Proceedings of the 2003 Winter Simulation Conference
S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.

CRYSTAL BALL FOR SIX SIGMA TUTORIAL

Lawrence I. Goldman
Ethan Evans-Hilton

Decisioneering, Inc.
1515 Arapahoe Street
Suite 1311
Denver, CO 80202, U.S.A.

Hilary Emmett

Decisioneering (UK) Ltd.
Broadgate Court
199 Bishopsgate
London, EC2M 3TY, U.K.

ABSTRACT

In an increasingly competitive market, businesses are turning to new practices like Six Sigma, a structured methodology for accelerated process improvement, to help reduce costs and increase efficiency. Monte Carlo simulation can help Six Sigma practitioners understand the variation inherent in a process or product, and in turn, can be used to identify and test potential improvements. The benefits of understanding and controlling the sources of variability include increased productivity, reduced waste, and sales driven through improved customer satisfaction. This tutorial uses Crystal Ball® Professional Edition, a suite of easy-to-use Microsoft Excel add-in software, to demonstrate how stochastic simulation and optimization can be used in a Six Sigma analysis of a technical support call center.

1 INTRODUCTION

1.1 Risk Analysis and Spreadsheet Models

An uncertain situation often involves risk, which is defined as the possibility of loss, damage, or any other undesirable event. Most people desire low risk, which translates to a higher probability of success, profit, or some form of gain. For example, if sales for next month are above a certain amount (a desirable event), then orders will reduce the inventory, and there will be a delay in shipping orders (an undesirable event). If a shipping delay means losing orders, then that possibility presents a risk.

When using spreadsheets, analysts traditionally handle uncertainty by using average or best-guess values for uncertain inputs, primarily because Excel only lets them enter a single value in a cell. These deterministic models provide a single outcome upon which a business or technical decision is made. To capture uncertainty, analysts can perform simple "what-if analysis" or "scenario analysis" by manually changing model variables and analyzing their effect on the key outputs. This approach provides a range of possible outcomes but does not impart an understanding of the likelihood, or risk, of any particular outcome.

1.2 Monte Carlo Simulation

One established solution to the limitations of spreadsheet risk analysis is Monte Carlo simulation. Since Excel alone does not have the ability to run and analyze simulations, modelers must rely on third-party programs such as Crystal Ball that add in and expand the features of Excel. Crystal Ball adds two techniques to Excel: the replacement of single values with probability distributions and the random simulation of a model. The result is a probability-enhanced spreadsheet with quantifiable outcomes, such as a 75% probability of staying under budget or a 90% certainty of 100 million barrels of oil within a geologic reservoir.

Monte Carlo simulation is a proven, efficient technique that only requires a random number table or a random number generator on a computer (Kelton and Law 1991). A random number is a mathematically selected value that is generated to conform to a probability distribution. Monte Carlo simulation was named for Monte Carlo, Monaco, where the primary attractions are casinos containing games of chance, such as roulette wheels, dice, and slot machines, that exhibit random behavior.

The random behavior in games of chance is similar to how Monte Carlo simulation selects variable values at random to simulate a model. When you roll a die, you know that a 1, 2, 3, 4, 5, or 6 will come up, but you don't know which for any particular roll. It's the same with the variables that have a known range of values but an uncertain value for any particular time or event (e.g., interest rates, staffing needs, stock prices, inventory, phone calls per minute). The multiple scenarios created through simulation can be analyzed to give more insight into the risks and mechanisms of the spreadsheet model. When used correctly, Monte Carlo simulation can provide valuable insights not available through deterministic models.

1.3 Six Sigma Methodology

How can Monte Carlo simulation be used to increase profit? For a growing number of companies, this question can be answered in just two words: Six Sigma. Six Sigma is a structured methodology for accelerated process improvement that aims for virtually error-free business processes (Pyzdek 2003). Catch phrases like "management by fact" embody the Six Sigma methodology, where standards of quality are set based on concrete statistics.

Six Sigma is divided into five distinct phases: Define, Measure, Analyze, Improve, and Control (DMAIC). A successful Six Sigma practitioner employs a variety of analytical tools, mixing and matching the appropriate tools during each of the different phases. Because many traditional product and process engineering tools fail to quantify the cash value of improved design, they are less useful for Six Sigma. The inherent flexibility of spreadsheets means that they can be widely applied and can account for quality and cost changes across the different phases of the improvement process.

Monte Carlo simulation has a critical role in the Define, Analyze, and Improve phases. The underlying connection between Monte Carlo simulation and Six Sigma is the variability inherent in all business processes. Monte Carlo simulation is a critical tool for understanding how a process or product varies and, therefore, for identifying and testing potential improvements. The benefits of understanding and controlling the sources of variability include increased productivity, reduced waste, and sales driven through improved customer satisfaction.

