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Spreadsheets as a Tool for Teaching Simulation

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Abstract

Simulation can be a difficult subject to teach, as most commercial software requires learning new approaches and time is limited, particularly in business overview courses. Spreadsheets have a distinct advantage in that most students developed a high level of expertise prior to taking management science courses. As such, they provide an ideal platform on which to learn the basics of simulation methodology. In this paper, we describe the use of spreadsheets as a tool for teaching simulation for both pure Monte-Carlo approaches (focusing on the advantages of using Excel add-ins), and for simple systems simulation models such as queueing.

Simulation models are logical descriptions of the interrelationships among elements of a decision problem, or the sequence of events that occur in a system over time. They capture probabilistic behavior and allow one to estimate key statistics such as means or tail probabilities of distributions that cannot be derived analytically. Simulation models can be categorized into two broad categories. *Systems simulation models* capture the dynamics and behavior of interacting elements of a system, such as a manufacturing facility or call center. These models are driven by changes that occur in the system over time. *Monte-Carlo simulation models*, on the other hand, are time-independent. They involve repeated sampling from probability distributions of model inputs to characterize the distributions of model outputs. Monte-Carlo simulation models generate distributions of potential outcomes of key model variables along with their likelihood of occurrence.

Simulation has been an important tool in management science throughout its history. Most applications of simulation have revolved around dynamic systems -- for instance, inventory control, project planning, queueing and scheduling, production, material handling and logistics, and service and communication systems [Pritsker, et al., 1994]. Although Monte-Carlo simulation has been around for decades, it is only recently that practitioners have demonstrated a renewed interest in the subject, particularly for risk assessment applications [Nichols, 1994; Whitford, 1997]. Risk simulation has become a significant tool in finance and marketing analysis, as well as other areas of application. The principal focus on simulation in most engineering schools has been on dynamic systems, while many business schools emphasize Monte-Carlo simulation. However, much cross-over exists, as Monte-Carlo simulation finds useful applications in engineering systems, and business process reengineering relies on dynamic system models.

Implementing system simulation models typically requires a commercial simulation package such as SLAM, Arena, Extend, SIMSCRIPT, or GPSS. While these powerful packages offer many significant advantages to commercial users, they can often be difficult to introduce in survey courses in management science, primarily because of the time involved in learning the terminology and procedures required to run the software. Although "point-and-click" object-oriented approaches have alleviated this significantly, commercial packages still require a high amount of startup, particularly in a short academic term for an introductory overview course.

Spreadsheets, on the other hand, offer many pedagogical advantages for learning simulation. These include

- Rapid start-up -- Because the basics of spreadsheets are taught in introductory courses such as accounting or statistics, students can easily understand model implementation issues in simulation.
- Integrated graphics -- Spreadsheets allow users to quickly and easily develop visualizations of data, and gain useful insights that typical simulation output does not provide.

- Dynamic updating -- New results can be immediately obtained as data are changed. Of particular interest from a teaching perspective is the dynamic updating of graphs and charts as new results are obtained.
- Statistics integration -- A full complement of statistical tools and functions allow users to perform on-the-spot analyses of results without having to transfer data to other software packages.

Monte-Carlo simulation is particularly well-suited to spreadsheet models. In fact, we conjecture that the recent popularity of Monte-Carlo risk analysis methods is due to technology advances: powerful desktop computers and user-friendly software designed around spreadsheets, such as *Crystal Ball* and *@Risk*.

The purpose of this paper is to discuss some key issues associated with teaching simulation methods using Excel spreadsheets and to provide some illustrative examples. We will discuss both Monte-Carlo simulation as well as dynamic systems simulation, focusing on implementation, advantages, and limitations.

Building Spreadsheet Simulation Models

In general, building a simulation model involves the following steps:

1. *Formulating the problem* to determine the objectives of the simulation study, the system performance measures to be computed, and the scenarios to be evaluated. A *scenario* is any specification of the controllable inputs, that is, a particular variation of the system that we wish to study. By comparing the performance of different scenarios, we expect to be able to draw conclusions as to which scenario is the best, if indeed there is a significant difference.
2. *Developing a logical model* of the system under study that describes key events and actions that take place. Visual models provide the basis for implementing the simulation model on a spreadsheet. For

systems simulations, the model is usually described with a flowchart; for Monte-Carlo simulations, one often uses an influence diagram.

