Eliciting Knowledge from Experts in Modeling of Complex Systems: Managing Variation and Interactions.

Per Wikberg

Department of Computer and Information Science
Linköpings universitet
SE-581 83 Linköping, Sweden

Linköping 2007
Acknowledgements

Making the decision to finally bring my PhD studies to completion was primarily a decision to allocate time to work on the thesis. In practice, such a decision is only made possible by a supportive family. My two kids, Jonathan and Selma, have had a father not always as focused on parenthood as I wish I would have been. My lovely Anna has, to a great extent, had to shoulder the responsibility of our family life by herself. You are the very centre of my heart and my acknowledgements are first and foremost given to the three of you.

A special acknowledgement also goes to my supervisor since 1992, Dr. Bo Strangert. It has been a privilege!

Dr. Erland Svensson also got engaged as a supervisor in the final phases of my PhD project. I am sincerely grateful for his commitment and advice.

Finally, I would like to thank all those who otherwise directly or indirectly have contributed to the thesis. Over the years, I have been engaged in a wide variety of different research projects and development activities. It has been the basis for testing and refining much of the ideas which have been extracted into this thesis. I find it very hard to make a complete and comprehensive list of all the engaged and professional people I have cooperated with in these endeavours. It has been inspiring, challenging, rewarding and, above all, fun.

September, 2007

Per Wikberg
PhD thesis:

Eliciting Knowledge from Experts in Modeling of Complex Systems: Managing Variation and Interactions.

Per Wikberg

The thematic core of the thesis is about how to manage modeling procedures in real settings. The view taken in this thesis is that modeling is a heuristic tool to outline a problem, often conducted in a context of a larger development process. Examples of applications, in which modeling are used, include development of software and business solutions, design of experiments etc. As modeling often is used in the initial phase of such processes, then there is every possibility of failure, if initial models are false or inaccurate. Modeling often calls for eliciting knowledge from experts. Access to relevant expertise is limited, and consequently, efficient use of time and sampling of experts is crucial. The process is highly interactive, and data are often of qualitative nature rather than quantitative. Data from different experts often vary, even if the task is to describe the same phenomenon. As with quantitative data, this variation between data sources can be treated as a source of error as well as a source of information. Irrespective of specific modeling technique, variation and interaction during the model development process should be possible to characterize in order to estimate the elicited knowledge in terms of correctness and comprehensiveness. The aim of the thesis is to explore a methodological approach on how to manage such variations and interactions. Analytical methods tailored for this purpose have the potential to impact on the quality of modeling in the fields of application.

Three studies have been conducted, in which principles for eliciting, controlling, and judging the modeling procedures were explored. The first one addressed the problem of how to characterize and handle qualitative variations between different experts, describing the same modeling object. The judgment approach, based on a subjective comparison between different expert descriptions, was contrasted with a criterion-based approach, using a predefined structure to explicitly estimate the degree of agreement. The results showed that much of the basis for the amalgamation of models used in the judgment-approach was concealed, even if a structured method was used to elicit the criteria for the independent experts’ judgment. In contrast, by using the criterion-based approach the nature of the variation was possible to characterize explicitly. In the second study, the same approach was used to characterize variation between, as well as within, different modeling objects, analogical to a one-way statistical analysis of variance. The results of the criterion-based approach indicated a substantial difference between the two modeling subjects. Variances within each of the modeling tasks were about the same and lower than the variance between modeling tasks. The result supports the findings from the first study and indicates that the approach can be generalized as a way of comparing modeling tasks. The third study addressed the problem of how to manage the interaction between experts in team modeling. The aim was to explore the usability of an analytical method with on-line monitoring of
the team communication. Could the basic factors of task, participants, knowledge domains, communication form, and time be used to characterize and manipulate team modeling? Two contrasting case studies of team modeling were conducted. The results indicated that the taxonomy of the suggested analytical method was sensitive enough to capture the distinctive communication patterns for the given task conditions. The results also indicate that an analytical approach can be based on the relatively straightforward task of counting occurrences, instead of the relatively more complex task of establish sequences of occurrence.
1. The aim and purpose of the thesis. The thematic core of the thesis is about how to manage modeling procedures in real settings. The view taken in this thesis is that modeling is a heuristic tool to outline a problem. Examples of areas of applications, in which modeling are used, include development of software and business solutions, design of experiments etc. As modeling often is used in the initial phase of such processes, then there is every possibility of failure, if initial models are false or inaccurate. Modeling often calls for eliciting knowledge from experts. The process is highly interactive, and data are often of qualitative nature rather than quantitative. Data from different experts often vary, even if the task is to describe the same phenomenon. As with quantitative data, this variation between data sources can be treated as a source of error as well as a source of information. The aim of the thesis is to explore a methodological approach to manage such variations and interactions. Analytical methods tailored for this purpose could impact on the quality of modeling in the fields of application. In order to address the purpose of managing the modeling procedure in practical settings, the thesis is founded on six basic considerations.

A. Eliciting knowledge from experts has a practical purpose. Thus, any modeling enterprise in this context is motivated by a real need of solving a practical problem. The general approach to solve these practical problems is by eliciting experience and assumptions from relevant expertise. Obviously, if there has been an existing solution to the problem, the modeling enterprise would not have occurred. Consequently, the elicitation, amalgamation, and validation phases of the modeling process are normally closely integrated, and the separation of them in research environments is often artificial. In general, research has overlooked the fact that in most real world problems, unique solutions do not exist (Shanteau, 2001, p. 232.). Even if it is possible to study the management of modeling enterprises in a randomized-assignment-to-controlled-treatments approach, there is the risk of excluding important aspects of the modeling procedure in practical settings. In line with this, the thesis is based on a case study approach with data from “real” modeling enterprises. The products from these modeling undertakings have subsequently been used in the Swedish Armed Forces development of command and control methods (Swedish Armed Forces, 2003, 2007).
B. Modeling is a limited part of a larger process. A related issue to the consideration above is that modeling is seldom undertaken to create a model per se. Instead, the purpose of a modeling enterprise is normally to create a foundation for a practical application such as computer software or a complex test design. The purpose of analyzing the modeling enterprise is thus often to decide whether the model is “good enough” to proceed to the next phase of the process.

