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THREE SOURCES OF SIMULATION INACCURACY (AND HOW TO OVERCOME THEM)

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ABSTRACT

There is much interest in how to ensure that the results obtained from a simulation model are accurate. This paper considers this from the perspective of three main sources of inaccuracy: the modelling, the data and the experimentation. For each of these sources the causes of inaccuracy are discussed and some advice is given on how to overcome them. An illustrative model is used to quantify some of the effects of inaccuracies in the data and the experimentation.

1 INTRODUCTION

The validity of a simulation model is typically defined as the model being 'sufficiently accurate for the purpose at hand' (Carson 1986). This suggests that the modeller and the decision-maker have some clear objective for developing and using the model, and that there is a level of accuracy that is required from the model if it is to achieve this objective. Because many simulation studies are carried out to predict the performance of a real world system, the level of accuracy required is often relatively high, say 90% or more. The level of accuracy may be less stringent when the model is primarily used for improving the understanding of the real world system.

This raises the question of how simulation modellers can assure the accuracy of their models. Some have attempted to answer this question by giving advice to modellers on how to go about developing and using simulation models, for instance, Shannon (1975), Szymankiewicz et al. (1988), Sadowski (1989), Hoover and Perry (1990), Law and Kelton (1991), Ulgen (1991), Dietz (1992), Musselman (1992), Nordgren (1995) and Banks et al. (1996). Gogg and Mott (1992) and Robinson (1994) give detailed descriptions of each stage in the life-cycle of a simulation study. Others discuss the question of assuring accuracy by concentrating on the requirements for model verification and validation. Among these are Gass (1983), Landry et al. (1983), Sargent (1992), Balci (1994) and Robinson (1999).

Another approach is to consider the critical success factors in a simulation study. Raju (1982), Bean et al. (1989), Law and McComas (1990) and Law (1993) all discuss this issue, providing a list of critical success factors. Although there are some variations in these lists, many common factors arise, among them are: support from senior management, the skills of the modeller, the relationship between the modeller and the end-user, involving the end-user, correct formulation of the problem, the accuracy of the data, using the right simulation software, the soundness/credibility of the model, communication and timeliness of the work. The papers above all discuss the critical success factors from the modeller's perspective. Robinson and Pidd (1998) interview the customers of simulation studies in order to understand their opinions on the factors critical to the success of a simulation study.

Meanwhile, others adopt the opposite approach, that is, understanding the reasons why simulation studies fail. Keller et al. (1991) argue that there are three main reasons why simulation projects fail: firstly, poor salesmanship when introducing the idea to an organisation; secondly, lack of knowledge and skills particularly in statistics, experimental design, the system being modelled and the ability to think logically; and thirdly, lack of time to perform a study properly. McHaney (1997) performs a survey of simulation users and concludes that failed studies are characterised by high costs and problems with the size and speed of the model. Law and McComas (1989) argue that too much emphasis is placed on simulation software selection and model coding in the belief that simulation projects are merely a complex exercise in computer programming. In a similar way to above, three sets of authors provide lists of reasons for simulation failure (Annino and Russell 1979; McLeod 1982; Law and McComas 1989). To all intents and purposes, these lists are simply the inverse of the critical success factors listed above.

This paper adopts the last approach by describing three sources of simulation inaccuracy. Figure 1 provides a simple outline of the modelling process, showing three key elements. The process of *modelling* involves the modeller in understanding the problem to be tackled, the development of a conceptual (mental) model, and the coding of a computer model. *Data* are extracted from the real world and are used in the model. *Experimentation* is then performed with the model to develop solutions to the real world problem and/or to increase the decision maker's understanding of the real world. It is failures in these three processes that are discussed in this paper. The discussion not only centres on the causes of failure but also provides some advice on how to overcome them. Before discussing these failures an example model is described that is used for illustrating their effect.

