore this is not addressed in detail here (Cambpell, 1979; 1985; 1988; 1997; McKelvey, 1999b). Instead, the following sections take a view at the micro – individual level of theory development and the role of modelling and simulation.

**Simulation & Theory Development**

One of the obvious uses of computational models is to aid in theory construction or explore processes for which there are no well established theories (Davis et al., 2007). In addition models are a way of implementing theories about phenomena that have been derived based on observations but cannot be applied (the big bang theory for example and application of fractals in silicon graphics applications) (Morgan and Morrison, 1999). In every case, the construction of the model involves more than the mere translation of theory and an abstract representation of reality. Validating a simulation model is directly related to the epistemic status of the knowledge it incorporates and is one of the central epistemological problems of computer simulation methods (Kuppers and Lenhard 2005). A model is partially independent from theory (or mental models) and from real world phenomena, i.e. there is no one to one correspondence with either of them. It is an intermediary artefact between theory and the world that can be used in a variety of ways to explore them. In this capacity it can be considered as part of the learning process. This conceptualisation is shown in the following figure.

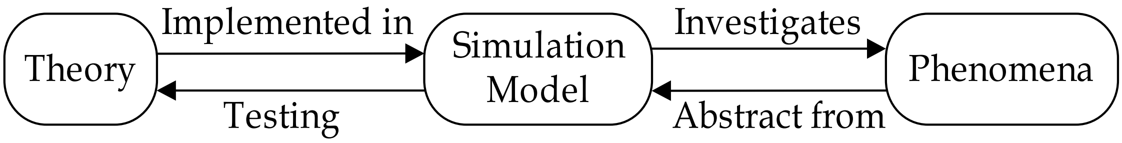


Figure 2. Theory, simulation models and real world phenomena

An important requirement in developing theories from case research, is the demonstration of their validity. This involves meeting the criteria of internal validity, construct validity, external validity, and reliability (Gibberr et al., 2008). A characteristic of published research in the top management journals for example, is that authors report and demonstrate on how they meet each one of these criteria. Modelling and simulation can be of use in meeting some of these criteria.

**Internal Validity**

This relates to the causal relationships identified or proposed after analysing a case study. It is imperative that the researcher provide some logical argument for them and demonstrate that they are plausible in order to support his research conclusions. It follows that internal validity is built in the data analysis phase of the study (Gibber et al., 2008). Internal validity must be aimed for from the outset, by formulating a clear research framework to enable the demonstration of outcome y as a result of a variable x, and avoid overdetermination or underdetermination. In order to arrive at underlying theoretical reasons for why the relationship exists between the ontological constructs, the case data must provide a good understanding of the dynamics that underlie the relationship. Then the internal validity can be assessed by comparing observed patterns to those derived from candidate theories or those inferred from other case studies (Denzin and Lincoln, 1994; Eisenhardt, 1989), or by looking at the data from different research perspectives which can involve different methods (Mingers and Gill, 1997; Yin, 1994) or different scientific paradigms (metatriangulation) (Gioia and Pitre, 1990;).

Nevertheless, metatriangulation is not a substitute for single – paradigm theory building, but rather an alternative for exploring complex phenomena from disparate theoretical and epistemological perspectives. It should be viewed as an extension of established strategies aimed at enhancing the potential insights available from existing literature, data, and the researcher's intuition. Metatriangulation follows many of Weick's (1989) prescriptions for building theory using "disciplined imagination," deliberately and dramatically increasing the quantity and diversity of literature reviewed, of analytical methods used, and of conjectures examined (Lewis and Grimes, 1999).

The role of simulation in enhancing the internal validity of case study is in providing a further test for the causes that are thought to generate the observed system behaviour and thus increase confidence in the research conclusions.

**Construct Validity**

Construct validity is a measure of the quality of the conceptualization or operationalization of the research design constructs. It reflects the quality of work in the data collection phase and consequently the extent to which an accurate observation of reality has been made, through the applied research process (Denzin and Lincoln, 1994). The construct validity of a case study can be improved in two ways: (i) by providing a clear chain of evidence to allow readers to reconstruct how the researcher went from the initial research questions to the final conclusions (Yin, 1994), and (ii) by studying the phenomenon from different angles, using different data collection strategies and sources.

Simulation can be of value as the documentation produced in the model development phase of a model, can provide at least part of such evidence. Following the methodology of any modelling method results in the construction of documentation and diagrams (apart from the model itself). Documenting a model while developing it, is a standard practice in every simulation method that includes documenting the assumptions, abstractions, producing flow charts or causal diagrams, producing variable descriptions and assigning units for each one. These can function as intermediate objects (for example causal loop diagrams in SD) from data collection to inference of the system's behaviour and conclusions and can facilitate better the reconstruction of the path the researcher followed. They provide an insider's view into the decisions and the process the researcher followed from data collection to research conclusions. They can thus function as a further means of communicating theory development process (Goldspink, 2002). For example, in SD modelling the construction and presentation of causal loop and stock and flow structure diagrams of the model is standard practice. It can be used as a guide post for other researchers to understand how the researcher progressed from an initial research question through data collection to final research conclusions (Homer and Oliva, 2001).

**External Validity**

External validity, or 'generalizability,' indicates the extent to which theories or insights derived from research, are valid in a broad range of contexts. While it is not possible to generalize using statistics, from a number of firm case studies to the population of firms in the same industrial sector (Yin, 1994; Numagami, 1998), it is possible to generalize from empirical observations to theory. Conducting a cross study of case studies ranging from four to ten, can be the basis of theory development (Eisenhardt, 1989). It is also possible to conduct multiple case studies of the same empirical setting instead of conducting and analysing multiple case studies of different ones. The possibility of using simulation here lies in the identification of causal mechanisms that generate the observed pattern of each case study so that both mechanisms and generated patterns can be compared. This would allow both identifying common mechanisms at work and corresponding similarities in patterns. On a meta level, the use of a model, specific to a case, would allow the researcher to state whether there is a common mechanism across case studies or not and thus reinforce analytical generalization.

System dynamics methodology includes tests for checking the external validity of a model in order to determine whether it is a model of a class of systems to which the particular one belongs (Sterman, 2000). This test involves checking whether the model can reproduce the range of behaviour that are specific to the class of systems (hence the name family test). This kind of generic model that produces a common behaviour pattern across documented cases is called canonical situation model (Lane and Smart, 1996). For example a model of Bass diffusion should be able to generate more than the classic S-shape adoption curve. In reality products may fail, or may be in fashion for a while but never be adopted. A canonical innovation model should be capable of capturing these patterns.

**Reliability**
High reliability is testament to the absence of random error in research, that enables researchers to repeat it and arrive independently at the same insights and conclusions (Denzin and Lincoln, 1994). The key attributes for case study reliability are transparency and replication. Transparency requires the careful documentation and clarification of the steps of the research process, in effect reporting how it was conducted. The supply of documentation (case study documents, and the narratives collected during the study) along with other supporting material, also facilitates replication (e.g., Leonard-Barton, 1990). In this respect a working model can function as an additional record of how the research was conducted (because it entails following a specific modelling methodology), and as concrete link between the data, the theory and the operationalization of its constructs.

