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WHY MODELLING STILL MATTERS IN DISCRETE SIMULATION

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BRIEFABSTRACT

A discrete event simulation model is a simplified representation of some system or other, usually constructed and used for some defined purpose, though the purpose may change through time. When developing a discrete event simulation model, an analyst must decide what elements of the system of interest should be included and must also consider the level of detail needed in their representation. The two key element types included in such a model are the sampling processes, usually employed to represent stochastic behavior, and a statement of the logical interactions between the entities, activities, events and processes that lead to the distinctive behavior of the system being simulated. In most models, both the logic and the sampling processes are approximations and are often deliberate simplifications. This model building has traditionally been regarded as a craft activity, best learned through apprenticeship. We address a simple question – can we do better than this?

1 INTRODUCTION

The focus of this paper is deliberately practical: why are models important and how can we improve their use? This is not to denigrate the enormous advances there have been in the theoretical aspects of computer simulation; in particular, in discrete event simulation. Since I have no experience of the use of models in, say, environmental change or financial markets, I will confine the discussion the organizational use of models. That is, the use of models and modelling in the application of Management Science. Others may wish to reflect on whether my remarks have a wider relevance. Some might wonder why an academic, with the usual books and papers to his credit, is focusing on practice. Wouldn't it be better for a practitioner to do this? Yes, probably it would; but few seem keen to do so.

Management Science models are used in many organizations and some of the success stories are told in journal such as Interfaces and reflected in prizes such as the Edelman Award. Not only do many organizations use such models, some are very reliant on them for their day-to-day decision making and to support their deliberations on strategic issues. Credit decision making and selling airline tickets are examples of routine business processes that are almost entirely dependent on Management Science models that automate many aspects of business processes that are crucial to the success of banks and airlines. This decision automation is probably fundamental to many e-business applications that support a very large number of transactions. At the opposite extreme, models are used to help people deliberate over larger, more strategic decisions in situations where there is disagreement over ends and well as means, often known as wicked problems (Rittel and Webber, 1973). Used in this way, models do not replace human decision making, but help people think through the consequences of actions that may be taken.

Pidd (2003, p12) suggests that an OR/MS model is an external and explicit representation of part of reality as seen by the people who wish to use that model to understand, to change, to manage and to control that part of reality. This definition avoids the question of what may constitute reality, which can become an important issue. It is not concerned whether a model involves a sophisticated mathematical formulation or whether it is just a simple flow diagram showing how entities are believed to relate to one another. It stresses that models are approximations, built with some intended use(s) in mind and that they are the product of human thought and ingenuity.

2 HOW ARE SIMULATION MODELS USED?

As far as I am aware, there has been no comprehensive study of the range of ways in which discrete event simulation models are used, hence my comments in this section are based on my own, less than complete, observations of the literature, attendance at conferences and conversations with others.

There are many different ways in which OR/MS models may be classified but, here, the focus is how models are used, rather than the nature of the models themselves. That is, the concern is with the decisions and processes that the models are intended to support and, in particular, the ways in which people will interact with those models. However, it would be a mistake to assume that the actual use of a model can always be known in advance – sometimes there are pleasant surprises; on other occasions, the surprise is less pleasant. Nevertheless, careful consideration of how a model may be used is clearly an important part of any modelling project.

It is also a mistake to assume that models of the same form (e.g. mathematical programming) can only be used in a single way. For instance, though mathematical programming formulations are usually associated with attempts to determine optimum policies, possibly on a routine basis, they may also prove useful in exploring options so as to understand a system rather than to make decisions. Likewise, models that take very different forms may be used in the same way.