3. *Specifying probabilistic assumptions* needed to drive the simulation, that is, the probability distributions of input variables. If historical data are available, we can use the empirical distribution to drive the simulation, or fit the data to a theoretical distribution using data fitting techniques. If not, then a distribution must be selected judgmentally.
4. *Implementing the model* on a computer to perform the necessary calculations required to evaluate the distribution of model outputs. One of the advantages of using spreadsheets is that an experienced spreadsheet user can develop a model rapidly by exploiting the built-in functions and structure of the spreadsheet.

We first illustrate an example of a Monte-Carlo simulation model using the capabilities of Excel as the simulation driver. Figure 1 shows a simple newsboy simulation with a demand distribution that is normal with a mean of 60 and standard deviation of 10. The basic data are given in the range A1:B9. Random normally-distributed demands in cell B8 can be generated using the Excel formula `=NORMINV(RAND(),60,10)` (although we assumed a continuous distribution, the random variate can easily be made discrete). Of course, any mechanism for generating random variates for the proper distribution can be used. This is, however, one of the limitations of Excel. Although Excel provides a random number generation routine through the Analysis Toolpak; the scope of available distributions is very limited. In many cases, the user must explicitly write a formula for generating random variates using the `RAND()` function, similar to the way one needs to implement simulations using general purpose languages such as FORTRAN or BASIC. Such generating formulas can be found in many simulation texts; for example, Law and Kelton (1991).

