Research Based on Two Pillars: Combining Qualitative Empirical Social Research and Simulation in Strategic Management

Florian Kapmeier
Universität Stuttgart
Betriebswirtschaftliches Institut
Lehrstuhl für Planung und Strategisches Management
Keplerstraße 17
70174 Stuttgart
Germany
Phone: +49 – (0)711 – 121 – 3465
FAX: +49 – (0)711 – 121 – 3191
Email: florian.kapmeier@bwi.uni-stuttgart.de

Abstract
This paper proposes a combined research approach of simulation and modeling and qualitative empirical social research. Modeling and simulating may reveal valuable insight into real world systems consisting of a complex structure. Yet, published data on structure, are oftentimes limited and stand side-by-side, without interrelation. Qualitative empirical social research might provide model builders with appropriate missing data. Though applying real-world data has long tradition in System Dynamcis, a comprehensive scientific explanation is still omitted. In this paper we view modeling from an outsider perspective, like, i.e., an alliance scholar who needs to be convinced about the benefits of simulation and modeling. Model quality and model acceptance, among other things, depend on realistic model input, including non-rationality or real-world policies. We analyze how qualitative empirical social research may ensure that the model builder works with real-world input that she might use for building the simulation model and for her analysis.

Keywords
System Dynamics, Simulation, Modeling, Case Study Research, Qualitative Empirical Social Research

1. Introduction

In this paper we describe the procedure we followed to do research in a widely studied management field in which holistic point of views and a dynamic perspective are oftentimes neglected. While alliances between competing firms become increasingly important for firm's success, they suffer from a high failure rate. Thus, alliances seem to consist of a highly complex structure – too complex for decision-makers and policy-designers to lead alliances to a success in many cases. Current alliance research identifies a wide range of reasons for alliance failure. Yet, the reasons most of the time stand side-by-side. A holistic and dynamic perspective may lead to valuable insight into the underlying structure of an alliance. In this article, we lay out, explain, and argue for the research approach conducted to connect the building blocks and to identify policy implications for successful alliance management: qualitative empirical research and simulation. Laying out briefly the field of alliances gives scholars necessary background information. We provide motivations to argue for the use and combination of qualitative research and quantitative simulations – which is oftentimes done by System Dynamicists but may be controversial to scientists outside the field of System Dynamics.

2. Problem Statement and Research Goal

In the 1970s, there was little tradition of firms entering alliances. In the meantime, alliances, even between competitors, have become an increasingly important strategic option for firms to achieve competitive advantage in all different kinds of business areas. Participants involved in alliances mostly start out with great enthusiasm. Studies have shown, however, that most alliances are terminated early with at least one parent firm disappointed and without reaching the prospective joint goals. The literature identifies various reasons for alliance failure. Though providing valuable insight, only some articles imply a dynamic approach (Lane *et al.*, 2001), (Khanna *et al.*, 1998), (Kumar *et al.*, 1998), or (Doz, 1996). The models being designed often concentrate on specific building blocks of the field of research on alliances and/or neglect a feedback-loop point of view (Kapmeier, pending publication). Yet, a dynamic perspective can lead to insight into how a cooperative venture between competitors might develop over time and why it might fail.

Managers often have difficulty managing alliances successfully due to their complex underlying structure. An analysis of an alliance structure might provide decision makers with necessary insight for successfully managing alliances. It requires simulation of the behavior of interrelating variables from a feedback perspective. For this purpose we combine two of the three research approaches suggested by ZENG AND CHEN, simulation and modeling and case study research (Zeng *et al.*, 2003). In contrast to other contributions to the field of study we do not demonstrate the existence of a new variable or test the strength of the correlation between two variables. Also, we do not report new data from another explorative study. Instead, we review the existing literature on interorganizational learning in depth and conduct a case study. The higher goal, which is beyond the scope of the present paper, is to represent our findings in feedback loops and develop and analyze a quantified simulation model. To achieve this goal, we combine simulation and qualitative empirical social research. The result is an internally consistent approach providing new insight into the success or failure of interorganizational learning in alliances. In this paper, we lay out the way to achieve the goal of designing a quantified simulation model, based on empirical social research.

After this brief introduction, we first review systems and models. We lay out that managers' mental models are the reason for erroneous inferences about reality. We explain how formal models may change mental models' structures so that decision makers and policy designers manage alliances more successfully. Furthermore, we discuss formal models, their characteristics, virtues, and drawbacks. We continue with classifying different simulation approaches – being formal models – and explain the use of simulation in management sciences. As qualitative information are necessary to design a simulation with real-world reference we argue why it is insightful to include findings from case study analyses into the design of simulation models. Finally, we share our procedure how we conducted our case study and integrate the findings into the simulation model. As stated above, we do not present model structures or policy runs but lay out scientific argumentation of combining modeling and simulation and case study research.

In the following, we first look at how simulation and modeling may enhance insight into complex system structure. Here, we focus on a specific field in strategic management in which current research has not considered simulation and modeling. As System Dynamicists, we thus need to step back from our insight into modeling and try to view modeling from an outsider perspective, like, i.e., an alliance scholar who is not convinced about the benefits of simulation and modeling. Model quality depends on realistic model input, including non-rationality or real-world policies. Therefore, we analyze how qualitative empirical social research may ensure that the model builder receives real-world input that she might use for building the simulation model.

3. Pillar One: Applying Simulation and Modeling to Analyze Complex System Structure

3.1 From Complex System Structure to Abstract Model Structure

In the following sections, we describe the necessity of building models from complex system structure that managers are too overwhelmed with, like, e.g., managing an alliance. Furthermore, we lay out various simulation approaches and present the variety of simulation applications in the field of management science in general and strategic management in particular.

The behavior of a social system is determined by its underlying structure (Richardson, 2001). The structure consists of a set of interacting elements, or variables. System elements and their interacting relationships form feedback loops ((Sterman, 2000) and earlier (Forrester, 1972). The dynamic behavior of the system arises from the temporal sequence of information fed back from the real world that produces decisions and actions which in turn have consequences which generate further information. These phases may not follow immediately after one another. There may be time delays between cause and effect, procrastinating effects arising.

Due to real systems' complexity, decision makers have difficulty examining in detail system structure which determines system behavior. Therefore, simplified models of such systems help us to gain deeper insight into the real system. Models designed may be quantified and used for computer simulation. Conclusions from simulation runs give hints about possible redesigning of managers' policies (Keough *et al.*, 1992). For the special case of alliances, this means that the simulation model supports decision-makers in redesigning their policies to manage alliances successfully.