C. Modeling is not the same as empirical testing. Ultimately, the sole quality measure of correctness of the model is empirical testing in an adequate environment. Empirical testing must be timely coupled with the modeling procedure and not just performed as a final check. However, considering the costs of running empirical tests, the possibility of validating aspects of models should be considered in the modeling procedure.

D. Quality assurance of the modeling process is of central importance. As modeling often is used in the initial phase of development, then there is every possibility of system failure, if initial precepts are false or inaccurate (Urquhart, 1998, p. 115). Analysis of the modeling process per se is thus of vital importance even from a practical point of view. Enhancing the stringency of how modeling enterprises are undertaken is of practical importance.

E. The available time for eliciting knowledge from experts is restricted. Experience from related studies is that the access to subject matter experts is limited (Klein, Calderwood & MacGregor, 1989, p. 464.; Wikberg et al., 2003, p. 8.; 2005, P. 13). Efficient use of time and resources is thus an important aspect of modeling. Viewing elicitation, integration, and validation of the modeling as closely integrated, calls for analytical tools and procedures adapted to these constraints. In contrast to many tools and procedures applied in research settings, the analysis must be possible to conduct more or less on-line. To handle qualitative variation by using complex analytical approaches is not a primary choice. Consequently, analytical methods for handling variation between experts must be kept simple.

F. Analysis of variation between experts should be possible to conduct irrespective of the modeling technique. A wide variety of modeling techniques has emerged. Which of these to use depends largely on the modeling task and the preferences of the analyst. Ideally, an analytical tool for managing the modeling process should not be restricted the use of specific modeling techniques.
2. **Modeling.** By definition, a model is a real or imaginary representation of a real system. The basic logic of a model is analogy in terms of patterns of similarity and differences between the model and the modeling subject (Harré, 2002, p. 54). By reducing the complexity of reality but still containing relevant information, the model might be used as a tool, a schema or a procedure to predict the consequences of an event. The properties of a model will be formally defined as a set of elements or conceptual terms, a set of rules for relations between the elements, a set of empirical elements and relations corresponding to the conceptual terms and relations, and finally, a set of rules for interpretation. Modeling, as conceived of here, is the construction of such a model based on data from a ‘system analysis’, by first selecting a suitable model format and then constructing a valid mapping relation between reality and the formal representation, through repeated translation exercises.

There are several definitions of the term ‘systems analysis’, but any definition usually involves some kind of procedure, more or less formal, for collecting and organizing data about an empirical phenomenon. There are a variety of systems analysis techniques and approaches, such as ‘task analysis’ (Annett et al., 1971; Drury et al., 1987), ‘job analysis’ (Harvey, 1991), ‘content analysis’ (Kolbe, 1991; Weber, 1990), ‘action analysis’ (Singleton, 1979), and ‘cognitive systems engineering’ (Hollnagel & Woods, 1983; Rasmussen et al., 1994). Despite the fact that these techniques differ somewhat when it comes to perspectives and procedures, they are rather similar. They are related to a scientific style of analytically approaching a certain phenomenon, in order to treat or analyze reality as a systematically connected set of elements (Gasparski, 1991, p. 16.).

2.1. **History.** Systems analysis has much of its origins from systems theory (von Bertalanffy, 1950, 1968). Despite that the theory originally was used to describe biological principles, virtually all phenomena might be defined as open systems with boundaries, but still interacting with the environment (Boulding, 1956). Accordingly, a lot of different aspects of life have been theorized according to the methodological principles of systems theory. For example, Katz and Kahn (1966) described organizations as open systems in reciprocal exchange with their environments. Particularly the book *The Systems Approach* by Churchman (1968) led to a widespread acceptance of the term systems analysis.

2.2. **The use of models.** The process of creating a model is often labeled ‘modeling’. A good modeling technique will help organize the important concepts and goals of the modeling subject.
It might be a way for the researcher to become familiar with the problem area (Bainbridge, Lenior & Schaaf, 1993, p. 1277.). Furthermore, it might be a common ground for understanding between researchers and practitioners with different backgrounds (Wikberg, 1997, p. 66). Yet another example is to use models to define particular phenomena to be investigated in an empirical study (Markham 1998). Accordingly, the model will fulfill several purposes, which broadly can be divided into comparison, prediction and design (Schaaf, van der, 1993, p. 1441.).

In science, modeling is a core activity. Scientific exploration might be seen as an interaction between the processes of discovery and justification, in which models are gradually developed, empirically tested and eventually matured into established theories of generalized predictive knowledge (Reichenbach, 1938). However, modeling must not be confused with validation of theories based on empirical testing. One of the basic notions of this thesis is that modeling is a part of a larger process and often used in the initial phase of a development process. Taking this view implies that modeling rather refers to the discovery phase of scientific exploration. It is a part of the initial “problem analysis” before more elaborated empirical testing takes place.

However, modeling has also increasingly been used in practical settings. Modeling is a way of structuring complex systems in order to construct simulations, a part of the design process, and a problem identifying process etc. Applications are found in as disparate areas as reconstruction of broken archaeological artifacts (Doerr, Plexousakis & Bekiari, 2001) and design of business solutions (Taveter & Wagner, 2001).

2.3. Fields of applications. One such field in which modeling is often applied is systems development. The process of developing and implementing new products or systems has become increasingly complex. Normally a development cycle is quite time-limited and is realized through iterative enhancements of a first prototype, a method often referred to as fast prototyping (Harton & Smith, 1991). The time limits are significant - more than half of Ericsson’s products were not on the market 18 months ago. The development process often takes the form of projects, in which it is necessary to involve several scientific disciplines and practical experts (Brooks & Jones, 1996, pp. 10-11). The development within the area of human-computer interaction might serve as an example of the development.