Replication of work and results is a necessary step in scientific progress and has been mostly absent from organizational research (Jick, 1979). Replicating a qualitative case study is not something attempted very often. Qualitative methods are problematic to replicate. On the other hand, quantitative methods are not when properly documented. In principle model documentation enables the replication and verification of its results and consequently the insights and causal explanations proposed. Furthermore it enables the application of the same model in a different context, thereby testing its generality. An added benefit to facilitating replication is that documenting the limitations of the case study and having a simulation model, provides a solid ground for further research and theoretical refinements. Here SD has an advantage as the range of software tools is more limited and model documentation is fairly standardised compared to agent based models (Schieritz and Milling, 2003). Most crucial is the fact that formal structural and behavioural validation procedures are available for SD modelling (Sterman, 2000). Despite efforts at constructing a general framework for designing, testing and analysing agent based models, for example in ecological modelling by Grimm et al. (2005) and Grimm et al. (2006), there seems to be no widely accepted framework yet (Richiardi et al., 2006).

# 5 Simulation For Evolutionary Theory Development

In order to argue for the benefits of modelling and simulation, the research and theory development process is conceptualised in three steps of variety, selection and retention. Modelling and simulation can offer specific benefits in each of these steps. This implies that it can be used in parallel with case study research.

Modelling in order to study a problem, always involves making a judgement about system boundaries i.e. how wide is the range of potential causal factors involved, considering the temporal nature of the phenomenon as well. Recognising this, highlights the fact that studying a system as a closed entity inevitably narrows its scope. Since all boundaries are transient (given enough time) and complex systems are sensitive to small changes (Richardson, 2005), boundary definition is important and it reflects the assumptions made, particular analysis needs, and aims rather than the systems themselves (Cilliers, 1998). In fact, a more accurate phrase is exploring their boundaries for the best way to draw them. This is particularly important in longitudinal case studies.

Simulation is an obvious tool with which to engage in exploring the implications of different system boundaries. It is an integral part of its methodology. For example, in SD it is called family member testing (Sterman, 2000). It can also facilitate the generation of a range of candidate alternative explanations by alternating the assumptions, the generative mechanisms and thus the boundaries of the model. Hence, the heterogeneity of the researcher's thought experiments is expanded beyond his individual capacity. Finally, selecting among them is easier since visualisation and quantification with simulation allows the consistent application of criteria or even the application of more diverse criteria. A characteristic that allows the parallel use of case study and modelling and simulation is the search for an explanation. It is an iterative process both in modelling and simulation (Sterman, 2000) and in case study research (Yin, 2003). Therefore the cycles of iteration in both methods, can follow from and feed to one another as shown in the figure below.

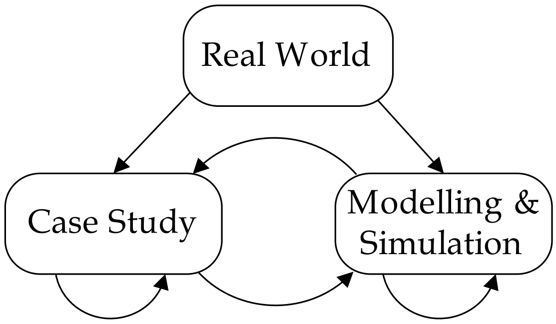


Figure 3. Iteration between case study and modelling and simulation

This diagrammatic depiction of the research process is discussed next in terms of the steps it involves. In each one a description of what it involves is followed by the relevant benefits of the application of modelling and simulation. Following Weick (1989) theory development process thus is viewed in terms of what simulation has to offer, in: (i) stating a problem by making explicit assumptions, increasing the accuracy and detail of the representation and making representation more detailed, (ii) formulating thought trials by increasing their number and heterogeneity, and (iii) selecting among thought trials by applying criteria consistently and simultaneously or applying more diverse criteria. It is thus argued that it provides an auxiliary means for the researcher to run a mini evolutionary system (Weick, 1989) and thus offers an increased possibility of seeing (Siggelkow, 2007. p23): "the world, …, in a new way." which is what is really sought in theory development.

**Step 1: Creating An Explanation Of Observed Patterns**

A necessary step to process theorization, i.e. the challenge of taking an ensemble of data and arriving at a theoretical understanding is postulating explanatory mechanisms for the process (Van de Ven, 1992; Langley, 1999). Analysing and developing theory about interdependent processes that generate non linear patterns is demanding. This is the case even when each one is understood separately, as the whole can be greater than the sum of its parts. Thus the empirical analysis of processes with complex interactions that include feedback has limited value, particularly when data are hard to obtain or are simply non existent (Harrison, 2007). Analysing this ensemble of data may not suffice for pattern exploration, and modelling and simulation may be necessary in order to really explore patterns and develop an understanding about how the world works (Sterman, 1994). However it is crucial that the data are not stripped of their richness, dynamism and complexity.

Simulation and modelling provides a powerful methodology for research on complex system behaviour. Modelling involves identifying the key underlying processes for the behaviour of the system and their pattern of interaction. Subsequently, these are formalized as mathematical equations or sets of computational rules that can be simulated. An advantage to the process is that the construction of a model is not bound to data availability. Consequently modelling and simulation can proceed, even when there are very little or no data to ground it on. It can even be used to explore the dynamics of theoretically postulated processes, even when there cannot be any immediate empirical assessment (Harrison et al., 2007).

A further benefit of simulation is the theoretical rigour it introduces in the research process. A phenomenon may appear to be well understood, but an attempt to specify an equation for it often exposes gaps in this understanding and may open new research avenues. The discipline of formalizing a process, forces researchers to face issues and assumptions they may have acknowledged but vaguely addressed, or perhaps not even recognized. Thus the minimum contribution of formalization is the emphasis on addressing this category of issues both in theory development and empirical work, and subjecting them to analysis and refinement (Harrison et al., 2007). In other words, simulation can help capture a more complete, holistic and contextual portrayal of the system under study. Coupled with case study research it can help the researcher probe further into the system's behaviour. Consequently, the use of more than one methods, can offer more than just a way to enhance the reliability and validity of research (Jick, 1979) as outlined in previous sections. The combination of case study and modelling and simulation does justice to the richness, dynamism and complexity of social phenomena while it remains understandable and useful to others with the added benefit that the codified model can be reproduced and enhanced for further research by others.

Nevertheless, postulating underlying causal explanations, is not sufficient (McKelvey, 2002). For scientific progress requires that the research arrives at the best possible set of causal mechanisms. This involves generating (step 2) and evaluating a set of alternatives (step3).

