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MODELLING AND SIMULATION

Operations management research methodologies using quantitative modeling

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Abstract *Gives an overview of quantitative model-based research in operations management, focusing on research methodology. Distinguishes between empirical and axiomatic research, and furthermore between descriptive and normative research. Presents guidelines for doing quantitative model-based research in operations management. In constructing arguments, builds on learnings from operations research and operations management research from the past decades and on research from a selected number of other academic disciplines. Concludes that the methodology of quantitative model-driven empirical research offers a great opportunity for operations management researchers to further advance theory.*

Introduction

Quantitative modeling has been the basis of most of the initial research in operations, labeled as operational research in Europe, and was also the basis of initial management consulting and operations research (OR) in the USA. Initially, quantitative modeling in operational research was oriented very much towards solving real-life problems in operations management (OM) rather than towards developing scientific knowledge. Especially in the USA, a strong academic research line in OR emerged in the 1960s, working on more idealized problems and thus building scientific knowledge in operations management. During that same period, however, much of this research lost its empirical foundations, and research methods have been primarily developed for these more or less theoretical research lines, leaving the more empirically-oriented research lines for more than 30 years in the blue with regard to research methodology.

Recently, this tide has however turned, and the need to develop explanatory and predictive theory regarding operational processes and OM has become apparent. Articles have been published that formulate requirements for theory development in OM (Schmenner and Swink, 1998; Amundson, 1998; Wacker, 1998) or that try to connect the knowledge generated along the various research lines into a more general theoretical framework (Melnyk and Handfield, 1998a).

In this article, we will give an overview of quantitative model-based research in OM, focusing on research methodology. OM is defined as the process of design, planning, controlling and executing operations in manufacturing and service industries. Our emphasis will be on model-based quantitative research,

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i.e. research where models of causal relationships between control variables and performance variables are developed, analyzed or tested. Performance variables can be either physical variables such as inventory position or utilization rate, or economic variables such as profits, costs or revenues. We will distinguish between empirical and axiomatic research, and furthermore between descriptive and normative research. We address the problem of assessing the academic quality of research work in this arena and present guidelines for doing so. In this paper, academic quality is defined as the rigor with which the standard for good academic research for the type of research conducted has been adhered to. To distinguish these types, we present a typology of model-based quantitative OM research, and present research guidelines for each of these types. In constructing our arguments, we will build on learnings from OR and OM research from the past century and on research from a selected number of other academic disciplines.

In our article, we will use the following working definition to distinguish quantitative model-based research in OM from other research in OM:

> Quantitative models are based on a set of variables that vary over a specific domain, while quantitative and causal relationships have been defined between these variables.

The rest of this article is organized as follows. In the next section we will give a short overview of the history of quantitative model-based research in OM, highlighting the strong and weak points of this type of research. Next, we give the major characteristics of model-based empirical and axiomatic research. The following section gives an overview of the literature that has addressed the methodology issue of this type of research. In the penultimate section, we discuss how to assess the quality of research articles in this area, while the final section concludes the article.

History of quantitative model-based OM research

Scientific management (Taylor, 1911) can be considered as the root of the development of quantitative OM, although not only the root of quantitative OM. In fact scientific management was not a science, but the application of systematic methods to the study of managerial problems on the shop floor. In line with the dominant mindset in the scientific arena in those days, scientific management applied analytic techniques to operational processes, analyzing the activities needed, identifying the smallest building blocks needed to achieve desired results, eliminating unnecessary activities, and grouping and sequencing activities such that maximum use of resource was achieved. The recent hype around business process re-engineering can be considered as a revival of scientific management, but now applied to a wider set of processes.

The essence of scientific management was the analysis of instances of real-life operational processes, based on systematic observations and measurements of these process instances, and the redesign of these processes in order to improve quality and productivity. As such, scientific management did not produce generic scientific knowledge about real-life operational processes.

Its claim was that applying the methods of scientific management to existing operational processes would improve their performance. Scientific management, therefore, was not a science but an engineering profession; it was a systematic working method to achieve something. However, unlike engineering professions such as mechanical engineering and chemical engineering, scientific management lacked the underlying generic scientific knowledge about operational processes. Nevertheless, despite this lack of scientific foundations, the scientific management approach was extremely successful in improving operational processes. This illustrates the power of learning by doing and copying; a method of working facilitated by the emergence of the consultancy profession. Scientific management laid the basis of the profession of management consultancy in the USA between the First World War and the Second World War. In the same period, courses in industrial management were introduced at the major industrial engineering colleges in the USA. For the purpose of teaching the applied methods and techniques at these colleges, the type of problems encountered in real life were simplified and formulated in general terms, that is:

- only those aspects of the problems were included that were assumed to be relevant from the perspective of the method and technique dealt with; and
- the problem was formulated independently of any particular instance of the problem in industry.

These are what we call idealized problems. Examples of such idealized operations management problems are inventory control problems, sequencing and scheduling problems, routing problems, statistical quality control problems and maintenance problems. Note that a model is always an abstraction from reality in the sense that not the complete reality is included. An idealized model is a model where, in addition, the abstraction from reality has been further extended so that essential trade-offs become very explicit, functions become one- or two-dimensional, differentiable, etc. in order to make the model tractable for mathematical analysis.