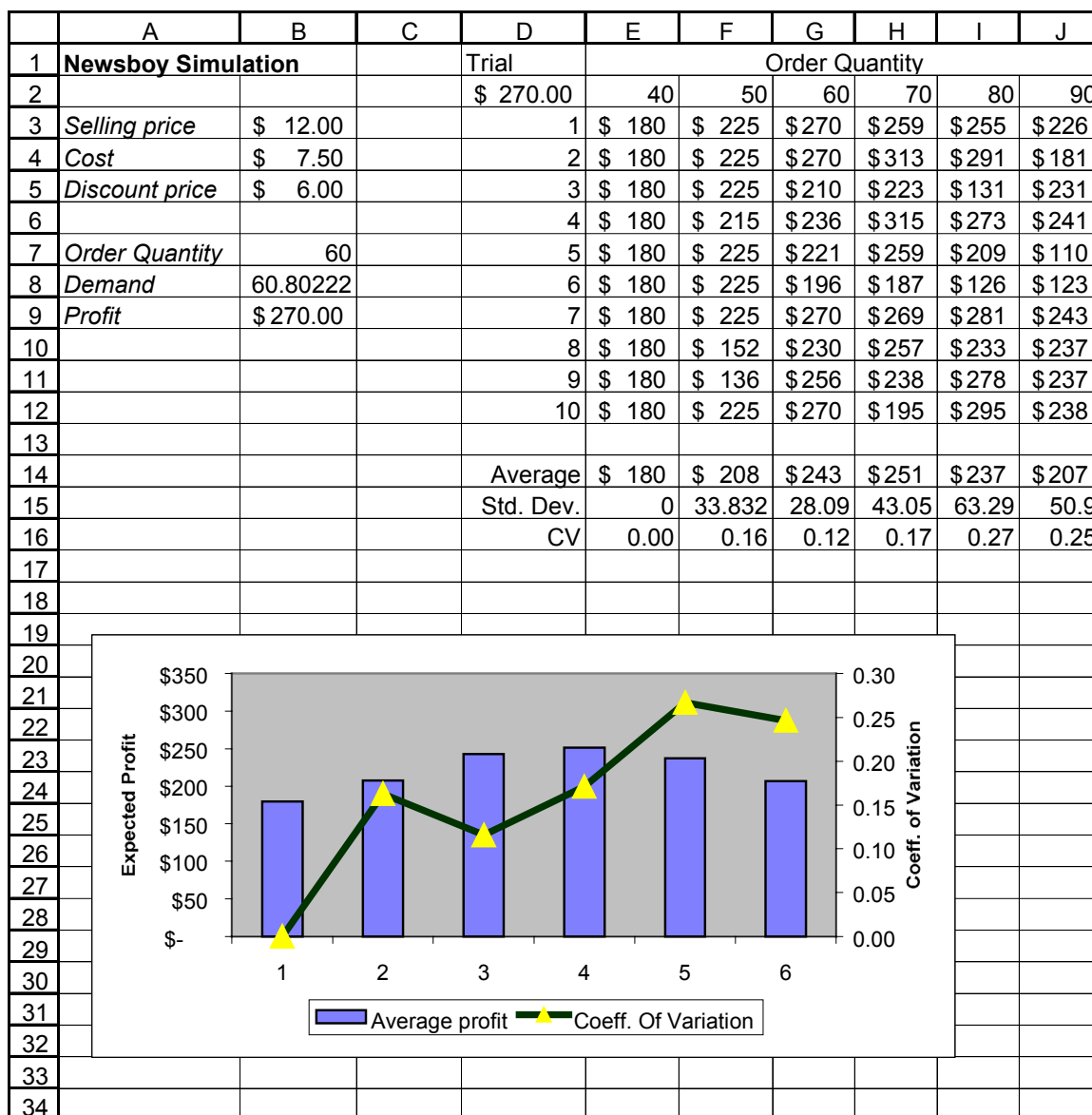


Figure 1: Spreadsheet model and data table simulation of a newsboy problem

The actual simulation is implemented using the Excel Data Table feature in cells D1:J12. Each row corresponds to a single trial, and each column evaluates an alternative order quantity. In this sense, Excel provides a significant advantage over general-purpose programming or simulation languages that would require the evaluation of each alternative independently within a programming loop. Several authors, such as Plane (1994), Ragsdale (1998) and Winston and Albright (1997) have described how data tables can be used to replicate samples in a Monte-Carlo fashion by selecting a blank cell for the column

input cell in the Excel dialog box. (The row input cell would be the order quantity, B7.) However, another Excel limitation is that it does not allow one to set a random number seed to control the stream of random numbers. Thus, each column represents an independent sample, and statistical techniques for variance reduction cannot be used.

Summary statistical information in the range D14:J16 is derived from standard Excel functions. These statistics can be graphed easily using the Excel charting procedure as shown in Figure 1. The integrated graphical features of spreadsheets

provide simple interpretations of the output data; in this example, we see that as the order quantity increases, so generally does the coefficient of variation, indicating a relatively higher level of risk to reward.

From a pedagogical perspective, graphics also provide the ability to illustrate variation associated with simulation output easily. For example, by pressing the F9 key, the entire simulation is replicated, allowing one to show changes in the output. For this example, repeated simulations will show different optimal order quantities and relative risk levels. In this fashion, students may begin to obtain a sense of risk associated with the recommendations from a simulation. These concepts can be easily tied into prior statistical concepts such as sampling from populations and the standard error of the mean.

We have noted some of the limitations of brute-force Excel simulations like this example. The major limitations are the lack of automation of the replication process and easy ability to analyze results. Fortunately, these are alleviated by add-ins such as *Crystal Ball*, which we discuss next. Add-ins also offer extensive random variate functions unavailable in Excel and the ability to develop customized applications through Visual Basic.

Crystal Ball for Monte-Carlo Risk Analysis

Crystal Ball is a simulation add-in to Microsoft Excel, and provides a far higher degree of flexibility and user-friendliness than using Excel alone. *Crystal Ball*, a product of Decisioneering, Inc., automates some of the more complex tasks required in Monte-Carlo simulations, such as generating random variates, replicating the spreadsheet, aggregating results, and computing statistics.

Crystal Ball requires the specification of two sets of cells in a spreadsheet model:

1. **Assumption Cells** - cells that represent uncertain inputs in the simulation model, and which are defined by some probability distribution
2. **Forecast Cells** - cells that represent the outputs of the simulation model

Selecting **Define Assumption** from the *Crystal Ball* menu will invoke the *Crystal Ball Distribution Gallery* (Figure 2) which will allow you to select the appropriate probability distribution and parameter settings. A variety of known distributions are available as well as the capability of defining a distribution from empirical data. The *Distribution Gallery* eliminates the need to write explicit functions for random variate generation. *Crystal Ball* also includes a data fitting capability that estimates best fits and parameter values for driving the simulation.

