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Conceptual modelling for simulation Part II: a framework for conceptual modelling

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Following on from the definition of a conceptual model and its requirements laid out in a previous paper, a framework for conceptual modelling is described. The framework consists of five iterative activities: understanding the problem situation, determining the modelling and general project objectives, identifying the model outputs, identify the model inputs, and determining the model content. The framework is demonstrated with a modelling application at a Ford Motor Company engine assembly plant. The paper concludes with a discussion on identifying data requirements from the conceptual model and the assessment of the conceptual model.

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Introduction

A previous paper (Robinson, 2007) set out the foundations of conceptual modelling for simulation. It provided an understanding of current thinking on the topic and gave a definition of a conceptual model. It also discussed the requirements for a conceptual model: validity, credibility, utility and feasibility. Such discussions are useful for informing a simulation modelling project, but they do not answer the question of how to develop a conceptual model. That is the question addressed in this paper whose key contribution is to provide an ordered and detailed framework for developing simulation conceptual models of operations systems (Wild, 2002). This is something that is largely missing from the current literature on simulation.

The framework that is presented provides a sequence of activities required for development of a conceptual model. For each of these activities, there is a discussion on how a modeller might approach them, with guidelines and methods suggested. The paper concludes with a discussion on how data requirements can be identified and how the model can be assessed against the four requirements of a conceptual model. The framework is illustrated with the example of the Ford Motor Company (Ford) engine assembly plant model described in the previous paper.

The framework presented here has been developed based on the author's experience, of nearly 20 years, with developing and using simulation models of operations systems, mainly manufacturing and service systems. By reflecting on the cognitive processes involved in reaching decisions about the scope and level of detail of models developed, a set of guidelines and methods have been devised. The framework aims to be useful for both novice and more expert modellers alike. For novice modellers, it provides a guide on how to make decisions about the nature of a simulation model that is to be developed for a specific project. For more experienced modellers, it provides a greater sense of discipline to the conceptual modelling activity. It is hoped that by providing more discipline, greater creativity can be encouraged as the more basic tasks are formalized (Ferguson *et al*, 1997). At present there appears to be very little discipline in conceptual modelling. Pidd (1999), for instance, sees modelling as a process of muddling through.

Two other groups may benefit from this framework. Teachers may find it useful for giving their students a basis on which to learn about conceptual modelling. Researchers may use the framework as a basis for further and much needed research in this important area of simulation modelling.

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A framework for developing a conceptual model

Figure 1 provides an overview of the conceptual modelling framework that is described in more detail below. In this framework, conceptual modelling consists of five key activities that are performed roughly in this order:

- understanding the problem situation,
- determining the modelling and general project objectives,
- identifying the model outputs (responses),
- identify the model inputs (experimental factors),
- determining the model content (scope and level of detail), identifying any assumptions and simplifications.

Starting with an understanding of the problem situation, a set of modelling and general project objectives are determined. These objectives then drive the derivation of the conceptual

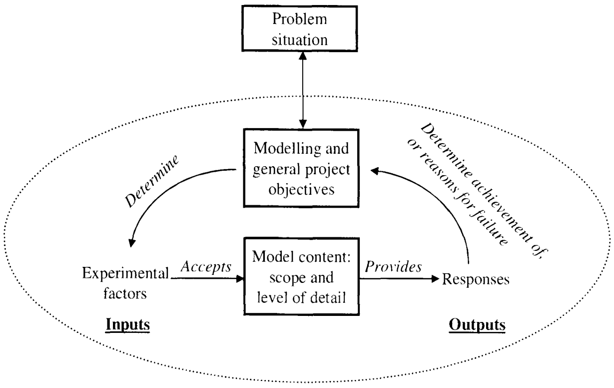

Figure 1 A framework for designing the conceptual model (revised from Robinson, 2004).

model, first by defining the outputs (responses) of the model, then the inputs (experimental factors), and finally the model content in terms of its scope and level of detail. Assumptions and simplifications are identified throughout this process.

The order of these activities is not strict as it is expected that there will be much repetition and iteration between them. For instance, the problem situation is rarely static and so continual revision to the conceptual model is required. Further to this, conceptual modelling is not performed in isolation, but is part of simulation study which itself is repetitive and iterative in nature, for instance, work carried out during model coding and experimentation may both lead to alterations in the conceptual model. (Indeed, the simulation study is normally just a part of a wider project which will also involve repetition and iteration.) For the purposes of explaining each of the conceptual modelling activities, however, it is useful to separate them and describe them in the order in which they would generally progress. This is the approach used below. Meanwhile, the reader is reminded to constantly bear in mind the repetitive and iterative nature of the modelling process.

Within this framework, the purpose of the model outputs is seen as twofold: first, to determine whether the modelling objectives are being met and second, if the objectives are not being met, to help determine why. As such, the objectives are central to determining the outputs. The experimental factors are also determined by the modelling objectives. Attempts are made to achieve the modelling objectives by changing the values of the experimental factors. Once the model inputs and outputs are determined, the content of the conceptual model must be designed in such a way as to ensure that it can accept the inputs and provide the required outputs, with sufficient accuracy. Model content consists of two elements. The scope is the boundary of the model in terms of its breadth. The level of detail is the boundary of the model in terms of the depth of detail modelled for each component within the scope. Throughout the process of developing the conceptual model various assumptions and simplifications are made. These should be explicitly recorded alongside the detail of the conceptual model.

It should be apparent from the description above that the modelling objectives are central to the conceptual modelling framework described here. It is for this reason that determining the modelling objectives is described as part of the conceptual modelling process. Since the understanding of the problem situation is central to the formation of the modelling objectives, it is also considered to be part of the conceptual modelling process, although not formally part of the conceptual model (Figure 1).

There now follows a more detailed description of the five activities outlined above. Following this, there is a discussion on the identification of data requirements and checking whether the model meets the four requirements of a conceptual model.

Understanding the problem situation

The requirement for a simulation model should always be driven by the need to improve a problem situation. Indeed, a simulation study would normally be commissioned because the clients perceive a problem and simulation as an aid to addressing that problem. As such, the starting point in any simulation study and, therefore, conceptual modelling for simulation, is to develop an understanding of that problem situation.

It is obviously necessary for the modeller to develop a good understanding of the problem situation if he/she is to develop a model that adequately describes the real world. The approach to this activity depends in large measure on the extent to which the clients and subject matter experts (domain experts) understand, and are able to explain, the problem situation. In this respect, there are three possible scenarios:

- The problem situation is clearly understood and expressed.
- The problem situation is apparently well understood and expressed, although it is not.
- The problem situation is neither well understood nor expressed.