It will be clear from this description that these idealized OM problems were not intended as scientific models of real-life managerial problems, in the sense that the models could be used to explain or predict the behavior or performance of real-life operational processes. They were just partial models of problems that operations managers may encounter. The models were partial because all aspects of the problem that were not related to the method or technique used were left out, the implicit assumption being that these aspects would not affect the effectiveness of the problem solutions based on these models. It was left to the practitioner to include these aspects into the solution based on his knowledge of reality and of the partial model of the problem. Operational processes can be very complex systems that are difficult to model scientifically from a performance point of view. This is because the performance of an operational process – generally measured in terms such as in product quality, production efficiency, cost, and in delivering speed and flexibility – can be affected by many different elements in the process. For instance, machine conditions in a factory may affect quality and volume of output; however the actual impact of machine conditions on the factory output may also depend on the knowledge, motivation and training of the personnel, and on the information systems and performance measurement systems used by management. An important shortcoming of the idealized problems is therefore that the effect of the human factor on the performance of the operational process is largely neglected. As a result, implementing problem solutions based on these models often turned out to be a tedious process, and also frequently failed.

Up to now OM research has not been very successful in developing explanatory or predictive scientific models of operational processes, that is, models that can be used to explain or predict the output or performance of the process as a function of process characteristics, process states and inputs to the process. This is a major roadblock for the development of the field, since the development of effective methods to improve performance assumes that scientific knowledge of the process is available.

At this point it is clear why the idealized operational management problems used for teaching OR cannot be considered as predictive scientific models of operational processes. In fact, they are idealized models of certain aspects of operational processes, which only serve to identify the aspect of the problem that can be dealt with by specific methods and techniques. Nevertheless, analysis of these idealized operational management problems has generated valuable knowledge about and insight into its solution. Starting from small-scale simple problem formulations, research has been performed on analyzing the problem and finding optimal or near optimal solutions. The problems were formulated in mathematical terms, and mathematical techniques were used for analysis and solution. Gradually the complexity of the problem formulations studied was increased, making use of progress made in mathematics, statistics and computing science, leading to the development of OR as a branch of applied mathematics and computer science. These idealized models have provided us with valuable insights in basic trade-offs, at a managerial level, but cannot be characterized as explanatory or predictive models of operational processes.

OR can be considered as part of the quantitative research in operations management. However, the scientific aspect of OR does not pertain to the modeling of operational processes, but to the analysis of the mathematical aspect-model of the process and the quality of the mathematical solutions. In OR hardly any attention is paid to the scientific modeling of operational processes, that is, describing the statics and dynamics of the processes that are the object of study in OM. Instead, an OR methodology has been developed mainly dealing with technique-oriented modeling of real-life problem instances and implementing of solutions derived from the model. An example of this OR methodology is the well-known hierarchical planning approach (Hax and Meal, 1975), where the problem is formulated in terms of a set of hierarchically positioned mathematical programming models.

Independent from the development of OR in the USA, during the Second World War in the UK operational research developed as another branch of quantitative modeling in OM (e.g. Keys, 1991). In operational research, teams of researchers with different disciplinary backgrounds, in close co-operation with the problem owner, work on developing a simple but sufficiently valid model of the problem, derive solutions to the problem based on this simple model, and test and implement the solution under problem-owner leadership. The operational research approach intends to include all aspects of operational processes that are relevant for explaining the behavior and actual performance of the process, including the knowledge, views and attitudes of the people at the operational level and the managerial level (see, e.g. Ackoff (1957) for an explanation of this phenomenon). However, also the operational research approach does not produce scientific knowledge about operational processes, since it is only interested in explaining and improving the performance of one specific operational process instance. Operational research studies are rich in terms of modeling the various aspects and details that are considered relevant for the problem at issue, but only to the opinion of the team consisting of problem owner(s) and researchers. Operational research studies generally lack in construct validity (for definitions and a discussion on construct validity in OM, we refer to O'Leary-Kelly and Vokurka (1998) and Yin (1994, p. 34)). Operational research can be viewed as a straightforward extension of the scientific management approach to solving operational process problems. The extension that operational research provides is the concept of working in multidisciplinary teams in close cooperation with and reporting to the problem owner(s).

As a result of the developments described above, which roughly took place between 1920 and 1960, quantitative scientific models of operational processes were virtually non existent. With scientific models we mean models which can be used to predict the behavior or performance of operational processes, and which can be validated empirically in an objective way. That does not mean, however, that the knowledge reported in the OR and operational research literature is of no value. In fact, the OR literature contains valuable knowledge about aspects of operational processes and OR literature contains valuable knowledge about problem instances. At this place, two important achievements from OR must be mentioned. The first achievement is the development of powerful short-term forecasting techniques, based on statistical analyses of historical data of the variables to be forecasted. These results have been consolidated in the work of Box and Jenkins (1976). It is interesting to note that their approach is based on discerning patterns in historical data that can be used to predict future data. This approach does not seek causal relationships to explain past behavior or predict future behavior, but considers the process that generates the data as a black box. The second achievement is in the area of inventory control, where a large amount of idealized inventory control problems have been studied and solved to optimality or good approximate solutions have been found. This work has been consolidated in the work by

Silver *et al.* (1998). Inventory control theory may well be the most frequently applied part of idealized models in operations research.