2.1 A spectrum of model use

With this in mind, figure 1 shows four archetypal modes of model use in Management Science and indicates where many discrete event simulation applications seem to be found. The position at the extreme left is labeled as decision automation and, as discussed earlier, covers applications such as credit scoring (Andreeva, 2006) and the selling of travel tickets and hotel rooms with almost no human intervention (apart from the customer, of course). Hidden away within ticket selling applications are dynamic pricing models (Elmaghraby and Keskinocak, 2003) that attempt to optimize income or profit, using price to match supply and demand. Decision automation models should not be confused with old-style, rather dumb, transaction processing systems, though there are some similarities.

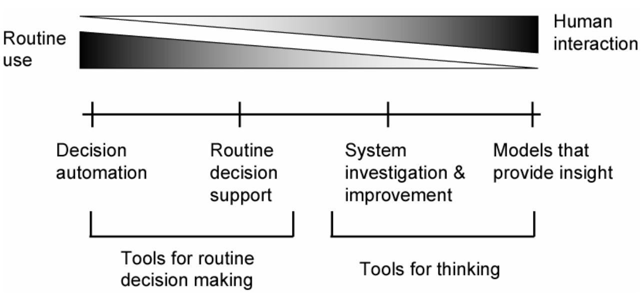

Figure 1: A spectrum of model use

The next position on the spectrum is labeled as routine decision support, which covers situations in which people are making relatively routine decisions and use the models to help them in this process. Examples might be operating room scheduling in hospitals or staff rostering. The models are used to generate good or optimal solutions, based on the information they process and the algorithms in the models. However, it is common for real-life to be more complex or rather less certain than can be encoded in the models. Hence, the models are used for decision support and the human decision makers and planners may sensibly over-ride them when appropriate. In essence, the models narrow down the range of options that a decision maker needs to consider.

The third position in figure 1 is labeled as modelling for investigation and improvement and is perhaps the idea most commonly underpinning Management Science textbooks and many papers. There are many such examples, such as the location of distribution depots (Sahli and Rand, 1989; Wiles and Brunt, 2001), the investigation of ways to improve performance in an accident and emergency department (Günal and Pidd, 2006; Fletcher et al, 2007), the design of business processes to support automated decision-making (Laguna and Marklund, 2005; Bhaskar et al., 1994), or the study of diseases to improve intervention and treatment (Brailsford et al., 1992; Davies et al, 2002).It is here than many discrete event simulation applications can be located. Whereas models developed for decision automation and routine decision support are expected to be used many times, models developed for investigation and improvement are typically used for a relatively short period to examine options so as to decide which is the best in the particular circumstances. Models used in the this way may need to be modified slightly, or even significantly, for some of the options being considered.

The final position on the spectrum of figure 1 is labeled as modelling to provide insight and is most common in ill-structured situations in which little data is available and there are clashes of interest between different stakeholders. When modelling for investigation and improvement, the model is typically used to compare means (options) within agreed or defined ends (objectives). However, when tackling ill-structured or wicked problems, there is usually disagreement about ends as well as means. For example, the question may not be 'how do we increase output by 10% and reduce costs by 10% in this factory?' Instead, it may be, do we want to be in manufacturing at all or could we find some other way to operate? It is probably not unusual for models to be built but not used in such situations. It is, though, important to realize that this does not negate the value of models. In such situations, modelling (the process of abstract and representation) may be what adds the value. See Chelst and Bodily (2000) for a discussion of this in decision analysis and decision trees.

3 SIMULATION MODELLING

The argument so far has located most discrete event simulation applications around the third point of figure 1: as modelling for investigation and improvement. Assuming, for the time being, that this is correct, what are the implications for simulation modelling and for simulation researchers? Following Pidd (forthcoming), we can consider this under several headings: data requirements, validation, value added by the modelling and dangers and pitfalls.

3.1 Data requirements

Pidd (2003, p94ff) discusses the use of data in developing and using Management Science models. It is important to realize that, though many organizations are awash with data, often automatically collected in transaction processing, it is not unusual for a modeler to find that the data needed to build and test a model is not available. Günal, Onggo and Pidd (2007) describes the development and use of a simulation model to help a police force improve the way it response to calls for help from the public. One of the most time-consuming aspects of the work, which required considerable ingenuity and detective work, was the generation of data sets for the model. This is not at all unusual.