In the first case, developing an understanding of the problem situation only requires discussion and careful note-taking. It is also useful for the modeller to confirm his/her understanding by providing descriptions of the problem situation for the clients. This acts as a means of validating the conceptual model as it is developed.

Unfortunately, the first scenario rarely exists. Very often, the clients and domain experts may believe they understand a problem situation and they may express that understanding, but further investigation reveals gaps and discontinuities in their knowledge. This can occur because they do not have a good grasp of cause and effect within the problem domain; hence the need for simulation! In a recent study of a telephone helpline, understaffing (cause) was being blamed for the poor level of customer service (effect). The simulation revealed, however, that extra staff had a negligible effect and that the business process was to blame.

Apart from having a poor grasp of the problem situation, there is the difficulty of each client and domain expert having a different view of the problem (Weltanschauungen (Checkland, 1981)). In a recent study of maintenance operators there were as many explanations of working practice as there were staff. This was further confounded when observations of the operators at work did not tie in with any of their explanations. This problem should not be a surprise, especially when dealing with systems involving human activity where the vagaries of human behaviour impact upon the performance of the system.

It is apparent that although on the face of it the modeller's role is to learn from the clients and domain experts in order to develop an understanding of the problem situation, the modeller has to play a much more active role. Speaking with the right people and asking searching questions is vital to developing this understanding. The modeller should also be willing to suggest alternative interpretations with a view to unearthing new ways of perceiving the problem situation. Such discussions might be carried out face-to-face in meetings and workshops, or remotely by telephone, email or web conference.

In the third scenario, where the problem situation is neither well understood nor expressed, the job of the modeller becomes all the more difficult. In such situations, there is opportunity to adopt formal problem structuring methods, such as soft systems methodology (Checkland, 1981), cognitive mapping (Eden and Ackermann, 2001) and causal loop diagrams (Sterman, 2000). Lehaney and Paul (1996) and Kotiadis (2006) are both examples of the use of soft systems methodology for problem structuring prior to the development of a simulation. Meanwhile, Balci and Nance (1985) describe a methodology for problem formulation in simulation.

As an alternative to the formal problem structuring methods listed above, some have recommended the use of simulation itself as a problem structuring approach (Hodges, 1991; Robinson, 2001; Baldwin *et al*, 2004). The idea is not so much to develop an accurate model of the system under investigation, but to use the model as a means for debating and developing a shared understanding of the problem situation. Validity is measured in terms of the usefulness of the model in promoting this debate, rather than its accuracy. This idea has been made more feasible with the advent of modern visual interactive modelling systems.

During the process of understanding the problem situation, areas of limited knowledge and understanding will arise. As a result, assumptions about these areas have to be made. These assumptions should be recorded and documented. Indeed, throughout the simulation study areas of limited understanding will be discovered and further assumptions will be made.

The problem situation and the understanding of it are not static. Both will change as the simulation study progresses. The simulation model itself acts as a catalyst for this change because the information required to develop it almost always provides a focus for clarifying and developing a deeper understanding of the real world system that is being modelled. Change is also the result of influences external to the simulation, for instance, staff changes and budgetary pressures within an organization. Such continuous change acts to increase the level of iteration between modelling processes across a simulation study, with adjustments to the conceptual model being required as new facets of the problem situation emerge.

The Ford Motor Company example: understanding the problem situation

In the previous paper (Robinson, 2007), the problem situation at the Ford Engine Assembly plant is described. Two models were developed: one for determining the throughput of the plant, the other for investigating the scheduling of key components. In order to illustrate the conceptual modelling framework, the development of a conceptual model for the throughput problem is described. Details of the framework as applied to the scheduling problem are available on request from the author.

The reader is referred to the description of the problem situation at Ford in the first paper (Robinson, 2007). In this case, there was a clear understanding of the problem among the clients and domain experts; they were uncertain as to whether the required throughput from the production facility as designed could be achieved.

Determining the modelling objectives

Key to the development of an appropriate model are the modelling objectives. They drive all aspects of the modelling process providing the means by which the nature of the model is determined, the reference point for model validation, the guide for experimentation, and a metric for judging the success of the study. The following sections show how the modelling objectives are used to develop the conceptual model.

Before concentrating on specific modelling objectives, it is useful to identify the overall *aims of the organization*. The aims are not so much expressed in terms of what the model should achieve, but what the organization hopes to achieve. Once the organizational aims have been determined, it is possible to start to identify how simulation modelling might contribute to these. In most cases, of course, the simulation model will probably only be able to contribute to a subset of the organization's aims. This subset is expressed through the modelling objectives.

The purpose of a simulation study should never be the development of a model. If it were, then once the model has been developed the simulation study would be complete. Albeit that something would have been learnt from the development of the model, there would be no need for experimentation with alternative scenarios to identify potential improvements. This may seem obvious, but it is surprising how often clients are motivated by the desire for a model and not for the learning that can be gained from the model. The objectives should always be expressed in terms of what can be achieved from the *development* and *use* of the model. As such, a useful question to ask when forming the objectives is 'by the end of this study what do you hope to achieve?'

Objectives can be expressed in terms of three components:

- *Achievement*: What the clients hope to achieve, for example increase throughput, reduce cost, improve customer service, improve understanding of the system.
- *Performance*: Measures of performance where applicable, for example increase throughput by 10%, reduce cost by £10 000.
- *Constraints*: The constraints within which the clients (modeller) must work, for example budget, design options, available space.

The clients may not be able to provide a full set of objectives. This can be the result of either their limited understanding of the problem situation, or their limited understanding of simulation and what it can provide for them. The latter might lead to the opposite problem, expecting too much from the simulation work. Whichever, the modeller should spend time educating the client about the potential for simulation, what it can and cannot do. The modeller should also be willing to suggest additional objectives as well as to redefine and eliminate the objectives suggested by the clients. In this way, the modeller is able to manage the expectations of the clients, aiming to set them at a realistic level. Unfulfilled expectations are a major source of dissatisfaction among clients in simulation modelling work (Robinson, 1998; Robinson and Pidd, 1998).

As discussed above, the problem situation and the understanding of it are not static. So too, the modelling objectives are subject to change. Added to this, as the clients' understanding of the potential of simulation improves, as it inevitably does during the course of the study, so their requirements and expectations will also change. This only adds to the need for iteration between the activities in a simulation study, with changes to the objectives affecting the design of the model, the experimentation and the outcomes of the project. The two-way arrow in Figure 1 aims to signify the iteration between the problem situation and the modelling objectives.