2 CRYSTAL BALL PROFESSIONAL EDITION

Crystal Ball Professional Edition is a general desktop software suite that features spreadsheet-based analysis tools for Monte Carlo simulation (Crystal Ball), time-series forecasting (CB Predictor), and optimization (OptQuest). The suite also includes Crystal Ball and CB Predictor Developer Kits for building custom interfaces and processes using Visual Basic for Applications (VBA).

2.1 Crystal Ball

Crystal Ball is an easy-to-use Excel add-in designed to help all levels of spreadsheet modelers perform Monte Carlo simulation. Crystal Ball lets users define probability distributions on uncertain model variables, and then uses simulation to generate random values from within the defined probability ranges. Spreadsheet modelers can create and analyze thousands of alternate scenarios and quantify their level of risk for any given scenario. You can apply Crystal Ball to existing or new spreadsheet models, and the enhancements provided by Crystal Ball do not alter the formulae or functions of the original spreadsheet. Crystal Ball also includes the CB tools, a series of seven wizard-driven add-ins that can assist in setting up and analyzing models.

2.2 OptQuest

OptQuest is a global optimization add-in created specifically for Crystal Ball. The optimizer enhances Crystal Ball by automatically searching for and finding optimal solutions to simulation models. OptQuest uses a mixture of techniques including scatter search and advanced tabu search to find the right combination of decision variables for the best possible results. As the program runs, adaptive and neural network technologies help it learn from past optimizations so that it achieves better results in less time. A setup wizard helps users define constraints, objectives, and requirements, and even to set up an efficient frontier option.

2.3 CB Predictor

CB Predictor is a wizard-driven Excel add-in that guides you through the process of time-series forecasting. CB Predictor analyzes historic data series and uses the level, trend, seasonality, and error of the data to project the series into the future. CB Predictor applies eight separate seasonal and nonseasonal time-series forecasting methodologies to data and can apply multiple linear regression in cases where the primary data series is dependent on other independent data series. The output forecasts can be defined as Crystal Ball assumptions and used in Monte Carlo simulation. CB Predictor will not be applied in this paper.

2.4 Developer Kits

The Crystal Ball and CB Predictor Developer Kits lets users with programming skills completely automate and control Crystal Ball simulations and CB Predictor forecasts from within a VBA program or any other language outside of Excel supporting OLE 2 automation. The kits consist of libraries of macro commands and functions that unlock the programmability of Crystal Ball and CB Predictor. With the kits, an analyst can automatically run multiple simulations to test different sets of assumptions, integrate Crystal Ball with other software tools, create turnkey applications that shield users from program intricacies, and even build custom reports or automate post-simulation analysis. The Developer Kits will not be applied in this paper.

3 TELECORP, INC. SIX SIGMA EXAMPLE

In this example, you are a member of a Six Sigma improvement team for Telecorp Inc., an outsourcing customer care company. Two years ago, Telecorp won a 24/7 contract to handle the inbound technical support calls for the software company DecSoft, Inc. As defined in the service level contract, a DecSoft customer should have to wait only 20 seconds before his or her inbound call is answered by a live Telecorp agent. The contract also dictates that, when a customer is on hold for longer than 20 seconds, Telecorp must pay a penalty for every additional second.

In the past year, Telecorp has had to pay a large amount of penalty fees, and the senior management wants your Six Sigma team to improve the quality of service and reduce the daily costs of the call center. Using the DMAIC methodology, your team must identify the source of the response delays, determine whether or not current staffing levels and allocations can be improved, and suggest ways in which operation costs can be reduced. Through this analysis, you will see how simulation and optimization can be applied to a Six Sigma project and how the methodologies fit within the five phases of DMAIC.

3.1 The Define Phase

The Define phase is primarily focused on customer and employee interviews to understand performance requirements. The Define phase is one of the most important phases, because it sets the framework and goals for the project. Simulation is not often used in this phase, but it can be used for projecting the potential financial value of improving a process or product. The Telecorp Six Sigma team defines its goals as understanding the variability around the call center activity, optimizing the allocation of staff, and minimizing the daily costs resulting from a combination of staff pay and call penalties.

3.2 The Measure Phase

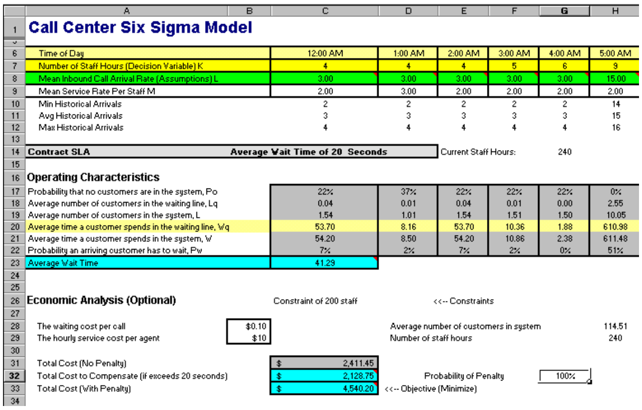
During the Measure phase, the Six Sigma team gathers data that describe the current state of call center operations. Some of this data may be new, and much of it has never been scrutinized before. The Six Sigma team must establish valid and reliable metrics to help monitor their progress towards the project goals.