2.3.1 Human-computer interaction research. Throughout the past three decades, human-computer interaction-research (HCI) has tried to integrate scientific concerns with the
engineering goals of an improved ‘usability’ of computer systems and applications (Carroll, 1997).

The tradition, being an intersection between psychology and the social sciences, on one hand, and computer science and technology on the other, has developed a body of technical knowledge and methodology. Caroll (1997) characterized the methodological approach as “psychology as a science of design”. This HCI-research tradition has evolved from “software psychology” (Schneiderman, 1980), with an approach of basic research on general and normative models of how humans interact with computers.

One basic problem, early recognized in HCI-research, was that a top-down approach to software development, manifested in the waterfall model (Royce, 1970), was not applicable in practical settings. As computer research diversified in the 70s and 80s, product development cycles were often compressed to less than a year (Carroll, 1997, p. 63). Furthermore, the ambition to develop general descriptions of users and framing these as general guidelines was pushed by researchers from a traditional, laboratory-based tradition. From a practical view, research from this period often focused on unrepresentative situations. In order to obtain experimental control, researchers often created contrasts never existing in real contexts. The critical step of using these guidelines in practical settings proved to be a frustrating matter (Carroll, 1997, pp. 63-64).

In the 80s and 90s the research area has developed to focus on the design process per se rather than on general guidelines of human performance. Within this rapid iterative approach based on empirical evaluation of real users and real systems, the cost of empirical studies early became a central issue. In practice, the R&D model is a design process including all stages from knowing the user and the development of a concept to providing support and maintenance and collecting data from the field.

In recent years focus has shifted from the dominant cognitive model of the individual operator towards a more social team-oriented approach to HCI, as the concept of computer supported cooperative work (CSCW) has become common in real applications (Bannon, 2001). Methodologically, much of this research has taken an ethnographic approach as an analytical framework for the research. A more comprehensive description of the development of HCI-research in the last decades is found in Carroll (1997) and Bannon (2001).

Consequently, the design process of software development relies heavily on the problem definitions of the intended users. Modeling has become a standard approach to structure systems.
UML, the Unified Modeling Language (Booch, Rumbaugh & Jacobson, 1997) is for example widely used to coordinate design of complex software.

2.3.2. Military experimentation. The user centered approach utilized in HCI has also been applied in the work of the present author. The work has focused on developing a "practice" based on a scientific approach to conduct experimentation in the context of the Defense Forces’ progressive development of command and control and still try to maintain a scientific rigor (Wikberg et al., 2005). The ambition has been to be able to empirically test the organization’s "best guesses" with a limited amount of resources as regards time, money, training, and technical aids, while still gaining knowledge from experimentation. The basic consideration has been that development of such complex systems should follow the principles of science. Ideas and assumptions underlying efforts of changes of organizations and systems should be made explicit and tested empirically as early as possible in a developmental cycle. The alternative that changes in an organizational system will be based on trial and error or collection of anecdotes is of course possible, but progress will be unsure, and relatively slow (Alberts & Hayes, 2005, p. 27).

In the context described above, modeling has been used as a methodological approach to work out experimental design in large-scale experimentation. The procedure is normally based on team interviews, where the result is summarized by a graphical representation with notations. One key issue is that it is often required that clients, i.e. the “owners” of the problem, and domain experts are involved in the modeling process. In this context, the perspective is that the purpose of the modeling is to explicitly translate the client’s assumptions of, and approach to, the problem into problem statements and hypotheses. The core in the modeling approach is that the modeling should produce a base for data collection about the stated problem, i.e. the foundation of the research design. Modeling procedures include extracting ideas from different kinds of experts and users of a system and formalize these into a hypothetical model, in order to empirically test important ideas and assumptions promptly. Seen in the context of science, this use of modeling may correspond to the discovery phase of scientific exploration (Reichenbach, 1938). Recent examples of this experimentation activity might be found in Wikberg, Danielsson & Holmström (2005), Cheah, Thunholm, Chew, Wikberg, Andersson, & Danielsson (2005) and Wikberg, Andersson, Berggren, Hedström, Lindoff, Rencrantz, Thorstensson & Holmström (2004).
3. Expertise. Experts are a major source of information for modeling enterprises. A basic notion is that researchers in general agree on considering expertise as domain specific (Cellier, Eyrolle & Mariné, 1997, p. 28.).

In cognitive psychology, expertise is often defined in terms of extent and organization of memory (Glaser, 1989, p. 272), and attempts have been undertaken to extend cognitive theories of problem solving and memory to the understanding of human expertise. Anderson (1982, 1983, 1987) has presented a general theory of skill acquisition, the cognitive architecture of ACT (The Adaptive Control of Thought). The main idea suggested in ACT is that skill learning consists of changing declarative knowledge to procedural knowledge (Ford & Kraiger, 1995, p. 5.; Cohen, 1984), and then modifying this procedural knowledge via application processes. Elements of knowledge are stored in memory as coherent chunks of information. New information is linked to such structures of knowledge, making it possible for experts to rapidly retrieve patterns when solving problems. Over time, domain specific knowledge becomes automated and unconscious in order to make the conscious processing capacity available for decision making and reasoning.

Ironically, the research has also shown that as an individual gains experience and eventually expertise, and thus, according to ACT*, transforms declarative knowledge to procedural knowledge, he also might lose his ability to describe his area of expertise (Anderson, 1982; Sweller, 1983).