OR and operational research did not provide a sufficient basis for the development of explanatory and predictive models of operational processes. Two important exceptions must be mentioned. The first exception is the achievement obtained by Forrester (1961), who developed a theoretical model of the interactions between flows of resources, materials and information in operational processes, which was able to explain the dynamic behavior of these processes. The industrial dynamics models of Forrester (1961) are scientific theoretical models of operational processes, as they can explain and predict the dynamic behavior and performance of the processes, and can be validated empirically. In this respect the work of Forrester was a major breakthrough, which has led to a general methodology for modeling dynamic systems known as system dynamics (Sterman, 2000). The second important major achievement in theoretical model-based research in OR is queuing theory (Buzacott and Shantikumar, 1993). Queuing theory provides us with a firm basis for understanding the performance of an operational process from its resource structure and the variability in order arrivals and resource availability (e.g. Hopp and Spearman, 1996). Just like industrial dynamics provides a theoretical framework for understanding the dynamic or non-stationary behavior of industrial systems from the feedback characteristics of the system, queuing theory provides a theoretical framework for understanding the steady-state or stationary behavior of the system from the variability in orders and resources. In addition to these two exceptions, we should also mention the work around the so-called "learning curve" (see Yelle (1979) for a review) and the modeling efforts by operations researchers of this phenomenon. The learning curve models the empirical finding that frequent repetition of an operation leads to a decrease in the time needed for the execution of the operation. The basic learning curve asserts that the relation of unit labor hours or production costs to the total number of items produced is linear in the logarithms of these variables. Note that the learning curve was discovered when observing data from real-life processes (Wright (1936) as referred to by Muth (1986)). As such, it was not a causal model, but a phenomenon that occurred in a systematic way. Later, efforts have been made to develop explanatory and predictive models (e.g. Muth, 1986). These models relate existing theory from areas such as psychology and organizational behavior to the observed power function in empirical learning curve studies and describe causal quantitative relationships.

Despite the rather underdeveloped scientific state of the field, in the last decades methods and techniques developed by OR have been starting to make a serious impact on the design and control of operational processes. This especially pertains to highly automated operational processes, or operational processes and operational decision problems where the impact of the human factor is negligible. A prominent field of successful application of mathematical optimization techniques is in the general area of static allocation problems where the objective is to optimize the allocation of a resource, such as in cutting stock problems (see Cheng *et al.*, 1994, for an overview) and vehicle routing problems (see Ball *et al.* (1995) for a comprehensive overview and Lenstra *et al.* (2001) for recent additions). In the 1970s and 1980s OR was already an established field as far as mathematical analysis was concerned. Major achievements have been achieved in the field of mathematical programming and other areas of discrete optimization. However, in those days, apart from the exceptions discussed above, its impact on the design and control of real-life operational processes was very limited. In the early 1970s, articles were published stating that OR research society was mainly talking to itself. In the late 1970s, one of the founding fathers of OR, Ackoff, wrote an article stating that "the future of OR is past" (Ackoff, 1979), expressing his frustration over the tremendous amounts of resources spent on analysis of problems that had only a weak relation to real-life operational processes. Their lack of impact on the management of operational processes could be attributed to the fact that many of the models and solutions provided were not recognized by managers as having close correspondence to the problems they struggled with. As a consequence, the real breakthrough developments took place in industry and were not driven by theoretical findings. We will give three examples to elaborate on this statement.

In the 1970s, in industry much time was spent on introducing information technology for the control of manufacturing processes, especially material requirements planning (MRP) systems (Wight, 1974). At the first instance, the OR research community did not consider these systems to be of any importance. However, the MRP systems evolution was a carrying wave for the American Production and Inventory Control Society (APICS) to start a real crusade to reduce inventories, increase efficiency, and increase delivering performance in US industry. The Society organized professional education, launched its own journals, and was highly successful in terms of membership and getting the profession (production and inventory control) to a higher level. Initially, scientists did not play an important role in this development. Eventually, however, the MRP system was adopted as a "way of working" and OR theorists started to analyze MRP-related problems, thereby creating insights into the working of MRP systems, but again without much impact on the profession.

A similar phenomenon was observed in response to the introduction of Japanese manufacturing techniques, as in the Toyota Production System (Schonberger, 1982). In the Toyota factories in Japan, in the 1950s and 1960s a way of organizing manufacturing processes had evolved which was quite different from the processes used in the West. The Japanese put emphasis on reliable machines, reliable products (quality) and flexibility, both in terms of machine set-ups and resource flexibility. The result was a manufacturing system that was not only more efficient than those used in the West, but at the same time more flexible, easier to control, and which could deliver high quality product. In short, their operational processes were superior to those used in the

West. Studying the Toyota production system, the West has learned the lessons, and consequently also used just-in-time techniques, total quality management, and total productive maintenance. In response, the OR research community has shifted its attention to new operational process problems, including *inter alia* elements of just-in-time manufacturing, and started to analyze these new problems, producing insight into the characteristics of these new manufacturing techniques.

Another example is the use of workload control to control throughput time in complex production systems. Workload control was already advocated as "input-output control" by Wight (1974) in his book on MRP and is now widely known as CONWIP (Hopp and Spearman, 1996). In the 1970s and 1980s, two research groups involved in empirical research in industry observed independently that workload control dramatically improved both throughput and throughput time (Bertrand and Wortmann, 1981; Wiendahl, 1987). The observed improvements could not be explained by conventional OR models. The conventional way for OR to model a complex production system is an open queuing network model. Analysis of open queuing network models reveals no improvement when applying workload control; on the contrary, the performance deteriorates if workload control is applied. However, in many real-life production situations workload control was adopted as an effective management tool and eventually OR theorists have picked it up as a research topic. Later research showed that workload control does improve performance under the assumption that management can influence the arrival of new orders to the system (Hopp and Spearman, 1996), thus closing the queuing network. However, the improvements observed in industry by Wiendahl (1987) were obtained without such control on new customer orders. Recent survey and field study research (Schmenner, 1988; Holström, 1994; Lieberman and Demeester, 1999) contains indications that one of the assumptions underlying the conventional queuing network models might be wrong. Other types of queuing network models might explain what is observed in real-life operational processes (Bertrand and Van Ooijen, 2002).

The discussion above shows how OR research can become more effective. OR should study models that are closer to real-life operational processes. In fact, models should be studied which can be validated as real-life processes, and also the results of the analysis should be tested in real life. In such a way, feedback is obtained regarding the quality of the model used for and the quality of the solutions obtained from the analysis. Thus theoretical quantitative research should be combined with empirical quantitative research. For a fine example of such research see Inman (1999) and DeHoratius and Raman (2000). In the next section, both theoretical quantitative research and empirical quantitative research are discussed more extensively and explicitly, and are positioned in a general quantitative modeling OM research.

