

© 1999 Elsevier Science Ltd. All rights reserved Printed in Great Britain 0263-2373/99 \$20.00

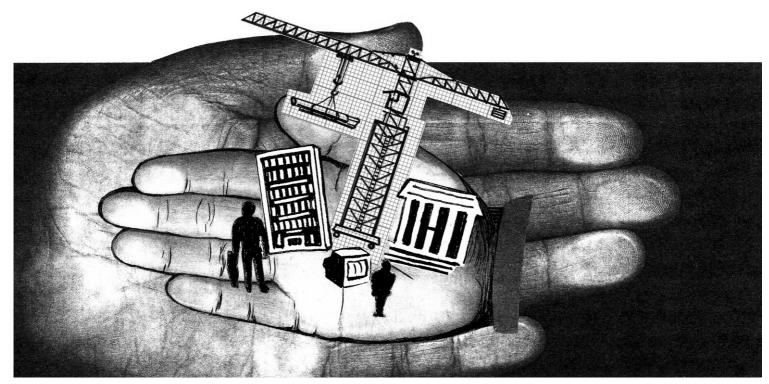
Simulation as a Research Tool in Management Studies

PETER BERENDS, *Maastricht University, The Netherlands* **GEORGES ROMME,** *Maastricht University, The Netherlands*

Simulation is still rarely used by management researchers, particularly those who study business and other systems as social rather than technical or mechanical entities. Why? This article explores this question. The validation issue in simulation research and several examples of good simulation practice are discussed. The main reasons for the low status of simulation research in management studies are: the emphasis on academic specialization rather than craftsmanship, the complicated systems rather than complex systems viewpoint, and the paradigm of the empirical sciences rather than design sciences which prevails in management studies. © 1999 Elsevier Science Ltd. All rights reserved

Introduction

The invention and further development of the computer has led to widespread use of simulation methods and tools in the medical, natural, technical and other disciplines. Medical researchers and surgeons are increasingly trying out operating techniques on a virtual patient before testing or using them on real patients; navigation and flight simulators are used to try out complicated manoeuvres by ships or aeroplanes; preliminary designs of complex machines, products and processes are tested by way of three-dimensional simulation software, and so forth.



By contrast, the enormous increase in informationprocessing capabilities of computers has not led to similar developments in the social sciences. Although user-friendly simulation software has been available for social scientists since about twenty years, social scientists and management researchers in particular do not appear to use simulation tools frequently. Table 1 illustrates this observation. It shows the number and percentage of articles using simulation methods which appeared in ten major journals over the past 12 years. With the exception of Management Science and European Journal of Operational Research, all the journals we looked at publish no or very few articles using simulation methods.¹ Moreover, there is clearly no significant trend towards increased use of simulation in the reported period.

The exceptionally high number of entries reported for *Management Science* and *European Journal of Operational Research* suggests that the use of simulation is largely restricted to operations research, dealing with optimization problems in manufacturing and logistical systems, which tend to be similar in nature to optimization problems in the technical sciences.

This paper therefore explores why simulation is still rarely used by management researchers, particularly those who study business and other systems as social rather than technical entities. In doing so, we focus on system dynamics as the most sophisticated simulation approach currently available for social scientists. First, an overview of simulation methods and tools is given. Subsequently, we will have a closer look at the system dynamics tool and the important issue of validation. We will then scrutinize a number of applications of simulation in management research, and finally, explore why simulation is not used much in management studies.

Please, note that the focus here is on simulation research rather than other applications of the simulation idea, such as role-playing, gaming and microworlds. The purpose of the latter applications tends to be training and teaching people, which falls outside the scope of this article.

What is Simulation?

Simulation as a social science research tool is defined by Dawson (1962) as the construction and manipulation of an 'operating' model, that is, a physical or symbolic representation of all or some aspects of a social or psychological process. For the social scientist, simulation leads to building a model of an individual or group process and experimenting with the replication of this process by manipulating the variables and their interrelationships within the model. By developing a model, the components and relationships which are hypothesized as crucial are abstracted from reality.

Simulation tools permit the experimenter to study processes in ways nature prohibits, because the simulation can be run many times with the values of the parameters modified between runs and the changes in outputs observed. The possibility to experiment with variables which can be manipulated is particularly useful in management research because moral and physical factors often prohibit experimenting with real people, systems and organizations.

Different forms of simulation can be distinguished and each of these is used in certain scientific communities. We distinguish the following types and applications (cf Figure 1): the most basic distinction in simulation approaches is that of physical versus mathematical simulation. *Physical* simulation entails experimenting with real objects which act as models of some subset of reality; examples include building models for planes and ships, whereas in the social sciences one could think of role playing.