The body of knowledge on experts in cognitive psychology is largely gained by studying expertise in environments and tasks which allow experimental control. One setting often used is the study of development of expertise in chess (Eysenck & Keane, 2000, p. 413.). The underlying assumption is that expertise can be treated as a unitary construct independent of the domain of expertise (Brauer, Chambres, Niedenthal & Chatard-Pannetier, 2004, p. 5.). Concerns about the validity of this assumption have been put forward stressing the need for expertise research for applied purposes (Ford & Kraiger, 1995, pp.37-39; Sonnentag, 1998, p. 703.). Furthermore, ACT is mainly concerned with expertise in routine tasks in contrast to expertise in creative tasks (Hatano & Inagaki, 1986). The concerns over ACT are relevant as the rationale of using experts in modeling is based on an assumption that they have conscious access to their skills and knowledge.
In contrast to the generally laboratory-based studies in cognitive psychology of expertise, there is also the human factors tradition of studying expertise in real settings. The basic notion is that expertise should be studied in their real context (Salas & Klein, 2001, p. 3.). As in the case of cognitive psychology, expertise has in many cases the same meaning as experience. In research, the most common definition of expertise is “years of experience”, even if there are other approaches such as graduate degrees, training experience, publication record, licensing etc (Mullin, 1989, p. 618.). In the concept of expertise, Hoffman, Shadbolt, Burton, and Klein (1995) include a set of general factors – experiential, social, cognitive and performance-related. Still they recognize that expertise is a development process, which in some cases might be a long process—more than a decade. It is possible to distinguish three general approaches to defining experts in this research (Cellier, Eyrolle, & Marné, 1997, p. 30.). The most widely used is expertise as acquisition from practice. Studies implicitly assume that the longer the practice the better the performance. Another approach is expertise in terms of efficiency assessed by performance, by colleagues or by job title. Finally, there is an approach of distinguishing between different subjects in terms of assumed knowledge, generic versus specialized. Studies have been conducted in a variety of settings with a focus on dynamic environments or ‘naturalistic decision making’. Reviews of such studies can be found in Klein, Orasanu, Calderwood, & Zsambok, (1993) and Zsambok & Klein, (1995).

An important aspect of this research is the importance of the workload of the studied task. Task characteristics are consequently an important feature to consider, when conclusions are made from studies (Stewart, Roebber & Bosart, 1997). Subsequently, findings from different studies must be carefully examined before generalizing over studies.

In summary, the prevalent operational definition of expertise is based on seniority. People enhance their competence with experience, or rather, deliberate practice (Ericsson & Lehmann, 1996, pp. 278-279). They become experts and manifest what is broadly termed expertise. However, degrees of seniority are empirically defined and thus arbitrary. Experts use considerable domain specific causal knowledge when solving induction problems in their area of expertise (Proffitt, Coley & Medin, 2000. p. 826). One cannot be sure whether experts are comparable from one study to another. Consequently, it is also important to include task and knowledge domain, when expert characteristics are considered (Stewart, Roebber & Bosart, 1997. p. 206.).
In addition, manifested expertise is not the same as ability to explicitly describe the specific domain of expertise. For example, Kuhn (1991) found that participants that held an opinion on a controversial matter often could not give evidence in support of that opinion. Thus, the extracted model of a modeling session might be the experts’ naïve psychological theory of the process, which will not stand up to empirical investigation. For example, Rasmussen (1993, p. 138) puts forward the risk that there will evolve a rational or mythological “operator logic” within professional domains that does not correspond to reality. Consequently, control of obtained data is important in modeling even in cases where access to highly skilled expertise is available.

4. The modeling procedure. As mentioned earlier, modeling is basically considered to be a problem solving process. The basic modeling procedure, as conceived here, is divided into the three phases of elicitation – collecting different expert knowledge of the modeling subject, amalgamation – integrating different expert descriptions into a joint model, and validation – judging the correctness and comprehensiveness of the model. These phases are more or less integrated depending on the modeling task and the chosen modeling technique. Presumably, any modeling procedure must be coordinated in some fashion.

Studies have also showed that efficient problem solving in complex settings is linked to well-structured flow of communication and role distribution (Rogalski & Samurçay, 1993). The coordinative process might be a serial and additive effort of instantiating specific plans or using analogical transformations to known solutions of similar problems, if the problem to be modeled is well structured (Carbonell, 1986). However, as the problem to be solved in modeling is often ill structured, the process is presumably better characterized as an iterative, non-linear interaction between overlapping and fuzzy domains. In addition, the problem domain which is to be modeled is often too complex for a single expert to master. Thus, it is often necessary to engage different individuals in a team effort in the modeling enterprise. Each of the participants is supposed to bring their specific competence and knowledge to the model. At a minimum, the modeling enterprise engages two persons, the analyst and the respondent. The model is constructed in an interactive process between these individuals. Consequently, the modeling procedure might be viewed as a group process. Coordinating the process – problem solving over time – is as an important aspect for group performance (Paulus, 2000, pp. 253-254.). The level of control of the interactive process varies between different modeling techniques. A rough classification of modeling procedures can be based on the extremes in terms of level of control: modeling based on information from independent respondents and modeling in teams.
Independent participants or one-participant modeling. In this case, the analyst is interacting with one participant at a time. The basic procedure is to first let different participants contribute independently to the modeling, and then synthesize a solution. Consequently, the end product evolves successively as different models are contrasted against each other. The group factor is controlled by independent sampling and of course by a standardized procedure. The analyst will have a great impact on the end result, as he will largely define the procedure of bringing different model representations into line with each other.

Interdependent participants or team modeling. In this case the modeling team consists of several participants interacting in a group effort. The basic procedure is to let the model successively evolve in the interaction between different participants. Synthesizing an end result is then embedded in the data eliciting procedure. The group factor is a part of the design of the modeling procedure. The process is however not solely about objectively piecing together knowledge. The process is highly social and both the participants’ “objective” level of expertise, as well as the extent to which expertise is recognized, will have an effect on this interaction (Littlepage & Mueller, 1997, p. 324.; Bromme, Rambow & Nückles, 2001). Thus, the analysis should focus on the variation in the interaction between participants.

There is a vast literature in psychology on research on small group processes covering a wide range of several research areas with relevance for the modeling procedure. Bales’ pioneering observational studies of groups revealed that the way members of a group contribute to group decisions can be broken down into task-related and socio-emotional behavior (Bales, 1970). Still research gives little guidance on how to design a time-limited modeling procedure.