Overview of OM research methodologies using quantitative modeling

Quantitative model based research can be classified as a rational knowledge generation approach (see Meredith *et al.*, 1989). It is based on the assumption that we can build objective models that explain (part of) the behavior of real-life operational processes or that can capture (part of) the decision-making problems that are faced by managers in real-life operational processes. It is important to stress that the relationships between the variables are described as causal, meaning that it is explicitly recognized that a change of value α in one variable will lead to a change of $f(\alpha)$ in another variable. In other types of quantitative research, such as survey research, also relationships are defined between the variables that are under study. However, generally in survey research the range over which the variables vary is not always defined explicitly, and the relationship between the variables is usually not causal, and in most cases not quantitative. With "quantitative" in this observation we mean that the extent to which the dependent variable changes when a specified change in the independent variable occurs is quantitative. An important consequence of the fact that relationships are causal and quantitative is that the models can be used to predict the future state of the modeled processes rather than be restricted to explaining the observations made. Within the model, all claims are therefore unambiguous and verifiable. It is important to realize that this is not valid for claims that pertain to the world outside the model. For the world outside, unambiguous and verifiable predictions are very hard to make and we will show that this issue has hardly been addressed in the academic literature. As a consequence, we see in the literature a clear distinction between empirical quantitative modeling research and axiomatic quantitative modeling research.

We may classify model-based OM research into two distinct classes. The first class of these is primarily driven by the (idealized) model itself. We will denote this type of research as axiomatic, in line with the terminology introduced by Meredith *et al.* (1989). In this class of research, the primary concern of the researcher is to obtain solutions within the defined model and make sure that these solutions provide insights into the structure of the problem as defined within the model. Axiomatic research produces knowledge about the behavior of certain variables in the model, based on assumptions about the behavior of other variables in the model. It may also produce knowledge about how to manipulate certain variables in the model, assuming desired behavior of other variables in the model, and assuming knowledge about the behavior of still other variables in the model. Formal methods are used to produce this knowledge. These formal methods are developed in other scientific branches, mainly mathematics, statistics and computer science. In fact theoretical model-based OM research heavily leans on results obtained in mathematics, statistics and computer science. As a result, the types of models that are studied in this research line are to a large extent determined by the available methods and techniques in mathematics, statistics and computer science, such as combinatorial optimization and queuing theory. In fact the researchers look at the operational process or the operational decision problem through the looking glass of the mathematical models that can be analyzed. Researchers in this line are trained in, for instance, decision theory, dynamic programming, mathematical optimization, Markov processes or queuing theory.

Typically, axiomatic research is normative, although descriptive research, aimed at understanding the process that has been modeled, is also present. Normative research is primarily interested in developing policies, strategies, and actions, to improve over the results available in the existing literature, to find an optimal solution for a newly defined problem, or to compare various strategies for addressing a specific problem. Almost all articles in the (US-based) OR domain fall into this normative area (e.g. allocation theory and inventory theory). Research in the area of queuing and game theory typically is descriptive in nature and in most cases model driven. Descriptive research is primarily interested in analyzing a model, which leads to understanding and explanation of the characteristics of the model.

The axiomatic model based research line has been very productive and a vast body of model-based knowledge has been developed over the last 50 years. Regularly this knowledge is consolidated in monographs and books. Good recent examples of such books are:

- Stochastic models of manufacturing systems (Buzacott and Shantikumar, 1993).
- Logistics of production and inventory (Graves *et al.*, 1993).
- Factory physics (Hopp and Spearman, 1996).
- Quantitative models for supply chain management (Tayur *et al.*, 1998).
- Local search in combinatorial optimization (Aarts and Lenstra, 1997).

The second class of model-based research is primarily driven by empirical findings and measurements. In this class of research, the primary concern of the researcher is to ensure that there is a model fit between observations and actions in reality and the model made of that reality. This type of research can be both descriptive and normative. Descriptive empirical research is primarily interested in creating a model that adequately describes the causal relationships that may exist in reality, which leads to understanding of the processes going on. Examples of this type of research is the industrial dynamics research conducted by Forrester in the 1950s (e.g. Forrester, 1961) and the research on clockspeed in industrial systems by Fine, Mendelson and Pillai in the 1990s (Fine, 1998; Mendelson and Pillai, 1998). Normative empirical quantitative research is primarily interested in developing policies, strategies and actions to improve the current situation. This area of research is very small. Some normative claims have been made within quantitative empirical articles (e.g. Blocher *et al.*, 1999), but the verification procedure is usually not very strong. As with any research with a longitudinal design where a change action is made during the research, it is very hard to assess which changes in performance are due to the specific action and which are due to other changing circumstances. In empirical OM research, controlling all relevant variables is impossible.

In contrast with axiomatic quantitative research, empirical quantitative model based research has not been very productive. Empirical model based research reports on the applications of theoretical research results in real-life operational processes. Researchers working in this line should have much knowledge about the relevant characteristics of the operational process under study. However, OM still lacks a well-defined, shared methodological framework for identifying and measuring the relevant characteristics of real-life operational processes. For instance important factors in a queuing model of an operational process are the capacity of the resources, the processing times of the operations, and the arrival rate of work orders. There is no objective, situation independent and generally accepted procedure that, observing a specific operational process by means of a queuing model, is used for measuring the capacity of the resources, the processing times of the operations and the arrival rate of the orders. Of course, in each application in a real-life situation, this construct problem is dealt with in some way or another; however, this is always done in a subjective, situation-dependent way that is seldom explicitly reported in publications. For that reason it is difficult to judge the scientific value of the results reported in these publications. However, given that the fact the quantitative model based research is a rational, objective, scientific approach, it must develop an objective, rational way to deal with the problems encountered when doing empirical research.