**Step 2: Imagining Alternatives**

The immersion in rich case data enables the use of cases as inspiration for new ideas and the development of alternative theories. This step entails making and varying assumptions, hypothesizing a range of relationships between explanatory variables and/or creating a range of different representations of the system based on different ontologies. Rather than holding onto a single perspective or theory, and trying to stretch it to fit the data, it is generally better to develop and juxtapose alternative perspectives, and then determine which theory better explains the data (Mitroff and Emshoff, 1979). The probability of arriving at a satisfying explanation, increases with the number of theoretical variations that are generated and tried out, and with the number and diversity of the selection criteria, that are applied to them.

This step can be conceptualised as the preparation and conduct of experiments with the aim of understanding a phenomenon and finding plausible causes. Here lies a fundamental constraint as this process of disciplined imagination takes place in the mind of the researcher (Weick, 1989), a boundedly rational individual (Simon, 1982; 2000). Inevitably, researchers are both the source of variation and the source of selection. They need to assert the consequences of theoretical arguments and assumptions they make, generate alternative explanations and hypotheses, and test the validity of proposed explanations. The exposition of the fallibility of human judgement in the previous sections points towards the use of modelling and simulation for extending the cognitive capacity of the analyst in running the mini evolutionary system of competing theories.

Modelling and simulation can facilitate this process of generating and testing the validity of a range of candidate explanatory mechanisms in replicating a phenomenon (Harrison, 2007). In effect this involves asking what if questions (Burton and Obel, 2011; Oreskes et al., 1994). The development and use of a simulation model and subsequently the analysis of its displayed behaviour, provides an unambiguous expression of a theory and at the same time it is a test of its ability to reproduce behaviour patterns (Lane, 2008).

**Step 3: Evaluation, Selection & Retention**

The third step involves addressing the ontological adequacy of the phenomena to model relationship, as well as selecting one among many alternative candidate explanations (McKelvey, 2002). This is a milestone as it allows for a temporary stop to the research process, in order to document the results and conclusions. This judgement should be made based on the criteria of parsimony, testability and logical coherency and on how well the model represents and accounts for the real phenomenon i.e. explanatory power (Pfeffer, 1982). Selection should also proceed by considering counterfactuals i.e. situations where the postulated causal mechanisms are tested for the possibility of generating some non plausible behaviour pattern. The complementarity with case studies is that it is possible to test for counterfactuals (Griffin, 1993) something that usually is not done with modelling and simulation. For example, the logic for constructing causal loop diagrams it to connect causes to manifest effects thus not addressing at least explicitly the possibility of counterfactuals. In addition the mechanisms under investigation, should not overdetermine or underdetermine the phenomenon under study, i.e. the proposed theory should include the necessary and sufficient, non unique causes for generating it. Ideally, the variables the model involves should be easy to operationalise and inform with real world data. This is an additional criterion that can be utilised especially regarding for policy making.

While it is possible to evaluate the parsimony and testability of theory, the requirement of internal logical consistency and over/under-determination is harder to assess based on a case study alone due to bounded rationality. In addition it involves some form of boundary exploration. Modelling and simulation provides a heuristic with which to accomplish this and increase the confidence in deciding between alternative truth claims as well as for substantiating theoretical validity (Goldspink, 2002). This is possible with models as they embody propositions which can be refuted logically or empirically, provided that the modelling methodology has been followed rigorously i.e. assumptions have been made explicit and the model has been submitted to adequate tests for validation (Barlas, 1996; Sterman, 2000).

Consequently, this allows its use for determining the range of conditions under which the proposed mechanisms are valid, and thus control for nomic necessity i.e. that (McKelvey, 1999a, p21): "one kind of protection against attempting to explain a possibly accidental regularity occurs when rational logic can point to a lawful relation between an underlying structure or force that, if present, would produce the regularity". In other words, modelling approaches enable a plurality of representations that can be compared by simulating them (Kuppers and Lenhard, 2005). This improves the comprehensiveness of the explanations considered and the end result will be a better explanation and a better theory. It is not possible to do this to the same extent mentally.

**Pattern Matching**

In theory development, it is possible that both an inductive and a deductive approach are utilised. In their combined use, some kind of pattern matching principle is used. The matching of patterns deduced from theory and patterns derived from observation, yields greater theoretical validity. Process theory development through case studies, provides explanations of a phenomenon or behaviour based on the series of events that drive it. Understanding these events is central to developing or improving process theory. Their sequence, their nature, and the way they interact (stochastic, deterministic, reinforcing or counterbalancing) is important (Mohr, 1982). Drawing on the raw data of the case study, to form an explanation of how events interact, requires analysing them, and their interactions in terms of the behaviour pattern they generate. The difficulty lies in that processes are not solely composed of discrete events and temporal phenomena. A range of other qualitative and quantitative information is usually required to create a complete pattern of how a process evolves.

One technique employed to explore this ensemble of data or for proposing theoretical patterns for consideration in subsequent studies, is pattern matching. It requires a theoretical pattern of expected outcomes, an observed pattern of effects and an attempt to match the two. The observed pattern encompasses the ensemble of collected data and their interrelationships. Depending on the level of noise of the real data, it provides a way of generating a description that contains less than the total description of the system, while still reflecting some fundamental understanding of it (Richardson, 2005). The theoretical pattern embodies a hypothesis about the expected behaviour of a system based on the relevant theoretical concepts and their interrelationships. Both patterns can comprise verbal descriptions, diagrams or a set of mathematical expressions. The idea is that the observed pattern is compared with that derived from the postulated explanatory mechanisms for the process (Trochim, 1989). It resembles hypothesis testing and model building approaches. Because of the range of forms allowed, detailed or complex hypotheses can be studied, from a multivariate rather than a univariate perspective.

If the two patterns match, then this increases the probability that the proposed theory explains the phenomenon. It is also important to demonstrate that there are no plausible alternative theories or explanatory mechanisms that account for the observed pattern. This requires that a series of plausible explanatory mechanisms be generated (step 2) and rejected (step 3) if they don't generate the expected pattern. Modelling the postulated explanatory mechanisms and simulating them is a rigorous and systematic way of implementing pattern matching. Such an approach has been explored for example in SD where the behaviour of the model is compared to the observed pattern of the real world (Barlas, 1989).

If there is no match, then the researcher should attempt to reconcile the differences by refining its explanation or searching for alternatives. In the process, the obscured dimensions of the phenomenon may be uncovered, for example by using simulation to focus on the timing of interactions among system elements. These additional viewpoints can produce insights discordant to the widely accepted theory and thus offer the opportunity to search for better explanations and refine them as in the case of Sastry (1997). Examples of such pattern oriented modelling applications exist in other scientific domains as well, for example in ecological modelling (Railsback and Johnson, 2011).

**Timing Of Interactions**

The analysis, comparison and explanation of patterns (empirical or theoretical) is incomplete without setting a reference time frame. Adopting different time frames can make phenomena appear incremental or abrupt. Therefore, any attempt at explaining them has to reveal also how they unfold in time and how events perturb the system as they may cause a different response at different time instances. Consequently, when looking at observed and proposed (postulated) patterns of processes through time, apart from matching the geometric pattern (change/stability), their timing must also be matched, i.e. the observed phenomenon and that derived from the postulated mechanisms must arise in the same point in time.