By viewing modeling as a problem solving process, decision making becomes a related area which has been the focus for a vast amount of research. The classical research approaches (Simon, 1957, Miller & Starr, 1967) viewed decision making as a problem solving task in terms of rational choices between defined alternatives. Research on group decision making typically focused on the processes involved in moving from a diverse set of individual positions or preferences to agreement on a consensus choice for the group (Kerr & Tinsdale, 2003, pp. 632-633). However, it was early concluded that it was difficult to translate this perspective into a normative model for more dynamic decision tasks (Rapoport, 1975).
In current research on decision making, the focus has shifted from preferences to information (Kerr & Tinsdale, 2003, p. 642). One way of characterizing the current decision research is by two overlapping perspectives: decision making as dynamic process control, (Brehmer & Svenmarck, 1995) based on control theory (Ashby, 1956), and decision making as intuitive judgment based on expertise and recognition of contextual factors (Klein, 1993). Research has generated findings that have some relevance for the modeling process. For example, differences between successful and less successful decision makers described by (Dörner, 1996), or principal problems when people are coping with complexity and dynamics in decision making (Brehmer, 2005) might perhaps serve as guidelines for designing the modeling process. Another example is the findings stemming from the “shared versus unshared information paradigm” (Stasser & Titus, 1985). The counterintuitive findings that groups have a tendency to ignore information that is not widely shared among group members has generated a line of research, which have been a central part of group research (Kerr & Tinsdale, 2003, p. 633). For example, results have revealed indications of the importance of “expert roles” for dissemination of information (Stasser, Stewart, & Wittenbaum, 1995) and session and speaking time (Diehl & Strobe, 1991). However, translating these findings into modeling practice is an elusive matter. The problem is that modeling can not solely be viewed as decision making process. Modeling in context is embedded with much of the processes that have occupied small group research. The research includes areas such as group problem solving, including social decision schemes (Schweiger, Sandberg, & Ragan, 1986, Davis, 1973), group polarization (Stoner, 1961) and groupthink (Janis, 1971). Another area is creativity, including research themes such as groups as idea generators (Sutton and Hargadon, 1996), groups as a part of organizational creativity (Woodman, Sawyer & Griffin, 1993), and divergent thinking (Baer, 1993). It is true that these studies have sometimes suggested some structured way to enhance problem solving and creativity with structured techniques such as brainstorming (Osborn, 1957), the Delphi technique (Dalkey, 1969), or to decisively reformulate problems (Mayer, 1995), to mention a few. However, a common criticism of much small group’s research is that it oversimplifies an obvious complex set of processes. Work has largely focused on linear relations between a limited set of variables, thus ignoring virtually all others (Kerr & Tinsdale, 2003, p. 642). Thus, if these structured techniques might be of value, their usability still has to be related to the modeling task.

In contrast to psychology, engineering research on data modeling has mainly studied the effect of modeling formalism and not specifically the interaction during the modeling (Topi & Ramesh, 2012).
 Much focus is on the problem of creating formalized descriptions from natural language (Frederiks & Weide, 2004, pp. 132-133). For example, Bommel, Proper and Weide (2005) stress the importance of a “controlled language” to convey information (pp. 1-2). Research on general problem solving has also resulted in a variety of specification languages (Fensel & Motta, 2001, p. 913). In their review of human factors research on data modeling, Topi and Ramesh (2002) suggest applied research on modeling processes as a focus in future research.

Outside academic research there are some team management models, which have been used in counseling, development and selection of management teams. Belbin’s (1993) model of group roles is one such example of taxonomy of different preferred styles of group participation. Controversies about this and similar models’ robustness have lead to little favor in academic research (see for example Furnham, Steele & Pendelton, 1993), even if there are examples of recent research which supports Belbin’s taxonomy. See for example Aritzeta, Senior & Swailes (2005). However, the model gives no assistance in designing the time-limited chain of actions that constitutes a modeling procedure.

Summing up these research directions, there are no unambiguous recommendations for how beneficial different types of knowledge are for group creativity and problem solving. Research has not undertaken studies that allow for conclusions about the interaction process per se (Paulus, 2000, p. 240.). For example, in commenting on cognitive task analysis, Chipman, Schraagen & Schalin (2000) conclude: “A large number of particular, limited methods are described repeatedly. However, little is said about how these can be effectively orchestrated into an approach that will yield a complete analysis of a task or system” (p. 5.). Lesgold (2000) stresses that “the processes whereby transferable knowledge is acquired that can be used to deal with problems that keep arising in complex enterprises” have to be addressed (p. 452).

Given the lack of theoretical and documented practical knowledge of managing variations between experts in the problem solving enterprise of a modeling session, procedures for analysis and coordination should be based on the very basic elements of a session. Such a basic perspective on group performance in problem solving is to view it as a combination of contributions of task relevant knowledge provided by each participant, and the process that combines the member contributions (Hinsz, 2001, pp. 23-24.). As mentioned earlier, a variety of
specific modeling techniques are available. At least three aspects have to be considered when defining the modeling procedure (Bainbridge, Lenior & Schaaf, 1993, p. 1278).

A. Tools. There are several possible formats for representing the modeling subject. For example, the same phenomenon can be represented by a verbal, graphical, mathematical model, statistical model or logical model (Flood, & Carson, 1990).

B. Skills. Which competences to engage vary between modeling techniques and procedures. Access to sufficient and relevant expertise is a central consideration, primarily due to whether the modeling procedure is based on modeling in teams or collecting data from individuals. Another aspect is critical knowledge domains in which the numbers of experts are few.

C. Standards. Criteria for the expected result of the modeling will also vary between modeling tasks. These criteria define the standard for the model and restrict which modeling procedures are possible or suitable to use. An example of standards is the timeframe for the modeling task.