The discussion above leads to a classification as shown in Table I.

Each of these four research types leads to different contributions to the general research questions in OM. Note that in large-scale research projects various of these research types could be combined.

Review of relevant methodological literature

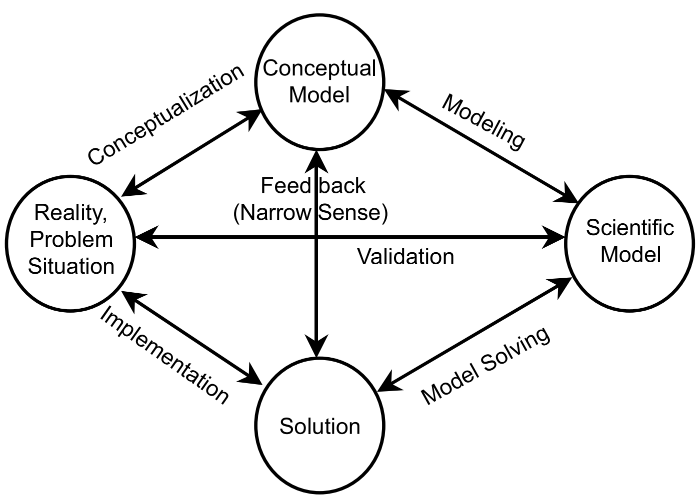
Research methodology in quantitative modeling in OM has traditionally not been perceived as an issue. There are a couple of explanations for this. The main point is that most of the reported work on methodology in OM has been on empirical research methodology. We refer to the special issue of the *Journal of Operations Management* (Melnyk and Handfield, 1998b) for an extensive set of articles on OM research methodology, and to Meredith *et al.* (1989) for an extensive discussion on methodology in OM research in a general way. In the other articles in the current special issue of the *International Journal of Operations & Production Management*, overviews are given on action science (action research), surveys and case studies. Methodology articles addressing

	Descriptive	Normative
Empirical	ED	EN
Axiomatic	AD	AN

Table I. Classification of quantitative (model-based) OM research types specifically the domain of quantitative modeling in empirical research have, however, not appeared in the academic literature. Keys (1991) addresses in his monologue some methodological issues in the field of operational research, as do Ackoff and Sasieni (1968) in their seminal book on OR. It is important to realize that their work is not so much concerned with research methodology in an academic sense. They are more interested in the methodology used by operations/operational researchers when solving relevant and specific problems, which, as discussed above, is distinct from the academic/scientific research methodology that we are addressing in this article. In this article we focus on research that is aimed to obtain generic results towards theory building in OM rather than results of solutions for specific problems without this generic contribution.

In the axiomatic domain, the discussion on methodology is largely absent. Instructions for referees in journals publishing this type of work do not mention the methodology issue. Rather, they focus on mathematical correctness (referring to the earlier mentioned fact that the line of reasoning must be unambiguous) and in some cases on a judgement of the referee on relevance of the problem. Reisman and Kirschnick (1994) further distinguish within the axiomatic research between what they call pure theory articles and those axiomatic articles that are tested using synthetic data. They do not address the methodology issue in their article. A special case is axiomatic research that uses computer simulation. Generally speaking, methodology is an issue in these articles. The methodology relies largely on statistics theory in experimental design and analysis, and has been well established in books such as Kleijnen and Van Groenendaal (1992) and Law and Kelton (2000).

An early contribution to the methodology discussion in OM is the seminal article by Mitroff *et al.* (1974). Mitroff *et al.*'s model is presented in Figure 1.



Source: Mitroff *et al.* (1974)

Figure 1.
Research model by Mitroff *et al.* (1974)

Mitroff *et al.*'s (1974) model is based on the initial approaches used when operational research emerged as a field. In his model, the operational research approach consists of a number of phases:

(1) conceptualization;

(2) modeling;

(3) model solving;

(4) implementation.

In the conceptualization phase, the researcher makes a conceptual model of the problem and system he/she is studying. The researcher makes decisions about the variables that need to be included in the model, and the scope of the problem and model to be addressed. In the next phase, the researcher actually builds the quantitative model, thus defining causal relationships between the variables. After this, the model solving process takes place, in which the mathematics usually play a dominant role. Finally the results of the model are implemented, after which a new cycle can start. Mitroff *et al.* (1974) argue that a research cycle can arguably begin and end at any of the phases in the cycle, provided that the researcher is aware of the specific parts of the solution process that he/she is addressing and, consequently, of the claims he/she can make based on the results of his/her research.

Additionally, they put forward the notion of shortcuts in the research cycle that are often applied and that lead to less than desirable research designs. For instance, they distinguish the "modeling – model solving – narrow feedback" cycle, and comment that many researchers following this cycle tend to mistake the model solving process for implementation. Alternatively, they name the "conceptualization – narrow feedback – implementation" cycle, which tends to mistake conceptualization for modeling, and thus distinguishing a flaw that characterizes some of the non-quantitative research. Mitroff *et al.*'s (1974) model is very helpful in identifying a specific methodological path that a specific article is following, and relating it to the validity of the claims that are made in the article.

As such, each of the four research types identified in the previous section can be positioned in this model. Since we are discussing quantitative model-based research, the "scientific model" is a central issue in all four types.

In AD research, the modeling process is central. The researcher takes a conceptual model – mostly from the literature – and makes a scientific model of this. Further, the researcher does some analyses on this scientific model to gain insight into the behavior of this model. The researcher typically does not move into the model solving phase. This extension is made in AN research, where the model solving process is the central research process reported. In many AN articles the modeling process is also included, and the results of the model are fed back to the conceptual model. This leads to the "modeling – model solving" shortcut. Mitroff *et al.* (1974) call this feedback in the narrow sense, and cite as the most common flaw that the researcher mistakes this feedback for implementation and puts forward the scientific claim accordingly.