3.3 The Analyze Phase

In the Analyze phase, the team works to identify ways to decrease the gap between the current performance level and the desired goal. Simulation returns to the toolset during the Analyze phase when the data are compiled into a model for interpreting the strengths and weakness in the current state of operations. The Six Sigma team has decided to use Crystal Ball and Monte Carlo simulation as a tool to help analyze the uncertainty around the call center operations. Before Telecorp implements any improvements, a spreadsheet simulation can test whether or not a pilot project will bring the desired impact.

3.3.1 Creating the Spreadsheet Model

Before applying Crystal Ball, the team's first task is to build a valid and verifiable Excel model. Using the data gathered in the previous phase, and the standard formulae for a queuing model (Anderson et al. 2003), you construct a spreadsheet model that represents the call center activity for a twenty-four-hour period. The model (Figure 1) looks at staffing, amounts of calls, and operating characteristics.



	A	B	C	D	E	F	G	H
1	Call Center Six Sigma Model							
6	Time of Day		12:00 AM	1:00 AM	2:00 AM	3:00 AM	4:00 AM	5:00 AM
7	Number of Staff Hours (Decision Variable) K		4	4	4	5	6	9
8	Mean Inbound Call Arrival Rate (Assumptions) L		3.00	3.00	3.00	3.00	3.00	15.00
9	Mean Service Rate Per Staff M		2.00	3.00	2.00	2.00	2.00	2.00
10	Min Historical Arrivals		2	2	2	2	2	14
11	Avg Historical Arrivals		3	3	3	3	3	15
12	Max Historical Arrivals		4	4	4	4	4	16
13								
14	Contract SLA	Average Wait Time of 20 Seconds		Current Staff Hours:			240	
15								
16	Operating Characteristics							
17	Probability that no customers are in the system, Po		22%	37%	22%	22%	22%	0%
18	Average number of customers in the waiting line, Lq		0.04	0.01	0.04	0.01	0.00	2.55
19	Average number of customers in the system, L		1.54	1.01	1.54	1.51	1.50	10.05
20	Average time a customer spends in the waiting line, Wq		53.70	8.16	53.70	10.36	1.88	610.98
21	Average time a customer spends in the system, W		54.20	8.50	54.20	10.86	2.38	611.48
22	Probability an arriving customer has to wait, Pw		7%	2%	7%	2%	0%	51%
23	Average Wait Time		41.29					
24								
25								
26	Economic Analysis (Optional)		Constraint of 200 staff		<<-- Constraints			
27								
28	The waiting cost per call	$0.10			Average number of customers in system			114.51
29	The hourly service cost per agent	$10			Number of staff hours			240
30								
31	Total Cost (No Penalty)		$ 2,411.45					
32	Total Cost to Compensate (if exceeds 20 seconds)		$ 2,128.75		Probability of Penalty		100%	
33	Total Cost (With Penalty)		$ 4,540.20	<<-- Objective (Minimize)				
34								

Figure 1: Call Center Spreadsheet Model

Currently, the call center pays its staff for 240 staff hours a day. The Average Wait Time is 41.29 seconds. The Total Daily Cost of the call center is $4,540.20, with $2,128.75 of that as a penalty charge. These are average values that do not reflect the variability of daily activity.

3.3.2 Launching Crystal Ball

With the Excel model designed and tested, you launch Crystal Ball and Excel through the Windows Start menu. Crystal Ball adds a new tool bar and three new menus to Excel. The tool bar has been designed from left to right to follow the modeling process from setup to simulation to the analysis and presentation of results. The final button is for online help.

The three Crystal Ball menus contain all of the functions on the tool bar plus a few additional features. The Cell menu contains all of the model setup functions, and the Run menu lists all of the simulation and analysis functions. The final menu, CBTools, opens other tools in the Professional Edition suite.

3.3.3 Defining Crystal Ball Assumptions

In Crystal Ball, probability distributions are referred to as assumptions and are used to define the uncertainty or variability in any model input. The best way to identify which variables to convert from single values to probability distributions is to decide which variables are known and which are "soft" and uncertain.

In this model, you know that Mean Inbound Call Arrival Rate for each hour are all variable, and so these are obvious candidates for Crystal Ball assumptions. In the Measure phase, you determined the minimum, maximum and average number of calls for each hour-long period.

To define an assumption, select a spreadsheet variable and click on the Define Assumption button on the toolbar. In the Distribution Gallery (Figure 2), Crystal Ball offers sixteen pre-defined distributions and one customizable distribution. The four most commonly used assumptions are the normal, triangular, uniform, and lognormal.