5. Roles in the modeling procedure. Modeling as a process of coordinating contributions of different task relevant knowledge implies that different participants develop and fulfill different roles during the modeling effort (McGrath, 1984, pp. 249-251.). Role theory assumes that people define roles for themselves and others based on social learning and reading (Merton, 1957). A role is the set of functions which is connected to a specific position in a social system. Role behavior refers to the role occupant’s actions that are attributable to the role (Katz & Kahn, 1966). Development of roles and understanding the other participants’ roles, role taking during a modeling enterprise, might then be viewed as an iterative process, which continues over time as a result of the different participants’ domain knowledge and social interaction (Merton, 1957). Research has also emphasized the importance of the roles of the participants’ in the exchange of information (Stasser, Stewart, & Wittenbaum, 1995). It is possible to identify different roles for the individuals participating in a modeling enterprise. An analyst, whose task is to coordinate the session, may manage the modeling. A domain expert is an individual who has developed knowledge and abilities in a certain area. A domain is an abstract or physical phenomenon in which it is possible to define specific knowledge and abilities. The system user or end user has a special case of domain expertise, i.e. specific knowledge of how the modeling subject would be used in a real context.
Presumably, participants are initially uncertain about which roles they are supposed to fulfill. The experts have to find ways to apply their expertise in the often unfamiliar situation of a modeling task by understanding the object of their activity (Norros, 1995, p. 146.). As a result of the interaction, role uncertainty decreases over time (Kahn, Wolfe, Quinn, Snook & Rosenthal, 1964). Participants might be viewed as ‘adapters’ to the problem solving strategy, the available data and assumptions about domain knowledge (Fensel & Motra, 2001, p. 916.). Consequently, this should be reflected as variation in behavior over time within and between participants. The implication is that any analytical method should capture the roles of different participants, how they interact and any differences between the same types of participants.

6. Variation. The distinction between common and unique variation is central for both analysis and control. Common variance might represent error as well as “true” variance depending on the conditions. Arguments have been put forward that consensus between experts is a necessary condition for expertise, also known as the “experts-should-converge-hypothesis” (Einhorn, 1974). However, this is seldom the case, and one problem is that data from different experts often diverge. In fact, disagreements between experts are to be expected (Shanteau, 2001).

Correspondingly, unique variance might represent error variance or creative or additional solutions. A need for innovative and creative solutions presupposes uncertainty. Uncertainty is equivalent to variation when it comes to data from experts. Hypothetically, if well established phenomena are modeled, variation between respondents could then be regarded as equivalent to error variance. In contrast, when modeling new, unexplored phenomena, variation between respondents could be a means to search out the range of a subject.

Consequently, the control of tools, skills and standards must be tailored to the aim of the modeling task. The often complex nature of the phenomena to be modeled calls for successive tests in an iterative fashion. Several possible approaches for such tests are possible. The result of the modeling can be tested on the original respondents. It is also possible to use an independent expert judging the result. Yet another possibility is that the analyst performs the test.

There are several possible sources of variation to control. One source of variation is of course the modeling procedure. The interactive process of constructing a model will inevitably lead to variation. The background of the participants and the form of communication, giving information or asking questions, are two general features of any interaction process. Variation
between experts, when the modeling is performed as a team effort, will be manifested in the interaction and not primarily in the final result of the modeling. In contrast, if the interaction effect between experts is excluded, then variation will be revealed in the results of the different participants.

Another general source of variation is the specific features of the modeling task. The maturity of knowledge of the problem to be modeled will have an effect on variation. The modeling task is characterized as goals to be achieved in relation to the maturity of knowledge of the problem (Althoff & Aamodt, 1996, p. 110).

It is important to stress that variation is not solely something that occurs naturally in modeling enterprises. In many cases divergence between participants is not desired. Consequently, variation might also be actively implemented by the analyst in order to create some kind of contrast.

7. On-line analysis of the modeling procedure in the practical context. In general, the analysis must be based on monitoring the progress of the modeling task in order to assess if the task will be accomplished. A post-modeling evaluation to decide whether all relevant ideas and domains have been considered is hardly a conceivable approach in practice. Consequently, this calls for an on-line analytical method. Any analytical method must capture the successive interactive process of suggestions and opinions that forms the basis of a solution. Analysis and documentation must be possible to perform with a minimum of effort from the analyst (Nielsen & Mack, 1994, pp. 19-20).

The analysis of the modeling procedure must also be possible to conduct in different modeling tasks and modeling procedures. The one-participant approach has the advantage in the eliciting phase of unbiased descriptions if independent sampling is utilized. The latter phases of amalgamation and validation are basically a matter of deciding by whom and by which principles this is realized. Irrespective of whether the amalgamation and validation is conducted by an independent expert, the analyst or the participants, this will of course have an effect in terms of subjective bias on the model (Kappel & Rubenstein, 1999, p. 132). Thus, the analysis should focus on the variations between the different models, which have been constructed independently of each other.
In team modeling, interaction is a part of the modeling procedure and will thus bias the different phases. The validation and amalgamation phases are closely integrated with the elicitation phase, which decreases the possibility of analytically separating these phases. Consequently, it will be more difficult to explicitly record variations between participants and the criteria by which the features of the model are defined and validated, especially if the analysis is to be utilized on-line. Thus, the analysis should focus on the variation in the interaction between participants.

The traditional approach in behavioral science to handle qualitative variation between different participants is to use an external judgment of obtained data, i.e. a verdict by some independent expert on the correctness of different participant models. This circumstance emphasizes the old clinical-statistical controversy on whether predictive accuracy is better achieved by criterion-based prediction or subjective judgment (Meehl, 1954). Decades of research has in general supported the statistical approach as superior in combining assessment data (Meehl, 1986; Dawes, 1994).

A criterion-based approach is consistent with the strategy of a hypothetical directed case study. Such a strategy uses a generic structure for comparing different empirical patterns. The structure could solely be used for comparing the participants’ model products and not inflicted on the individual expert’s own modeling effort. Analogical to statistical analysis of variance, the qualitative variation between participants could be expressed in the data agreement with the attributes and values of the generic structure. An example of a generic structure is the distinction between the attributes of tasks, agents and settings. Another example is the knowledge domains represented in a modeling enterprise. By categorizing the elements of different participant models by means of such a structure, variance might be estimated in terms of agreement on these subcategories. For example, if a well-established phenomenon is modeled, then different independent experts should describe the same subcategories of the generic structure. Qualitative deviations might then be regarded as error variance in terms of relative agreement.