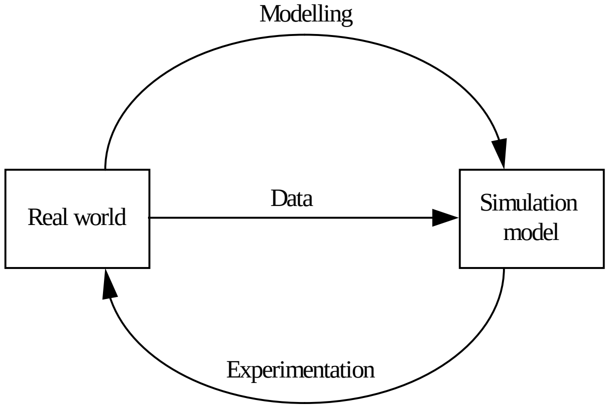


Figure 1: The Simulation Modelling Process (Simple Outline)

2 EXAMPLE MODEL FOR ILLUSTRATIVE PURPOSES

For illustrative purposes, the results from a simulation model and a queuing model of a simple bank queue are compared. Details of the model are shown in Figure 2. The queuing model has the advantage that it is able to give exact results on the performance of the system. By introducing various errors into the simulation model and comparing the results to those obtained from the queuing model, it is possible to quantify the effect of the errors on the results for the bank example. Such comparisons are made in sections 4 and 5. Obviously the effect of a modelling error is very much dependent on the specific model. Consequently, the results presented in this paper should be taken as illustrations and not as general statements about the size of errors caused by different modelling failures.

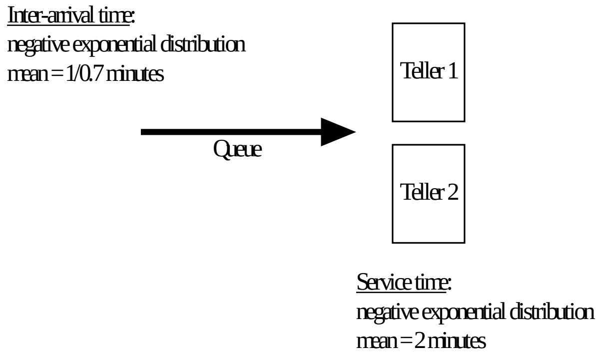


Figure 2: Simple Bank Queue Model

For an M/M/2 system, such as the one in Figure 2, queuing models can be used to calculate performance measures as follows:

Probability that there are no customers in the system:

$$P_0 = \frac{1}{1 + (\lambda / \mu) + \frac{(\lambda / \mu)^2}{2}\left(\frac{2\mu}{2\mu - \lambda}\right)}$$

Average number of customers in the queue:

$$L_q = \frac{(\lambda / \mu)^2 \lambda\mu}{(2\mu - \lambda)^2} P_0$$

Average waiting time in the queue:

$$W_q = \frac{L_q}{\lambda}$$

Where:

λ = arrival rate
μ = service rate for each service point

For the bank example these performance measures are as follows:

$$\lambda = 0.7, \mu = 0.5$$
$$P_0 = 0.18, L_q = 1.35, W_q = 1.92$$

The average waiting time (W_q) is used here for comparing the simulation and queuing model results. After performing 100 replications with the simulation model, each of 6 hours of simulated time, there is a close agreement between the two modelling approaches, the simulation giving an average waiting time result of 1.88 minutes. This represents an error of only -1.8% which is not unexpected since the simulation relies upon random sampling. Details of these results can be found in section 5.1.

3 SOURCE 1: MODELLING

One of the main skills of an expert simulationist is his/her ability to understand the problem to be tackled and correctly identify the model that is required. It is also one of the least understood skills (Willemain 1994; 1995). Three problems that arise at this stage are now discussed.

First, if the problem situation is poorly understood then a model of the wrong problem is likely to be developed. Balci (1994) refers to this as a Type III error. In order to avoid such an error the modeller needs to work closely with the client organisation to develop a good understanding of the problem situation. Various problem structuring methods could be employed, for instance, cognitive mapping (Eden et al. 1992) or soft systems methodology (Checkland 1981). Meanwhile, Balci and Nance (1985) describe a means for verifying the formulated problem.