Models, we know, are approximations and, in discrete simulation, this usually means the static rules of entity interaction, which lead to the dynamically emergent behavior observed in a simulation run. That is, these static rules are, usually, approximations, rather like the protocols followed by call centre staff in responding to phone calls. That is, they do not and cannot capture the full range of behavior in the system being simulated. If we add to this, the inevitably approximate data used with these static rules, it almost seems a miracle that a model is any use at all!

However, we must recognize that the value of simulation models often lies as much in the modelling as in the models. That is, the process of teasing out and representing the rules of entity interactions, together with the data needed for the model, is often of enormous value to those involved. That is, even simple models can be surprisingly useful in complex problems when used to support human decision making.

3.2 Validation

There is no shortage of papers on the validation of simulation models. For example, Sargent (1986) and Balci (1994) cover most of the technical issues, describing various tests that can be applied to both model and real system data in some form of Turing test. Many authors refer to this as black box validation, due to its conceptual similarity with a Turing test. There is also, though, what many refer to as white- or transparent-box validation in which the internals of a model are subject to detailed scrutiny

Zeigler (1976) provides an extensive discussion of model validation as part of a general theory of modelling, stressing the importance of an experimental frame in doing so. Kleindorfer et al (1998) examine the issues from a philosophical standpoint arguing that some form of 'beyond reasonable doubt' criterion is most appropriate, as in a law court and Thus, there seems to be general agreement that, in practice, fitness for purpose is the main focus of validation efforts and also a realization that no model will ever be wholly valid, except within defined circumstances.

The problem, of course, is that most models, when used for system investigation and improvement, are pushed beyond those tightly defined circumstances; that is, they are used to demonstrate how something might work that currently does not exist or is best not attempted in reality

3.3 Added value with dangers and pitfalls

Given our inability to demonstrate that models are wholly valid, what value can they add when used to support system investigation and improvement? Are we handing ourselves a carte blanche for sloppy, ill-considered work hidden behind fancy graphics? It will be no surprise that I regard models used in this way as tools for thinking, that is they are to supplement human thinking and deliberation; figure 2 shows the basic idea. The model alone simply cannot match the variety exhibited by the system being simulated, otherwise it would be just as complex. It is the human: model system that has the variety to do so; which, of course, assumes an intelligent, purposeful user.

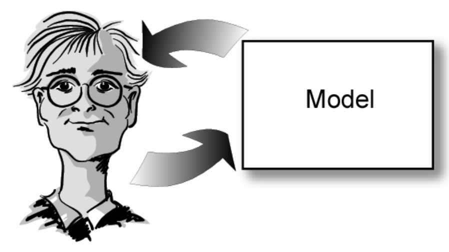

Figure 2: The model:user system

This strongly suggests that the process of developing and using a simulation model for system investigation and improvement is not wholly technical. Such a process includes elements that are social, political and even intuitive, as discussed in Pidd (2007), which examines the use of the unfortunately named 'soft OR' methods in supporting simulation practice.

4 PICKING THINGS APART AND PUTTING THEM TOGETHER AGAIN

It is fairly clear what implications these ideas have for simulation practice, but what about simulation research? How does this affect the sub-communities of analysis methodologists and modelling methodologists? An obvious point is that both sub-communities need to recognize the ways in which simulation models are generally used – something which software developers have done for many years, stressing rapid model development and graphics that aid people's thinking.

It perhaps means that we need to move beyond rather simple models when demonstrating the effectiveness, or otherwise, the various statistical tools at our disposal. It also may suggest that that an over-enthusiastic focus on simulation optimization will, though fascinating and challenging for researchers, have little or no impact on simulation practice.

But there is surely more to say and the rest of the paper will make some admittedly, speculative, arguments.

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