The elicitation phase might be enhanced by a more stringent characterization of differences between experts in terms of unique and common contribution. Primary this will be applicable in the one-participant approach but also in team modeling. This characterization might then be used in the amalgamation phase as a basis for making decisions on which model features to include or exclude in a joint model. Finally, the same approach should be possible to use when the correctness and comprehensiveness of the model is estimated.
8. Conducted studies. In this thesis an approach to handle qualitative variation between experts and modeling tasks has been suggested. Experts vary in opinion and ability to describe their area of expertise, which in turn is manifested in different modeling products. In addition, the interactive process of modeling procedures contributes to variation. The methodological contribution of this thesis should enhance the possibility to manage and judge variation and interaction in a modeling process. The results will have implications for both scientific theorizing about modeling processes as well as for more pragmatic applications.

The case study approach advocated by Yin (2003) has been used in this thesis. Yin defines case study research as "an empirical inquiry that investigates a contemporary phenomenon within its real-life context when the boundaries between phenomenon and context are not clearly evident" (p.13). The rationale for choosing this approach is the assumption that central aspects of modeling, such as problem solving and creativity, must be put in their adequate context. Being concerned with context in research practice is to introduce variables, which exceed the number of available data points (Yin, op.cit.).

The case research method is based on the logic of analytical generalization and the experimentation isolation paradigm rather than on statistical generalization and the randomized-assignment-to-treatments model (Campbell, p.x in Yin, 2003; Silverman, 2005, pp. 126-127.). Theoretical replication is concerned with the construction of cases, which are meaningful, because they embrace criteria, which are used to develop and test theoretically motivated, rival hypotheses (see also Mason, 1996).

The theoretically defined contrasts are translated into corresponding empirical contrasts. In general, the operationalization includes a set of multiple contingent factors, corresponding to a hypothetical pattern of criteria. This thesis includes three such case studies in which the principles for eliciting, controlling, and judging variation in qualitative information were explored. On all occasions, the author of this thesis had the role of the analyst.

Figure 1 illustrates the dimensions which characterizes the context for the different case studies. The first dimension is whether modeling is based on independent participants or participants interacting in a group effort (interdependent participants). The second dimension refers to the basic modeling procedure spanning from elicitation of information to judgment of correctness and comprehensiveness. Finally, the third dimension represents the variation in maturity of
knowledge of the modeling subject. Is the modeling conducted early or late in the development process?

The first study addressed the problem of how to handle and characterize qualitative variations between different experts describing the same modeling object. The judgment approach based on subjective comparison between different expert descriptions was contrasted with the criterion-based approach based on a predefined structure to explicitly estimate degree of agreement. The purpose was to explore tools and procedures for valid modeling in order to be able to analyze common and unique variance between experts. Using the dimensions shown in Figure 1, the modeling task is characterized by the use of independent participants and a modeling object being late in the development process. In addition, the early phases of the modeling included eliciting of knowledge, which successively was judged in the later phases.

The judgment method used additional independent experts to judge the accuracy of the amalgamation of the different expert models, i.e., according to the basic approach often used in behavioral science. Thus, estimating similarities and differences between participant models were based on subjective judgments. The criterion-based method estimated deviations from a generic structure in terms of the models' agreement on defined elements. Variations would then be estimated in terms of relative deviations in defined elements and relations.

In the first study it was not possible to estimate the discriminating construct validity of the joint model. The problem is to judge whether a model is specific enough as a useful representation of reality. Therefore, in the second study the same analytical approach was used to characterize
variation between, as well as within, different modeling tasks, analogical to a one-way statistical analysis of variance.

The starting-point for the second study was that if a novel phenomenon is to be modeled, there is a problem of deciding what constitutes a reasonable array of expert information or descriptions in order to synthesize a common model. How should the novel model be tested for convergent and discriminating construct validity (Campbell & Fiske, 1959)? To solely estimate the within-task variance may give some indication of convergent validity but does not establish the model as a distinctive representation. By contrasting a novel model with models of established phenomena in terms of variance of expert descriptions, some evidence for estimating the discriminating validity of the novel model may be obtained. The two modeling tasks of the second study can in general be characterized by the dimensions shown in Figure 1 in the same way as the first study. However, the modeling subjects differed in level of knowledge maturity. One of subjects had been organizationally implemented for a long period, while the other was early in a development process.

The third study focused on the process of team modeling and how to characterize and manipulate the interaction between experts. Two different modeling situations were contrasted. The assumption was that the process of creating the model is dependent on the characteristics of the task in terms of complexity of task structure, ambiguity of task content and form of task presentation. The analytical method was based on the background of the participants, the form of communication, i.e. giving information or asking question, and knowledge domains identified as important for the task. Two contrasting case studies, A and B, were conducted in order to explore the validity of this analytical approach. The characteristics of the modeling tasks of the third study in terms of the dimensions shown in Figure 1 are a use of interdependent participants and the process of judging correctness and comprehensiveness of the model integrated in the modeling task. The two cases contrasted in the phase of the model development process, which was reflected in a variation in the degree of abstraction of the end user structure and the degree of role specification for participants.

9. Conclusions. The view taken in this thesis is that modeling is a heuristic tool to outline a problem. Access to relevant expertise is limited, and consequently, efficient use of time and sampling of experts is crucial. Modeling is also normally conducted in a context of a larger development process. Consequently, modeling often consists of a series of modeling sessions
which vary in task, procedure and standards. The heuristic approach of modeling makes it possible to more efficiently make advances in a development process.