Determining the general project objectives

The modelling objectives are not the only concern when designing a simulation conceptual model. The modeller should also be aware of the general project objectives. *Time-scale* is particularly important. If time is limited, the modeller may be forced into a more conservative model design. This would help reduce model development time as well as lessen the requirements for data collection and analysis. It would also quicken the run-speed of the model, reducing the time required for experimentation. If the problem situation is such that it requires a large scale model, the modeller may consider the use of a distributed simulation running in parallel on a number of computers. This should improve the run-speed of the simulation, but it may increase the development time.

The modeller should also clarify the nature of the model and its use since this will impact on the conceptual model design. Consideration should be given to some or all of:

- *Flexibility*: The more it is envisaged that a model will be changed during (and after) a study, the greater the flexibility required.
- *Run-speed*: Particularly important if many experiments need to be performed with the model.
- *Visual display*: Whether a simple schematic through to a 3D animation is required.
- *Ease-of-use*: Ease of interaction with the model should be appropriate for the intended users.
- *Model/component reuse*: Proper conceptual model design can aid model and component reuse.

The Ford Motor Company example: objectives

Figure 2 gives the modelling and general project objectives for the Ford throughput model.

Identifying the model outputs (Responses)

Once the objectives are known, the next stages are to identify the outputs and inputs to the model, depicted as the responses and experimental factors in Figure 1. It is much easier to start by giving consideration to these, than to the content of the model (Little, 1994). It is also important to know the responses and experimental factors when designing the content of the conceptual model since these are the primary outputs and inputs that the model must provide and receive respectively. In general, it does not matter in which order the responses and experimental factors are identified. The responses are placed first because it is probably a little easier to think initially in terms of what the clients want from a model rather than what changes they might make while experimenting with the model.

Identification of the appropriate responses does not generally provide a major challenge. The responses have two purposes:

- To identify whether the modelling objectives have been achieved.
- To point to the reasons why the objectives are not being achieved, if they are not.

In the first case, the responses can normally be identified directly from the statement of the modelling objectives. For example, if the objective is to increase throughput, then it is obvious that one of the responses needs to be the throughput. For the second case, identification is a little more difficult, but appropriate responses can be identified by a mix of the modeller's past experience, the clients' understanding and the knowledge of the domain experts. Taking the throughput

Organisational Aim

The overall aim is to achieve a throughput of X units per day from the assembly line. (Note: the value of X cannot be given for reasons of confidentiality.)

Modelling Objectives

- To determine the number of platens required to achieve a throughput of X units per day, or
- Identify the need for additional storage (and platens) required to achieve a throughput of X units per day.

The second objective only needs be considered if throughput cannot be achieved by increasing platens only.

General Project Objectives

- *Time-scale*: 30 working days.
- *Flexibility*: limited level required since extensive model changes beyond changes to the data are not expected.
- *Run-speed*: many experiments may be required and so a reasonable run-speed is important, but not at the forfeit of accuracy.
- *Visual display*: simple 2D animation. (The model is largely required for performing experiments and obtaining results, communication through detailed graphics is not a major need especially as the client is familiar with simulation. Therefore, the level of visual display needs only to enable effective model testing and aid the diagnosis of problems during experimentation.)
- *Ease-of-use*: simple interactive features will suffice since the model is for use by the modeller.

Figure 2 The Ford throughput model example: modelling and general project objectives.

example, reports on machine and resource utilization and buffer/work-in-progress levels at various points in the model would be useful for helping to identify potential bottlenecks. Quade (1988) provides a useful discussion on identifying appropriate measures for the attainment of objectives.

Once the required responses have been identified, consideration should also be given to how the information is reported. Options are numerical data (eg mean, maximum, minimum, standard deviation) or graphical reports (eg time-series, bar charts, Gantt charts, pie charts). These can be determined through consultation between the simulation modeller, clients and domain experts. Consideration should also be given to the requirements for model use as outlined in the general project objectives.

The Ford Motor Company example: determining the responses

Figure 3 shows the responses identified for the Ford throughput model. Daily throughput is selected as the response to determine the achievement of the objectives because it is the measure of performance identified in the modelling objectives. The three reports identified will enable an analysis of the distribution of daily throughput and its behaviour over time. Utilization reports are selected as the means for determining the reasons for failing to meet the modelling objectives. This is because the level of disturbance caused by breakdowns (expected to be a key reason for failure to meet throughput) can be identified by the percentage of time each machine is broken, as well as, in part, the time machines spend idle and blocked. Further to this, any system bottlenecks and a shortage or surplus of platens can be identified by idle and blocked machines.

Outputs (to determine achievement of objectives)

- Time-series of daily throughput
- Bar chart of daily throughput
- Mean, standard deviation, minimum and maximum daily throughput

Outputs (to determine reasons for failure to meet objectives)

- Percentage machine utilisation: idle, working, blocked and broken

Figure 3 The Ford throughput model example: responses.

Identifying the model inputs (experimental factors)

The experimental factors are the model data that can be changed in order to achieve the modelling objectives. They may either be quantitative data (eg number of staff or speed of service) or qualitative (eg changes to rules or the model structure). Using this definition, the experimental factors are

Experimental Factors
• The number of platens (maximum increase 100%) • The size of the buffers (conveyors) between the operations (maximum increase of 100%)

Figure 4 The Ford throughput model example: experimental factors.

a limited subset of the general input data that are required for model realization.

As with the responses, identification of the experimental factors is driven by the modelling objectives. The experimental factors are the means by which it is proposed that the modelling objectives will be achieved. They may be explicitly expressed in the modelling objectives, for instance, 'to obtain a 10% improvement in customer service by developing effective *staff rosters*', or 'to increase throughput ... by changing the *production schedule*'. Alternatively, they can be obtained by asking the clients and domain experts how they intend to bring about the desired improvement to the real system. The modeller can also provide input to this discussion based on his/her experience with simulation. Altogether, this might lead to a substantial list of factors.

Although the general expectation is that the clients will have control over the experimental factors, this is not always the case. Sometimes, it is useful to experiment with factors over which there is little or no control, for example, the customer arrival rate. Such experimentation can aid understanding of the system or help plan for future events.

Where the objective of the model is, at least in part, to improve understanding, then the list of experimental factors may be a more subtle. The modeller needs to determine, with the clients and domain experts, what factors might be most useful to help improve understanding.

Apart from determining the experimental factors, it is useful to identify the range over which the experimental factors might be varied (eg the minimum and maximum number of staff on a shift). The simulation model can then be designed to accept this range of values, potentially avoiding a more complex model that allows for a much wider range of data input. Methods of data entry should also be considered, including: direct through the model code, model based menus, data files or third party software (eg a spreadsheet). The requirement depends upon the skills of the intended users of the model and the general project objectives.

In the same way that the problem situation and modelling objectives are not static, so the experimental factors and responses are subject to change as a simulation study progresses. The realization that changing staff rosters do not achieve the required level of performance may lead to the identification of alternative proposals and, hence, new experimental factors. During experimentation, the need for additional reports may become apparent. All this serves to emphasize the iterative nature of the modelling process.