A second problem occurs when the wrong model is developed for the problem situation. This is a result of poor conceptual modelling. The conceptual model is a software independent description of the model that is to be constructed. This may either be a mental model or a model that is explicitly expressed possibly using a diagramming technique such as an activity cycle diagram (Pidd, 1998). The development of conceptual models is again poorly understood, albeit vital for effective simulation modelling. Validation of the conceptual model acts as an aid to ensuring that the conceptual model is adequate. Such validation is discussed by Sargent (1992), Balci (1994) and Robinson (1999).

Finally, having developed a conceptual model it is then converted into a computer model by implementing it within a simulation software package or coding it from scratch. Failures can occur in this process of conversion leading to errors in the model. Model verification is the means by which the modeller aims to ensure that the model has been converted into a computer model satisfactorily. Simulation verification is discussed by various authors, for instance, Sargent (1992), Balci (1994) and Robinson (1999).

4 SOURCE 2: THE DATA

4.1 The Data as a Cause of Inaccuracy

There are two main ways in which the data for a simulation study can lead to inaccuracies in the results obtained from a model. The potential effects of failures in both these areas are demonstrated with reference to the simple bank example.

4.1.1 Inaccurate Data

The data that have been collected may in themselves be inaccurate. This could be a result of poor data collection methods leading to errors in the data. It could also be caused by an inadequate sample size meaning that it is not possible to make accurate inferences about the full population of the data. Alternatively, the data may simply not be available for collection because the real world system does not yet exist, or because there is insufficient time or money to obtain a significantly large enough sample within the constraints of the project. In these cases, the data are typically estimated, leading to uncertainties concerning the accuracy of the estimates.

To illustrate the effect of inaccurate data the service time in the simple bank model is reduced and increased by 10%, giving values of $\mu = 0.556$ and $\mu = 0.455$ respectively. The results from 100 replications are shown in Figures 3 and 4. Figure 3(a) shows the estimated mean waiting time, calculated as a cumulative average across the replications, when the service time is underestimated by 10%. The high and low range of a 95% confidence interval is shown by the dashed line. The expected value of the mean, calculated from the queuing model with accurate data (i.e. $\mu = 0.5$), is also shown. What becomes immediately apparent is that there is a significant error in the results obtained from the simulation model, the expected value of the mean not even falling within the range of the confidence interval after the first few replications.

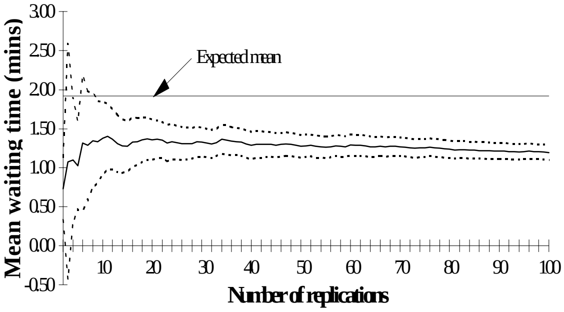
Figure 3(b) shows the percentage error between the results of the simulation model (cumulative mean queuing time) and the expected value of the mean calculated from the queuing model. This shows that for the simple bank model a 10% underestimate in the service time data has lead to an underestimate of more than 30% in the results of the model after 100 replications.

Figures 4(a) and 4(b) show similar information for a 10% overestimate in the service time. Here the error is even greater, giving an overestimate in the order of 60% after 100 replications.