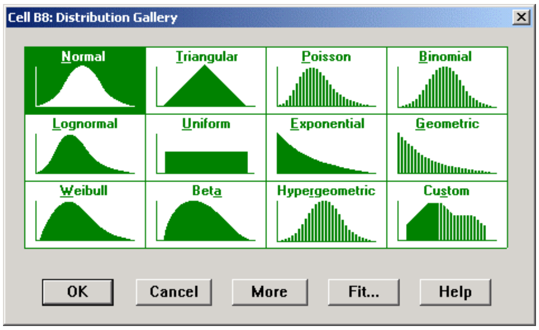
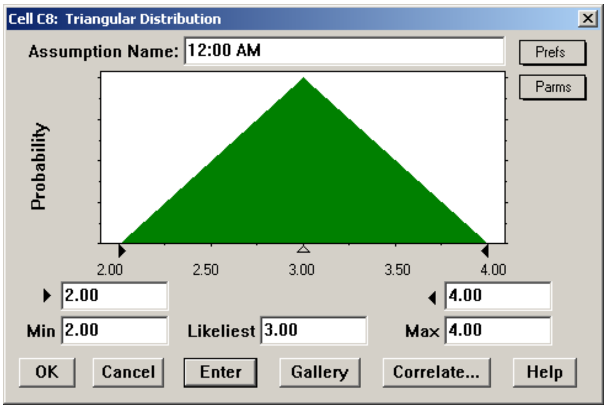


Figure 2: Distribution Gallery

Crystal Ball can also fit continuous distributions to available data and can define correlation coefficients between related pairs of assumptions. For Mean Inbound Call Arrival Rate for 12:00 AM to 1:00 AM, you know that two to four calls may arrive, and that the average number of calls for the period is three. You use these parameters to define a simple triangular distribution that represents the uncertainty of the activity during that period (Figure 3).



Assumption Name: 12:00 AM

▸ 2.00 ◂ 4.00

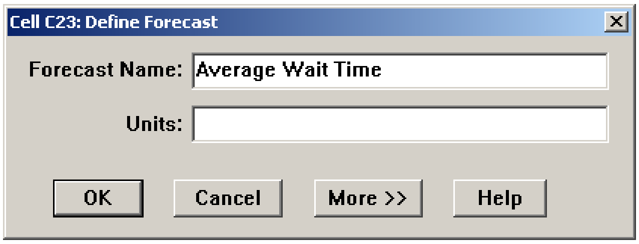
Min 2.00 Likeliest 3.00 Max 4.00

Figure 3: Assumption for Mean Inbound Call Arrival Rate

3.3.4 Defining a Crystal Ball Forecast

After defining the assumptions for the other eleven time periods, you need to define the outputs, or forecasts, that you want to examine with Crystal Ball. A forecast is any formula cell that you assign Crystal Ball to track during a simulation. As with assumptions, there is no limit to the number of forecasts you can define, although for more forecasts, more memory is required to store the simulated values.

In this model your primary forecasts are Average Waiting Time, Total Compensation Cost (the penalty charge), and Final Costs. To define a forecast for Average Waiting Time, you select the cell, click on the Define Forecast button to open the Define Forecast dialog (Figure 4), enter a unique name, and click on OK.



Forecast Name: Average Wait Time

Units:

Figure 4: Defining a Forecast Cell

3.3.5 Setting the Simulation Run Preferences

Crystal Ball gives you full access to the simulation controls. These settings include the number of trials to run, what sampling method to use, where and when during the simulation cycle to run macros, ways to increase the speed of simulations, and Precision Control, a method of confidence testing that lets you achieve a desired level of accuracy in your forecasts based on simulation statistics.

Crystal Ball offers two sampling methods: Monte Carlo and Latin Hypercube. With Monte Carlo, the generated random numbers are completely independent of one another. With Latin Hypercube sampling, Crystal Ball divides an assumption’s probability distribution into segments of equal probability, and during a simulation generates random numbers for each segment. In this example, you use Latin Hypercube simulation for 5000 trials.

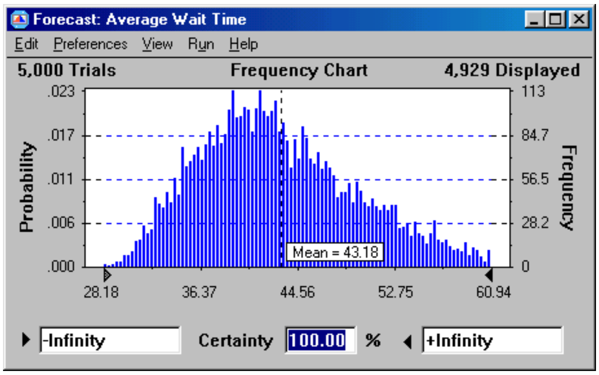
3.3.6 Testing and Running the Simulation

Before running the simulation, you can check that the model is functioning properly by clicking on the Single Step button on the toolbar. Each single step is a random trial in Crystal Ball. In one step, Crystal Ball generates a random number for each assumption, and Excel automatically recalculates the model. You may discover calculation errors with this test when the model recalculates for alternate scenarios.