This requires tracing events over time and compiling the narrative of the case in a temporal sequence. Narratives are inherently longitudinal and they are likely to involve many different types of data and variables and not limited to a single independent or dependent variable. Whether it is explicitly constructed or implicitly assumed, the utility of this sequence lies in investigating and determining the causality of events from the start of the phenomenon to finish. The analytic goal is to compare the observed sequence of events, with that predicted by some explanatory theory. Evaluating the match of the two patterns in terms of timing entails observing the following conditions (Yin, 2003):

- Some events precede others while the reverse is impossible.
- Some events occur contingent on others.
- Some events can only follow other events with a pre-specified delay.
- Certain types of events occur only during specific time periods.

Locating events temporally involves a further complication in that different kinds of events can be found at different levels of analysis (Lerner and Kaufman, 1985; Abbott, 1990). While the validity of the temporal pattern of observed events is given, the validity of the theoretically derived pattern in terms of time has to be demonstrated. Drawing on an analogy from biology, the evolution of a single organism can occur at a different pace than that of the wider group and/or species to which it belongs. In organizational studies, a firm adapts to its environment at a different pace than the entire business sector it belongs to. In general the pace of events at a single level, influences the pace of processes at another. The demonstrated limitations of humans on making inferences about temporal processes that occur at a single level of analysis obviously necessitates resorting to auxiliary methods for analysis of multi level phenomena.

**From Narrative To Model And Back**

The model of the game of avalanche (Lane, 2008) provides an exemplary case, of selecting among competing explanatory propositions as suggested by Weick (1989). It illustrates that purely verbal explanations cannot always give an adequate account of some social phenomena even when cause and effect are temporally and spatially proximal and real life experiments can be conducted. Apart from being used to learn something valuable about team building and self-organization, modelling and simulation can also support the process of scientific discovery in the social sciences. Several verbal accounts can be produced as explanations of what happens in the game. However, if they remain verbal then their degree of plausibility is limited with no direct means of choosing between competing arguments and explanations. Although an open ended inductive research approach, offers considerable potential for theory development, facing the uncertainty of selecting between alternative arguments and explanations may potentially delay the decision on when a satisfactory explanation has been constructed. Generating one is different than actually recognising one.

When the model can reproduce the phenomenon of interest then the focus of the research process can move from data collection to system analysis and conclusions. Obviously the same logic applies in exploring alternative explanations (step 2) or when the one originally considered is refuted. In either case, the model can provide some guidance as to the amount and kind of data required to proceed further. In this respect, the construction of a simulation model provides an additional means to the decision making involved in research and the data collection process. This in effect follows from the perspective that theory guides observation (Chalmers, 1982; Sterman, 2000).

The rationale is that in postulating explanatory mechanisms for the behaviour of the system, the researcher initially has a rough idea about the kind of data that are required to support his claim. However, as the system description is progressively enriched, it becomes difficult to see how structure may be linked to behaviour and where research should be focused. Relying solely on narrative descriptions and mental experiments faces limiting returns. Shifting from case study description to modelling (figure 3), entails moving from detailed, accurate description to simplification and thus reveal the system structure that is essential to its behaviour. It can also provide insights into whether more should be added or included in greater detail and thus provide guide posts for further case development and hypothesis refinement in an iterative manner (Homer and Oliva, 2001). In this way the modelling is construed as a heuristic reflective process for furthering the study of a phenomenon rather than the end to a process (Oreskes et al., 1994).

A central characteristic of case studies is the use of qualitative data along with quantitative. Any simulation method can handle numerical data. However, if qualitative data are not to be excluded, they have to be included somehow with soft variables. There are ways to address this issue in various modelling methodologies. For example any textbook on SD covers the principles and offers guidelines for modelling decision making and human behaviour, and for formulating nonlinear relationships, including soft variables (for example, Sterman, 2000). The use of soft variables in SD simulation covers a wide range of applications in management and social sciences (Sterman 1985; Oliva and Sterman 2001; Sastry, 1997, Rudolph and Repenning, 2002). A model can also be constructed precisely because real data about a system may be unavailable. In this event a simulation can function as a source of data about the world (Winsberg, 2006).

Notable examples of using simulation for developing process theory include Cyert and March (1963) (behavioural theory of the firm), Cohen, March and Olsen (1972) (garbage can model of organizational choice), Sastry (1997) (formalization of the punctuated equilibrium model of change) and Lant and Mezias (1992) (organizational learning). These models exhibit considerable simplicity and generality but are generally weak in terms of accuracy. They may utilise real data that were collected at some time and inspired the ideas behind the model. These models have several advantages. They provide a virtual laboratory for risk free experimentation assuming that their basic assumptions are intuitively reasonable. The disadvantage of not relying directly on real measured quantities has the benefit that they enable the study of theoretical constructs that are unobservable in reality (for example managerial energy in the garbage can model). Third, they may question aspects of, and/or allow the detection and correction of inconsistencies in existing theoretical frameworks (eg Papachristos, 2011, Sastry, 1997). The greatest strength these models exhibit is to demonstrate how a small set of plausible mechanisms, can generate the complex behaviour patterns that are observed in reality.

A benefit in the combined application of the research strategies under consideration, is that generating a case study narrative is not only intended as a stand alone description of phenomena or as input for models and outlining phenomena. It is also of value in evaluating and contextualising the results of the model (Winsberg, 2006), interpreting and evaluating their implications because the resultant type of knowledge is itself complex and is a statement of options and their constraints (Pidd, 2004). This point is of particular relevance when it comes to modelling social systems. In this case, it is not possible to restrict the evaluation of the model to results available in a numerical form, in order to evaluate the fit of a mode to the real system behaviour. Considerable relevant knowledge is in descriptive, qualitative form, contained in the experience of those that have conducted a case study of the system and are familiar with its history of performance and artifacts (Randers, 1973).

Extending the argument further, communicating a theory or model requires eventually reverting to narrative to some extend (for example the IPCC scenarios). Thus the feedback between real phenomena and model closes where the real world narrative overlaps with the generated model behaviour (Goldspink, 2002). This is directly relevant to the correspondence of the model to the actual real world patterns. Demonstrating this, is not really a case of comparing numerical results to reality, because as argued forcefully by Oreskes et al. (1994) this is not possible. Assessing the results of the model and their validity, is an empirical task and this leads to iterating cycles between validation and experimentation, case study and modelling (Goldspink, 2002). A measure of the correspondence of the model to the world is provided by the extent to which description and model generated behaviour patterns match.