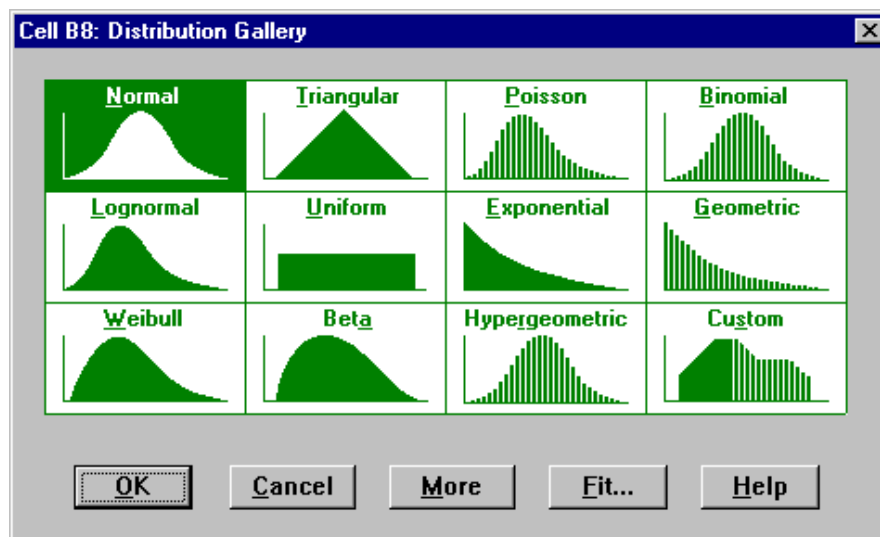


Figure 2: *Crystal Ball* Distribution Gallery screen

Implementing the newsboy simulation in *Crystal Ball* requires only specification of the basic model parameters in cells A1:B9 in Figure 1. Cell B8 is defined as an assumption cell with a normal distribution chosen from the *Distribution Gallery*. A data table can be used to evaluate a range of decision variables, with each entry in the data table being defined as a *Crystal Ball* forecast cell.

Crystal Ball generates a forecast window for each forecast cell, an example of which is shown in Figure 3 for 1000 trials. The spike in the distribution corresponds to the profit associated for demands exceeding the order quantity of 80. The forecast window can be manipulated graphically to evaluate probabilities for specified ranges or to evaluate ranges for certainty levels. In addition *Crystal Ball* provides basic statistical information as shown in Figure 4.