During a simulation, Crystal Ball runs as many trials as you request and saves the forecast values for later analysis. To run the simulation, click on the Start Simulation button on the toolbar. As the simulation begins and the NPV forecast (or frequency) chart builds, you can watch the spreadsheet values change as Crystal Ball inserts randomly generated values (from the probability distributions) into the assumption cells.

3.3.7 Analyzing the Forecast Chart

When the 5,000 trials are completed, you can analyze these results using the forecast chart, an interactive histogram that contains all of the statistics for the 5000 trials. How likely is Average Wait Time to exceed the 20-second penalty limit? Based on the current call center staffing (Figure 5), the simulation reveals that there is an 100% certainty that a DecSoft customer will be on hold for longer than 28 seconds. The Average Wait Time mean is 43.18 seconds, two seconds longer than the base case.

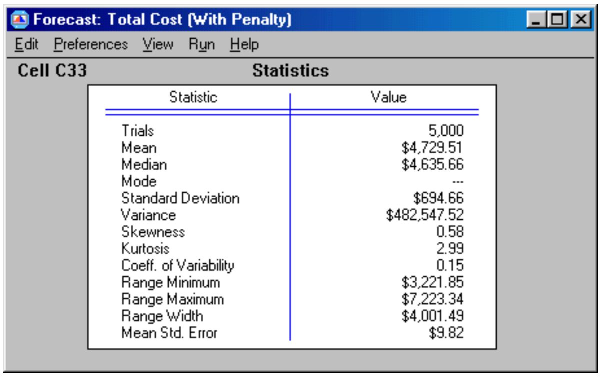


5,000 Trials — 4,929 Displayed

-Infinity Certainty 100.00 % +Infinity

Figure 5: Forecast Chart for Average Wait Time

The Statistics view (Figure 6) can help you gain additional insight into your call center costs. Because of the call penalty and the uncertainty surrounding the number of calls received, the daily Total Cost can vary between $3,221.85 and $7,223.34. The average daily cost is $4,729.51, with a standard deviation of $694.66.


Forecast: Total Cost (With Penalty)
Edit Preferences View Run Help

Cell C33 Statistics

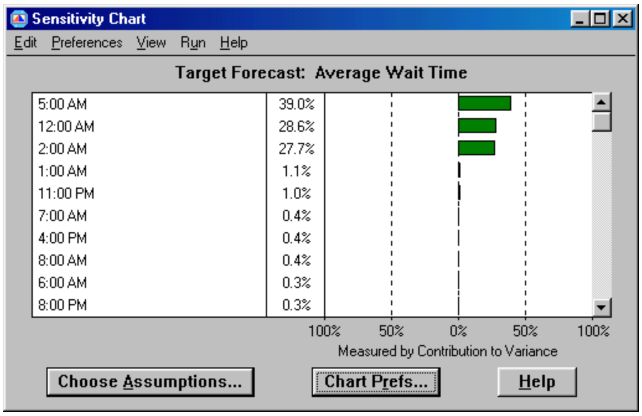
Statistic	Value
Trials	5,000
Mean	$4,729.51
Median	$4,635.66
Mode	---
Standard Deviation	$694.66
Variance	$482,547.52
Skewness	0.58
Kurtosis	2.99
Coeff. of Variability	0.15
Range Minimum	$3,221.85
Range Maximum	$7,223.34
Range Width	$4,001.49
Mean Std. Error	$9.82

Figure 6: Forecast Statistics View

With your simulation complete, your Six Sigma team now has a better understanding of the current operating status of the call center. Telecorp is currently paying approximately $800 to $4,800 per day in penalty fees. The average penalty of $2,318 per day translates to a yearly penalty cost of almost $850,000. What could be responsible for such a range of results? Crystal Ball's sensitivity analysis can point to the key factors responsible for the variation in the forecasts.

3.3.8 Sensitivity Analysis

As the simulation runs, sensitivity analysis uses Rank Correlation to calculate the relationships among the 24 assumptions and the forecast. The sensitivity chart (Figure 7) displays these relationships as correlation coefficients or as percentage values. The top listed assumptions have the greatest effect on the forecast, and the direction of the bar indicates a direct or inverse relationship.



Target Forecast: Average Wait Time

5:00 AM	39.0%
12:00 AM	28.6%
2:00 AM	27.7%
1:00 AM	1.1%
11:00 PM	1.0%
7:00 AM	0.4%
4:00 PM	0.4%
8:00 AM	0.4%
6:00 AM	0.3%
8:00 PM	0.3%

Figure 7: Sensitivity Chart for Average Wait Time

In your analysis, the staff hours for three early morning shifts, 12:00 AM, 2:00 AM, and 5:00 AM had the greatest impact on Average Wait Time. These three assumptions were responsible for over 95% of the variability in the forecast. The other cost forecasts showed a similar result, which suggests that there may be more calls than expected in the early shifts and that those shifts may need a boost in staffing.

