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SOME THOUGHTS ON CONCEPTUAL MODELLING: PERFORMANCE, COMPLEXITY AND SIMPLIFICATION

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ABSTRACT:
The conceptual modelling stage in a simulation project is very important and yet is still generally regarded as more of an art than a science. This paper sets out some of my views on conceptual modelling. The meaning and nature of conceptual modelling are discussed. The overall aim should be to choose the best model for the project and so conceptual models can be evaluated by predicting their performance, and eleven aspects of model performance are set out. Common advice is to keep the model as simple as possible and yet there is no accepted definition or metric for complexity in the context of conceptual modelling. More specific attributes may, in fact, be more useful. Model simplification can also be very beneficial particularly in improving understanding and yet there is no methodology for this. Future research in all these areas would provide a better understanding of the conceptual modelling process with the ultimate aim of helping both novices and experts achieve greater success for their simulation projects.

Keywords: Conceptual Model, Performance, Complexity, Simplification

1. INTRODUCTION

Conceptual modelling is a vital part of a simulation project. In contrast to most other aspects of the simulation process little research has been done on conceptual modelling and it is still regarded as more of an art than a science. Most textbooks devote only a few pages to the topic, with one notable exception being Robinson [1]. The aim of this paper is to provide an overview of some of my views on conceptual modelling based on various research studies I have carried out in the past 12 years.

1.1 MEANING OF CONCEPTUAL MODELLING

The term conceptual modelling itself seems to cause some confusion because of its slightly different uses. In particular there is a considerable amount of technical literature in computer science and artificial intelligence on conceptual modelling that focuses on modelling techniques and ontologies (such as UML) for modelling thoughts, knowledge and concepts. In the context of operational research (O.R.) projects, the usage is rather broader in that it refers to the whole process (however it is carried out) of deciding what to include in the model. Thus typical project tasks are problem formulation, conceptual modelling, model building, verification and validation, experimentation, analysis of results, and implementation of findings. Brooks and Robinson [2] define the conceptual model as "a software independent description of the model that is to be constructed". The conceptual model therefore needs to specify all the elements included in the model and the rules that determine their behaviour. How this is actually implemented in the model depends on the software used and, in principle, the conceptual model could be built using any suitable software. Of course, the modelling process as a whole is not generally a simple linear process and so the conceptual model may be reconsidered at various points during the project. As a result of the ease of use of modern software, in practice the model may be constructed for some small scale projects as it is defined so that conceptual modelling and model building take place together in an iterative manner.

Documentation of the conceptual model probably varies considerably in different projects from none at all (where the actual model built gives the only evidence) to detailed specifications. Possible formats for recording aspects of the conceptual modelling information include diagrams (such as a process diagram or activity cycle diagram), a list (such as the elements or the assumptions and simplifications) or just a written description.

1.2 ADVICE ON CONCEPTUAL MODELLING

Advice given in the literature on the process of deciding what to include in the model tends to be fairly general and brief. For example, even though Law [3] states "I now strongly feel that the most difficult aspect of a study is that of determining the appropriate level of model detail.", Law and Kelton [4] devote only two pages out of over 700 pages in their text book to this issue and their advice is to consider the following: the study objectives, the outputs required, the advice of those who know about the real system, the model credibility required, the data available and the budget for the study. They also suggest using sensitivity analysis (although, in fact, this can only be done once the initial model is built), and they warn against the temptation of including too much detail.

Pidd [5] identifies the modelling method and the experimental frame of Zeigler [6] as factors affecting the conceptual model. The modelling method (e.g. discrete event or system dynamics) will certainly affect the elements and relationships in the model, although I would consider the choice of method as part of the conceptual modelling decisions in that it specifies the nature of the rules in the model. The experimental frame is the circumstances to be investigated using the model and so relates to considering the objectives and required outputs. In [7], Pidd also sets out 6 principles of modelling in management science, several of which focus on different aspects of keeping the model simple.

Robinson [1] gives much more emphasis to conceptual modelling, devoting two chapters to it. He provides a very good discussion of many of the issues in this paper including a definition, concepts for evaluating the conceptual model, documentation and model simplification. A framework for developing a conceptual model is also presented consisting of a process with stages of understanding the problem, deciding on the objectives of the project, specifying the inputs and outputs of the model, and finally determining the model content. This is consistent with previous comments from the literature on the importance of relating the conceptual model to the objectives and experimental frame. However, presenting this as a step by step logical process and providing an in depth discussion with examples makes this a much more useful practical guide.

2. MODEL PERFORMANCE AND THE NATURE OF CONCEPTUAL MODELLING

In considering conceptual modelling, it is useful to start by identifying its objective. Conceptual modelling specifies the model to be used in the project and so it has a big impact on all the other modelling tasks and on the success of the project as a whole. The aim in conceptual modelling should therefore be to choose the model that will result in the most successful project. This involves considering how the model will affect the different aspects of model performance, in particular the following eleven elements specified in [8]:

Results

1.The extent to which the model output describes the behaviour of interest (whether it has adequate scope and detail).

2.The accuracy of the model's results.

3.The ease with which the model and its results can be understood.

Future use of the model

4.The portability of the model and the ease with which parts of the model can be reused in future models.

Confidence in the model (verification, validation and credibility)

5.The probability of the model containing errors.

6.The accuracy with which the model output fits the historical data.