Generally speaking, models feature three main characteristics (Stachowiak, 1973). First, models are representations of natural or man-made original systems, and second, models are simplifications and abstractions of things that could be models themselves. This abstraction simplifies the system so that we are able to analyze the model. Third, models only replace systems for the time period necessary for certain mental or actual operations by individuals who want to gain insight into the system. Thus, models help people to understand systems better. However, due to the same reasons, one has to realize that the models humans base their decisions on are incomplete and incorrect; they are simply wrong (Sterman, 2000) and (Sterman, 2002). This is explained in more depth in the following.

Decisions are made on the basis of models (Forrester, 1971) or (Keough *et al.*, 1992). Every individual intuitively uses models. The question is not whether or not to apply a model but which model to apply (Forrester, 1975). More specifically, decisions are the consequence of applying a policy to information about the real world as the decision maker perceives it (Forrester, 1961) and (Sterman, 2000). Policies, strategies, and structures are embedded in humans' mental models. Humans create mental models to reduce the complexity of real social systems. These models are suited for a gaining a better "understanding of obscure behavior characteristics more effectively than could be done by observing the real system" (Forrester, 1961). Mental models contain intuitive and implicit knowledge (Nonaka *et al.*, 1995).

Mental models are flexible in their structure. Or, as Forrester puts it, "within one individual a mental model changes with time and even during the flow of a single conversation" (Forrester, 1975). A mental model can cover a broader scope of information than merely numerical data. It can be modified when supplementary information becomes accessible. To sum up, mental models can be interpreted as the filters through which humans interpret the world on the basis of their personal experience (Sterman, 1991).

However, mental models also have shortcomings. According to Forrester, mental models are fuzzy, incomplete, and imprecise (Forrester, 1975). They are dynamically deficient and insensitive to nonlinearities. They ignore the feedback processes that the real world consists of and fail to acknowledge time delays between cause and effect (Sterman, 2000). In other words, mental models are ambiguous and unquantified (Meadows, 1980). This is why mental models are difficult for others to understand, for instance in conversations, and result in different interpretations. This occurs although structures of mental models are usually very simple. "Often these mental models are also flawed" (Sterman, 1991) as humans often make mistakes in deducing the effects of underlying assumptions. Hence, humans make erroneous inferences about the dynamics of systems. Humans are not even able to mentally simulate the simplest possible feedback structure without error (Sterman, 2000). Keeping in mind that real social systems like alliances consist of multiple nonlinear feedback loops, it can be expected that managers will often fail to see long-term effects of their decisions which may lead to policy resistance (Sterman, 2000).

Formal models, like simulation models, can support humans in their decision making to overcome mental models' drawbacks (Doyle *et al.*, 1998). Information contained by mental models needs to be verbalized and translated into formal models. Formal models represent numerical values that were formally part of vague mental constructs (Forrester, 1972). As stated above, formal models are generally useful in situations that are too dangerous or unethical to experiment with in reality, too slow because of long time delays or too fast, too large, or too small to be studied in depth in the real world. In formalizing social systems like alliances, model runs provide the possibility to experiment with strategies that would lead to the alliance's failure on the basis of the managers' mental models. Managers have the possibility to challenge their mental models by experimenting in the virtual world.

The virtues and shortcomings of formal models could be seen as a mirror image of mental models. Formal models are explicit, precise and present a clear picture of the phenomenon. The mathematical language used for building them is standardized and unambiguous. Their notation is clear and therefore easier to understand than mental models. Underlying model assumptions are, or should be, stated. Consequently, individuals of different educational backgrounds are able to comprehend formal models (Forrester, 1972) and (Forrester, 1975).

Oftentimes, however, formal models are complex and poorly documented. High model complexity prevents model users from developing confidence in the consistency or correctness of the model. This makes it hard for users to comprehend and accept the underlying assumptions. Moreover, formal models might not be capable of capturing relationships and factors that are either challenging to quantify, or for which numerical data do not exist, or that lie beyond the expertise of the modeler (Sterman, 1991).

To conclude, insight from models of all types can be transferred to the real world. Model builders or users may gain a good knowledge of the structure of the original (Stachowiak, 1973). However, as stated above, the human intellect is only limitedly capable of simulating mentally. Therefore, formulization seems to be necessary for people to fully understand the underlying system structure and its implications for system behavior (Sterman, 2000).

3.2 Modeling and Simulation

3.2.1 Simulation Models

Techniques like optimization or simulation can be used to analyze models. Yet, the techniques are suited for different circumstances (Forrester, 1994b). Optimization models are prescriptive. This means that they provide hints regarding how to use an opportunity as successfully as possible. They offer a good tool in situations where people optimize choices. They have some limitations. First, one of the problems is the specification of the objective function that indicates the goal or objective. Second, the majority of optimization models assume linear relationships – nonlinearities, being one of the main characteristics of social systems, are not captured. Third, many optimization models ignore feedback effects that the real world consists of. Finally, many optimization models are static and only provide the optimal solution for a particular point in time. They therefore ignore the dynamics of the system and its environment. Even though optimization models might be well suited for some problem sets, due to the limitations presented, they are not appropriate for gaining insight into the development of alliances. They do not illustrate how people actually behave.

Simulation models make up for the limitations of optimization models. Generally speaking, simulations illustrate the models' behavior over time (Weber, 2004) and (Engel *et al.*, 1995). The term simulation is used differently depending on the field of research. In addition to experimental simulations which are carried out in laboratories, theoretical simulations also exist. Simulations are called theoretical if a system is being simulated mathematically. Theoretical simulations are based on symbolic models and can be deterministic, probabilistic, stochastic, continuous, or discrete (Gramelsberger, 2001) and (Schleichert, 1995). If theoretical simulations are done with a computer, they are called computer simulations. They are used for analyzing behavior over time. This is of special interest if the systems are too complex for mental simulations and exact mathematical-analytical methods (Schleichert, 1995). The characteristic of high complexity holds for complex natural systems like analyzing climate as well as for complex social systems like managing alliances. In the meantime, computer simulations have become increasingly important for heuristics and they replace real experiments to a greater extent (Gramelsberger, 2001). Concluding, a simulation model mimics the real system (Sterman, 2000). It is descriptive which means that it shows what would happen in a given situation. This characteristic leads to a wide range of applications. Simulation models can be used for forecasting, optimizing, theory testing, illustrating relations, training, or learning (Sterman, 2000) and (Gramelsberger, 2001).[1] In simulating social systems like alliances, simulations provide the possibility to experiment with strategies that would lead to the alliance's failure on the basis of the managers' mental models. Managers have the possibility to challenge their mental models by experimenting in the virtual world.

---

[1] See Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin McGray-Hill: Boston, Madison, and others for virtues of simulation models.