3.4 The Improve Phase

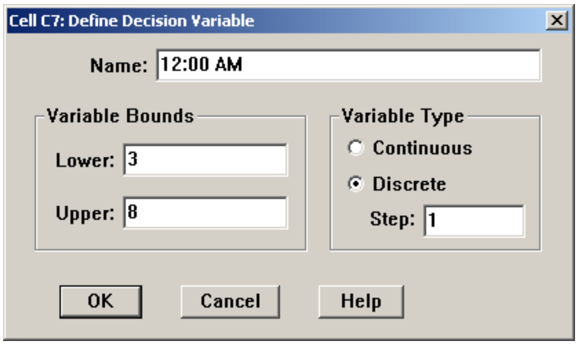
Now that you better understand the effects of uncertainty on the costs and operation of the call center, you are ready to make improvements to the process. While you cannot remove the variability of incoming support calls, you can reduce the penalty costs by addressing the appropriateness of the current staffing levels. An obvious solution to avoiding penalties would be to simply hire more staff, but this is not an option given current budget restraints. In fact, the company would actually like you to reduce the number of staff hours at the center.

In the Improve phase, your team will use simulation and optimization together to reduce the overall number of staff hours and to reallocate the remaining hours to better reduce the average percentage of penalized calls. These changes will help to minimize the center costs while improving the overall efficiency of the support service.

3.4.1 Defining Decision Variables

To run an optimization, your team must first identify the decision variables in your spreadsheet. Decision variables are model inputs over which you have control. In the previous call center simulation, you held the staff hours per period at the current levels, but these are actually decision variables that you can change to improve the process. Management would like you to reduce the current staff hours from 240 to 225, while reallocating the remaining hours to the periods where most of the penalties are incurred.

To define a decision variable, select a spreadsheet cell and click on the Define Decision button on the toolbar. In the Define Decision Dialog, you select the upper and lower bounds for the decision and whether the range should be continuous or discrete. If discrete, you must define the step size of the discrete values. For the 12:00 AM to 1:00 AM period, you want to decide three and eight agents to staff the center (Figure 8). Next, you define the decision variables for the other 23 periods in your model.



Cell C7: Define Decision Variable

Name: 12:00 AM

Variable Bounds

Lower: 3

Upper: 8

Variable Type

○ Continuous

● Discrete

Step: 1

Figure 8: Define Decision Variable Dialog

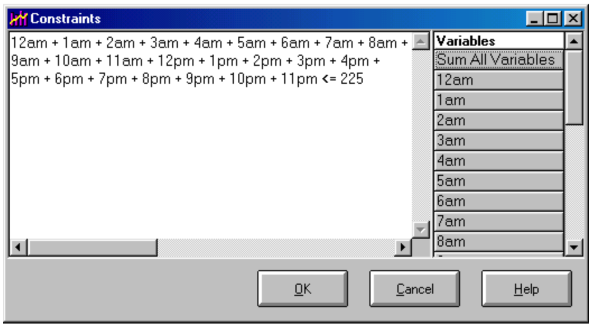
3.4.2 Launching OptQuest

If Excel and Crystal Ball are running, you can then open OptQuest by selecting the program from the CBTools menu. OptQuest is a Crystal Ball add-in that cannot run outside of Crystal Ball. Once OptQuest is open, the step-by-step wizard guides the process of defining constraints, specifying the objective of the outcome, and setting the requirements. In the first step, OptQuest shows you all of the model's 24 decision variables, which you will use in your optimization.

3.4.3 Defining Optimization Constraints

In the second step, you can set a constraint on your decision variables. A constraint restricts the decision variables to specific combinations of values. In this case, you have been told that the staff hours per day cannot exceed 200, so the sum of all of the decision variables (the hours per period) should be less than or equal to 200.

You define constraints in the Constraints window (Figure 9), which you can open using the Constraints option in the Tools menu or by clicking on either the Wizard or Constraints button on the OptQuest tool bar. The left side of the Constraints window is the Constraint editor, and the right side of the Constraints window contains buttons that insert decision variables or create an equation that sums all the decision variables. To define this constraint, you can click on Sum All Variables and make them less than or equal to 225.



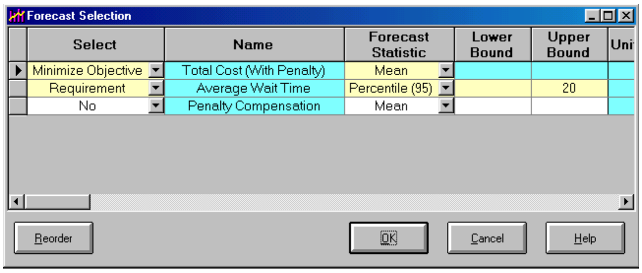
Constraints

```
12am + 1am + 2am + 3am + 4am + 5am + 6am + 7am + 8am +
9am + 10am + 11am + 12pm + 1pm + 2pm + 3pm + 4pm +
5pm + 6pm + 7pm + 8pm + 9pm + 10pm + 11pm <= 225
```

Figure 9: OptQuest Constraints Window

3.4.4 Defining the Objectives and Requirements

The final task in OptQuest is to define the objective of the optimization. You define the objective in the Forecast Selection window (Figure 10), which you can open using the Forecasts option in the Tools menu or by clicking on either the Wizard or the Forecast Selection button on the OptQuest tool bar. All model forecasts are displayed in this window, and you select which forecast to minimize or maximize. For this project, your goal is to minimize the Total Cost (With Penalty) forecast.