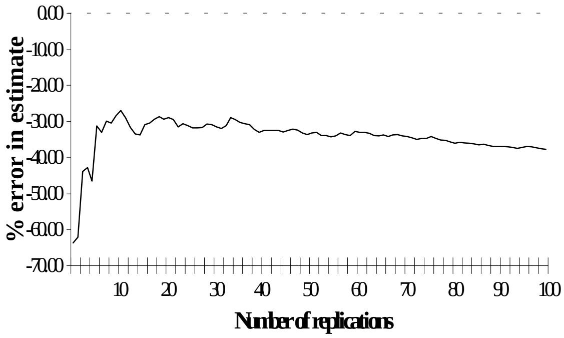
4.1.2 Poor Data Analysis

Poor analysis of the data that have been collected is a second cause of modelling inaccuracies. Apart from simple mathematical errors in the data analysis, a key area of concern is whether the correct probability distributions are used in the model. The effect of using the wrong probability distributions is demonstrated by changing the service time distributions to a gamma and normal distribution while maintaining a mean service time of 2 minutes. The gamma distribution represents a less significant error than the normal distribution because it is closer in shape to a negative exponential distribution, that is, it is skewed to the left. The results are shown in Figures 5 and 6 respectively.

Figure 5(b) shows that there is an error of approximately 25% caused by the use of the gamma