In *mathematical* simulation the relations of a system are expressed in mathematical formulae, which can be done in two ways: analytical and numerical. In the case of analytical simulation, the modeler will be able to derive one single optimal solution. Game theory is an example of this kind of simulation (cf. Fudenberg and Tirole, 1991). Finally, numerical

 Table 1
 Relative Use of Simulation in Research Published in Organization (Related) Research (Percentage of Total Articles)

| | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 |
|-----------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| ASQ | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 |
| SMJ | 3 | 0 | 0 | 0 | 2 | 0 | 2 | 0 | 2 | 0 | 0 | 2 | 0 |
| AMJ | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |
| ORS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MCI | 7 | 6 | 11 | 8 | 7 | 8 | 13 | 8 | 4 | 7 | 7 | 7 | 9 |
| EMJ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| EJO | 7 | 18 | 7 | 7 | 6 | 3 | 9 | 5 | 6 | 5 | 6 | 7 | 5 |
| Total (%) | 5 | 8 | 6 | 5 | 5 | 3 | 7 | 4 | 4 | 3 | 4 | 4 | 3 |
| | | | | | | | | | | | | | _ |

ASQ, Administrative Science Quarterly; SMJ, Strategic Management Journal; AMJ, Academy of Management Journal; ORS, Organization Studies; MCI, Management Science; EMJ, European Management Journal; EJO, European Journal of Operational Research.

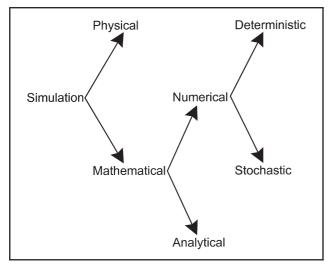


Figure 1 Overview of Simulation (Adapted from Guetzkow, 1962)

simulation deals with behavior of systems and not so much with optimal solutions (Forrester, 1961).

There are two kinds of numerical simulation. Deterministic numerical simulation entails fixing the values of parameters, whereas stochastic numerical simulation uses some kind of distribution function as input for the variables. Monte Carlo simulation is an example of the stochastic approach in which the simulation will use a scheme of random values with a uniform distribution. Apart from being well grounded in the literature, Monte Carlo simulation allows the modeler to perform robustness tests. Most spreadsheet simulations serve as an example of the deterministic approach. System dynamics modeling is an example of numerical simulation in which both deterministic and stochastic modeling is possible.

Many numerical simulation processes are relatively free from complex mathematics, making them more widely comprehensible than other more complex systems of formal mathematical analysis. Malcolm (1962) stresses that simulation is easily understood, relatively free of mathematics and often quite superior to mathematical methods that may be too complex or even not available. Moreover, Forrester (1961) asserts that mathematical or analytical solutions to problems with more than five interrelated variables become impossible.

Another issue in simulation research is the required balance between parsimony and complexity of the model. In general, the social sciences attempt to develop and test models that explain as much as possible of the social system under study with as few as possible variables. Put differently, the more parsimonious, the more preferable the model is. This approach tends to result in elegant, parsimonious models that greatly simplify the complex interactions characteristic of any social system. The use of simulation tools offers researchers the possibility to enter into the model as many variables as they think suitable to explain as much as possible. If this is done too extremely, the result may be that the model is too complex to provide understanding of the real system being modeled. This means that simulation should be used in a way which creates a balance between parsimony requirements and the complexity of the system modeled.

Systems Thinking and Simulation

Systems thinking often involves building models to facilitate understanding and communication at the level of both the individual and the larger group or team. As individuals we all view the world differently. This is to be expected since we are conditioned over time by our cultural traditions, personal experiences and educational backgrounds (Stacey, 1993; Argyris et al., 1985; Forrester, 1961). While such diversity has a latent value, it can also be the source of misunderstanding and increased complexity in our social systems because of the assumptions we unwittingly make in communicating with fellow workers and citizens. We are referring here to the 'soft' dimensions of the workplace — the complex web of value systems, understanding and human relationships that forms the 'real' organization (social systems).

Social systems are composed of people living, playing or working together in a shared environment. This includes people having thoughts; articulating these thoughts; communicating these thoughts to others; listening to the communication; understanding the communication and responding appropriately. People in social systems are observers of the system; they engage in conversations through the use of a shared language. It is this ability to share language that leads to shared mind-sets, values and beliefs. Systems thinking enriches this ability to languageand problem-solve which leads to more effective team work, empowerment and participative management (Senge, 1990; Checkland and Scholes, 1990; Morecroft and Sterman, 1994).