Forecast Selection

Select	Name	Forecast Statistic	Lower Bound	Upper Bound	Uni
Minimize Objective	Total Cost (With Penalty)	Mean			
Requirement	Average Wait Time	Percentile (95)		20	
No	Penalty Compensation	Mean			

Figure 10: Forecast Selection Window

You can also use this window to set a requirement, which is a restriction on a forecast statistic. While constraints ensure that OptQuest will only run optimizations using satisfactory combinations of decision variables, you are in no way assured of a desirable, or feasible, solution. By setting a requirement on one or more forecasts, you ensure that OptQuest will reject all solutions that do not meet your set criteria. In this project, you want to make sure that an acceptable percentage of all calls fall below the 20-

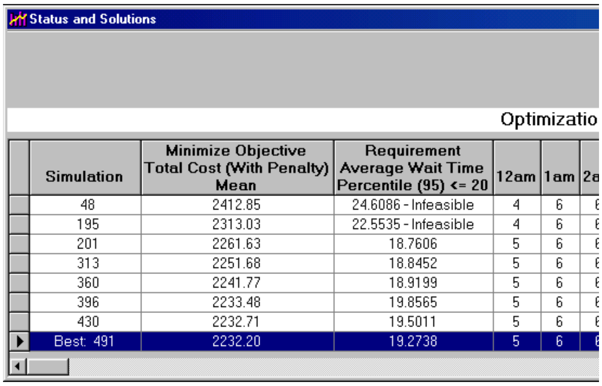
second contract penalty. Senior management would be satisfied with a penalty rate of 5% or less, so you set a requirement on Average Wait Time for 95% of all calls to fall below the 20-second hold time.

3.4.5 Running an Optimization

At the basic level, OptQuest selects a value for each decision variable, enters those values into your spreadsheet, runs a Monte Carlo simulation on the spreadsheet, records the results, and repeats the process. You could manually perform this sort of analysis, but as you increase the number of decision variables, the number of possible variable combinations becomes unwieldy.

On a more advanced level, OptQuest does a much better job at finding optimal solutions than is possible with manual calculations. OptQuest surpasses the limitations of genetic algorithm optimizers because it uses multiple, complementary search methodologies, including advanced tabu search and scatter search, to help find the best global solutions. While running solutions, OptQuest also checks for compliance with the constraints and requirements. In addition, OptQuest applies adaptive and neural network technologies to help it learn from past optimizations so it can achieve better results in less time.

As you run an optimization, you have several ways to view your progress. The Status and Solutions window (Figure 11) shows you the progress of your optimization, how many solutions OptQuest has run, and what the current best result is. Each time OptQuest generates a new best result, it adds a line to the table so you can view past best results.



	Simulation	Minimize Objective Total Cost (With Penalty) Mean	Requirement Average Wait Time Percentile (95) <= 20	12am	1am	2a
	48	2412.85	24.6086 - Infeasible	4	6	6
	195	2313.03	22.5535 - Infeasible	4	6	6
	201	2261.63	18.7606	5	6	6
	313	2251.68	18.8452	5	6	6
	360	2241.77	18.9199	5	6	6
	396	2233.48	19.8565	5	6	6
	430	2232.71	19.5011	5	6	6
▶	Best: 491	2232.20	19.2738	5	6	6

Figure 11: OptQuest Status and Solutions Chart

The Performance Graph (Figure 12) is useful for gauging OptQuest's progress. As the graph levels off and remains unchanged, you can decide whether or not you have converged on an optimal solution.

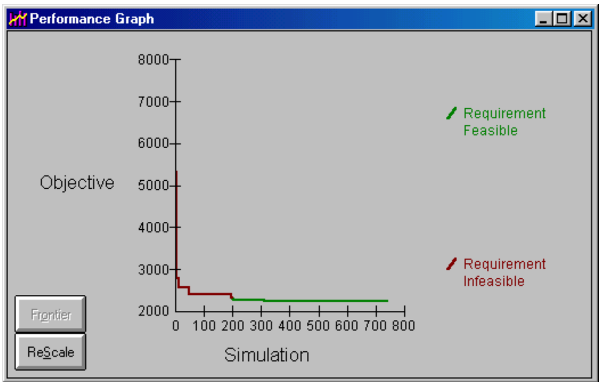
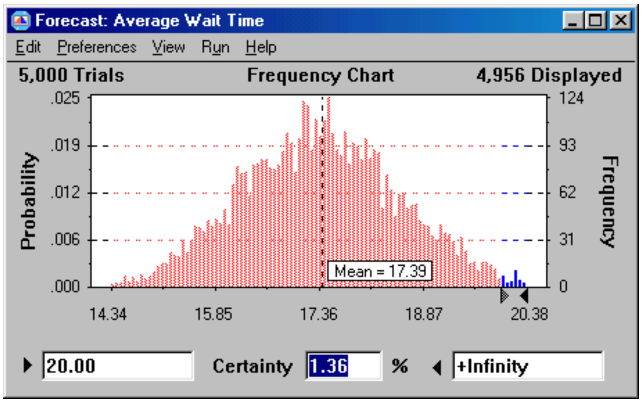