In ED research, the researcher typically follows a cycle of "conceptualization – modeling – validation". It is interesting to note that the main risk that Mitroff *et al.* (1974) notice is an overconcern with validation, i.e. the researcher wants to make a perfect fit between the model and reality. Earlier in this article, we noticed that reality in operations management cannot be fully captured and an over-axiomatic approach in empirical research should therefore be avoided. Finally, the most complete form of research is EN, where the entire "conceptualization – modeling – model solving – implementation" cycle is conducted. As discussed above, in many cases, this research builds upon earlier published research that is in the AD category and has already developed paths for the "modeling – model solving" stages.

How to conduct quantitative research OM

In this section we will discuss more specifically how to conduct good axiomatic quantitative research and how to conduct good empirical quantitative research in OM.

Axiomatic quantitative research

Axiomatic quantitative OM research starts with a condensed description of the characteristics of the operational process or the operational decision problem that is going to be studied. This corresponds with the conceptual model in Figure 1. The conceptual model description should use as much as possible concepts and terms that are accepted as standards published in scientific OM literature on the subject under study. Generally what is studied is a variant of a process or a problem that has been studied before. Therefore, in the conceptual model description reference is given to generally accepted anchor articles which contain descriptions of the general characteristics of the process or problem studied in the research line in which the current research fits (e.g. economic lot sizing, queuing, or inventory control) and to the recent articles which study processes or problems that are closely related to the process or problem under study. In this way the process or problem under study is clearly positioned in the scientific literature. Note that studying a process can be considered as descriptive, whereas studying a problem can be considered as normative research.

The scientific relevance of the research is mainly determined by what the research intends to contribute by the existing literature. We can distinguish two types of contribution. The first type of contribution is the study of a new variant of the process or problem, using well-known solution techniques the second type of contribution is to study a process or problem that has been studied before, but provides a new, or in some respects better, solution to the problem, either by applying new types of solution techniques to the problem, or by achieving better results with accepted solution techniques.

The second phase in axiomatic quantitative research is specification of the scientific model of the process or problem. The scientific model must be presented in formal, mathematical terms, such that either mathematical or numerical analysis is possible, or computer simulation can be carried out. Thus researchers in this field must be well educated in mathematical analysis, numerical analysis or computer science. In case computer simulation is used as research tool, knowledge is also needed about experimental design and statistical analysis. The scientific quality of the research is mainly determined by the "optimality" of the result, given the scientific model. In case of normative research, "optimality" pertains to the extent to which the result can be proven to be the best possible solution for the problem given. In case of descriptive research, "optimality" pertains to the extent to which the results can be proven to give the exact characteristics of the process given.

Proofs generally can only be delivered with mathematical analysis. Therefore in axiomatic research a strong mathematical background is needed for doing high quality research. This is also needed to be able to judge which scientific problem formulations, given the current state of mathematical knowledge, are good problems, that is, problems for which high quality results can be obtained. High quality solutions result from insight into what might be a solution, in combination with a mathematical proof of the quality of the solution. Criteria for the correctness of the proof are found in the branch of mathematics used in the research. This is not discussed in this article. Both in finding a solution and in proving the correctness of the solution, intuition plays an important role. Thus good research is not just the result of analytic skills or applying a methodology, but the result of good intuition in combination with analytical skills and a good methodology.

From the above discussion it follows that the main body of a theoretical quantitative OM article generally contains sections that cover the subjects outlined below:

- conceptual model of the process or the problem;
- scientific model of the process or the problem;
- solution;
- proof of the solution;
- insights relating the solution to the conceptual model.

Sometimes the order is slightly different and the authors find it more convenient to present a mathematical analysis of the problem that uniquely leads to solutions or to characteristics of the process.

Axiomatic quantitative research using simulation

A slightly different approach is taken when the result is not obtained with mathematical analysis but with computer simulation. This technique is used in case the model or problem is too complex for formal mathematical analysis. This type of research generally leads to lower scientific quality results than research using mathematical analysis, but the scientific relevance of the process or problem studied may be much higher. This is because computer simulation can deal with a much wider variety of scientific models than can mathematical analysis. So the trade-off here often is between scientific relevance of the process or problem studied and scientific quality of the result.

Research that uses computer simulation requires a number of additional steps. A very important step in simulation research is the justification of this research method. Since the scientific quality of the results generally will be lower – rather than mathematical proofs, only results with some statistical significance can be reached, it is only justified to use this method if it can be shown that it is not possible to solve the problem in an analytical way. A well-known example here is use of computer simulation to test heuristic methods for solving combinatorial optimization problems. Articles that report on this research always contain a section in which it is demonstrated that the problem cannot be solved to optimality in polynomial time of the problem parameters. This is an accepted standard for justifying research on heuristics.

The second step is the justification of the solution or hypothesis to be tested. In research based on mathematical analysis, it is acceptable to just present the solution and the related proof. There the solution is justified by the proof. In simulation research no proof is possible, so we need to be very careful in selecting our heuristic solution or hypothesis. Generally articles of this kind contain a section where evidence from previous research is used to reason why this heuristic might perform well, or why this hypothesis regarding the characteristics of the process might come close to the true characteristics.