The iterative process (steps 1 to 3) involves matching of patterns and their timing and can come to a conclusion through a number of ways. The creativity in applying different perspectives naturally may diminish, or some of the perspectives may converge in a way that points towards a satisfactory explanation, or a particular perspective may emerge as the dominant one among others (Richardson et al., 2001). Thus the end of the process does not necessarily come with the arrival to a single dominant explanations. In complexity based analysis a more democratic rather than authoritarian or imperialist style of research is the norm (Flood, 1989) allowing room for quantitative, qualitative or intersubjective viewpoints.

The three steps outlined, emphasize the continuous refinement and development nature of theory development process. They are at the core of case study research which requires the rich, detailed qualitative description, but it is also at the core of modelling and simulation methods, for example system dynamics (Homer, 1996). The search for an explanation is an iterative process in modelling and simulation (Sterman, 2000) and in case study research (Yin, 2003). Thus they can be applied in parallel rather than in a serial manner for identifying and developing further generally applicable causal structures. These, derived from the experience gained in one dynamic situation, can then be transferred to another (Saysel and Barlas, 2006; Paich, 1985; Senge, 1990; Lane and Smart, 1996; Wolstenholme, 2003). The conceptualisation developed in section 4 and 5 is illustrated in figure 4.

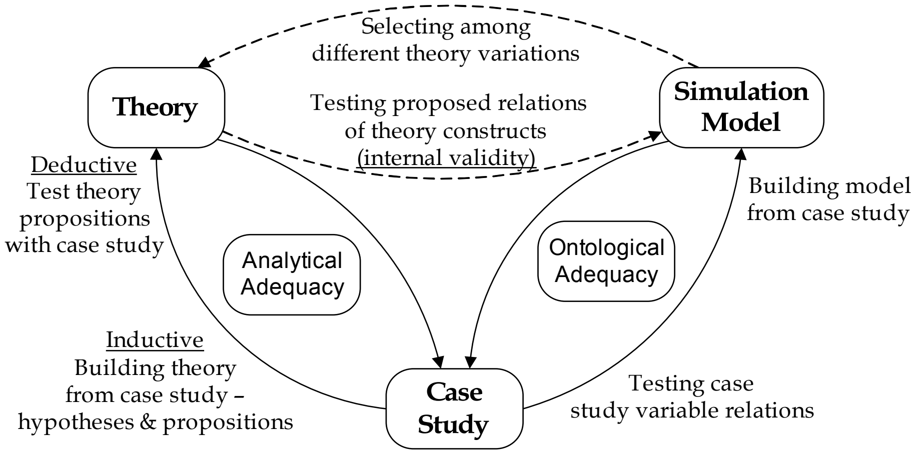


Figure 4. Theory, case study and simulation modelling

## 6 Case Studies & SD: Retaining The Essentials

Some strengths of case study theory building also lead to weaknesses. It is an approach where theory is produced from detailed data. However, the intensive use of empirical evidence can yield theory which is overly complex. An attribute of good theory is its parsimony and grounding to reality, but given the use of voluminous empirical data, there is a risk of producing theory which is exceedingly detailed and complex. Researchers working with case studies at some point have to elevate themselves above the level of intricate details in order to provide a broader perspective. Without cross case comparison they may be unable to retain essential relationships from idiosyncratic ones in order to increase the generality of the theory (Eisenhardt, 1989).

A second challenge is to develop a theory that does not overdetermine the phenomenon. Consequently from all the candidate explanations for a phenomenon one should be selected that goes beyond the particular details of the case study and strikes a balance between generality, simplicity and accuracy (Weick, 1979) by including the minimum set of possible causes for the phenomenon. Inevitably in this process the analyst will have to make choices, assumptions and simplifications (Siggelkow, 2007). Modelling and simulation can facilitate this process. The development and analysis of a simulation model provides an overview of the range of outcomes that causal mechanisms generate. This increases their level of specificity by avoiding surplus detail while retaining their internal validity.

In the modelling examples on organizational research cited earlier, the benefits of combining qualitative and quantitative methods to form a more complete picture of a phenomenon in organizational research, far outweighed the costs of time and effort. Implementing this methodological strategy, however, requires researchers to be more familiar and comfortable with the ontological, epistemological, and methodological foundations of both qualitative and quantitative research (Shah and Corley, 2006). The conjoint application of two methods for research, may place considerable burden on analysts (Brocklesby, 1997). It can therefore be broken down in two parts: (i) the theory – model, and (ii) model – phenomena comparisons that correspond to analytical and ontological adequacy (see figure below). When a model that reproduces a real world phenomenon is developed then in the first part theoreticians can work on developing further formalized models and then through applied research their utility can be assessed. Finally, empirically oriented researchers, can compare models with functionally equivalent real world structures (McKelvey, 2002). This has the added benefit of looking into both sides of the trade off between theory accuracy and simplicity-generality.

**From Accuracy To Simplicity**

While this paper looks at two strategies only, there are several that can be employed in process research. Some rely more on raw data (narrative strategy and grounded theory) and result in higher accuracy. Others trade this for increased parsimony and generality, by being more reductionist (quantification and simulation). Together, they define a narrative – quantification continuum where operating at either extreme runs the risk of sacrificing key data dimensions. In between lies an array of alternative strategies broadly conceptualised as grounding, organizing and replicating strategies (Langley, 1999).

| Strategy | Accuracy | Simplicity | Generality |
|---|---|---|---|
| Narrative | High | Low | Low |
| Grounded Theory | | | |
| Temporal bracketing | | | |
| Visual mapping | | | |
| Synthetic strategy | | | |
| Quantification | | | |
| Computer simulation | Low | High | High |

Table 1. Research strategies for process theory (adapted from Langley, 1999)

The focus of each strategy ranges from the meaning of processes for individuals (grounded theory and narrative), to identifying temporal patterns (visual mapping, quantification and grounded theory) and causal mechanisms in a process (alternate templates, temporal bracketing and quantification) (Langley, 1999). The strategies close to the narrative strategy offer ways of systematically generating structured descriptions. In this capacity they are primarily used in the initial stages of research when there is little prior understanding or theory, for a phenomenon. They are used to describe events, define constructs, and formulate hypotheses and propositions.

Quantitative and simulation strategies can be conceptualised as replicating strategies since they represent different ways of decomposing the data for the replication of theoretical propositions. These strategies can draw on almost any or all of the others. The question of choice of strategies is more than just a trade off between desired levels of accuracy, simplicity and generality as shown in Table 1, and more than just a case of picking logically linked combinations. It is also a question of taste, of research objectives, the kinds of data available and of moving from one to the other in a creative manner.

From the list of strategies in table 1, the narrative, visual mapping, quantification and computer simulation are amongst those that are used in SD methodology as well. In that context they are used to move progressively from qualitative description of a problem (narrative), to visual mapping (causal loop diagram in SD terminology), to a working model simulation (quantification and simulation) (Sterman, 2000). The properties from table 1 are used in figure 6 to conceptualise the progression from the specific and the qualitative, through abstraction and disciplined imagination, to understanding and generalization which may involve the construction of quantitative models.