The Ford Motor Company example: determining the experimental factors

Figure 4 shows the experimental factors identified for the Ford throughput model. Both of these factors are derived directly from the modelling objectives.

Determining the model content: scope and level of detail

The framework separates the identification of the scope of the model from the model's level of detail. These are logically different, the former identifying the boundaries of the model, the latter the depth of the model. Procedures for selecting the scope and level of detail are described below as well as the identification of assumptions and simplifications made during the modelling process.

Before making decisions about the scope and level of detail of the proposed simulation model, the use of simulation should be questioned. Is simulation the right approach for the problem situation? Robinson (2004) discusses the prime reasons for the selection of simulation as variability, interconnectedness and complexity in the systems being modelled. He also identifies the relevance of discrete-event simulation for modelling queuing systems as a prime reason for its choice. Most operations systems can be conceived as queuing systems. Along side an understanding of these reasons, the definition of the problem situation, the objectives, experimental factors and responses will help to inform the decision about whether simulation is the right approach.

Up to this point, most of the discussion is not specific to conceptual models for simulation. It is possible that another modelling approach might be adopted. It is from this point forward that the conceptual model becomes specific to simulation.

Determining the model scope

In general terms, simulation models can be conceived in terms of four types of component: entities, active states, dead states and resources (Pidd, 2004). Here these are referred to as entities, activities, queues and resources, respectively. Examples of each component type are as follows:

- *Entities*: Parts in a factory, customers in a service operation, telephone calls in a call centre, information in a business process, fork lift truck in a warehouse.
- *Activities*: Machines, service desks, computers.

- *Queues*: Conveyor systems, buffers, waiting areas, in/out-trays, computer storage.
- *Resources*: Staff, equipment.

Unlike the first three components, resources are not modelled individually, but simply as countable items. Some substitution is possible between using resources and a more detailed approach using individual components. For instance, a machine could be treated as an activity and modelled at some level of detail, or it could be modelled as a resource (equipment) that needs to be available to support some other activity.

The author's experience suggests that these four component types are sufficient for most simulations of operations systems; at least those that are discrete in nature. This is largely because they can be conceived as queuing systems. Readers may be able to think of additional component types, for instance, transporters and elements of continuous processing systems (eg pipes). The framework can quite easily be extended to include additional component types.

Determining the scope of a model requires the identification of the entities, activities, queues and resources that are to be included in the model. The question is, how can a modeller make this decision? The following three step approach is suggested.

Step 1: Identify the model boundary. The experimental factors and responses provide a good starting point for identifying where the edges of the model might lie. The need to experiment with inter-arrival times provides an obvious entry point into a model. The requirement to report factory throughput strongly suggests that the last operation before work exits the factory needs to be included in the model. Beyond the experimental factors and responses, careful consideration of the system being modelled is important. At this point, the knowledge of the clients and domain experts is vital.

Step 2: Identify all the components (entities, activities, queues and resources) in the real system that lie within the model boundary. It is of particular importance to identify all components that directly connect the experimental factors to the responses, for instance, in a fast food restaurant the number of service staff (an experimental factor and resource) with waiting time (a response related to a queue). The connection between these is the service tasks. This can be thought of as the critical path, that must be modelled in order to get the most basic representation that connects the experimental factors with the responses. Apart from direct connections, all interconnections also need to be considered, for the example above this might be the supply of food and drink.

Step 3: Assess whether to include/exclude all components identified. For each component assess whether it is important to the validity, credibility, utility and feasibility of the model. If they are not needed to fulfil any of these requirements, then exclude them from the model. Judgements need to be made concerning the likely effect of each component on the accuracy of the model, and as such its validity. Will removing a component reduce the accuracy of a model below its requirement for sufficient accuracy? These judgements are, of course, confounded by interaction effects between components, for instance, the effect of removing two components may be much greater than the sum of the effects of removing them individually. Past experience will no doubt help in making such judgements. A cautious approach is advised, keeping components in the model where there is some doubt over their effect on validity.

Similarly, the effect on credibility also needs to be considered. It may be that a component is not particularly important to the accuracy of the model, but that its removal would damage the credibility of a model. In this case, it should probably be included. Indeed, a wider scope (and more detail) may be included in a model than is strictly necessary for validity, simply to increase its credibility.

Consideration should be given to the issue of utility. The inclusion of a component may significantly increase the complexity of a model or reduce its run-speed. Both could reduce the utility of the model. The effect of each component on feasibility should also be considered. It may be that the data for modelling a component are unlikely to be available, or the complexity of modelling a component would mean that the simulation study could not meet its time-scale.

A careful balance between validity, credibility, utility and feasibility must be sought. For a component, where any one (or more) of these is seen as being of vital importance, then it should be included in the model. If it appears that a component is of little importance to any of these, then it can be excluded. In performing Step 3, the model boundary may well become narrower as components are excluded from the model. In Zeigler's (1976) terms, Steps 1 and 2 are about identifying the base model (at least to the extent that it is known) and Step 3 about moving to a lumped model.

In order to work through these three steps, a meeting or sequence of meetings could be arranged between the modeller, clients and domain experts. This is probably most effective in bringing the differing expertise together rather than holding meetings with smaller groups or relying on telephone or electronic media. Step 2 could consist of a brainstorming session, in which all parties identify potential model components without debate about the need, or otherwise, to include them. It is expected that there will be a number of iterations between the three steps before the model scope is agreed.

The discussions about the scope of the model need to be recorded to ensure that there is agreement over the decisions

Table 1 The Ford throughput model example: model scope

Component	*Include/exclude*	*Justification*
Entities		
Engines	Include	Response: throughput of engines
Platens	Include	Experimental factor
Sub-components	EXCLUDE	Assume always available
Activities		
Line A	Include	Key influence on throughput
Head Line	Include	Key influence on throughput
Line B	Include	Key influence on throughput
Hot Test and Final Dress	EXCLUDE	Limited impact on throughput as large buffer between Line B and Hot Test
Queues		
Conveyors	Include	Experimental factor
Resources		
Operators	EXCLUDE	Required for operation of manual processes, but always present and provide a standardised service. They cause no significant variation in throughput
Maintenance staff	Include	Required for repair of machines. A shortage of staff would affect throughput

that are being made. The records also provide documentation for model development, validation and re-use. A simple table format for documenting the model scope is suggested (see Table 1). The first column provides a list of all the components in the model boundary (Steps 1 and 2). The second column records the decisions from Step 3, and the third column describes the reasoning behind the decision to include or exclude each component. Having such a record provides a representation around which the modeller, clients and domain experts can debate and reach an accommodation of views on what should be in the model scope.