A typical visual output of systems thinking is a model or series of models, which attempts to explain the workings of the system under investigation. Accepting the principle that there is generally no single linear cause-and-effect sequence (life is not that simple), the value of these models lies in their ability to help us view complexity from the position of numerous inter-linked cause and effect situations (Forrester, 1987). As a consequence, we may perceive the unintended effects of our actions or strategies that are often counter-intuitive. This is frequently the source of significant personal and organizational learning brought about by the sharing of mental models.

Validation of a System Dynamics Model

It is important to note that simulation research emphasizes the similarities in dynamical patterns between the simulation and the real system under study rather than absolute comparison between systemic behavior and simulated results. Nevertheless, validation of simulation models is necessary if we want to apply simulation models in a scientific context and if we want to gain real understanding of the system under study.²Although it is possible to use as many variables as one likes, the individual relationships must be tested in order to validate it. In general, the rule is that the more relationships are used, the more elaborate the validation procedure should be. Thus, as in the case of other scientific models, simulation models should be guarded against a too high number of relationships and variables.

Most system dynamics scholars agree that testing the relationships in a simulation model econometrically greatly increases its potential impact and acceptance (Hall, 1976; Forrester and Senge, 1980; Barlas, 1989; Homer, 1997). Among system dynamics practitioners a well-laid out framework exists along which modelers can go to enhance refutability and thus reliability of the model (Barlas, 1989; Gujerati, 1988; Hall, 1976; Ford and Sterman, 1998; Forrester and Senge, 1980).

The validation framework roughly consists of two phases that should be followed consecutively. First, a researcher should check whether her model complies with common sense of the actors within the system under study. This first phase is called structural validation. In this respect, Lane and Oliva (1998) offer a taxonomy of current practices to elicit models from system insiders, in which the authors recognize that a system dynamics intervention influences the environment of the participants in the modeling effort. This approach boils down to analyzing the different worldviews the participants hold by a technique also known as enquiry (cf. Argyris et al., 1985). The authors then suggest formulating formal relationships of the system, incorporating differences in mental models of the participants.

The second phase, called *behavioral validation*, involves two steps. First, the assumed relationships should be tested empirically. This step involves estimation of parameters and validity of the relationships. A problem that frequently occurs is the unavailability of data to measure assumed relationships directly. Two common methods are suggested to go around this threshold: the first method is to find good proxies for the original data (Gujerati, 1988) and the second one is to check the importance of the variables in the relationships via complex sensitivity analysis (Graham, 1980). If a variable is of critical importance to the model, data are needed. If, on the other hand, the variable is of no critical importance to the model, the data needed to estimate a process known as calibration (Gujerati, 1988) could generate the relationship. This technique changes the value of parameters automatically until the simulation results best approximate the reference behavior of the system. Of course, one should always test for sensitivity of the model to changes in the parameter value. The final check is whether the patterns of the model comply to the patterns found in the real system. The R^2 (or adjusted R^2) is a commonly used statistic to evaluate the performance of the model.

Examples

A widely cited example of good simulation practice is the study of the demise of the Saturday Evening Post by Hall (1976). Hall's paper is built up around the system dynamics methodology. A model is built in which it is important to set feasible boundaries to the system under study. As Hall puts it: 'The system dynamics view of a company and its environment leads to the notion that the structure of the system accounts for a large part of the company's own peculiar growth and development.' (p. 188). Hall constructs the model from several subsystems within the company which are first tested separately empirically and are connected in a later stadium of the modeling process. This procedure is commonly used if a system is too complex to model at once. In this case, the model comprised a management information system (accounting information flow), a remuneration structure, a set of controllable levers with which management tries to control the business (particularly involving price setting), and a set of variables which depict the relationship with the environment.

Hall (1976) notes: 'A model is a theory. Acceptance of a computer program as "good" social theory is dependent upon one's acceptance of the responsible theorist and his assumptions. It is important to know both (p. 186). To the extent that these assumptions are unreasonable, the validity of the model is decreased, and to the extent that a model contains formal theoretical relationships not empirically obtained, the relevance of the model is decreased.' (p. 186).

The validation of the model was conducted via estimation of the parameters in the equations via least squares regression. Furthermore, theory formed the basis of the primal assumptions that proved valid after testing. Simulation of the model, finally, generated behavior that was similar to behavior in the real system, gaining an R^2 of at least 0.95 (Hall, 1976, p. 192).