Findings or learnings from running simulation models can be transferred to the real world. Figure 1 depicts the relationship between learning from the real world and formal models, referred to as virtual worlds here (Sterman, 2000). Information feedback gained from virtual worlds can accelerate the reorganization of the structures underlying mental models. Changes in the structure of mental models change the structure of the system, creating different decision rules, and new strategies (Sterman, 2000). This is when learning takes place; in particular double-loop learning (Argyris *et al.*, 1978).

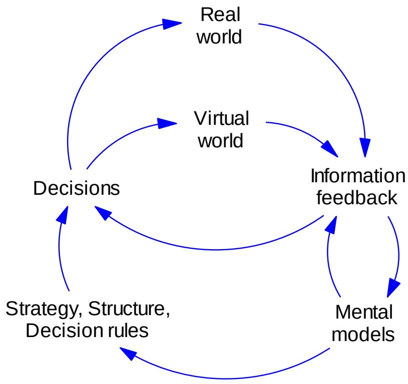

Figure 1: Formal models as virtual worlds as part of the learning feedback loop.[2]

Simulations, however, also have pitfalls. Sterman identifies them in the accuracy of the decision rules, the choice of model boundary, and the quantification of soft variables (Sterman, 1991). The latter is of special interest for the purpose of this study as alliances in general often rely on soft variables like trust or knowledge and learning in alliances. The majority of variables influencing decision making have not been measured and are therefore soft data. However, according to STERMAN they should be included if they are important for the purpose of the model (Sterman, 2002). FORRESTER states that “[t]o omit such variables is equivalent to saying they have zero effect – probably the only value that is known to be wrong” (Forrester, 1961). Soft variables are critical for understanding the structure of alliances. Therefore, instead of only working with hard variables that can be quantified, we also include soft variables in the model. However, when running a computer simulation, the computer calculates with finite and rounded numbers. Even with the smallest mistakes in the numbers, real systems work quite differently. Therefore, predictions from computer simulations have to be viewed with caution (Gramelsberger, 1996).The purpose of simulation models should therefore lie rather in the development of the policy makers’ intuition and judgment, which may be of bounded rationality (Morecroft, 1983), (Morecroft, 1985) and (Sterman, 1987). Under these circumstances, simulation models make explicit the assumptions made and show the consequences of these assumptions (Forrester, 1985).

Despite these shortcomings, simulating formal models can overcome the decision makers’ erroneous mental models. Simulating mentally or building a qualitative model of the problem structure might already reveal interesting insight. People’s mental models might indeed already change due to the outcomes. However, only formal models that are tested via computer simulation imply and show real world components like feedback or time delays. This might lead to radical changes of the user’s mental model. This can be achieved via two different approaches: either the individual whose mental model should be changed joins the

[2] Source: Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin McGray-Hill: Boston, Madison, and others and Sterman JD. 1994. Learning in and about Complex Systems. *System Dynamics Review* **10**(2-3): 291 - 330.

modeling processes or models herself, for example, going through the modeling process, or, the individual uses a pre-designed simulation model which is called a management flight simulator. Concluding, simulation models of different kinds speed and strengthen learning feedbacks (Sterman, 1994).

3.2.2 Simulation Approaches

Social scientists have used simulations for analyzing system structure and behavior for five decades. The mathematician V. NEUMANN (von Neumann, 1963) and the management and social scientist SIMON (Simon, 1969) were the first scientists to use programs for computer simulation (Hoßfeld, 1993). Until the 1960s computer power increased immensely, and so did the field of simulation applications proliferate. The emergent simulation techniques can be classified into three categories (Troitzsch, 2004): discrete event simulations, equation-based modeling, and agent-based modeling.

Discrete event simulations and equation-based modeling both came up at approximately the same time in the 1960s.[3] Examples of discrete event simulations include queuing models for workflow management. Such models include static and dynamic elements, sources and sinks, and an event list. An event list records all the predictable events that might occur and that have to happen in the given order. The system only changes if an event takes place. After the change the system is stable until the next event, which is why this simulation technique is called discrete. Due to its discreteness feature, discrete event simulation would not be an appropriate technique for analyzing the dynamics of interorganizational learning in alliances in which events happen continuously.

The second approach is called equation-based modeling and also emerged in the 1960s. FORRESTER used computer simulations for his publications on oscillations in the industry sector, the dynamics of urban growth and of growth in a finite world (Forrester, 1961), (Forrester, 1969, 1971). They were the focus of public attention and people became much more aware of computer simulations. The publications provide differential and difference equations and they led to the field of System Dynamics. System Dynamics is based on feedback loops, it incorporates accumulations and flows, and it takes into account a continuous view of structure and dynamics. These characteristics make System Dynamics an appropriate method to analyze the dynamics of alliances.

Last, a more recent simulation technique is the agent-based simulation. Its virtue is the option of designing models of any given number of different objects – the agents – that are connected via different types of interrelation. Agent-based models are most suitable for application in situations where important emerging behavior stems from heterogeneity in the attributes of the agents and from the network structure of their interactions. Applications range from land use and land cover changes (Parker *et al.*, 2001), spread of disease (Rahmandad, 2004), and organizational learning (Carley, 1992), trust between market participants (Gorobets *et al.*, 2004), to processes of organizational change (Levinthal, 1997) in the field of management. Agent-based models have also been designed to study the dilemma of competition and cooperation (Axelrod, 1997b). In general, agent-based models are able to cover more detail complexity than system dynamics models. However, agent-based models are also more difficult to communicate. As the purpose of the simulation model developed in

[3] See Morecroft JDW, Robinson S. 2005. Explaining Puzzling Dynamics: Comparing the Use of System Dynamics and Discrete-Event Simulation, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston, Mass. for a recent comparison of discrete event simulation and equation-based modeling.

this study is policy analysis and learning, a system dynamics approach seems more appropriate. In the following, we therefore discuss the application of the simulation method in management sciences first. Then we explain the features of System Dynamics modeling in more detail in the subsequent section.

3.2.3 Simulation in Management Sciences and Strategic Management

Simulation in Management Science

While applying simulations in natural science has always been common – even before computers were invented – they have also become accepted and applied in social sciences. At the beginning of the 1970s, FORRESTER (Forrester, 1971) and MEADOWS ET AL. (Meadows *et al.*, 1974) published their study on the limits to growth. The study of scenarios of the development of the world situation was based on a System Dynamics model. Its popular scientific edition by Meadows, Meadows, Randers, and Behrens III was a huge success, being translated into 29 languages. In the meantime, the simulation approach is widely acknowledged in social sciences[4] and has also become popular in supporting theory development in strategic management (see (Zott, 2003)).