It may be helpful in some circumstances, particularly where there are differences in opinion, to generate a number of alternative model scopes and then to compare and debate the relative merits of each. Such a debate could focus on the validity, credibility, utility and feasibility of each model version.

Along side the scope table it is probably useful to have a diagram of the system and identify the model scope. A visual representation provides a more accessible view of the decisions being made about model scope, but it can only provide limited information. Meanwhile, the table is able to provide more detail, especially concerning the justification of the model scope.

The Ford Motor Company example: determining the model scope

Table 1 shows the model scope for the Ford throughput model. This is shown diagrammatically in Figure 5. The main opportunity for scope reduction comes from the exclusion of the Hot Test and Final Dress areas.

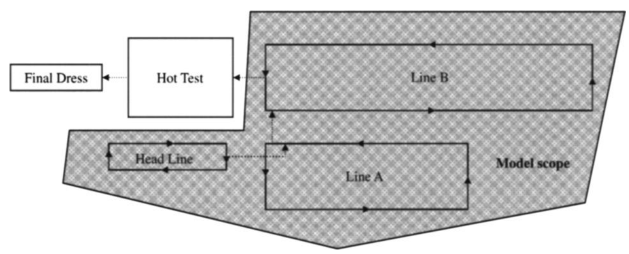

Figure 5 The Ford throughput model example: model scope shown as the shaded area.

Determining the model level of detail

Determining the level of detail requires decisions about the amount of detail to include for each component in the model scope. That is, determining the level of detail for each entity, activity, queue and resource to be included in the model. Table 2 provides a list of details that could be considered for each component type. This is not intended to be an exhaustive list, as indicated by the 'other' category, but it does provide a useful starting point. Again, the reader may be able to think of additional details that could be listed against each component type. These can simply be added to those listed in Table 2.

The modeller, clients and domain experts can work through the details in Table 2 for each component in the model scope, determining whether the detail should be included or excluded, and also deciding on how each detail should be modelled. In a similar fashion to the model scope, the decision on whether to include a detail or not should be guided by its perceived effect on the validity, credibility, utility and feasibility of the model. These decisions might be made at a meeting between the modeller, clients and domain experts. Decisions about the level of detail can be made with reference to:

- The judgement of the modeller, clients and domain experts.
- *Past experience*: Particularly on behalf of the modeller.

Table 2 Template for level of detail by component type

Component	*Detail*	*Description*
Entities	Quantity	Batching of arrivals and limits to number of entities Grouping so an entity represents more than one item Quantity produced
	Arrival pattern	How entities enter the model
	Attributes	Specific information required for each entity, for example type or size
	Routing	Route through model dependent on entity type/attributes, for example job shop routing
	Other	For example, display style
Activities	Quantity	Number of the activity
	Nature (X in Y out)	For example, representing assembly of entities
	Cycle time	
	Breakdown/repair	Nature and timing of breakdowns
	Set-up/changeover	Nature and timing of set-ups
	Resources	Resources required for the activity
	Shifts	Model working and break periods
	Routing	How entities are routed in and out of the activity
	Other	For example, scheduling
Queues	Quantity	Number of the queue
	Capacity	Space available for entities
	Dwell time	Time entities must spend in the queue
	Queue discipline	Sequence of entities into and out of the queue
	Breakdown/repair	Nature and timing of breakdowns
	Routing	How entities are routed in and out of the queue
	Other	For example, type of conveyor
Resources	Quantity	Number of the resource
	Where required	At which activities the resource is required
	Shifts	Working and break periods
	Other	For example, skill levels, interruption to tasks

- *Data analysis*: Analysis of preliminary data about the system.
- *Prototyping*: Developing part of the model and testing the effect of including and excluding details.

Prototyping (Powell, 1995; Pidd, 1999) is useful for reducing the judgemental aspect of the decisions. In particular, the development of small computer models to test ideas can aid decisions about the level of detail required for a component. Indeed, prototyping can also aid decisions about model scope, particularly through the use of high level models in which sections of the model can be sequentially included or excluded to determine their effect on the responses.

A simple table format for recording these decisions is suggested, as shown in Table 3. This shows the components in the scope and each of the details, as listed in Table 2. The third column shows whether the detail is to be included in the model or excluded, while the fourth column provides a justification for the decision. Apart from listing details in the second column, it also provides a brief explanation of how a detail is to be modelled, but only for those details that are included in the model. This table provides a way of showing how the base model (the full list of details) is converted into a lumped model, by outlining what is to be included in the model and how it is to be represented.

The Ford Motor Company example: determining the level of detail

Table 3 shows the level of detail for the Ford throughput model. Note that an 'operation' is the type of activity, while a 'machine' is the equipment that performs that operation. There is more than one machine for some operations.

Identifying assumptions and simplifications

In determining the scope and level of detail of the model, various assumptions and simplifications are made. As a reminder, assumptions are made when there are uncertainties or beliefs about the real world being modelled, while simplifications are incorporated into a model to enable more rapid model development and use. For the purposes of clarity, it is useful to explicitly list the assumptions and simplifications.

In large measure, the assumptions and simplifications can be identified with reference to those components and details that have been excluded from the model. Indeed, a component or detail will have been excluded on the basis that it is an assumption, simplification or a fact, the latter category referring to truisms about the real system. For instance, in the Ford throughput model (Table 3), set-ups/change-overs are excluded because it is known that there are no set-ups or