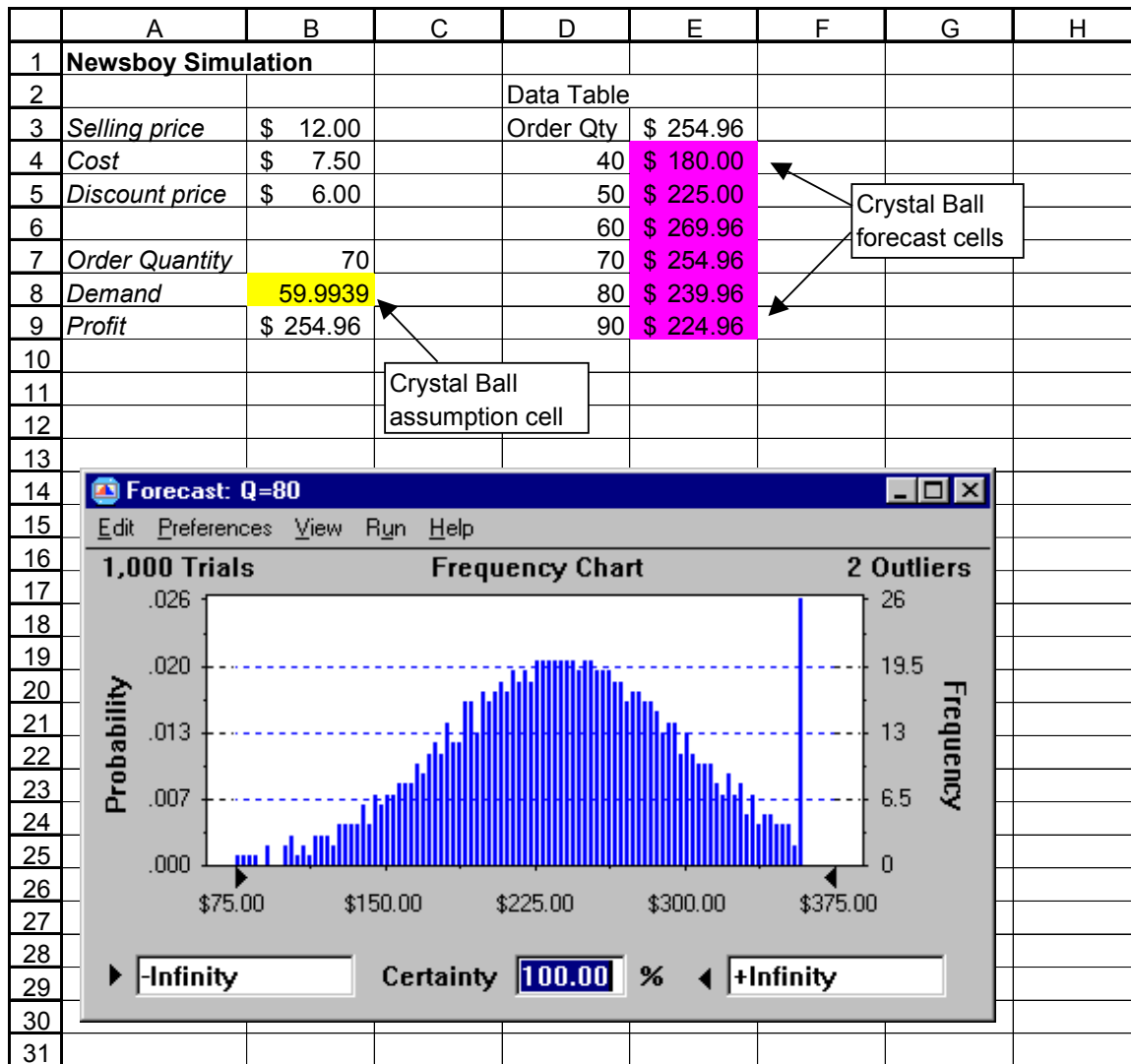


Figure 3: *Crystal Ball* newsboy simulation

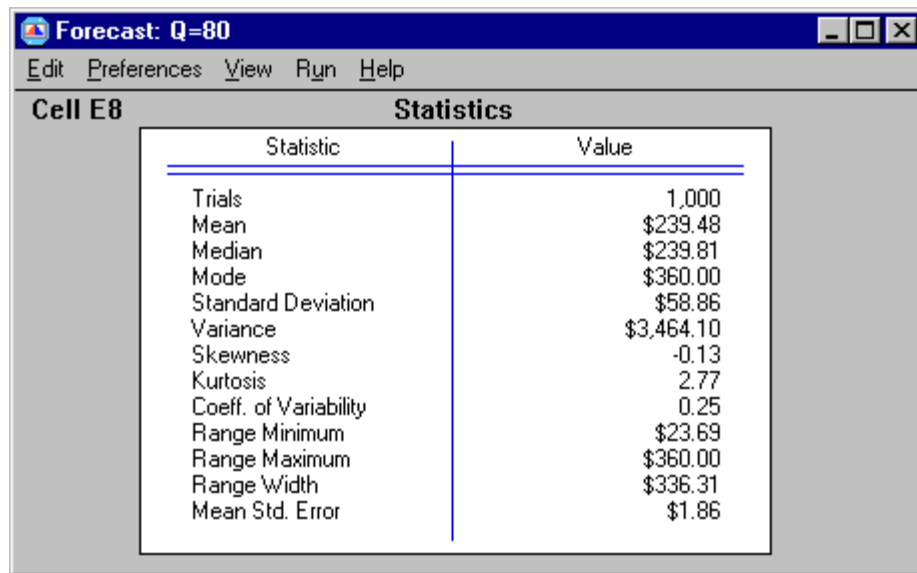


Figure 4: *Crystal Ball* statistics for newsboy simulation

A summary of other salient features of the software is given below.

- In addition to the distribution gallery, *Crystal Ball* provides a set of functions that may be used as any other Excel function for generating random variates and accessing output information for customized reports.
- A distribution fitting procedure allows ranked comparisons of goodness of fit to distributions in the *Distribution Gallery*.
- Assumptions may be correlated with each other.
- Multiple forecasts may be superimposed on a single chart for comparisons.
- Trend charts show probability bands for multiple forecasts, particularly useful for those over time.
- A sensitivity chart option shows the impact of assumption cells on forecast values.
- Custom reports in Excel may be easily created.
- Random number seeds may be defined to facilitate variance reduction.

These features provide a powerful tool for developing and evaluating probabilistic models. Moreover, the software is extremely easy to learn with minimal guidance. In addition, the latest version, *Crystal Ball Pro*, includes OptQuest, a neural-network-guided search procedure that allows the user to perform optimization of selected statistics using *Crystal Ball* models. Using OptQuest, for example, one could identify the best order quantity easily for the example in Figure 3 without requiring the use of data tables. This is especially useful if the range of the decision variable is large, or if more than two decision variables are defined. The reader is encouraged to visit Decisioneering's web site: www.decisioneering.com for further information.

Dynamic Simulation Models

Spreadsheets clearly do not have the flexibility to model many practical problems involving dynamic systems. Nevertheless, it is not too difficult to model basic queueing and inventory systems to provide a simple and convenient way to introduce these topics and illustrate basic concepts. These avenues have been explored by Winston (1996), Evans and Olson (1998), and Grossman (1998).

Figure 5 shows a process-oriented spreadsheet model for a single server queueing system with Poisson arrivals and exponential services (an event-oriented model can also be developed). The model simulates 500 customers. The logic is relatively straightforward except for computing the number in the queue in column F. This column shows the number in the queue *at the time of arrival* of each customer. This can be used to *approximate* the average number in the queue as a function of time. It is important to recognize that service completions are not explicitly represented

in a strict chronological fashion along with arrivals as would be done in an event-oriented simulation. Nevertheless, this information can be used to develop a graph showing the transient and steady state behavior of the queue as shown in Figure 6 by mapping the average number in the queue against the time of each customer arrival. The solid horizontal line is the expected value at steady state using standard analytical formulas (cell B8 in Figure 5). Similar graphs for average percent idle time and average waiting time can be developed as shown in Figures 7 and 8.