Generally, the research process can be differentiated in inductive and deductive approaches. The deductive approach assumes a system of axioms from which scholars derive statements. In an inductive approach scholars first collect data concerning certain facts. Scholars then derive statements on this basis, mostly using statistical methods. Computer simulations stand between both approaches (Axelrod, 1997a) and (Heine *et al.*, 2003).Here, as with the deductive approach, scholars define a set of assumptions. However, theorems are not developed. Yet computer simulations generate data on structures and relations that scholars analyze. As this is typical of an inductive approach, it can therefore be proposed that simulations can be understood as a mixed approach with the characteristics of thought experiments (Chmielewicz, 1994).

Simulations can be applied to various steps of the research process. First, simulations can be used to describe observed dynamic phenomena, as illustrated above. Next, simulations may support scholars in developing theories. Here, with the descriptive form of simulation, scholars can learn how simple assumptions may lead to complex system behavior (Axelrod, 1997a) and (Heine *et al.*, 2003). Moreover, simulations can be applied to confirm the explanatory value of existing theories that are based on empirical datasets (Weber, 2004).While empirically observed phenomena may consist of many interrelated effects their interdependence may be so complex that verbal or mathematical representations may be too intricate. Also, there may be several theories for explaining cause and effect. With simulation, scholars apply a holistic view covering insight from multiple theories. This enables more comprehensive explanation of empirical analyses. Finally, simulations are used for policy design (Chmielewicz, 1994).Once a phenomenon is explained, its underlying influence factors are identified. Thus, simulations can be used to adjust the system toward the alliance policy-designer's goal of successfully managing an alliance.

For the purpose of the underlying study, we apply simulations to the first step of the research process when transferring the above-mentioned phenomenon on interorganizational learning into a formal model. Furthermore, we test existing theories on interorganizational learning. To

[4] Issues range from management to dynamics of diabetes, to the arms race during the cold war, to the battle between HIV and the human immune system, to the welfare reform (see Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin McGray-Hill: Boston, Madison, and others).

design the simulation model we use findings from two types of different sources: on the one hand we use data from empirical analyses published in the literature. This original information is mostly derived inductively by the authors. We also use information obtained in interviews from our case study on interorganizational learning.

Simulation in Strategic Management

Designing a simulation model seems to be an appropriate approach for analyzing the dynamics of interorganizational learning between two alliance partners. The underlying situation is of a complex structure with nonlinear relationships and time delays. LANT AND MEZIAS (Lant *et al.*, 1990), CROSSAN AND BERDROW (CROSSAN *ET AL.*, 2003), and ZOTT (ZOTT, 2003) have used simulation models for studying various topics in organizational learning. To our knowledge, for the special case of dynamics of interorganizational learning for example, this has only been done recently by KAPMEIER (KAPMEIER, 2002, 2003, 2005, PENDING PUBLICATION) and OTTO AND RICHARDSON (Otto *et al.*, 2004) who used the System Dynamics methodology for their analyses inside the field of interorganizational learning with different foci.

We use System Dynamics modeling to describe a dynamic phenomenon, testing existing theory while consulting the literature and carrying out a related case study, which are leading to policy recommendations. Using modeling and simulations for these tasks in social sciences has become widely accepted. In particular, researchers and practitioners have applied System Dynamics to the field of management. Subjects cover, for instance, strategic management (see (Morecroft *et al.*, 2002) and (Warren, 2002)) in general, and in particular the learning curve (Sterman *et al.*, 1995) and (Morrison, 2005), the analyses of industries like the credit-card business (Lyneis, 1999), origin of commodity cycles in aircraft (Lyneis, 1999), pulp and paper (Sterman, 2000), plastics (Coleman-Kammula *et al.*, 2005), or the real estate (Sterman, 2000) industry, quality erosion in the service industry (Oliva *et al.*, 2001), capability traps and self-confirming attribution errors in the dynamics of process improvement (Repenning *et al.*, 2002), dynamics of project management (Roberts, 1978), (Ford, 1995), (Taylor *et al.*, 2005), impact of leasing strategies on new car sales in the automobile industry (Sterman, 2000), process and performance implication of firm diversification (Gary, 2005), competing for and through sophisticated customers (Rockart, 2001), diffusion of new technologies (Sterman, 2000), (Struben, 2004), (Struben, 2005), path dependence and positive feedback in the economy (Sterman, 2000), or demand bubbles and phantom orders in supply chains (Goncalves, 2003), (Goncalves *et al.*, 2005). System Dynamics has also been applied for confirming existing theories like punctuated change (Sastry, 1997), fire fighting in new product development (Repenning, 2001, 2002), (Rahmandad, 2005), or organizational collaboration (Black *et al.*, 2004). In the meantime, business consultants also use simulation models for learning about their clients' industries and finding strategies (Oriesek *et al.*, 2003). As can be seen from the examples, it is widely accepted to apply System Dynamics models as decision-support in strategic management (Morecroft, 1988, 1994).

As the case study provides additional insight into the underlying structure of the model, we explain qualitative research as another methodological basis in the following section.

4. Pillar Two: Conducting Qualitative Empirical Social Research For Real World Model Input to Analyze Complex System Structure

4.1 Case Study as Part of Qualitative Empirical Social Research

In the following, we define case study research as part of qualitative empirical social research. Then we first lay out a general procedure of how to conduct case studies and then we explain how we carried out our case study.

We decided to conduct a case study for a number of reasons. First, numerical data accessible in the literature only contain a small fraction of the information in the written database, which again is small compared to the information available in people's mental models (Sterman, 2000) and (Luna-Reyes *et al.*, 2003). Forrester identifies such qualitative data as a key source of information in the modeling process (Forrester, 1994a). As with soft data, omitting "variables known to be important because numerical data are unavailable is … less scientific and less accurate than using … [the] best judgment to estimate their values" (Sterman, 2000). Hence, qualitative information is crucial for understanding and modeling complex systems. Second, including companies' actual decision policies in realistic form in the System Dynamics model has been an important assumption in the field since its beginnings (Repenning, 2003). We receive this information from interviews and field observation – not necessarily from what is written in the literature. LUNA-REYES AND ANDERSEN note that the use of qualitative data is ever-present during all stages of System Dynamics modeling from problem articulation to policy formulation and evaluation (Luna-Reyes *et al.*, 2003).