Table 3 The Ford throughput model example: model level of detail

Component	*Detail*	*Include/ exclude*	*Justification*
Entities			
Engines	Quantity: produced. Model engines as an attribute of a platen (full/empty) to count engines produced	Include	Response: throughput of engines
	Arrival pattern	Exclude	Assume an engine block is always available to be loaded to the platen
	Attribute: engine derivative	Exclude	No effect on machine cycles and therefore no effect on throughput
	Routing	Exclude	Engines are only modelled as an attribute of a platen
Platens	Quantity: for Line A, Head Line and Line B	Include	Experimental factor
	Arrival pattern	Exclude	All platens are always present on the assembly line
	Attribute: full/empty. Needed to count engines produced as platen leaves last operation on the line	Include	Response: throughput of engines
	Routing	Exclude	Routing determined by process not platen
Activities			
Line A	Quantity: quantity of machines for each operation	Include	Model individual machines as each may have a significant impact on throughput
	Nature	Exclude	Sub-components are not modelled and so no assembly is represented
	Cycle time: fixed time	Include	Required for modelling throughput. Assume no variation in time for manual processes
	Breakdown: time between failure distribution	Include	Breakdowns are expected to have a significant impact on throughput
	Repair: repair time distribution	Include	Breakdowns are expected to have a significant impact on throughput
	Set-up/change-over	Exclude	No set-ups in real facility
	Resources	Include	Identify number of maintenance staff required to perform repair of machines
	Shifts	Exclude	No work takes place outside of on-shift time
	Routing: next conveyor including routing to re-work areas after test stations	Include	Routing of platens defines the key interaction between system components
Head Line	*As for Line A*		
Line B	*As for Line A*		
Queues			
Conveyors	Quantity: 1	Include	All conveyors are individual
	Capacity	Include	Experimental factor
	Dwell time: model as index time for platens	Include	Affects movement time and so throughput
	Queue discipline: FIFO	Include	Affects movement time and so throughput
	Breakdown/repair	Exclude	Failures are rare and so have little effect on throughput
	Routing: to next machine including routing logic to operations with more than one machine	Include	Routing of platens defines the key interaction between system components
	Type: accumulating conveyors	Include	Enables maximum utilization of buffer space andso improves throughput
Resources:			
Maintenance staff	Quantity	Include	Because there are fewer maintenance staff than machines, it is possible for staff shortages to be a bottleneck affecting throughput
	Where required: identify machines that require maintenance staff for repair	Include	Required to allocate work to maintenance staff
	Shifts	Exclude	No work takes place outside of on-shift time
	Skill level	Exclude	Assume all staff can repair all machines

Modelling Assumptions

- Capacity of the buffer before hot test and final dress is sufficient to cause minimal blockage to the assembly line from downstream processes.
- Manual operators are always present for manual processes and provide a standardised service.
- An engine block is always available to be loaded to a platen.
- No work is carried out during off-shift periods, therefore shifts do not need to be modelled.
- Conveyor breakdowns are rare and so have little impact on throughput.
- All staff can repair all machines.

Figure 6 The Ford throughput model example: modelling assumptions.

change-overs in the real system. This is a fact. It should be noted that the assumptions and simplifications (indeed facts) are not listed in the excluded items alone. For instance, under activities for line A in Table 3, there is an assumption about the cycle time of manual processes. This suggests that the modeller should not only look under the excluded components and details in the scope and level of detail tables for assumptions and simplifications, but he/she should pay careful attention to those items included in the model as well.

Once all the assumptions and simplifications have been identified it may be useful to assess each of them for their level of impact on the model responses (high, medium, low) and the confidence that can be placed in them (high, medium, low). This should be jointly agreed between the modeller, clients and domain experts. Obviously such assessments can only be based on judgement at this stage. This process, however, can be useful for ensuring that all the assumptions and simplifications seem reasonable and for ensuring all parties agree with the modelling decisions that are being made. Particular attention might be paid to those assumptions and simplifications that are seen to have a high impact and for which the confidence is low. Where necessary, the conceptual model might be changed to mitigate concerns with any of the assumptions and simplifications.

One issue that is not discussed here is how to select appropriate simplifications. The identification of opportunities for simplification is largely a matter of the experience of the modeller, although discussion between the modeller, clients and domain experts may also provide ideas for simplification. Beyond this, it is useful to make reference to a standard set of simplifications. A range of simplification methods exist, such as, aggregating model components, replacing components with random variables and excluding infrequent events. These have been the subject of a number of publications (Morris, 1967; Zeigler, 1976; Innis and Rexstad, 1983; Courtois, 1985; Ward, 1989; Robinson, 1994).

The Ford Motor Company example: assumptions and simplifications

Figures 6 and 7 list the assumptions and simplifications for the Ford throughput model.

Model Simplifications

- Sub-components are always available.
- No variation in time for manual processes.

Figure 7 The Ford throughput model example: model simplifications.

Identifying data requirements

Apart from defining the nature of the model, the level of detail table also provides a list of data requirements. Three types of data are required for a simulation study: contextual data, data for model realization and validation data (Pidd, 2003). Contextual data are required for understanding the problem situation and as an aid to forming the conceptual model (eg a layout diagram of the operations system and preliminary data on service times). Data for model realization can be directly identified from the level of detail table. Data for validation (eg past performance statistics for the operations system, if it currently exists) need to be considered in the light of the model that is being developed and the availability of data for the real system. Here, we shall only consider data for model realization.

It is a fairly straightforward task to identify the data for model realization from the level of detail table. This can be done with reference to the components and their details that are to be included in the model. This approach supports the idea that the model should drive the data and not vice versa (Pidd, 1999).

Once the data for model realization are identified, responsibility for obtaining the data should be allocated with clear direction over the time when the data need to be available. Of course, some data may already be available, other data may need to be collected and some may be neither available nor collectable. Lack of data does not necessitate abandonment of the project. Data can be estimated and sensitivity analysis can be performed to understand the effect of inaccuracies in the data. Even where data are available or can be collected, decisions need to be made about the sample size required and care must be taken to ensure that the data are sufficiently

Data Requirements

- Planned quantity of platens on each assembly line.
- Machines: quantity for each operation, cycle time, time between failure distribution, repair time distribution, routing rules (e.g. percentage rework after a test station).
- Conveyors: capacity, index time for a platen, routing rules (e.g. split to parallel machines).
- Maintenance staff: quantity, machines required to repair.

Figure 8 The Ford throughput model example: data requirements for model realization.

accurate and in the right format. For a more detailed discussion on data collection, see Robinson (2004).

If data cannot be obtained, it may be possible to change the design of the conceptual model so that these data are not required. Alternatively, the modelling objectives could be changed such that an alternative conceptual model is developed that does not require the data in question. During data collection it is almost certain that various assumptions will have to be made about the data; these assumptions should be recorded along with those identified from the conceptual model. This all serves to increase the iteration in the modelling process, with the conceptual model defining the data that are required and the availability of the data defining the conceptual model. In practice, of course, the modeller, clients and domain experts are largely cognizant of the data that are available when making decisions about the nature of the conceptual model.

The Ford Motor Company example: data requirements

Figure 8 shows the data that are required for the Ford throughput model. These have been identified from the details of the included components in the level of detail table (Table 3).

Model assessment: meets the requirements of a conceptual model?

Throughout the development of the conceptual model, the extent to which the proposed model meets the requirements for validity, credibility, utility and feasibility needs to be checked and questioned. In doing so this provides an assessment of the conceptual model.

Conceptual model *validity* is 'a perception, on behalf of the modeller, that the conceptual model can be developed into a computer model that is sufficiently accurate for the purpose at hand' (Robinson, 2007). It is not possible to measure the accuracy of the conceptual model until at least a full computer representation is available, if it is possible to do so then (Pidd, 2003; Robinson, 1999). The modeller, however, is able to form an opinion about whether the proposed model is likely to deliver sufficient accuracy for the purpose to which it will be put. This opinion will largely be based on a belief as to whether all the key components and relationships are included in the model. The modeller's opinion must also be based on a clear understanding of the model's purpose (modelling objectives) and the level of accuracy required by the clients. Further to this, input from the clients and especially the domain experts is important in forming this opinion about validity.