Traditional explanations for the demise of newspaper companies were, among others, competition with other media, sharply increased postal and printing costs, substantial increase in cost of acquiring additional readers, lost touch with readers, erratic and unpredictable behavior of advertisers, and mismanagement. Instead, Hall (1976) finds that the deterioration of the newspaper was induced through a reinforcing feedback loop in which management tried to take corrective measures by increasing the subscription rate — a measure that proved successful in an earlier period — thus losing regular subscribers. Further diminishing profits made management realize that subscription rates should be lowered again and, instead, advertising rates were increased. Hall concludes, 'unfortunately, the rate of increase in readers did not match the rate of increase in the advertising rate, which rose 25 per cent per page per thousand readers and thus induced advertisers to exit.'

Findings of the study support the idea that structure induces behavior, in the sense that locally rational and sensible action by management lead to an uncontrollable situation. This kind of process and its unintended outcome is characterized by delays between action and its effects and difficult to grasp interconnections between the subsystems.

Another well-known study is by Sterman (1989), who applied the system dynamics methodology to the area of decision-making. His pioneering work deviates from the bulk literature on decisions in that it tries to model how people make decisions without theorizing on how people should make decisions. He conducts an experiment in which individual 'sound' decision-making in a simple situation with four people leads to patterns of undesired results for all four individuals involved.

Sterman (1989) uses simulation in two ways. First, in order to monitor decision-making he uses a gaming structure, the so-called Beergame, which is based on a simple model of a production-inventory chain (also see: Senge, 1990). Second, Sterman uses a computer simulation model to test different modes of decision-making. That is, given the information available to the individual actors and given different theories on decision-making, he tests what mode individuals use and whether this mode is universally applicable over the different subjects (n = 40). Econometric methods are used to estimate parameters, robustness and variance explained by the model.

Sterman (1989) finds that individuals consistently use a decision rule that is sensitive to adaptation and an anchoring point of some desirable property of the individual state. Both the extent to which individuals form their expectations and the extent to which they are sensitive to a gap between the desired state and the current state is highly individualistic. Nevertheless, Sterman models this behavior using the same generic heuristic. The results of the study indicate that people use simple heuristics when deciding on actions. Individuals tend to misperceive the feedback and delay structure in which they act, even in the presence of rich information on structure, interrelationships between actors and information on exogenous factors. This study therefore shows that the 'efficacy and robustness of decision strategies lies not only in the availability of *outcome* feedback, but depends crucially on the nature of *action* feedback between decisions and changes in the environment which condition future decisions' (p. 338, emphasis in original).

Finally, Homer (1993) conducted a study into the use of cocaine in the United States where drug policy decisions have been taken for many years on the basis of national survey data giving an indication of national drug use. These survey data show that cocaine use leveled out from 1982 to 1996, where until 1982 the population of drug users grew substantially. Critical in Homer's model is reporting reliability, or the likelihood of honest reporting of an individual. Homer argued that the reporting rate dropped as a consequence of changes in categories of users, image of the drug (social desirability) and the prevalence of crack in the mid-eighties.

Analogous to Hall's (1976) study, Homer constructed two models that were later coupled to assess systemic behavior. The first model dealt with reporting probability and the second was a user-estimation model based on the data that were widely available, such as historical initiation rate, drug price, police reports, drug arrests and accompanied amount of drug seizures. Unable to measure the variable directly, he thus made use of proxy data in which he compared historical relationships with current relationships.

After simulation of the total model Homer found that the simulated reporting rate matched that of the real reporting rate (number of persons that reported use). In addition, the simulated actual drug use showed a dramatic gap between estimated use by means of the survey and estimated use by means of the simulation. Additional investigations also suggested the simulation results are more likely than the survey-based estimations. The implications of this study are twofold. First, it indicates that presumed success of antidrug policies cannot be validated based on the instruments used and second, that rigorous modeling offers the opportunity of powerful insights in a system as compared to verbal stories of the system.

Discussion

The examples given in the previous section illustrate the added value of simulation, particularly for complex social systems in which structure — in terms of the pattern of relationships between variables induces behavior. We now turn to the key question here: why is simulation still rarely used by management researchers, particularly those who study systems as social entities? Our answer to this question can be summarized in terms of three dimensions:

- Specialization or craftsmanship (as solution to training problem)
- Complicated or complex systems (as solution to conceptualization problem)
- Empirical or design approach (as solution to utilization problem).