Figure 12: OptQuest Performance Graph

3.4.6 Analyzing the Optimization Results

Once you have completed the optimization, OptQuest copies the best decision variable values back to the call center spreadsheet model. You can then view your model and the forecast chart for the optimal outcome. Optionally, you can use OptQuest's Solution Analysis feature to compare the optimal and sub-optimal results for any useful trends in decision variable results.

After 740 optimizations, Crystal Ball has converged on an optimal solution. OptQuest found a solution for 222 staff hours where the certainty of a penalty (calls on hold over 20 seconds) was less than 2%, and the total daily cost of the call center operation was $2,231.34. OptQuest also identified several similar staff configurations (Figure 13) that would satisfy the constraints and requirements. Your Six Sigma team can report these results to the senior management and begin the process of implementing the new staffing allocation.



20.00 Certainty 1.36 % +Infinity

Figure 13: Optimized Average Wait Time

3.5 The Control Phase

The Control phase completes the Six Sigma methodology. In this continuing process, members of Telecorp monitor the status of the call center to detect when fine tuning or new improvements are necessary. For example, if DecSoft releases a new product version, the current staffing balance may need to be adjusted for a temporary increase in support calls following the product release.

4 CONCLUSION

Monte Carlo simulation and optimization have a crucial role to play in multiple phases of a Six Sigma analysis project. Without the ability to run simulations, spreadsheets alone can provide only a limited understanding of the variability surround a process or project. Crystal Ball Professional Edition overcomes the limitations of spreadsheets by enhancing Excel with user-friendly tools for Monte Carlo simulation, global optimization, and time-series forecasting. By moving to a probabilistic methodology, Six Sigma analysts can better quantify the effects of variability and can implement process improvements with greater insight and confidence.

APPENDIX: CRYSTAL BALL RESOURCES

A variety of Six Sigma models are available for free on the Decisioneering web site's example model library <www.crystalball.com/models/model_index.html>. Other free resources on the site include white papers, articles, tutorials, case studies, and Internet links. Free downloadable trial versions of the software and tutorials are available to all site visitors.

REFERENCES

Anderson, D. R., Sweeney, D. J., and T. A. Williams. 2003. *An Introduction to Management Science, Quantitative Approaches to Decision Making, 10th Edition*. Mason, OH: South-Western.

Kelton, W. D., and A. Law. 1991. *Simulation Modeling & Analysis*. New York: McGraw Hill, Inc.

Pyzdek, T. 2003. *The Six Sigma Handbook*. New York: McGraw Hill, Inc.

AUTHOR BIOGRAPHIES

LAWRENCE GOLDMAN is a product marketing manager at Decisioneering in Denver, CO. He joined the company in June 1997 as a program manager with the product development group and has held positions as webmaster, web producer, trainer, and newsletter editor. His current focus is educational and training materials and seminars for Crystal Ball. Prior to working for Decisioneering, Lawrence was employed as a trainer and technical support assistant for Techbase, a company specializing in mining and engineering database software. He has an M.S. in geology from the University of Cincinnati and a B.A. in geology from Cornell University. His email address and Web address are <lgoldman@crystalball.com> and <www.crystalball.com>.

ETHAN EVANS-HILTON is a trainer and product consultant at Decisioneering in Denver, CO. He joined the company in April 2003. His current focus is centered on Crystal Ball integration into the Six Sigma environment. Prior to working for Decisioneering, Ethan was employed as a trainer and instructional designer for TeleTech Inc., a company specializing in customer care management solutions for global clientele. He received a B.A. in education from King's College in London, England and has taught numerous classes in customer care management, technical courses, and corporate methodology. His email address and Web address are <ehilton@crystalball.com> and <www.crystalball.com>.

HILARY EMMETT is a senior product consultant with Decisioneering (UK) Ltd. in London, UK. Emmett joined Decisioneering in June of 2000 as an account manager in Denver, CO. In the intervening years, she has held positions as technical support engineer, sales engineer, and trainer. She has provided consulting, training, and Visual Basic for Applications (VBA) modeling services for a variety of clients, with an emphasis in the use of simulation for Six Sigma applications. Emmett joined the UK team in early 2003 as part of Decisioneering's commitment to provide expanded analytical services to customers in Europe, Asia, the Middle East, and Africa. Emmett received a B.A. in mathematics from Graceland University in Lamoni, Iowa. Her email address and Web address are <hemmett@crystalball.com> and <www.crystalball.com>.