Credibility meanwhile is defined as 'a perception, on behalf of the clients, that the conceptual model can be developed into a computer model that is sufficiently accurate for the purpose at hand' (Robinson, 2007). Judgement about the credibility of the model relies on the clients' opinions. This is formed by the past experience of the clients and their experience with the current project, much of which is a reflection upon their interaction with the modeller (Robinson, 2002). In particular, the clients need to have a good understanding of the conceptual model. A clear description of the conceptual model is therefore required. This can be delivered through a project specification which outlines all the phases of conceptual model development as described above, from the understanding of the problem situation and the modelling objectives through to the scope and level of detail of the model and the assumptions and simplifications. Ultimately, the modeller and the clients must have confidence in the conceptual model, reflected in the validity and credibility of the conceptual model, respectively.

The *utility* of the conceptual model is 'a perception, on behalf of the modeller and the clients, that the conceptual model can be developed into a computer model that is useful as an aid to decision-making within the specified context' (Robinson, 2007). Issues to consider are the ease-of-use, flexibility, run-speed, visual display and potential for model/component reuse. These requirements are expressed through the general project objectives. All must be of a sufficient level to satisfy the needs of the project. For instance, if the model is to be used by the modeller for experimentation, then ease-of-use is of less importance than if the model is to be used by the clients or a third party.

The final requirement, *feasibility*, is 'a perception, on behalf of the modeller and the clients, that the conceptual model can be developed into a computer model with the time, resource and data available' (Robinson, 2007). Can the model be developed and used within the time available? Are the necessary skills, data, hardware and software available? The modeller, clients and domain experts need to discuss these issues and be satisfied that it is possible to develop and use the conceptual model as proposed.

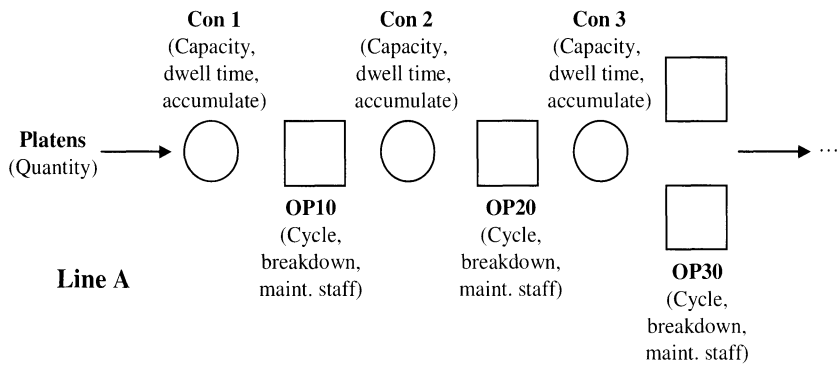

Figure 9 An illustrative process flow diagram of part of the Ford throughput conceptual model.

It may be useful for the modeller to generate several conceptual model descriptions and then to compare them for their validity, credibility, utility and feasibility. The model that is perceived best across all four requirements could then be selected for development.

All of the above is contingent on being able to express the conceptual model in a manner that can be shared and understood by all parties involved in a simulation study. In the terms of Nance (1994), this requires the expression of the modeller's mental conceptual model as a communicative model. The tables derived in the conceptual modelling framework described above provide one means for communicating the conceptual model; see Figures 2, 3, 4, 6 and 7 and Tables 1 and 3. Beyond this, diagrammatic representations of the model are also useful (Figures 5 and 9), and possibly more beneficial as a communicative tool (Crapo *et al*, 2000). A range of such methods have been used for representing simulation conceptual models, for instance:

- Process flow diagrams (Robinson, 2004), see Figure 9,
- Activity cycle diagrams (Hills, 1971),
- Petri nets (Torn, 1981),
- Event graphs (Schruben, 1983; Som and Sargent, 1989),
- Digraphs (Nance and Overstreet, 1987),
- UML (the unified modelling language) (Richter and März, 2000),
- Object models (van der Zee, 2006),
- Simulation activity diagrams (Ryan and Heavey, 2006).

Pooley (1991) provides a useful review of diagramming techniques that might support simulation modelling. The conceptual model could, of course, be represented using the visual display facilities of the simulation software, without the need for coding the detail of the model. Figure 9 shows a simple process flow diagram for a portion of the Ford throughput model.

Conclusion

The conceptual modelling framework described above provides a series of iterative activities for helping a modeller to design a simulation conceptual model for a specific problem situation. Each activity is documented with a table summarizing the decisions made. The use of these tables (along with diagrammatic representations of the model), provides a means for communicating and debating the conceptual model with the clients and domain experts. As a result, it provides a route to agreeing upon the nature of the simulation model that is required to intervene in the problem situation.

In conclusion, we consider the question of whether there is a right conceptual model for any specified problem. For two reasons the answer is 'no'. First, we have identified conceptual modelling as an art. Albeit that the framework above provides some discipline to that art, different modellers will not come to the same conclusions. Any other expectation would be akin to expecting an art class to paint exactly the same picture of the same subject. There has to be room for creativity in any art, including conceptual modelling. There are, of course, better and worse conceptual models. The four requirements of a conceptual model (validity, credibility, utility and feasibility) provide a means for distinguishing better from worse.

A second reason why there is no right conceptual model is because the model is an agreement between more than one person (the modeller, clients and domain experts). Each has his/her own preferences for and perceptions of what is required. These preferences and perceptions are expressed through the four requirements of a conceptual model. The framework provides a means for communicating and debating the conceptual model, with a view to reaching an agreement, or at least an accommodation of views, over the nature of the model. The conceptual model is, therefore, some compromise between alternative preferences and perceptions of the world.

In short, there is no absolutely right conceptual model because the model is dependent on the preferences and perceptions of the people involved in the simulation study. It would seem that the idea of developing conceptual modelling frameworks that will always lead to a single best model is futile. Instead, our aim should be to provide frameworks that provide a means for communicating, debating and agreeing upon a simulation conceptual model, while also releazing the potential for creativity in the modelling process. This is what the conceptual modelling framework described here aims to provide.