	A	B	C	D	E	F	G	H	I	J	K
1	Single Server Queueing		CUSTOMER	TIME BET.	ARRIVAL	NUMBER	START	SERVICE	COMPLETION	WAIT	IDLE
2	Simulation Spreadsheet			ARRIVALS	TIME	IN QUEUE	TIME	TIME	TIME	TIME	TIME
3									0.00		
4			1	0.1312	0.1312	0.0000	0.1312	0.0222	0.1534	0.0000	0.1312
5	Mean arrival rate	2	2	0.2425	0.3737	0.0000	0.3737	0.6955	1.0692	0.0000	0.2203
6	Mean service rate	3	3	0.4404	0.8140	1.0000	1.0692	1.0056	2.0748	0.2552	0.0000
7			4	0.1918	1.0058	2.0000	2.0748	0.1176	2.1924	1.0690	0.0000
8	Expected No. in Queue	1.333	5	1.3260	2.3318	0.0000	2.3318	0.9426	3.2743	0.0000	0.1394
9	Expected Waiting Time	0.667	6	0.0377	2.3695	1.0000	3.2743	0.0475	3.3218	0.9049	0.0000
10	Expected % idle time	33%	7	1.0546	3.4241	0.0000	3.4241	0.2447	3.6688	0.0000	0.1022
11			8	0.7618	4.1859	0.0000	4.1859	0.0847	4.2705	0.0000	0.5171
12			9	0.3542	4.5400	0.0000	4.5400	0.1184	4.6584	0.0000	0.2695
13			10	0.9278	5.4679	0.0000	5.4679	0.2208	5.6887	0.0000	0.8094

	L	M	N	O	P
1	AVERAGE	CUMULATIVE	AVERAGE	CUMULATIVE	AVERAGE
2	NO. IN QUEUE	WAIT TIME	WAIT TIME	IDLE TIME	% IDLE TIME
3					
4	0.0000	0.0000	0.0000	0.1312	86%
5	0.0000	0.0000	0.0000	0.3515	33%
6	0.5410	0.2552	0.0851	0.3515	17%
7	0.8191	1.3241	0.3310	0.3515	16%
8	0.3533	1.3241	0.2648	0.4909	15%
9	0.3636	2.2290	0.3715	0.4909	15%
10	0.2516	2.2290	0.3184	0.5932	16%
11	0.2058	2.2290	0.2786	1.1102	26%
12	0.1898	2.2290	0.2477	1.3797	30%
13	0.1576	2.2290	0.2229	2.1891	38%