One of the key problems in organizing universities and scientific research is the training problem: how to prepare researchers in spe for a career in the academic or corporate research world. In general, the social sciences have responded to this problem by increasing specialization. The advantages of this development are, amongst others, the high economies of scale within a highly focused specialized research field. The main disadvantage is of course that one tends to neglect the interrelationships between disciplines or even between sub-disciplines. For example, many corporate finance researchers study the relationship between financial structure and stock exchange prices and many strategy researchers study how certain strategic moves affect corporate profitability, but the interaction between financial structure, stock exchange prices and strategic moves is hardly ever studied.

The studies described in the previous section illustrate that simulation is especially worthwhile when a system (industrial or corporate) is studied as a whole. Moreover, the examples also show that simulation is best used in combination with econometric research tools, for validation and other purposes. Simulation as a research tool therefore requires an emphasis on all-round *craftsmanship*, rather than specialization, in training and educating management researchers. Evidently, the prevalent emphasis on specialized training and career systems in the field of management research is a major barrier for the diffusion of simulation as a research tool.

Another explanation of why simulation is not used much arises from the distinction between complex and complicated (Cilliers, 1998; Sherman and Schultz, 1998). Some systems, such as an automobile or a CD-player, have a very large number of components and perform sophisticated tasks, but in a way that can be analyzed accurately. Such systems are complicated and can be understood in terms of relatively static models, tested by some form of regression or variance analysis (or both. Other systems, such as the human brain, are constituted by such intricate sets of non-linear relationships and feedback loops, that they are best understood in terms of complex patterns of interaction between the elements of the system. These systems are complex in nature.

If social systems, such as firms or industries, are seen

as complicated systems, they are (implicitly) reduced to their constituent elements rather than the interaction between these elements. If they are assumed to be complex in nature, these systems cannot be approached and understood with simple resources, but only with complex resources. Cilliers (1998, p. 10) argues that a 'complex system cannot be reduced to a collection of its basic constituents, not because the system is not constituted by them, but because the process.' Most management research tends to conceptualize the systems under study as complicated rather than complex, which clearly is another explanation of the limited use of simulation.

The so-called utilization problem is the third context in which the limited use of the simulation method can be understood. The impact of management theory on the practice of management and on the performance of organizations is widely seen as a crucial issue. However, there have been serious doubts with respect to the actual utilization of management research by the practitioners' communities (Beyer and Trice, 1982; Hambrick, 1994). This problem is usually conceptualized in terms of the dilemma between rigor and relevance of management research. However, following Van Aken (1998) we think a more serious dilemma is at work here: the choice between the paradigm of the empirical sciences and that of the design sciences.

The *empirical science* approach, which the social sciences have adopted primarily from physics, heavily relies on an observer perspective in order to describe, explain and predict social systems. The *design science* approach, which prevails in the medical and engineering sciences, suggests we try to develop tested and grounded rules for management of and intervention in social systems (Van Aken, 1998). This approach requires extensive forms of partnership and collaboration between the research community and the actors in relevant social systems. The low status of simulation in management research is in all likelihood (partly) determined by the predominance of the empirical rather than design science approach.

The emphasis on academic specialization, the complicated systems viewpoint and the paradigm of the empirical sciences together form a strong set of forces driving management research in the direction of conventional research tools and away from simulation tools. Increasing computational speed in combination with the growing availability of simulation software and validation techniques may support the diffusion of simulation in management research. However, a substantial increase in the use of simulation depends on more structural changes in academic training and career systems, in the way social systems are conceptualized, and in how the relationship between research and practice is understood and organized.

Conclusions

This paper explored why simulation is still rarely used by management researchers, particularly those who study business and other systems as social rather than technical or mechanical entities. In doing so, we focused on system dynamics as the most sophisticated simulation approach currently available for social scientists. We looked at the validation issue in simulation research and at several examples of good simulation practice. Finally, training, conceptualization and utilization problems and their implications for simulation research were discussed. In sum, the emphasis on academic specialization, the complicated rather than complex systems viewpoint and the paradigm of the empirical sciences together form a strong set of forces pulling researchers away from state of the art simulation research.

Notes

- 1. A search in the major sociological outlets *Sociology, Annual Review of Sociology, American Journal of Sociology* and *International Sociology* resulted in a zero number of articles using simulation in the reported years. Also note highly specialized journals such as *Simulation* and *System Dynamics Review* have been excluded from this examination.
- 2. Note that a study with a major consultancy that applies both hard (i.e empirically validated) and soft (informal) modeling in client projects found that hard modeling leads to more satisfaction with the clients (Sterman, 1989).