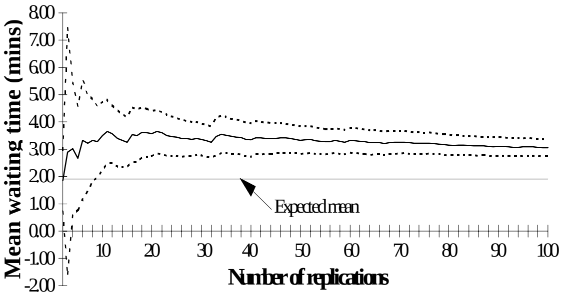


(a) Mean Waiting Time and Expected Mean

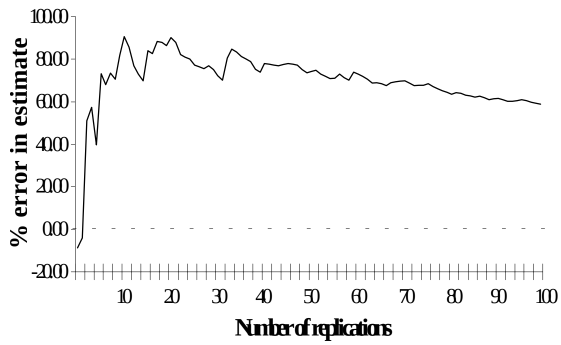


(b) Error in Mean Waiting Time

Figure 3: Effect of 10% Underestimate in Service Time

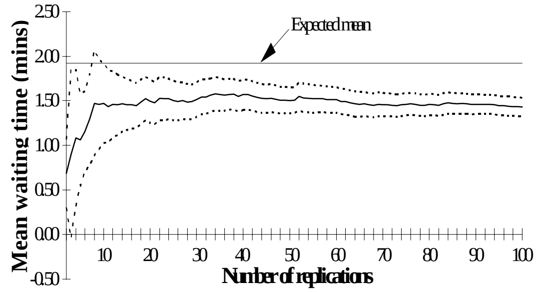


(a) Mean Waiting Time and Expected Mean

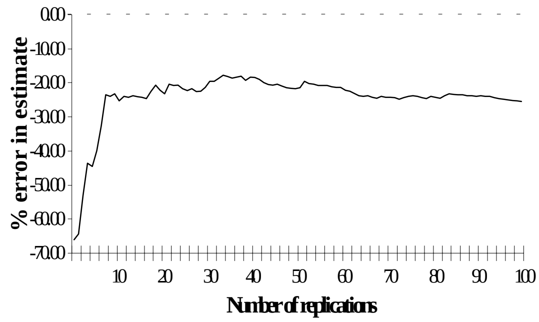


(b) Error in Mean Waiting Time

Figure 4: Effect of 10% Overestimate in Service Time

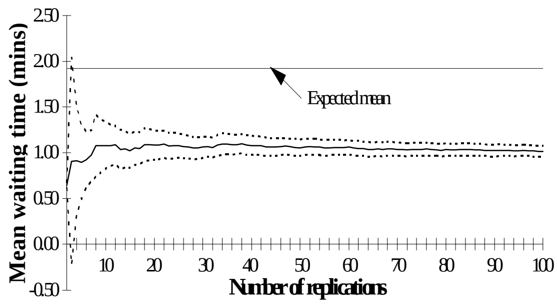


(a) Mean Waiting Time and Expected Mean

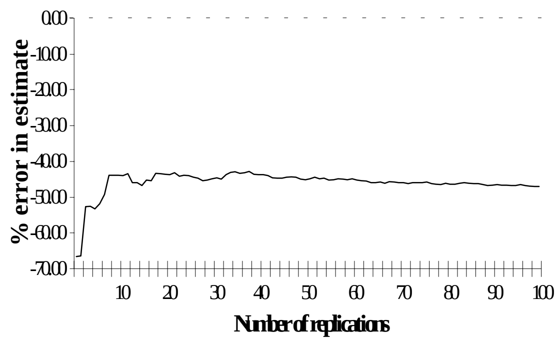


(b) Error in Mean Waiting Time

Figure 5: Effect of Wrong Service Time Distribution - Gamma (2, 1)



(a) Mean Waiting Time and Expected Mean



(b) Error in Mean Waiting Time

Figure 6: Effect of Wrong Service Time Distribution - Normal (2, 0.2)

distribution, while the error from the use of the normal distribution is in the region of 45% (Figure 6(b)). In both cases the simulation is underestimating the mean waiting time, suggesting that the operation of the bank will be better than it will in practice. The reduction in mean waiting time is a result of the selected gamma and normal distributions reducing the variance in the service time over that obtained from the negative exponential distribution.

4.2 Overcoming Inaccuracies Caused by the Data

The results presented above suggest that inaccuracies in the data can lead to serious errors in the model's results. It is vital, therefore, that every effort is made to ensure that the data are accurate.

If data have already been collected and are given to the modeller then it is important that the source of that data is investigated with particular reference to the possibility of errors entering the information. The modeller should ascertain who collected the data, how they were collected and for what purpose. It is useful to draw graphs of the data, such as scatter charts and histograms, to look for any unusual patterns or outliers. The modeller must ensure that the data are in the right format for the simulation and as such needs to be aware of how the simulation software interprets any data that are entered.

Where the data need to be collected careful consideration should be given to the data collection exercise. Samples should be carefully selected and an adequate sample size obtained. Efforts should be made to ensure that errors in the data collected are avoided, or at least identified when they occur. One possibility is to cross check the data against a second source. Again, the format of the data required for the simulation software must be taken into account.

For those data that cannot be collected one option is to estimate the data. As the results above show, however, small errors in these estimates can lead to larger errors in the results. It is important, therefore, to perform a sensitivity analysis by varying estimated data to ascertain a measure of their effect on the final results. The results may be insensitive to the accuracy of the estimates, in which case no further action need be taken. Alternatively, they may be highly sensitive, in which case efforts should be made to obtain more accurate estimates, or the results of the sensitivity analysis should be reported so the decision maker can assess the risk involved in various courses of action. Another approach is to regard these data as experimental factors and ask the question: what values do these data need to attain to achieve the desired result? This is appropriate where the decision maker has some control over the values of these data. If neither of these approaches should suffice then it may be necessary to reduce the scope of the simulation study such that the data that are not available are no longer required for the simulation model.

Ensuring that the correct statistical distributions are employed in the model in part depends on the quality of the data that are available. Beyond that, various techniques exist which can help identify the best fitting distributions, for instance, P-P plots, Q-Q plots and the chi-square test. These are embodied in a number of simulation analysis packages, such as, ExpertFit (Averill M. Law and associates) and Stat::Fit (Geer Mountain Software). If there is some uncertainty over the correct distribution to employ, then sensitivity analysis can prove a useful means for understanding the effect of using different statistical distributions.

For more detailed discussions on data collection and analysis, and distribution fitting, see Law and Kelton (1991), Robinson (1994) and Banks et al. (1996).