The third step is the set-up of the experimental design. This needs to be done very carefully and in accordance with accepted standards (Kleijnen and Van Groenendaal, 1992). All factors in the scientific model that can have an impact on the quality of the solution or results must be identified and have to be varied in the simulation over a sufficiently large range of values with sufficient detail. Thus computer simulation articles always contain a section in which the experimental design is presented and justified. Justifications are often based on results of existing research, either analytical or simulation based, which provide information about what is already known with certainty about related problems. Since we are dealing with theoretical research on a computer model of the scientific model, there are – apart from storage, space and computer time – no limits to size and detail of the model. Simulation-based theoretical research therefore is only limited by computing power. However powerful computers are or will be, their limitations urge us to decide carefully on the complexity of the model to be investigated. Further, the number of factors to be considered in the experimental design should be kept sufficiently low so that efficient simulation and effective data analysis is possible.

The fourth step concerns the statistical analysis of the results of the computer simulations. There is a wide spectrum of statistical techniques available for this purpose, and the choice must be based on the type of research question to be answered. For performance testing, the t-statistic could be used to test the statistical significance of the difference between the performance obtained in the simulation with some benchmark, i.e. the performance of the best heuristic found in literature. For testing the sensitivity of the performance for parameter values in the model, analysis of variance could be used. Researchers involved in simulation-based theoretical research should be well trained in experimental design and statistical analysis, since the state of knowledge in this field determines what research questions can be approached with these techniques.

The fifth step concerns the interpretation of the results of the analysis related to the research questions in the conceptual model. In this step the results are considered in the context of the conceptual problem description and the researchers derive conclusions about the extent to which the original questions are answered and what new questions emerge from these results.

The main body of a computer simulation based theoretical research article in OM therefore contains sections dealing with the issues shown below:

- conceptual model of the process or the problem;
- justification of the research method;
- scientific model of the process or the problem;
- justification of the heuristic or hypothesis;
- experimental design;
- analysis of results;
- interpretation of results.

Empirical model-based quantitative research

Quantitative model-based empirical research is concerned with either testing the (construct) validity of the scientific models used in quantitative theoretical research, or with testing the usability and performance of the problem solutions obtained from quantitative theoretical research, in real-life operational processes. In Figure 1, these core processes are identified as implementation and validation. Quantitative empirical research is still in its infancy and there therefore exists much less consensus about what is good quantitative empirical research than about what is good quantitative axiomatic research.

Empirical scientific research tests and challenges the validity of theoretical models, and tests and challenges the usability and performance of the solutions of theoretical problems. Empirical scientific research should be carefully distinguished from the use of axiomatic research results in improvement projects. These latter projects aim at improving the performance of an operational process by either changing its structure or its control. The use of theoretical research results in such projects is based on the belief that the underlying process models are valid and the theoretical solutions are useable and will perform well. However, this belief is seldom tested during the project, although the methodological rules for the practice of operational research prescribe that the model assumptions should be checked (e.g. Ackoff and

Sasieni, 1968). It is not surprising that the assumptions in operational research projects are seldom checked, because doing so would be very time consuming and costly, due to the effort involved in collecting all the data needed for checking all the underlying model assumptions. This explains why real-life operational process improvement projects seldom produce scientific knowledge about operational processes.

As stated before, quantitative empirical research must be designed to test the validity of quantitative theoretical models and quantitative theoretical problem solutions, with respect to real-life operational processes. This is in line with the more general concept of theory-driven empirical research in OM (Melnyk and Handfield, 1998a; Handfield and Melnyk, 1998). Model-driven empirical research takes advantage of the large body of axiomatic quantitative research in OM and designs the empirical research accordingly. Examples are the work by Fisher and Raman (1999), by Inman (1999), and by Schalla *et al.* (2000). The essence of their work is validating either the conceptual model or the solution proposed by axiomatic research results. Fisher and Raman (1999) analyze the accuracy of inventory records in retail and, using available models, assess the consequences of these inaccuracies on the results that have been obtained in the axiomatic studies. Inman (1999) validates the assumptions commonly made in axiomatic research about the processing times and order arrival times in production systems. Schalla *et al.* (2000) analyze the decision modeling process in advanced planning software, and compare the theoretical assessment to the empirical observations they make. Their empirical observations are driven by hypotheses that are based on the theories developed earlier in primarily axiomatic research settings.

A major problem here is that real-life operational processes are all different, although there are structural similarities within classes of operational processes. The similarities are often caused by the type of manufacturing technology used. Well-known classes of operational processes are, for instance, the continuous flow shop (e.g. assembly line), for high volume production of similar products, and the job shop for low volume production of a large variety of different products. However, depending on the work organization, the information system used, the level of education of the workforce, etc., different flow lines and different job shops may have different operational process characteristics, and these characteristics may evolve over time. Therefore empirical quantitative research should aim at validating the basic assumptions about the operational processes and problem characteristics for well defined classes of operational processes, underlying the theoretical models and problems.

From these observations, we can derive the steps that need to be taken when doing empirical quantitative research. The first step is the identification of the basic assumptions regarding the operational process underlying the theoretical models or problems. In the OM literature, we can distinguish different research streams that share common assumptions about the operations process or operational decision problem. For instance, there is a research stream that is based on a queuing model view on the production process. We call this a basic assumption.

The second step is that researchers should identify the type of operational process and the type of decision problem regarding this operational process, to which the basic assumptions are assumed to apply. For instance it is assumed that decisions about the resource structure of a job shop production system should be based on a queuing model of the flow or orders along the work centers.

The third step is that operational, objective criteria must be developed for deciding whether or not a real-life operational process belongs to the class of operational processes considered (i.e. a job shop) and for identifying the decision system in the operational process that represents the decision problem considered. These criteria should be objective, that is, each researcher in OM using these criteria would come to the same decision regarding the process and the decision system.

The fourth step is to derive, from the basic assumptions, hypotheses regarding the behavior of the operational process. This behavior refers to variables or phenomena that can be measured or observed at the operational process in an objective way. The more different testable hypotheses are derived from the basic assumptions, the stronger the research is.