The core point is that modeling should not solely be based on the use of a standardized procedure. Instead, an analysis of the modeling task forms the basis for deciding which modeling technique in the toolbox to use. Irrespective of specific modeling technique, variation and interaction during the model development process should be possible to characterize in order to estimate the elicited knowledge in terms of correctness and comprehensiveness. This thesis explores such an approach.

By selecting theoretically and practically contrasting cases it has been possible to explore the process of managing and characterizing the modeling process. The results show that a criterion-based approach could characterize common and unique variance, although relatively simple generic structures were used. In the independent one-participant cases, Study 1 and 2, the analytical method utilized a distinction between task, agent and setting in order to separate common and unique qualitative variation. In the team modeling cases of Study 3, the analytical method was based on the factors of participant and knowledge domain, which were relevant for the task and communication form. The general, basic result is that a criterion-based approach using a relative simple generic structure could be applied as a tool to manage and analyze modeling in a time-efficient fashion.

The implication is that the analyst, based on a preliminary task analysis, should structure the modeling task theoretically prior to the modeling sessions. The dimensions of this theoretical structure, for example relevant knowledge domains, basic model structure or communication pattern, forms the basis for definitions of hypotheses about the modeling task at hand. Subsequently, the operationalized indicators of these dimensions can be empirically contrasted against the expected outcome in terms of variation within and between participants and tasks. In practice, every modeling session can be viewed as a case study.

The theoretical dimensions used in the present cases to manage modeling might be changed to other means of representation. For example, it is possible to imagine the use of cybernetics (Ashby, 1956) or Rasmussen’s (1983) model of levels of cognitive control to mention a few theoretical candidates. Of course, the specific focus of the modeling task will affect which knowledge domains to include. The analyst also has to decide on how these components should
interact in a specific modeling procedure. Which representation to choose must be decided through an initial task analysis. A prerequisite is that simple and perspicuous criteria are possible to define in terms of generic structures as the basis for the analysis.

The characteristics of the task will define or constrain appropriate methods for eliciting knowledge (Hoffman, Shadbolt, Burton, & Klein, 1995, p. 149). One would imagine that in early phases, in the context of discovery, models should be as unspecific as possible. During later phases more tailored and specific models must be used.

In conclusion, the suggested approach to utilize qualitative variation might be seen as a complement in the toolbox available for the analyst to model complex phenomena. Even if research has showed that statistical prediction is superior to judgmental prediction, it would be naïve to believe that subjective judgments can be excluded from that toolbox. In fact, the suggested approach presupposes some moments of subjective verdict. Presumably, the ‘mechanical composite’ approach suggested by Sawyer (1966) with the statistical combination of judgmental and mechanical data would often be the most suitable analytical strategy.

Finally, it is important to once again note that even though modeling includes data collection from informed and experienced experts, it normally does not include critical testing. The bottom line is that modeling is about theorizing on a problem. Consequently, development of scientific as well as pragmatic knowledge should embrace both modeling and empirical testing in real or simulated contexts.
References


No 582 Vanja Josifovski: Design, Implementation and


| No 2 | Stefan Cronholm: Metodverktyg och användbarhet - en studie av datorstödd metodbaserad syste-
| No 3 | Anders Avdi: Användare och utvecklare - om an-
| No 4 | Owen Eriksson: Kommunikationskvalitet hos in-
| No 5 | Mikael Lind: Från system till process - kriterier för
| No 6 | Ulf Melin: Koordinering och informationssystem i
| No 7 | Pär J. Ågerfalk: Information Systems Actability - Under-
| No 8 | Ulf Seigerroth: Att förstå och förändra
systemutvecklingsverksamheter - en taxonomi
| No 9 | Karin Hedström: Spår av datoriseringens värden -
| No 14 | Benneth Christiansson, Marie-Therese Chris-
tiansson: Mötet mellan process och komponent - mot ett ramverk för en verksamhetsnära kravspeci-

| No 1018 | Ioan Chisalita: Communication and Networking
| No 1019 | Tarja Susi: The Puzzle of Social Activity - The
Significance of Tools in Cognition and Coopera-
| No 1021 | Andrzej Bednarski: Integrated Optimal Code
| No 1022 | Peter Aронsson: Automatic Parallelization of
| No 1030 | Robert Nilsson: A Mutation-based Framework for
Automated Testing of Timeliness, 2006, ISBN 91-
85523-35-6. |
| No 1034 | Jon Edwardsson: Techniques for Automatic
Generation of Tests from Programs and Specifica-
| No 1045 | Genevieve Gorrell: Generalized Hebbian
Algorithms for Dimensionality Reduction in Natu-
ral Language Processing, 2006, ISBN 91-85643-
88-2. |
| No 1051 | Yu-Hsing Huang: Having a New Pair of
Glasses - Applying Systemic Incident Models on
| No 1054 | Åsa Hedenskog: Perceive those things which can-
not be seen - A Cognitive Systems Engineering per-
| No 1061 | Cécile Åberg: An Evaluation Platform for
Semantic Web Technology, 2007, ISBN 91-85643-
31-9. |
| No 1073 | Mats Grindal: Handling Combinatorial Explosion
9. |
| No 1075 | Almut Herzog: Usable Security Policies for
Runtime Environments, 2007, ISBN 91-85715-
65-7. |
| No 1079 | Magnus Wahlström: Algorithms, measures, and
upper bounds for satisfiability and related prob-
| No 1083 | Jesper Andersson: Dynamic Software Archite-
| No 1086 | Ulf Johansson: Obtaining Accurate and Compre-
hensible Data Mining Models - An Evolutionary
| No 1089 | Traian Pop: Analysis and Optimisation of
Distributed Embedded Systems with Heterogene-
ous Scheduling Policies, 2007, ISBN 91-85715-
27-5. |
| No 1091 | Gustav Nordh: Complexity Dichotomies for CSP-
| No 1106 | Per Ola Kristensson: Discrete and Continuous
| No 1112 | Jessica Lindblom: Minding the body - Interacting
socially through embodied action, 2007, ISBN 978-
91-85831-48-7. |