5 SOURCE 3: THE EXPERIMENTATION

5.1 The Experimentation as a Cause of Inaccuracy

Four ways in which the experimentation can lead to inaccuracies in the results and conclusions drawn from a simulation model are identified here.

5.1.1 Ignoring the Initial Transient Period

Many simulation models pass through an initial transient period before reaching steady-state (Law and Kelton 1991). It should be noted that other behaviours do exist, particularly transient models that never reach a steady-state. Where a model does reach a steady-state the analysis should ignore the transient period in order to avoid any bias in the results. The modeller has two options for achieving this. One is to run the model for a warm-up period before collecting any results. The other is to place the model in a realistic starting condition at the beginning of the run, completely removing the transient period.

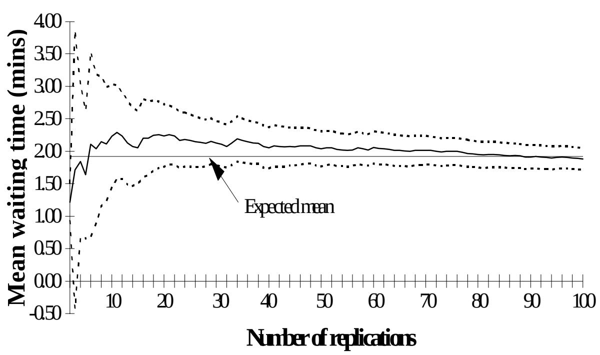
To illustrate the potential effects of ignoring the initial transient period, the bank model has been run with a starting condition of five customers in the queue. After 100 replications the mean waiting time result is 1.97 minutes. The result without the starting condition included is 1.88 minutes (see section 2) representing an error of -4.57%.

5.1.2 Insufficient Run-Length or Replications

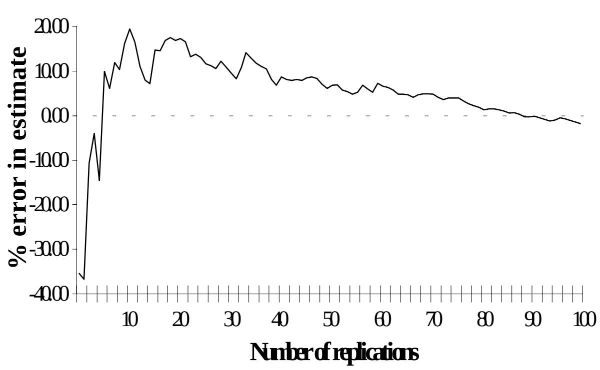
A second inaccuracy occurs in experimentation when the run-length is too short or there are insufficient replications. When the author was involved in modelling an engine assembly line the results indicated a significant shortfall in throughput based on a simulation run of one week of production. It was not until the model was run for a much longer period that it was realised that the random sampling in the model was leading to particularly poor results for the first week, and that the average throughput was much higher than indicated by the one week run.

Again the modeller is faced with two options for overcoming this problem. The first is to run the model for longer, the second is to perform multiple replications (re-running the model with different random number streams). In general multiple replications are preferred since the runs are independent and so confidence intervals can be easily calculated. Long runs do have the key advantage, however, that the warm-up period need only be run once for each experimental scenario, saving on experimentation time. Long runs also have an intuitive appeal in that the operations that are being simulated work similarly on a rolling basis; a week cannot be replicated in practice!

Figure 7 illustrates the effect of performing different numbers of replications with the bank model. Here the model parameters are set to the correct levels. What this shows is that if the modeller only performed one or two replications then the results would be more than 30% inaccurate. As expected, when the number of replications is increased, so the trend is a reduction in the inaccuracy. After 100 replications the simulation gives a mean waiting time result of 1.88 minutes which represents an error of only -1.8%.