7.The strength of the theoretical basis of the model including the quality of input data.

Resources required

8.The time and cost to build the model (including data collection, verification and validation).

9.The time and cost to run the model.

10.The time and cost to analyse the results of the model.

11.The hardware requirements of running the model.

There is evidence from Willemain's experiment [9] that expert modellers do go through a process of mentally evaluating alternative conceptual models. Willemain's experiment is a particularly interesting study of the O.R. modelling process, in which experts spoke aloud their thoughts for the first hour of tackling an artificial problem. Tape recordings were made and transcripts produced and analysed, which provided valuable insights into the nature of the experts' modelling approaches. There was a lot of switching between different modelling topics, particularly between "structure" (conceptual modelling) and "assessment" (verification and validation) as modellers evaluated and revised the conceptual model. Willemain comments that even though only the initial stage of the modelling process was studied the experts did "conduct thought experiments involving the other stages as an integral part of the formulation stage". Therefore the experts were probably predicting the performance of the conceptual models through these thought experiments as a basis for the choice of conceptual model.

Willemain also carried out a survey of the modellers who participated in his experiment, and the findings included a strong sense of the importance of creativity in the modelling process [10]. The words and phrases given by the experts for important qualities of an effective modeller included creative (2 experts), creativity (2 experts), imaginative, insightful, inspired, willingness not to pigeon hole problems, and open-minded. There were also 7 point Likert scale questions with a strong overall response under "the way the experts model" for several questions including "look for analogies" rather than "start from scratch", "start small and add" rather than "start big and subtract", and "always draw / doodle" rather than "never draw / doodle".

Predicting the effect of the choice of model on model performance and balancing the different performance elements is a difficult task. Experts can use past experience as a basis for predicting performance, but studies that investigate the effect of different model attributes on performance would also provide useful information.

A further complication is that the relative weight of these performance elements can differ substantially between different projects. For example, improved understanding could be the main aim of a research project rather than making accurate predictions. A short timescale, strict deadline and small budget would mean that the resources required are particularly important. In a client project, the context of the project and attitude of the client may influence the process of obtaining confidence in the model.

The nature of the conceptual modelling problem will also depend on the project, in particular on the complexity of (the modeller's perceptions of) the system and the problem. A more complex system is likely to mean a greater choice of plausible conceptual models as there are more combinations of factors that could be included. One guideline is that some factors may be able to be ignored or averaged if they vary on a quite different time or spatial scale to the overall model [11].

3. COMPLEXITY, LEVEL OF DETAIL AND SIMPLIFICATION

A very common piece of modelling advice is to keep the model as simple as possible, even relating this back to Ockham's (or Occam's) razor from the 14th Century that can be translated from the Latin as "entities should not be multiplied without necessity". The other term often used in the literature is level of detail, with complexity and level of detail appearing to be synonymous. As well as the textbook advice referred to in section 1.1, various other authors have set out advantages of a simple model compared to a complex model including being easier to understand, easier to change and update, quicker to run and analyse, requiring less data and fewer resources, and having a greater chance of acceptance by the client (e.g. [12], [13]). A simple model is identified as a key factor in O.R. project success in the survey by Tilanus [14].

Nevertheless, although we may have an intuitive idea of the level of detail and complexity of a model (e.g. we may be confident in a comparative ranking of the complexity of certain models) there is no precise definition for model complexity or agreed way of measuring it. Indeed it is quite a broad concept and narrower attributes may be more useful. For example, Brooks and Tobias [8] suggested size, connectedness and calculational complexity as sub-components of complexity although, even then, there are various ways of measuring these. Identifying metrics for both key model attributes and the performance elements and then measuring the effect of changes in the attribute on performance for specific models may be a way of obtaining a better understanding of model performance leading to better predictions of model performance.

A relevant issue for conceptual modelling is model simplification. Any model is a simplification of the modeller's understanding of the real system and so the choice of conceptual model can be regarded as finding the most appropriate set of simplifications. One approach to studying the conceptual modelling problem is to compare alternative models for a system and these alternative models can be developed by taking a complex model and simplifying it in various ways [15][16]. This can also be a good strategy in a modelling project, particularly where the main aim is increased understanding [17]. The result is a hierarchy of models where the simple model is easier to use and understand but where the confidence in the simple model comes from a comparison with the more detailed model. Greater confidence in the detailed model results from its stronger theoretical basis as there is a direct correspondence with observed elements and known relationships. Techniques I used in model simplification were sensitivity analysis and examining the detailed workings of the model and the results. This resulted in interesting insights and in several cases a new analytical model was developed. The simplifications included developing a probability based model of plant population genetics simulation, using aggregate variables in a wheat model, and bottleneck analysis of a manufacturing system simulation [17] [18]. However, simplification is time consuming [19] and risky as there is no guarantee of success. Ways of simplifying a model have been discussed in the literature (e.g. [1], [6], [20]) but there is no established methodology.

4. CONCLUSIONS

Conceptual modelling is the stage in the simulation process that has received the least amount of attention. The conceptual model is the model specification and the aim is to choose the model that will give the best overall performance for the project. However, more research is needed in this area, including research on the relationships between model attributes and performance, how experts (and novices) approach conceptual modelling and on methodologies for model simplification. A better understanding of conceptual modelling could be particularly valuable in training novice modellers but may also help experts to improve their modelling skills leading to even greater success in simulation projects.

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