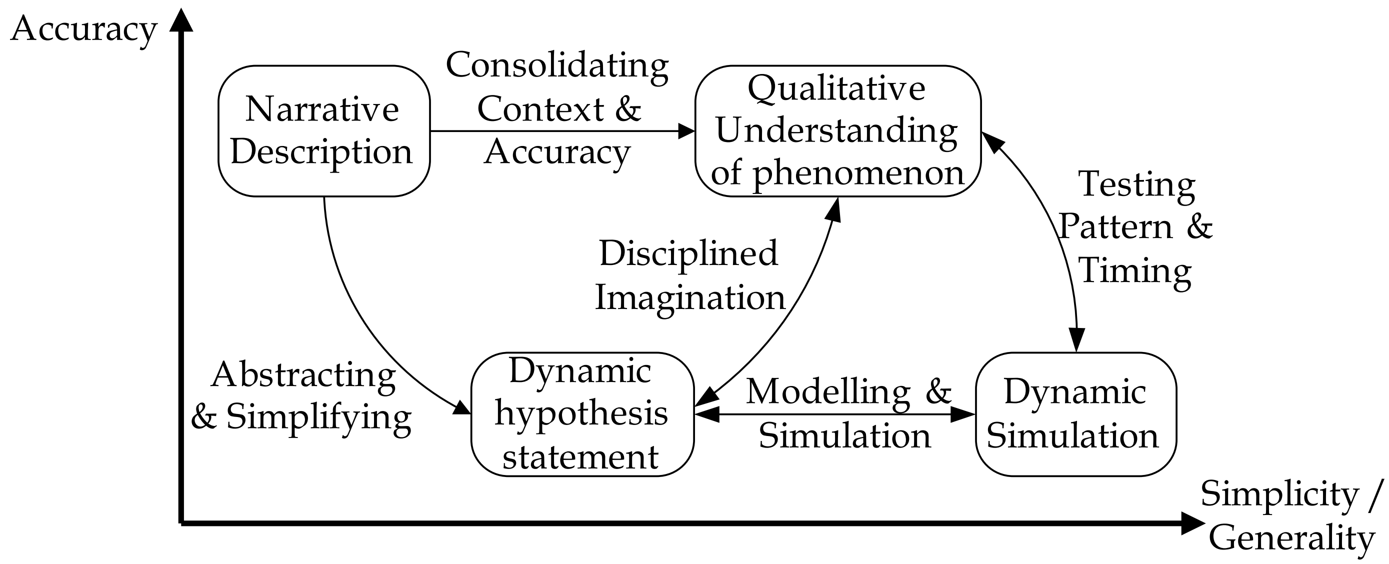


Figure 5. Progressing from accuracy to generality

## 7 Conclusions

The paper had as its main focus the process of developing a causal explanation of an observed or experienced phenomenon or problem. This requires its careful observation and the structure surrounding it. Two methods for addressing this task were discussed, SD and case study research. While SD provides the tools for transferring observations into feedback structures it is less so equipped for observation. The claim of this paper is that case study can be such a method which used in a complementary way can enhance theory development.

Conceptualising the theory development process in terms of three evolutionary steps, the two methods are brought side by side and the potential complementarities and benefits each one offers are explored. An account of how the overall process fits together has been created, and how it progresses from accuracy to simplicity and theoretical parsimony. Specific requirements in such a process are discussed, such as pattern matching and iterating between case study and modelling. Reflecting on the character of the overall process reveals an evolutionary perspective, the implications of which are worth pursuing further.

In keeping with the line of argument developed in this article about the partial viewing imposed by any methodology, it is suggested that a viable goal for SD is the development of middle range theories (Merton, 1968) with a high level of generalizability that apply to certain classes of systems only instead of overarching theories of social life. In effect it should not try to account for all the aspects of a system (Kopainsky and Luna-Reyes, 2008; Schwaninger and Grosser, 2008). This is a conclusion that is in line with the history of SD which from its inception dealt with such large-scale issues. (see, for example, Forrester, 1961; 1969; 1971, Meadows, Meadows, Randers and Behrens (1972) and Meadows, Randers and Meadows, 2004).

Overall, the inductive capability of case study method can help to build relevant dynamic models, grounded in data, and with an increased chance of arriving at relevant generic structures with rigour. The latter is accomplished through modelling and simulation by abstracting and testing hypotheses about how real world phenomena unfold. This hypothetico – deductive combination then increases the probability of arriving at a satisfactory explanation with confidence by clarifying which of the hypothesized structures generate the observed phenomena. This pendulum like process oscillates between context and structuring process and spirals towards better insights and better theory, while guarding against theory becoming overly complex.

## 8 References


Abbott, A., 1990. A primer on sequence methods. Organizational Science, 1(4), 375 – 392

Abell, P., 2001. Causality and low frequency complex events: The role of comparative narratives. Sociological Methods & Research, 30(1), 57 – 80

Abell, P., 2004. Narrative explanation: An alternative to variable centered explanation?. Annual Review of Sociology, 30, 287 – 310

Barlas, Y., 1989. Multiple tests for validation of system dynamics type of simulation models. European Journal of Operational research, 42, 59 – 97

Barlas, Y. 1996. Formal aspects of model validity and validation in system dynamics. System Dynamics Review, 12(3): 183–210

Bergman, N., Haxeltine, A., Whitmarsh, L., Kohler, J., Schilperoord, M., Rotmans, J., 2008. Modelling sociotechnical transition patterns and pathways. Journal of Artificial Societies and Social Simulation, 11, 3

Brehmer, B., 1980. In one word: Not from experience. Acta Psychological, 45, 223 – 241

Brocklesby, J., 1997. Becoming multimethodology literate: An assessment of the cognitive difficulties of working across paradigms. In (eds) Mingers, J., Gill, A., Multimethodology. Wiley, Chichester, pp 189–216.

Burton, R.M., Obel, B., 2011. Computational modelling for what-is what-might be and what-should be studies and triangulation. Organization Science, 22(5), 1195 – 1202

Campbell, D.T., 1979. A Tribal Model of the Social System Vehicle Carrying Scientific Knowledge. Knowledge, 2, 181−201

Campbell, D.T., 1985. Toward an Epistemologically-Relevant Sociology of Science. Science Technology and Human Values, 10, 38−48.

Campbell, D.,T., 1988. A general 'selection theory' as implemented in biological evolution and in social belief-transmission with modification in science. Biology and Philosophy, 3, 171 – 177

Campbell, D.,T., 1997. From evolutionary epistemology via selection theory to a sociology of scientific validity. Evolution and Cognition, 3(1), 5 – 38

Carley, K.M., 2009. Computational modelling for reasoning about the social behaviour of humans. Computational and Mathematical Organisational Theory, 15(1), 47–59

Chalmers, A., 1982. What is this thing called science?. University of Queensland Press, Australia

Cilliers, P., 1998. Complexity and Postmodernism—Understanding Complex Systems. Routledge, London.