There are various possibilities of data collection that give access to qualitative information (Luna-Reyes *et al.*, 2003) and (Friedrichs, 1990). We have decided to conduct a case study, as its essence lies in shedding light on decisions or sets of decisions. This includes background information on reasons why decisions were made, how policies were implemented, and which results were achieved (Yin, 1994). The case study method is part of qualitative empirical social research, of which a high degree of openness regarding the outcomes is a major characteristic (Lamnek, 1995); also (Spöhring, 1989), (Schnell *et al.*, 1999), (Friedrichs, 1990). Therefore a qualitative approach is suitable for explorative questions. Its subtlety enables the researcher to grasp contexts that are either difficult or not possible to pick out as a central theme when using standardized questionnaires. This open and non-standardized survey method facilitates insight into otherwise concealed subjects. This is the kind of information we are looking for when designing the simulation model, as it enlarges the written database to be used in the modeling process (Luna-Reyes *et al.*, 2003). Even though YIN points out that case study research is a way of investigating an empirical topic by following a set of prespecified procedures, an exact definition does not exist (Yin, 1994). YIN suggests a definition stating that a case study is "an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin, 1994).

For our special case of analyzing interorganizational learning in alliances, for example, we use a single-case study design to confirm, challenge, and broaden existing theory (Yin, 1994). This way we contribute to research, whether the theory's suggestions are accurate or whether some alternative sets of explanations might be more appropriate.

Despite the virtues mentioned above, the literature on case study designs reveals some shortcomings (Yin, 1994). The first complaint is that case studies usually take too long and produce too many unreadable documents. Nevertheless, the time needed to design the interview guides and conduct the interviews is not much different from the time needed to do other kinds of field study. Also, in this study we do not present everything said during the interviews. Yet, we present interviewees' statements at appropriate points to support or refute what is mentioned in the literature to support model building. Second, there is concern that case studies provide little basis for generalization. However, as with scientific experiments scholars can draw conclusions from single-case studies. Our focus lies in expanding and generalizing existing theories and not in enlarging incidences. Last, the greatest concern is the lack of rigor. Indeed, qualitative research may be designed in such a way that even some generalization is not possible. However, this criticism does not hold by and large. It is possible to meet this criticism by explaining the case study process and the results in enough detail that other scientists can easily comprehend it. In the following we present the process of how we conducted the case study.

4.2 Case Study Modus Operandi

When looking for a case study we made sure certain criteria regarding an alliance were met (see Figure 2 for the steps of the modus operandi). First, the present case study is a typical example of an alliance between two companies competing in the same market segment. Also, the two parent companies are independent of each other. Additionally, they have agreed to cooperate for a set time period of three years in an alliance. Moreover, the two parent companies have agreed to work on certain alliance goals. Finally, both parent companies have knowledge that is of interest for joint research.

Figure 2: Steps for case study preparation.[5]

First discussion of the possibility of gaining the two companies for a case study took place in 2003. In late summer of 2004 the non-disclosure agreement was signed. The actual period of the survey was in the fall of 2004. To conduct initial research about the two participating companies we reviewed annual reports, newspaper reports, and publicly accessible industry

[5] Source: authors' representation.

analyses. We developed two different semi-structured interview guides (Vennix, 1998) in fall 2003 and spring 2004 for both organizational levels in the alliance, here referred to as manager and scientist level. The interview guides were tested in separate pretests on relevance and comprehensibility as a final test run (Yin, 1994), (Friedrichs, 1990). The pretest on the manager level was done with a manager of a first-tier automobile supplier. His department does joint research with several original equipment manufacturers. The pretest on the scientist level was done with a scientist working for an original equipment manufacturer in the automobile industry. He has joined multiple collaborative research projects with partners. After the pretest we revised the interview guides with reference to the order of the questions or their wording (Schnell *et al.*, 1999). The pretests were purposely not done with members of the actual case study companies in order to prevent bias at subsequent interviews.

After signing the non-disclosure agreement we were invited to join an exchange meeting of the alliance members. We were introduced to the team members by the project leaders. They invited the members of both companies' teams to be available to participate in our interviews. During the meeting we had the opportunity not only to observe the working atmosphere between the members of both teams, but also to get to know the participants before running actual interviews. This is part of what is called direct observation in case study research (Yin, 1994), (Friedrichs, 1990). It had a positive influence on the creation of an atmosphere of trust later during the interviews. We made sure to establish contact with participants on the scientist and the manager level of both parent companies to guarantee balanced positions in the survey.

4.3 Case Study Data Collection and Analysis and Use of Data in Modeling

All the desired interviews were able to be carried out during a three-month period in 2004 (see Figure 3). We consulted the managers of both parent firms as well as one and two scientists, respectively. The interviews lasted between 90 and 300 minutes. As we talked to each interviewee intensively, the interviews can be categorized under what is also called expert interviews in case study research. The participants allowed us to tape the conversations, which were then transcribed in their entirely (Yin, 1994), (Friedrichs, 1990), (Vennix, 1998). They also allowed us to cite them under the premise of anonymity (Yin, 1994). When doing so we refer to the interview passage in the footnote with a code that consists of two components: a document number and quote number.[6]

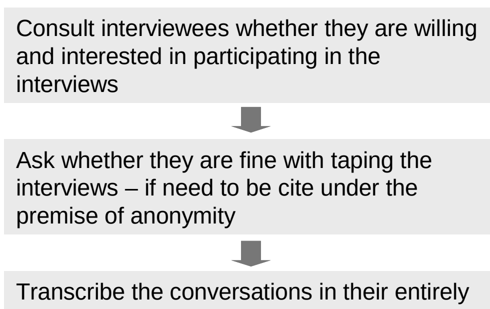

Figure 3: Case study data collection.[7]

[6] The software in use, ATLAS.ti, automatically assigns both consecutive document and quote numbers, separated by colons. Among other things, this makes it easy to find citations again. For example, a quote may be P3: 45 for quote 45 within document 3.

[7] Source: authors' representation.

To accomplish the present study, we used different sources of confirmation. We conducted semi-structured, open-ended, and focused interviews with the participants. We also looked at archival records and documents. Among other things, the documents include parts of the alliance agreement. Finally, we were able to carry out direct observation when we joined the exchange meeting. The procedure of using multiple sources is called triangulation (Yin, 1994), (Spöhring, 1989). It enables the researcher to gain a broader scope of historical, attitudinal, and behavioral issues and hence balance the drawbacks of one method with the advantages of others (Yin, 1994).

FRIEDRICHS indicates that different scholars use different terms for focused interviews, from open questioning to talks to qualitative interviews (Friedrichs, 1990). Focused interviews form the central point of this study. The interviewee is asked for her assessment in a conversational manner while the interviewer follows a certain set of questions. The interviews all began with general questions about the informants' roles and tasks in the alliance. Then the interviews proceeded with four sets of questions for the managers and five for the scientists on the subjects relating to interorganizational learning. The set of questions was designed to gain deeper insight into different aspects of the factors determining the long-term success of research alliances. Last, the interviewees were asked about their thoughts on what other topics we should have talked about to get a better understanding of the issue and who we should talk to in order to get a wider picture. The interviews ended with personal questions.