Figure 5: Spreadsheet model for process-oriented queueing simulation

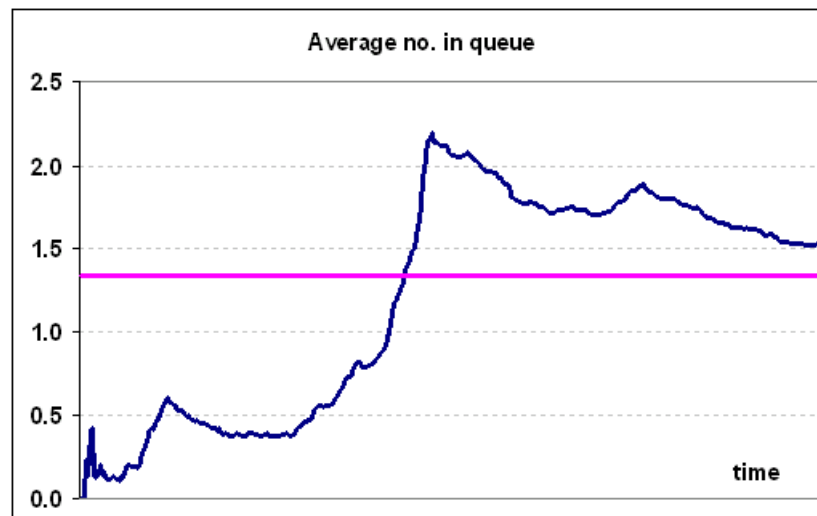


Figure 6: Approximate time plot of average number in queue

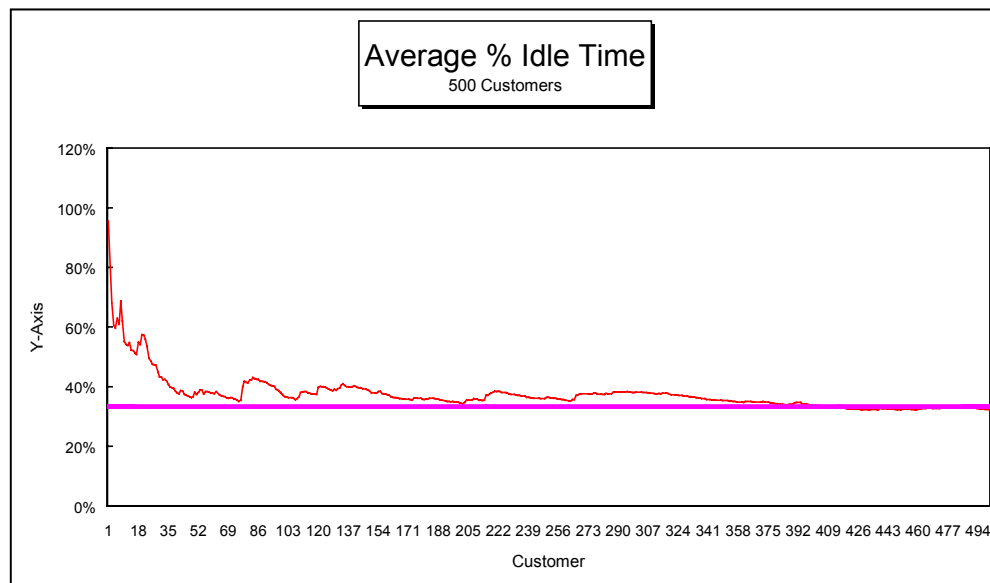


Figure 7: Graph of average percent idle time

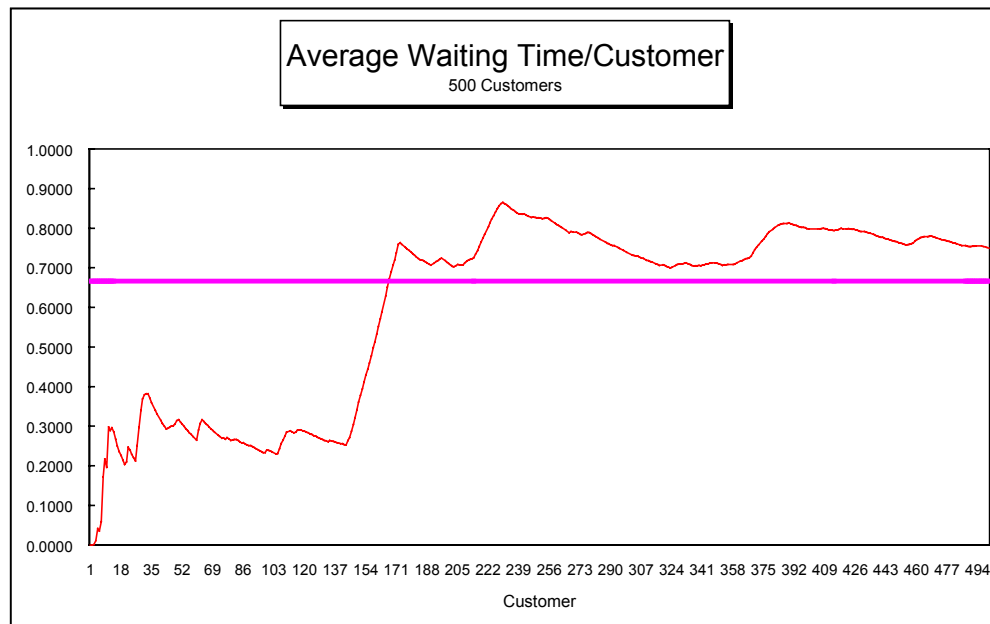


Figure 8: Graph of average waiting time

Here again, the ability to replicate the entire simulation by pressing the F9 key allows one to illustrate that individual simulations will vary considerably during the transient period, yet eventually approach the steady state expected value. The models can also be used to examine the sensitivity of results to changes in parameters such as the arrival or service rates.

Crystal Ball can be used to automatically replicate the entire queueing model to show the distribution of queueing statistics as illustrated in Figure 9. One need only define the last value in columns L, N, and P in Figure 5 as forecast cells

(no assumption cells are needed as the stochastic assumptions are built into the formulas for the arrival and service times). As Figure 9 illustrates, the average number in the queue over the 500-customer simulation varies considerably, from 0.45 to over 4; however, the average is very close to the expected value of 1.33. Such an analysis provides useful insights into the nature of variability in dynamic phenomena and the relationship with analytical steady state results. Such high-volume replication is essentially impossible to perform using commercial simulation packages like SLAM or Arena.