Cronin, M., Gonzalez, C., 2007. Understanding the building blocks of system dynamics. System Dynamics Review, 23(1): 1–17.

Cronin, M., Gonzalez, C., Sterman, J.D., 2009. Why don't well-educated adults understand accumulation? A challenge to researchers, educators, and citizens. Organizational Behavior and Human Decision Processes, 108(1): 116–130.

Denzin, N.K., Lincoln, Y.S., 1994. Handbook of Qualitative Research. Sage: Thousand Oaks, CA

Diehl, E., Sterman, J.D., 1995. Effects of feedback complexity on dynamic decision making. Organizational Behavior and Human Decision Processes, 62(2), 198–215

Eisenhardt, M.K., 1989. Building better theories from case study research. Academy of Management review, 14(4), 532 – 550

Flood, R.L., 1989. Six scenarios for the future of systems 'problem solving'. Systems Practice, 2(1), 75–99

Forrester, J.W., 1961. Industrial Dynamics. Waltham, MA: Pegasus Communications.

Forrester, J.W., 1969. Urban Dynamics. Waltham, MA: Pegasus Communication

Forrester, J,W., 1971. World Dynamics. Wright-Allen Press: Cambridge, MA

Funke, J., 1991. Solving complex problems: Exploration and control of complex systems, in (eds) Sternberg, R., Frensch, P., Complex problem solving: Principles and mechanisms, Hillsdale, N.J. Erlbaum

Gibberr, M., Ruigrok, W., Wicki, B., 2008. What passes as a rigorous case study. Strategic Management Journal, 29, 1465 – 1474

Giddens, A. 1984. The Constitution of Society. Polity: Cambridge

Gioia, D.A., Pitre, E., 1990. Multiparadigm perspective on theory building. Academy of Management Review, 15 (4), 584–602

Goldspink, C., 2002. Methodological implications of complex systems approaches to sociality: simulation as a foundation for knowledge. Journal of Artificial Societies and Social Simulation, 5, 1 http://jasss.soc.surrey.ac.uk/5/1/3.html

Griffin, L.T., 1993. Narrative, event structure analysis and causal interpretation in historical sociology. American Journal of Sociology, 98(5), 1094 – 1133

Grimm, V., Revilla, E., Jeltsch, F., Mooij, M.W., Railsback, F.S., Thulke, H.H., Weiner, J., Wiegand, T., DeAngelis, L.D., 2005. Pattern - Oriented modelling of agent based complex systems: lessons from ecology. Science, 310, 987 – 991

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, K.S., Huse, G., Huth, A., Jepsen, U.J., Jørgensen, C., Mooij, M.W., Muller, B., Peer, G., Piou, C., Railsback, F.S., Robbins, M.A., Robbins, M.M., Rossmanith, E., Ruger, N., Strand, E., Souissi, S., Stillman, A.R., Vabø, R., Visser, U., DeAngelis, L.D., 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198, 115–26

Hatch, M.J., 1997. Organization theory: Modern, Symbolic and post modern perspectives. Oxford University Press, US

Harrison, J.R., Zhiang, L., Carroll, G.R., Carley, K.M., 2007. Simulation modelling in organizational and management research. Academy of Management Review, 32(4), p1229 – 1245

Homer, J., Oliva, R., 2001. Maps and models in system dynamics: a response to Coyle. System Dynamics Review, 17(4), 347 – 355

Jick, T., 1979. Mixing qualitative and quantitative methods: Triangulation in action. Administrative Science Quarterly, 24, 602-611.

Kleinmuntz, D.N., 1985. Cognitive heuristics and feedback in a dynamic decision environment. Management Science, 31(6): 680–702

Kohler, J., Whitmarsh, L., Nykvist, B., Schilperoord, M., Bergman, N., Haxeltine, A., 2009. A transitions model for sustainable mobility. Ecological Economics, 68, 2985 – 2995

Lane, D.C., Smart, C., 1996. Reinterpreting genetic structure evolution application and limitations of a concept. System Dynamics Review, 12(2), 87 – 120

Lane, D.C., 2008. Formal theory building for the avalanche game: explaining counter-intuitive behaviour of a complex system using geometrical and human behavioural/physiological effects. Systems Research and Behavioural Science, 25(4), 521 - 542.

Langley, A., 1999. Strategies for theorizing from process data. Academy of Management Review, 24(4), 691 - 710

Lerner, R.M., Kauffman, M.B., 1985. The concept of development in contextualism. Developmental Review, 5, 09 – 333

Leonard-Barton, D., 1990. A dual methodology for case studies: synergistic use of a longitudinal single site with replicated multiple sites. Organization Science 1(3): 248–266.

Maturana, H.R., Varela, F.J., 1980. Autopoiesis and cognition: The realization of the living. D. Reidel Publishing, Dordrecht

McGrath, J. E., Martin J., Kulka, R.A. 1982. Judgement Calls in Research. Sage, CA, US

McKelvey, B., 1999a. Complexity Theory in Organization Science: Seizing the Promise or Becoming a Fad?. Emergence, 1(1), 5-32

McKelvey, B., 1999b. Toward a Campbellian realist organization science. in (eds.) Baum, J.A.C., Bill McKelvey, B., Variations in Organization Science: In Honor of Donald T. Campbell, Thousand Oaks: SAGE, 383–411.

McKelvey, B., 2002. Model-Centered Organization Science Epistemology. in (ed) Baum, J.A.C., Companion to Organizations, Sage Publications, Thousand Oaks, CA, US, Sage, pp. 752–780

Meadows, D.H., 1980. The unavoidable a priori. in (ed) Randers, J., Elements of the System Dynamics Method, Pegasus Communications: Waltham, MA.

Meadows, D.H., Meadows, D.L., Randers, J., Behrens, W.W., 1972. The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind. Earth Island: London

Meadows, D.H., Randers, J., Meadows, D., 2004. Limits to growth: The thirty year update. Chelsea Green, US

Meadows, D.H., 2008. Thinking in systems: A primer. Chelsea Green Publishing, Vermont, US

Merton, R.K., 1968. Social Theory and Social Structure. The Free Press, New York.