After the transcription we used different sets of analyses to examine the interviews. The textual information received can be used to support the assumptions of the System Dynamics model (Luna-Reyes *et al.*, 2003). Quotations with main insight help to support model building. There are different types of designs for examining interviews (Schnell *et al.*, 1999). The analysis tools used here mainly include grounded theory and content analysis (Luna-Reyes *et al.*, 2003) (see Figure 4).

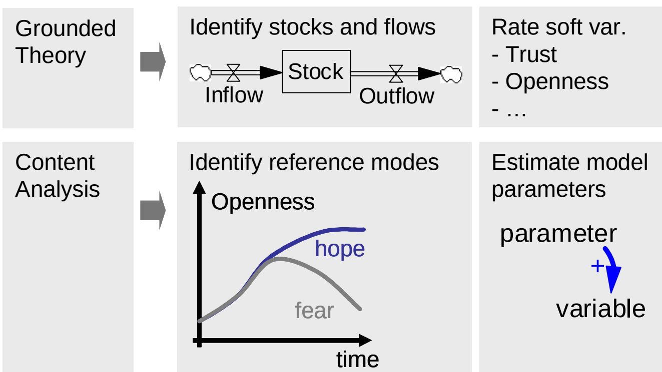

Figure 4: Analysis tools for examining interviews.[8]

Referring to grounded theory, GLASER AND STRAUSS stress that the researcher should approach the problem set principally with an open mind. This means that the scholar should conduct the analysis without any previous literature work. Instead, theory should emerge from the empirical data set (Glaser *et al.*, 1967), (Glaser, 1978). Referring to System Dynamics modeling LUNA-REYES AND ANDERSEN point out that grounded theory can indeed be helpful. Identifying stocks and flows, or rating of particular soft variables can be quantified more easily through relating and linking themes or concepts across texts (Luna-Reyes *et al.*, 2003).

8 Source: authors' representation.

Content analysis is powerful for identifying reference modes and estimating model parameters (Spöhring, 1989) and (Luna-Reyes *et al.*, 2003). To do so, we defined a set of codes that we used to examine the interviews objectively and systematically (Vennix, 1998).Via the coding process we reduced the volume of data sets into analyzable units by generating categories on the basis of the current data (Coffey *et al.*, 1996). This way we identified the interviewees' statements on certain topics. We were then able to link these to the theoretical concepts presented in the literature.

In our full publication (Kapmeier, pending publication), we present the alliance and the two parent companies involved in the case study. Moreover, findings from the case study analysis are cited throughout the complete work. We employ findings and comments from the interviews with alliance members. For example, we refer to interviewees when presenting and discussing factors determining alliance dynamics and when describing the simulation model in separate chapters. Moreover, findings from qualitative empirical social research are embedded in the model policies that determine model behavior. Real-world policies enhance the assumption of the rational homo economicus by capturing people's actual beliefs, desires, intentions, computational capabilities incl. limited foresight, doubts how smart others are, etc. (Camerer, 2003) – which is a requirement by the structure assessment test (Sterman, 2000). Referring to and including insight from case study research at the appropriate places ensures a consequent, rigorous, transparent and hence comprehensible integration of the findings in the System Dynamics model.

5. Conclusion

We first explained the problem statement and gave an overview of the goal of this research. By referring to alliances, we identified a phenomenon to do research on: while alliances become increasingly important for companies' long-term success, they suffer from a large failure rate. Yet, scholars to-date analyze reasons for failure more or less as separate building-blocks. The aim of the present research is to show how combining simulation and modeling with qualitative empirical social research enhances insight into the structure of complex systems like alliances. We first explained and put simulation and modeling into scientific perspective. Then, we described the case study method and showed how to integrate findings from qualitative empirical social research in quantitative modeling. Not only increase simulation and modeling approaches linkages between separate building blocks and interrelating feedback loops transparency. With applying findings from qualitative empirical social research we integrate real world soft data into the model structure. Hence, combining case study analyses and modeling enables modelers to conduct case study driven experimental theory-building and theory-testing in a virtual world.

Acknowledgements

We are indebted to Oliver Simoneit for illuminating the ideas of empirical social research, Meike Tilebein for endlessly discussing the topics in depth, Susan Klemm and Rachel Teear for patiently proofreading, and three reviewers for giving valuable feedback.

Bibliography

Argyris C, Schön DA. 1978. *Organizational Learning: A Theory of Action Perspective*. Addison-Wesley: Reading, Mass., Menlo Park, and others

Axelrod RM. 1997a. Advancing the Art of Simulation in the Social Sciences. In P Terna (Ed.), *Simulating Social Phenomena*: 21 - 40. Springer-Verlag: Berlin, Heidelberg and others
Axelrod RM. 1997b. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton University Press: Princeton and Chichester
Black LJ, Carlile PR, Repenning NP. 2004. A Dynamic Theory of Expertise and Occupational Boundaries in New Technology Implementation: Building on Barley's Study of CT Scanning. *Administrative Science Quarterly* **49**(4): 572 - 607
Camerer CF. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton University Press: Princeton and New York
Carley KM. 1992. Organizational Learning and Personnel Turnover. *Organization Science* **3**(1): 20 - 46
Chmielewicz K. 1994. *Forschungskonzeptionen der Wirtschaftswissenschaft* (3rd ed.). Schäffer-Poeschel Verlag: Stuttgart
Coffey A, Atkinson P. 1996. *Making Sense of Qualitative Data: Complementary Research Strategies*: Thousand Oaks
Coleman-Kammula S, Burton LPJ, Sterman JD, Andersen DF, Richardson GP. 2005. A System Dynamics Study of a Commodity Plastics Industry, *Proceedings of the 23rd International System Dynamics Conference*. System Dynamics Society: Boston
Crossan MM, Berdrow I. 2003. Organizational Learning and Strategic Renewal. *Strategic Management Journal* **24**(11): 1087 - 1105
Doyle JK, Ford DN. 1998. Mental Models Concepts for System Dynamics Research. *System Dynamics Review* **14**(1): 3 - 29
Doz YL. 1996. The Evolution of Cooperation in Strategic Alliances: Initial Conditions or Learning Processes? *Strategic Management Journal* **17**(1): 55 - 83
Engel A, Möhring M. 1995. Der Beitrag sozialwissenschaftlicher Informatik zur sozialwissenschaftlichen Modellbildung und Simulation. In J Klawitter (Ed.), *Modellbildung und Simulation in den Sozialwissenschaften*: 39 - 60. Röll Verlag: Dettelbach
Ford DN. 1995. The Dynamics of Project Management: An Investigation of the Impacts of Project Process and Coordination on Performance, *Sloan School of Management*. Massachusetts Institute of Technology: Cambridge, Mass.
Forrester JW. 1961. *Industrial Dynamics*: Cambridge, Mass.
Forrester JW. 1969. *Urban Dynamics*: Portland
Forrester JW. 1971. *World Dynamics*: Cambridge, Mass.
Forrester JW. 1972. *Grundzüge einer Systemtheorie*: Wiesbaden
Forrester JW. 1975. Counterintuitive Behavior of Social Systems. In JW Forrester (Ed.), *Collected Papers of Jay W. Forrester*: 211 - 244. Wright-Allen Press, Inc.: Cambridge, Mass.
Forrester JW. 1985. "The" Model versus a Modeling "Process". *System Dynamics Review* **1**(1): 133 - 134
Forrester JW. 1994a. Policies, Decisions, and Information Sources for Modeling. In JD Sterman (Ed.), *Modeling for Learning Organizations*: 51 - 84
Forrester JW. 1994b. System Dynamics, System Thinking, and Soft OR. *System Dynamics Review* **10**(2-3): 245 - 256
Friedrichs J. 1990. *Methoden empirischer Sozialforschung* (14th ed.). Westdeutscher Verlag: Opladen
Gary MS. 2005. Implementation Strategy and Performance Outcomes in Related Diversification. *Strategic Management Journal* **26**(7): 643 - 664
Glaser BG. 1978. *Theoretical Sensitivity. Advances in the Methodology of Grounded Theory*. The Sociology Press: Mill Valley