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- Robinson S (2004). *Simulation: The Practice of Model Development and Use*. Wiley: Chichester, UK.
- Robinson S (2004). Designing the conceptual model in simulation studies. In: Brailsford SC, Oakshott L, Robinson S, Taylor SJE (eds). *Proceedings of the 2004 Operational Research Society Simulation Workshop (SW04)*. Operational Research Society: Birmingham, UK, pp 259–266.
- Robinson S (2006). Issues in conceptual modelling for simulation: Setting a research agenda. In: Garnett J, Brailsford S, Robinson S, Taylor S (eds). *Proceedings of the Third Operational Research Society Simulation Workshop (SW06)*. The Operational Research Society: Birmingham, UK, pp. 165–174.
- Robinson S (2006). Conceptual modeling for simulation: Issues and research requirements. In: Perrone LF, Wieland FP, Liu J, Lawson BE, Nicol DM and Fujimoto RM (eds). *Proceedings of the 2006 Winter Simulation Conference*. IEEE: Piscataway, NJ, pp 792–800.

The Ford engine plant example is used with the permission of John Ladbrook, Ford Motor Company.

References

Balci O and Nance RE (1985). Formulated problem verification as an explicit requirement of model credibility. *Simulation* **45**: 76–86.

Baldwin LP, Eldabi T and Paul RJ (2004). Simulation in healthcare management: A soft approach (MAPIU). *Simul Model Pract Theory* **12**: 541–557.

Checkland PB (1981). *Systems Thinking, Systems Practice*. Wiley: Chichester, UK.

Courtois PJ (1985). On time and space decomposition of complex structures. *Commun ACM* **28**: 590–603.

Crapo AW, Waisel LB, Wallace WA and Willemain TR (2000). Visualization and the process of modeling: A cognitive-theoretic view. In: Ramakrishnan R, Stolfo S, Bayardo R and Parsa I (eds). *Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM Press: New York, pp 218–226.

Eden C and Ackermann F (2001). SODA—The Principles. In: Rosenhead JV and Mingers J (eds). *Rational Analysis for a Problematic World Revisited, 2nd edition*. Wiley: Chichester: UK, pp 21–41.

Ferguson P *et al* (1997). Results of applying the personal software process. *Computer* **30**: 24–31.

Hills PR (1971). *HOCUS*. P-E Group: Egham, Surrey, UK.

Hodges JS (1991). Six (or so) things you can do with a bad model. *Opns Res* **39**: 355–365.

Innis G and Rexstad E (1983). Simulation model simplification techniques. *Simulation* **41**: 7–15.

Kotiadis K (2006). Extracting a conceptual model for a complex integrated system in healthcare. In: Garnett J, Brailsford S, Robinson S and Taylor S (eds). *Proceedings of the Third Operational Research Society Simulation Workshop (SW06)*. The Operational Research Society: Birmingham: UK, pp 235–245.

Lehaney B and Paul RJ (1996). The use of soft systems methodology in the development of a simulation of out-patient services at Watford General Hospital. *J Opl Res Soc* **47**: 864–870.

Little JDC (1994). On model building. In: Wallace WA (ed). *Ethics in Modeling*. Pergamon: New York, pp 167–182.

Morris WT (1967). On the art of modeling. *Mngt Sci* **13**: B707–B717.

Nance RE (1994). The conical methodology and the evolution of simulation model development. *Ann Opns Res* **53**: 1–45.

Nance RE and Overstreet CM (1987). Diagnostic assistance using digraph representation of discrete event simulation model specifications. *Trans Soc Comput Simul* **4**: 33–57.

Pidd M (1999). Just modeling through: A rough guide to modeling. *Interfaces* **29**: 118–132.

Pidd M (2003). *Tools for Thinking: Modelling in Management Science*, 2nd edition. Wiley: Chichester, UK.

Pidd M (2004). *Computer Simulation in Management Science*, 5th edition. Wiley: Chichester, UK.

Pooley RJ (1991). Towards a standard for hierarchical process oriented discrete event diagrams. *Trans Soc Comput Simul* **8**: 1–41.

Powell SG (1995). Six key modeling heuristics. *Interfaces* **25**: 114–125.

Quade ES (1988). Quantitative methods: Uses and limitations. In: Miser HJ and Quade ES (eds). *Handbook of Systems Analysis: Crafts Issues and Procedures*. Wiley: Chichester: UK, pp 283–324.

Richter H and März L (2000). Toward a standard process: The use of UML for designing simulation models. In: Joines JA, Barton RR, Kang K and Fishwick PA (eds). *Proceedings of the 2000 Winter Simulation Conference*. IEEE: Piscataway: NJ, pp 394–398.

Robinson S (1994). Simulation projects: Building the right conceptual model. *Ind Eng* **26**: 34–36.

Robinson S (1998). Measuring service quality in the process of delivering a simulation study: The customer's perspective. *Int Trans Opl Res* **5**: 357–374.

Robinson S (1999). Simulation verification validation and confidence: A tutorial. *Trans Soc Comput Simul Int* **16**: 63–69.

Robinson S (2001). Soft with a hard centre: discrete-event simulation in facilitation. *J Opl Res Soc* **52**: 905–915.

Robinson S (2002). General concepts of quality for discrete-event simulation. *Eur J Opl Res* **138**: 103–117.

Robinson S (2004). *Simulation: The Practice of Model Development and Use*. Wiley: Chichester, UK.

Robinson S (2007). Conceptual modelling for simulation Part I: Definition and requirements. *J Opl Res Soc* (doi:10.1057/palgrave.jors.2602368).

Robinson S and Pidd M (1998). Provider and customer expectations of successful simulation projects. *J Opl Res Soc* **49**: 200–209.

Ryan J and Heavey C (2006). Requirements gathering for simulation. In: Garnett J, Brailsford S, Robinson S and Taylor S (eds). *Proceedings of the Third Operational Research Society Simulation Workshop (SW06)*. The Operational Research Society: Birmingham: UK, pp 175–184.

Schruben LW (1983). Simulation modeling with event graphs. *Commun ACM* **26**: 957–963.

Som TK and Sargent RG (1989). A formal development of event graphs as an aid to structured and efficient simulation programs. *ORSA J Comput* **1**: 107–125.

Sterman JD (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill: New York,

Torn AA (1981). Simulation graphs: A general tool for modeling simulation designs. *Simulation* **37**: 187–194.

van der Zee DJ (2006). Building communicative models—A job oriented approach to manufacturing simulation. In: Garnett J, Brailsford S, Robinson S and Taylor S (eds). *Proceedings of the Third Operational Research Society Simulation Workshop (SW06)*. The Operational Research Society: Birmingham: UK, pp 185–194.

Ward SC (1989). Arguments for constructively simple models. *J Opl Res Soc* **40**: 141–153.

Wild R (2002). *Operations Management*, 6th edition. Continuum: London.

Zeigler BP (1976). *Theory of Modeling and Simulation*. Wiley: Chichester, UK.

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