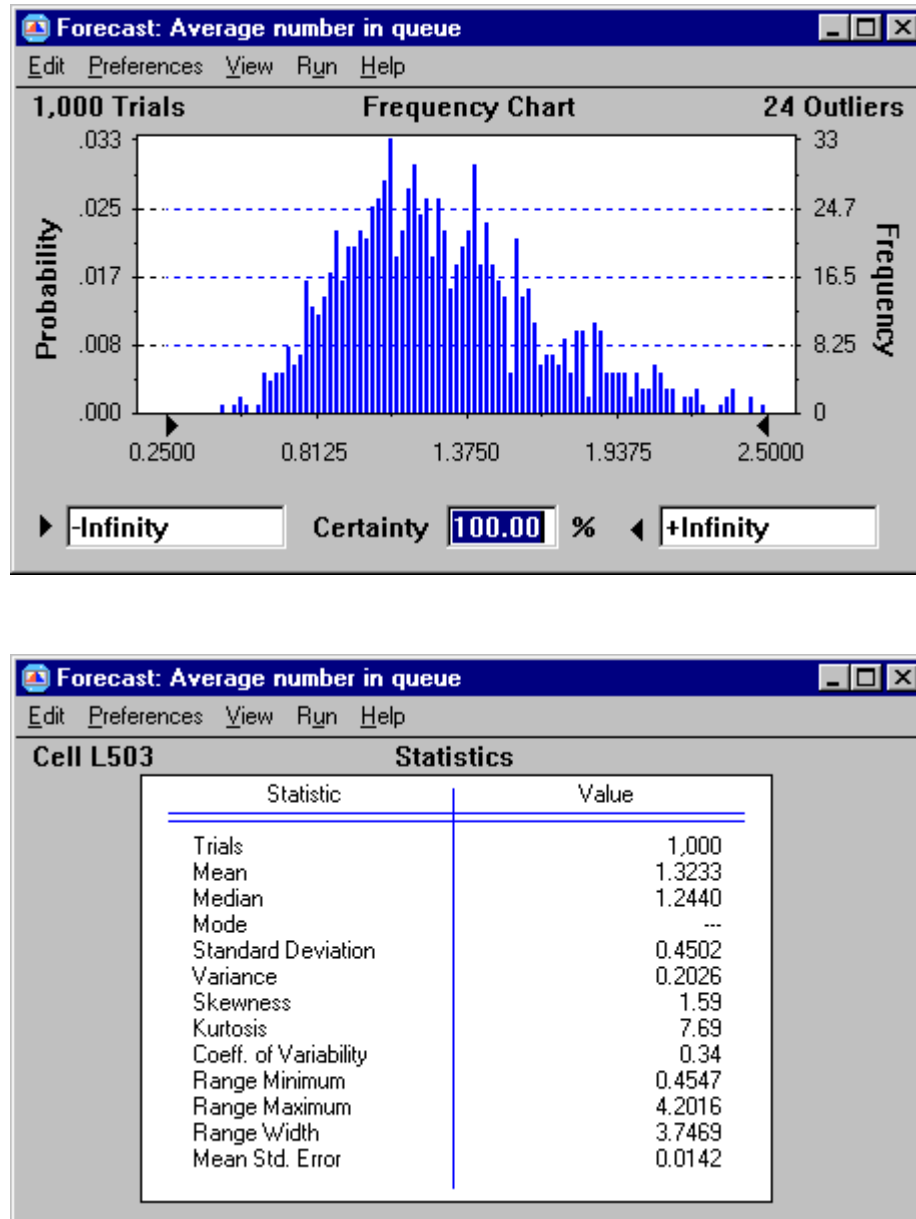


Figure 9: Crystal Ball simulation results for single server queuing model

Nevertheless, the limitations of using spreadsheets for dynamic systems are obvious:

- Spreadsheets cannot be used for more complex and realistic problems. For example, while it is possible to implement multiple server queueing models and various inventory models, the spreadsheets become large and complex, requiring formulas often beyond the ability of novice spreadsheet users, and cannot be changed simply by changing one parameter in the model.
- Non-event-oriented models make it difficult to plot time persistent output variables precisely as functions of time, limiting the scope of results that can be obtained.
- Spreadsheets lack state-of-the-art animation capabilities of commercial packages that are quite useful to establish user-friendliness and face validity.

Despite these limitations, simple dynamic spreadsheet models can be useful teaching tools to introduce dynamic simulation.

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