Glaser BG, Strauss AL. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Aldine Atherton: Chicago and New York
Goncalves PM. 2003. Demand Bubbles and Phantom Orders in Supply Chains, *Sloan School of Management*. Massachusetts Institute of Technology: Cambridge, Mass.
Goncalves PM, Sterman JD. 2005. Overordering Games in Supply Chains, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston
Gorobets A, Nooteboom B. 2004. Agent Based Computational Model of Trust. Erasmus Research Institute of Management, Erasmus University Rotterdam: Rotterdam
Gramelsberger G. 1996. Theorie - Simulation - Experiment, *Lehrstuhl für Philosphie mit Schwerpunkt Analytische Philosophie / Wissenschaftstheorie*. Universtität Augsburg: Augsburg
Gramelsberger G. 2001. Semiotik und Simulation: Fortführung der Schrift ins Dynamische, *Fachbereich Philosophie und Geisteswissenschaften*. Freie Universität Berlin: Berlin
Heine B-O, Kunz J. 2003. Die Computersimulation als Methode in der betriebswirtschaftlichen Forschung. *Controlling & Management* **47**(6): 374 - 378
Hoßfeld F. 1993. Wissenschaftliches Rechnen - Motor der Rechnerentwicklung. In H Weberpals (Ed.), *Das wissenschaftliche Rechenzentrum der Zukunft*: 5 -17. Saur: München, New Providence, and others
Kapmeier F. 2002. Dynamics of Interorganizational Learning, *Proceedings of the 20th International Conference of the System Dynamics Society*. System Dynamics Society: Albany, NY: Palermo
Kapmeier F. 2003. Dynamics of Common Learning in Learning Alliances, *Proceedings of the 21st International Conference of the System Dynamics Society*. System Dynamics Society: Albany, NY: New York
Kapmeier F. 2005. Private and Common Goals in Learning Alliances, *Proceedings of the 23rd International Conference of the System Dynamics Society*. System Dynamics Society: Albany, NY: Boston, Mass.
Kapmeier F. pending publication. *Dynamics of Interorganizational Learning in Learning Alliances*
Keough M, Doman A. 1992. The CEO As Organization Designer: An Interview with Professor Jay W. Forrester, the Founder of System Dynamics. *The McKinsey Quarterly* **28**(2): 3 - 30
Khanna T, Gulati R, Nohria N. 1998. The Dynamics of Learning Alliances: Competition, Cooperation, and Relative Scope. *Strategic Management Journal* **19**(3): 193 - 210
Kumar R, Nti KO. 1998. Differential Learning and Interaction in Alliance Dynamics: A Process and Outcome Discrepancy Model. *Organization Science* **9**(3): 356 - 367
Lamnek S. 1995. *Qualitative Sozialforschung: Methoden und Techniken* (3rd ed.): Weinheim
Lane PJ, Salk JE, Lyles MA. 2001. Absorptive Capacity, Learning, and Performance in International Joint Ventures. *Strategic Management Journal* **22**(12): 1139 - 1161
Lant TK, Mezias SJ. 1990. Managing Discontinuous Change: A Simulation Study of Organizational Learning and Entrepreneurship. *Strategic Management Journal* **11**(Summer Special Issue: Corporate Entrepreneurship): 147 - 179
Levinthal DA. 1997. Adaptation on Rugged Landscapes. *Management Science* **43**(7): 934 - 950
Luna-Reyes LF, Andersen DL. 2003. Collecting and Analyzing Qualitative Data for System Dynamics: Methods and Models. *System Dynamics Review* **19**(4): 1 - 26
Lyneis JM. 1999. System Dynamics for Business Strategy: A Phased Approach. *System Dynamics Review* **15**(1): 37 - 70
Meadows DH. 1980. The Unavoidable A Priori. In J Randers (Ed.), *Elements of the System Dynamics Method*: 23 - 57. The MIT Press: Cambridge, Mass. and London