Mingers, J., Brocklesby, J., 1997. Multimethodology: Towards a framework for mixing methodologies. Omega, 25(5), 489 – 509

Mingers, J., Gills, A., 1997. Multimethodology. Wiley, New York, US

Mitroff, I., Emshoff J., 1979. On strategic assumption making: a dialectical approach to policy and planning. Academy of Management Review, 4(1), 1 – 12

Mohr, L.B., 1982. Explaining organizational behaviour. Jossey-Bass, San Fransisco

Morgan, M., Morrison, M., 1999. Models as mediating instrument. in (eds) Morgan, M., Morrison, M., Models as Mediators, Cambridge University Press, Cambridge, UK

Morgan, G., 1983. Beyond method. Newbury Park, Sage, US

Moxnes, E., 2000. Not only the tragedy of the commons: Misperceptions of feedback and policies for sustainable development. System Dynamics Review, 16(4), 325 – 348

Oliva, R., Sterman, J.D., 2001. Cutting corners and working overtime: Quality erosion in the service industry. Management Science, 47(7): 894–914

Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, validation and confirmation of numerical models in the earth sciences. Science, 263, 5147, 641 – 646

Paich, M., 1985. Generic structures. System Dynamics Review, 1(1): 126–132

Pala, O., Vennix, J.AM., 2005. Effect of system dynamics education on systems thinking inventory task performance. System Dynamics Review, 21(2), 147 - 172

Papachristos, G., 2011. A system dynamics model of socio-technical regime transitions. accepted for publication in Environmental Innovation and Societal Transitions,1 (2), 202 - 233

Pettigrew, A.M., 1990. Longitudinal field research on change: theory and practice. Organization Science, 1(3), 267 - 292

Pfeffer, J., 1982. Organizations and organization theory. Marshfield, MA: Piiman

Pidd, M., 2004. Bringing it all together. in (ed) Pidd, M., Systems modelling: Theory and practice. Wiley, Chichester, UK

Railsback, S.F., Johnson, M.D., 2011, Pattern oriented modelling of bird foraging and pest control in coffee farms, Ecological Modelling, 222(18), 3305 – 3319

Randers, J., 1973. Conceptualizing dynamic models of social systems: Lessons from a study of social change. PhD thesis, MIT, US

Raven, R., 2007, Niche accumulation and hybridisation strategies in transition processes towards a sustainable energy system: An assessment of differences and pitfalls, Energy Policy, 35, 2390 – 2400

Richardson, K.A., 2001. On the Status of Natural Boundaries: A Complex Systems Perspective. Proceedings of the Systems in Management - 7th Annual ANZSYS conference November 27-28, 2001: 229-238, ISBN 072980500X.

Richardson, K.A., Cilliers, P., Lissack, M., 2001. Complexity science: A gray science for the stuff in between. Emergence, 3(2), 6 – 18

Richardson, K.A., 2004. On the relativity of recognising the products of emergence and the nature of physical hierarchy, Conference Paper Presented at the Second Biennial International Seminar on the Philosophical, Epistemological and Methodological Implications of Complexity Theory, January 7–10th, Havana, Cuba.

Richardson, K., 2005. The hegemony of the physical sciences: an exploration in complexity thinking, Futures, 37, 615 - 653

Richiardi, M., Leombruni, R., Saam, N., Sonnessa, M., 2006. A common protocol for agent based social simulation. Journal of Artificial Societies and Social Simulation, 9, 1

Rivkin, J.W., 2000. Imitation of complex strategies. Management Science, 46(6), 824–844.

Rudolph, J.W., Repenning, N.P., 2002. Disaster dynamics: Understanding the role of quantity in organizational collapse. Administrative Science Quarterly, 47, 1-30

Sastry, M.A., 1997. Problems and paradoxes in a model of punctuated organizational change. Administrative Science Quarterly, 42: 237–275

Saysel, A.K., Barlas, Y., 2006. Model simplification and validation with indirect structure validity tests. System Dynamics Review 22(3): 241–262

Schieritz, N., Milling, P.M., 2003. Modelling the forest or modelling the trees: a comparison of system dynamics and agent-based simulation. 21st International Conference of the System Dynamics Society, New York, USA

Schwaninger, M., Grosser, S., 2008. System dynamics as model based theory building. Systems Research and Behavioural Science, 25, p447 – 465

Senge, P.M., 1990. The Fifth Discipline: The Art and Practice of the Learning Organization. Doubleday: New York

Shah, S.K., Corley, K.G., 2006. Building better theory by bridging the quantitative qualitative divide. Journal of Management Studies, 43(8), 1821 - 1835

Siggelkow, N., 2007. Persuasion with case studies. Academy of Management Journal, 50(1), 20 - 24

Simon, H.A., 1979. Rational Decision Making in Business Organizations. American Economic Review, 69, 493 – 513

Simon, H.A., 1982. Models of Bounded Rationality. MIT Press, Cambridge, US

Simon, H.A., 2000. Bounded rationality in social science: Today and tomorrow. Mind and Society, 1(1), 25 – 39

Smith, V.G., Suchanek, G., Williams, A., 1988. Bubbles, crashes and endogenous expectations in experimental spot asset markets. Econometrica, 56(5), 1119 – 1152

Sterman, J.D., 1994. Learning in and about complex systems, System Dynamics Review, 10(2-3), p 291 - 330

Sterman, J.D., 1985. The growth of knowledge: testing a theory of scientific revolutions with a formal model. Technological Forecasting and Social Change 28(2), 93–122

Sterman, J.D., 1989a. Misperceptions of feedback in dynamic decision making. Organizational Behaviour and Human Decision Processes, 43(3), 301 – 335

Sterman, J.D., 1989b. Modelling managerial behaviour: Misperceptions of feedback in a dynamic decision making experiment. Management Science, 35(3), 321 – 339

Sterman, J.D., 2000. Business Dynamics: Systems Thinking and Modelling for a Complex World. New York: Irwin McGraw-Hill

Sterman, J.D., 2002. All models are wrong: reflections on becoming a systems scientist. System Dynamics Review, 18, 501 – 531

Sterman, J.D, Sweeney, L.B., 2002. Cloudy skies: assessing public understanding of global warming. System Dynamics Review 18(2): 207–240.

Sterman, J.D, Sweeney, L.B., 2007. Understanding public complacency about climate change: adults' mental models of climate change violate conservation of matter. Climatic Change, 80(3–4), 213–238.

Sterman, J.D., 2010. Does Formal system dynamics training improve people's understanding of accumulation?. System Dynamics Review, 26(4), 316 – 334

Sweeney, L.B., Sterman, J.D. 2000. Bathtub dynamics: initial results of a systems thinking inventory. System Dynamics Review. 16(4): 249–286

Van den Berg, A. 1998. Is sociological theory too grand for social mechanisms?. In (eds) Hedstrom, P., Swedberg, R., Social Mechanisms: An analytical Approach to Social Theory, . Cambridge University Press, 204 – 237.

Van de Ven, A.H., 1992. Suggestions for studying strategy process: a research note. Strategic Management Journal, 13, 169 – 188

Weick, K.E., 1989. Theory construction as disciplined imagination. Academy of Management Review, 14(4), 516 – 531

Winsberg, E., 2006. Models of success versus the success of models: Reliability without truth. Synthese, 152, 1 – 19

Wolstenholme, E.F., 2003. Towards the definition and use of a core set of archetypal structures in system dynamics. System Dynamics Review 19 (1), 7–26.

Yin, R.K., 1981. The case study crisis: Some answers. Administrative Science Quarterly, 26, 58 – 65

Yin, R.K., 2003. Case study research: Design and methods, 3rd edition, Sage Publications, CA, US