(a) Mean Waiting Time and Expected Mean



(b) Error in Mean Waiting Time

Figure 7: Effect of the Number of Replications on the Accuracy of the Results

5.1.3 Insufficient Searching of the Solution Space

Simulation experimentation entails changing the levels of the experimental factors in order to obtain a better understanding of the model's behaviour and to seek out target or optimum levels of performance. If only a limited number of experiments are performed then the quality of the findings will be limited. In other words the modeller will only gain a partial understanding of the model's behaviour, and there is a risk of finding just local optima, or reaching the target performance, but without the optimum combination of levels for the experimental factors. By not searching the solution space sufficiently, the conclusions drawn from the experimentation with the model are likely to be erroneous, which in itself is a source of inaccuracy.

5.1.4 Not Testing the Sensitivity of the Results

The need to test the sensitivity of the results to data about which there are uncertainties is discussed in section 4.2. Beyond this, the robustness of the solution should also be tested. This entails changing the data in the model and determining at what points the proposed solution (the levels of the experimental factors) is likely to alter. It may be that the solution is very robust and is applicable across a wide range of values for the data. On the other hand, only small perturbations in the data may lead to shifts in the proposed solution. Such analysis is necessary because there are always uncertainties in the real world. As a result, any proposed course of action identified by a simulation model should as far as possible be robust, or at least the potential effects of uncertainties should be understood as much as possible.

5.2 Overcoming Inaccuracies Caused by the Experimentation

The inaccuracies described above can largely be overcome by adopting sound experimental procedures. Various methods exist for identifying the initial transient period. Welch's method (Welch 1983; Law and Kelton 1991) is a popular one.

The run length of a model is in some cases determined by a natural end point such as the end of the day in service systems or the end of the week when a weekly production schedule is being tested. Such simulations are referred to as 'terminating'. For the situation where no natural end point exists (a 'non-terminating' simulation), Robinson (1995) describes a method for determining a suitable run-length.

The number of replications required is normally determined by continuing to perform replications until a sufficiently narrow confidence interval is obtained. Law and Kelton (1991) and Robinson (1994) discuss the use of confidence intervals for selecting the number of replications required.

A series of experimental design techniques exist that aid in the efficient searching of the solution space. They can also help in performing sensitivity analysis. A useful introduction can be found in Law and Kelton (1991). The aim is to select a limited number of scenarios from the total set available, and to use these to learn about the performance of the system. Such methods may attempt to predict the outcome of those scenarios that have not been run, or they may attempt to identify those combinations of the experimental factors that are likely to provide a good result. In recent years much attention has been given to the idea of simulation optimisation (Carson and Maria 1997), with many simulation software vendors offering an ‘optimiser’ with their packages. These automate the process of searching for an optimum or a target, although an optimum cannot be guaranteed.

Above all, allow time for thorough experimentation. Ultimately it is impossible to test every idea and analyse fully the sensitivity of the proposed solution. But the more that can be done the better. In designing and building a simulation model much effort should go into ensuring that the model will run as quickly as possible, a doubling in run-speed enabling twice the experimentation in the same time-frame. Indeed, it might be that a simpler (less accurate) model gives more accurate results because it is possible to perform more detailed experimentation.

6 CONCLUSION

The discussion above describes various sources of inaccuracy in simulation modelling. It also quantifies the effect of some of these inaccuracies via an illustrative model. What this demonstrates is that these sources can lead to some quite significant errors in the results obtained from a simulation study. Should a number of these sources of inaccuracy occur in a single study then their cumulative effect could render the results of little value and possibly lead to damaging conclusions.

What these results show is the need to make strenuous efforts to assure the validity of a simulation by reducing to a minimum the sources of inaccuracy. In so doing it should be possible to ensure that a model is sufficiently accurate for the purpose at hand. Some comments and guides on how to overcome these inaccuracies are included in this paper with references for more detailed study.

Finally, it should be reiterated that the results obtained from the simple bank model are purely illustrative and in no way can be taken as general conclusions about the effects of various inaccuracies. Indeed, because there are only a small number of variables in this model it is likely that perturbations to their values will have a much greater effect than in a model with many more variables. What it does provide, however, is a warning to simulation modellers and simulation consumers alike on the need to make every effort possible to minimise all potential sources of inaccuracy.

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