Meadows DL, Behrens III WW, Meadows DH, Naill RF, Randers J, Zahn EOK. 1974. *Dynamics of Growth in a Finite World*. Wright-Allen Press, Inc.: Cambridge, Mass.
Morecroft JDW. 1983. System Dynamics: Portraying Bounded Rationality. *OMEGA - The International Journal of Management Science* **11**(2): 131 - 142
Morecroft JDW. 1985. Rationality in the Analysis of Behavioral Simulation Models. *Management Science* **31**(7): 900 - 916
Morecroft JDW. 1988. System Dynamics and Microworlds for Policymakers. *European Journal of Operational Research* **35**(3): 301 - 320
Morecroft JDW. 1994. Executive Knowledge, Models, and Learning. In JD Sterman (Ed.), *Modeling for Learning Organizations*: 3 - 28
Morecroft JDW, Robinson S. 2005. Explaining Puzzling Dynamics: Comparing the Use of System Dynamics and Discrete-Event Simulation, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston, Mass.
Morecroft JDW, Sanchez R, Heene A (Eds.). 2002. *Systems Perspective on Resources, Capabilities, and Management Processes*. Pergamon: Amsterdam, London, and others
Morrison BJ. 2005. Implementation As Learning: An Extension of Learning Curve Theory, *23rd International System Dynamics Conference*. System Dynamics Society: Boston
Nonaka I, Takeuchi H. 1995. *The Knowledge Creating Company. How Japanese Companies Create the Dynamics of Innovation*: Oxford
Oliva R, Sterman JD. 2001. Cutting Corners and Working Overtime: Quality Erosion in the Service Industry. *Management Science* **47**(7): 894 - 914
Oriesek DF, Friedrich R. 2003. Blick in die Zukunft. *Harvard Business Manager* **25**(5): 65 - 71
Otto P, Richardson GP. 2004. Interorganizational Learning: A Dynamic View on Knowledge Development in Strategic Alliances. In SD Society (Ed.), *Proceedings of the 22nd International Conference of the System Dynamics Society*: Oxford, GB
Parker DC, Berger T, Manson SM (Eds.). 2001. *Agent-Based Models of Land-Use and Land-Cover Change: Report and Review of an International Workshop*: Irvine, Calif.
Rahmandad H. 2004. Heterogeneity and Network Structure in the Dynamics of Contagion: Comparing Agent-Based and Differential Equation Models, *Proceedings of the 22nd International Conference of the System Dynamics Society*: Oxford
Rahmandad H. 2005. Dynamics of Platform-Based Product Development, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston
Repenning NP. 2001. Understanding Fire Fighting in New Product Development. *Journal of Product Innovation Management* **18**(5): 285 - 300
Repenning NP. 2002. A Simulation-Based Approach to Understanding the Dynamics of Innovation Implementation. *Organization Science* **13**(2): 109 - 127
Repenning NP. 2003. Selling System Dynamics to (Other) Social Scientists. *System Dynamics Review* **19**(4): 303 - 327
Repenning NP, Sterman JD. 2002. Capability Traps and Self-Confirming Attribution Errors in the Dynamics of Process Improvement. *Administrative Science Quarterly* **47**(2): 265 - 295
Richardson GP. 2001. System Dynamics. In CM Harris (Ed.), *Encyclopedia of Operations Research and Management Science*, 2nd ed.: 807 - 810. Kluwer Academic Publishers: Boston, Dordrecht and London
Roberts EB. 1978. A Simple Model of R&D Project Dynamics. In EB Roberts (Ed.), *Managerial Applications of System Dynamics*: 293 - 314: Cambridge, Mass. and London
Rockart SF. 2001. Calling Spirits from the Deep: Competing for and through Sophisticated Customers, *Sloan School of Management*. Massachusetts Institute of Technology: Cambridge, Mass.

Sastry MA. 1997. Problems and Paradoxes in a Model of Punctuated Organizational Change. *Administrative Science Quarterly* **42**(2): 237 - 275
Schleichert H. 1995. Simulation. In J Mittelstrass (Ed.), *Enyclopedie Philosophie und Wissenschaftstheorie,* Vol. 3: 807 - 809. Verlag J.B. Metzler: Stuttgart and Weimar
Schnell R, Hill PB, Esser E. 1999. *Methoden der empirischen Sozialforschung* (6th ed.). R. Oldenburg Verlag: München, Wien, and Oldenburg
Simon HA. 1969. *The Sciences of the Artificial*. M.I.T. Press: Cambridge, Mass. and London
Spöhring W. 1989. *Qualitative Sozialforschung*. Teubner Studienskripten: Stuttgart
Stachowiak H. 1973. *Allgemeine Modelltheorie*. Springer-Verlag: Wien and New York
Sterman JD. 1987. Testing Behavioral Simulation Models By Direct Experiment. *Management Science* **33**(12): 1572 - 1592
Sterman JD. 1991. A Skeptic's Guide to Computer Models. In MJ Garrett (Ed.), *Managing a Nation: The Microcomputer Software Catalog*, 2nd ed.: 209 - 229. Westview Press: Boulder, San Francisco, and Oxford
Sterman JD. 1994. Learning in and about Complex Systems. *System Dynamics Review* **10**(2-3): 291 - 330
Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin McGraw-Hill: Boston, Madison, and others
Sterman JD. 2002. All Models Are Wrong: Reflections on Becoming a Systems Scientist. *System Dynamics Review* **18**(4): 501 - 531
Sterman JD, Henderson R, Beinhocker ED, Newman LI. 1995. A Behavioral Analysis of Learning Curve Strategy: 33. Massachusetts Institute of Technology, Sloan School of Management: Cambridge, Mass.
Struben J. 2004. Technology Transitions: Identifying Challenges for Hydrogen Vehicles, *Proceedings of the 22nd International Conference of the System Dynamics Society*: Oxford
Struben J. 2005. Space Matters Too! Mutualistic Dynamics between Hydrogen Fuel Cell Vehicle Demand and Fueling Infrastructure, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston
Taylor T, Ford DN, Johnson ST. 2005. Why Good Projects Go Bad: Managing Development Projects Near Tipping Points, *Proceedings of the 23rd International Conference of the System Dynamics Society*: Boston
Troitzsch KG. 2004. Simulationsverfahren. *Das Wirtschaftsstudium* **33**(10): 1256 - 1268
Vennix JAM. 1998. *Group Model Building: Facilitating Team Learning Using System Dynamics*. John Wiley & Sons: New York, Brisbane, and others
von Neumann J (Ed.). 1963. *Collected Works*. (Vol. V: Design of Computers, Theory of Automata and Numerical Analysis). Pergamon Press: Oxford, London, and others
Warren K. 2002. *Competitive Strategy Dynamics*. John Wiley & Sons: Chichester
Weber K. 2004. Der wissenschaftstheoretische Status von Simulationen. In U Frank (Ed.), *Wissenschaftstheorie in Ökonomie und Wirtschaftsinformatik: Theoriebildung und -bewertung, Ontologien, Wissensmanagement*: 171 - 187. Deutscher Universitätsverlag: Wiesbaden
Yin RK. 1994. *Case Study Research: Design and Models* (2nd ed.): Thousand Oaks, London, and New Delhi
Zeng M, Chen X-P. 2003. Achieving Cooperation in Multiparty Alliances: A Social Dilemma Approach to Partnership Management. *Academy of Management Review* **28**(4): 587 - 605
Zott C. 2003. Dynamic Capabilities and the Emergence of Intraindustry Differential Firm Performance: Insights from a Simulation Study. *Strategic Management Journal* **24**(2): 97 - 125