The fifth step is to develop an objective way to do measurement or to make the observations. This is a very crucial step that requires documentation. The reason for this is that, in operational process research, there exists no formalized construct for variables such as processing time, machine capacity, production output, production throughput time, etc., nor do generally accepted ways of measuring there variables exist. This illustrates the weak position of quantitative empirical research in OM. The situation being as it is, empirical OM researchers must develop their own way of measuring and document this carefully. This requires that the researcher knows how to identify the relevant characteristics of the operational process, and knows how to change or influence and measure the relevant characteristics of the process. Thus, model based empirical research cannot be done without a systematic approach for identifying and measuring real-life operational processes. This is what is called, by Mitroff *et al.* (1974), the conceptual modeling of a system. Conceptual models define the relevant variables of a system under study, the nature of their relationships and their measurements.

The sixth step consists of applying the measurement and observation systems and collecting and documenting the resulting data.

The seventh step is the interpretation of the data, which generally will include the use of statistical analysis. Here special techniques are needed since the data are not the result of an experimental design where variables in the system can be manipulated at will, but result from observations on a real-life system that cannot be manipulated in an arbitrary way. Sophistical statistical techniques have been developed for this type of research in some branches of research in social sciences (e.g. Herzog, 1996; Marcoulides and Schumacker, 1996). When developing the hypotheses regarding the behavior of the operational process in step 4, it should be taken into account what type of behavior can be expected of the process under the given real-life circumstances, within the time frame that the process can be observed; the hypotheses should be restricted to behavior in the expected range and time frame. It makes, for instance, no sense to develop the hypothesis that a job shop will have an average order throughput time of 60 weeks under a steady state capacity utilization of 95 per cent, if a reliable measurement of the work order throughput time under a capacity utilization of 95 per cent requires that the process is measured for 10,000 years. Thus developing effective hypotheses and an efficient operational measurement system requires that the researcher is quite familiar with the type of operational process and the type of decision problem concerned, and is very familiar with the statistical techniques available for analysis of field data.

Finally, the eighth step in quantitative empirical research consists of the interpretation of the research results related to the theoretical models or problems that gave rise to the hypotheses that were tested. This step completes the validation process and may result in confirmation of (parts of) the theoretical model in relation to the decision problem and in relation to the operational process considered, but may also lead to (partial) rejections and suggestion for improving the theoretical models.

The main body of a research article on model-based quantitative empirical research therefore contains sections dealing with the issues outlined below:

- identification of process or problem assumptions;
- identification of types of operational process and decision problems considered;
- developing operational definitions of the operational process and the decision system;
- derivation of hypothesis regarding process behavior;
- development of measurement system;
- results of measurements and observations;
- interpretation of data and observations in relation to the hypotheses;
- confirmation and/or rejection of the theoretical model assumptions.

Relevance

In OM, relevance is generally justified by referring to real-life situations to which the model or problem might apply. Assessing relevance has had a long history in the OR journals. The main debate addresses the so-called "gaps" between OR theory and OR practice, basically bringing forward two issues:

(1) Why do researchers not address more practically relevant problems in terms of complexity, design and definitions; and

(2) Why do practitioners not make more use of all available tools and results that have been developed by the OR research community?

In this article, we will not go into this debate, but refer to other articles, such as Corbett and Van Wassenhove (1993), Ormerod (1997), and Reisman and Kirschnick (1995). An important observation in these articles is that progress in operations research seems to develop along a line that Reisman and Kirschnick denote as "ripple research". With this, they refer to research that is conducted on small extensions of previous axiomatic research, and thus cannot bridge the gap that, according to these articles, apparently exists between the results of axiomatic research and the real-life need of decision makers. It should be noted that in some areas, e.g. allocation theory and inventory theory, series of small extensions have lead to very useful models that have been applied in business practice at a large scale.

The relevance issue cannot be seen apart from the fact that mathematics, statistics and computer science do not (yet) provide us with sufficiently powerful methods of analysis to address problems that come close to the complexity that is observed in most real-life operational processes. The type of model studied in OR is therefore restricted to those models that allow the researcher to do analysis and to make scientific claims. This leads to the fact that for the axiomatic research the relevance criterion (with regard to the validity of the model versus reality) is usually applied very lightly. In many cases, relevance is motivated by referring to earlier articles addressing similar issues, or by referring to general trends in the industry, rather than tying the relevance to actual observations in reality. The model is considered "acceptably relevant" if the modeled problem can be recognized, possibly as an aspect model of reality. We would like to add an important criterion for relevance, apart from the validity issue. This is the question whether the solution of the model assists managers in making decisions in the real world. This is the case if the aspect-model-based solution covers the most important part of the solution, and the context factors (not included in the model) are less relevant to the actual solution.

Conclusions

In this article, we have discussed research methodologies used in quantitative modeling based OM literature. We have distinguished this set of literature from the OR and operational research domain. Further, we have presented a typology which analyses the subject matter, methodology and scientific claims for various types of articles in the domain reviewed in his article.

We may conclude that the methodology issue has not received an abundance of explicit attention in the literature. Especially in the axiomatic research lines, methodological issues appear to be restricted to the narrow-scoped mathematical rigor concept. We have argued that a more broad-sensed methodological rigor needs to grow as a concept in the OM literature, such that a common frame of reference with regard to rigor and relevance can be developed.

A major opportunity for quantitative, model-driven, empirical research has been identified, where the rich pond of axiomatic results, based on advances in mathematics over the past decades, is fished to create more rigorous empirical scientific knowledge in the field of OM. In such exemplary articles, given axiomatic models from OR is validated empirically in real-life operational processes, giving way to a real theory-building process.

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