References

- Argyris, C., Putnam, R. and McLein-Smith, D. (1985) Action Science. Jossey Bass Publishers, San Francisco.
- Barlas, Y. (1989) Multiple tests for validation of system dynamics type of simulation models. *European Journal of Operations Research* 42, 59–87.
- Beyer, J.M. and Trice, H.M. (1982) The utilization process: a conceptual framework and synthesis of empirical findings. *Administrative Science Quarterly* **27**, 591–622.
- Checkland, P. and Scholes, J. (1990) Soft Systems Methodology in Action. Wiley, Chichester.
- Cilliers, P. (1998) Complexity and Postmodernism: Understanding Complex Systems. Routledge, London.

- Dawson, R.E. (1962) Simulation in the social sciences. In *Simulation in Social Science: Readings*, ed. H. Guetzkow. Prentice Hall, Englewood Cliffs, NJ.
- Ford, D.N. and Sterman, J.D. (1998) Dynamic modeling of product development processes. *System Dynamics Review* 14, 31–68.
- Forrester, J.W. (1961) Industrial Dynamics. MIT Press, Cambridge, MA.
- Forrester, J.W. (1987) Nonlinearity in high-order models of social systems. *European Journal of Operations Research* 30, 104–109.
- Forrester, J.W. and Senge, P.M. (1980) Tests for building confidence in system dynamics models. In System dynamics, eds A.A. Legasto, J.W. Forrester and J.M. Lyneis. *TIMS Studies in the Management Sciences* 14, 109–228.
- Fudenberg, D. and Tirole, J. (1991) *Game Theory*. MIT Press, Cambridge, MA.
- Graham, A.K. (1980) Parameter estimation in system dynamics modeling. In System dynamics, eds A.A. Leagasto, J.W. Forrester and J.M. Lyneis. *TIMS Studies in the Man*agement Sciences 14, 229–245.
- Guetzkow, H. (ed.)(1962) Simulation in Social Science: Readings. Prentice Hall, Englewood Cliffs, NJ.
- Gujerati, D.N. (1988) Basic Econometrics McGraw-Hill, New York.
- Hall, R.l. (1976) A system pathology of an organization: the rise and fall of the old Saturday Evening Post. *Administrative Science Quarterly* **21**, 185–211.
- Hambrick, D.C. (1994) What if the academy actually mattered? Academy of Management Review 19, 11-16.
- Homer, J.B. (1993) A system dynamics model of national cocaine prevalence. *System Dynamics Review* **9**, 49–78.
- Homer, J.B. (1997) Structure data, and compelling conclusions: notes from the field. System Dynamics Review 13, 293–309.
- Lane, D.C. and Oliva, R. (1998) The greater whole: towards a synthesis of system dynamics and soft systems methodology. *European Journal of Operational Research* 107, 214– 235.
- Malcolm, D.G. (1962) System simulation a fundamental tool for industrial engineering. In *Simulation in Social Science: Readings*, ed. H. Guetzkow. Prentice Hall, Englewood Cliffs, NJ.
- Morecroft, J.D. and Sterman, J.D. (eds)(1994) *Modeling for Learning Organizations*. Productivity Press, Portland, OR.
- Senge, P.M. (1990) The Fifth Discipline. Doubleday, New York. Sherman, H. and Schultz, R. (1998) Open Boundaries. Perseus
- Books, Reading, MA. Stacey, R.D. (1993) *Strategic Management and Organisational Dynamics*. Pitman Publishing, London.
- Sterman, J.D. (1989) Modeling managerial behavior: misperception of feedback in a dynamic decision making experiment. *Management Science* 35, 321–339.
- Van Aken, J.E. (1998) Management theory development on the basis of the design paradigm. Unpublished paper, Eindhoven University of Technology.



PETER BERENDS, Maastricht University, Faculty of Economics and Business, P.O. Box 616, 6200 MD Maastricht, The Netherlands.

Peter Berends is a Ph.D. candidate working on a dissertation in the area of system dynamics and industry analysis. He holds degrees

from Nijenrode University and Maastricht University.



GEORGES ROMME, *Maastricht University, Faculty of Economics and Business, P.O. Box 616, 6200 MD Maastricht, The Netherlands.*

Georges Romme is Associate Professor in Strategic Management at Maastricht University. He holds degrees from Tilburg University and

Maastricht University, and has published widely on strategic decision making, new organizational forms and strategic change.