Guide to Using

@RISK for Six Sigma

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Welcome

Welcome to @RISK, the world's most powerful risk analysis tool! @RISK has long been used to analyze risk and uncertainty in any industry. With applications in finance, oil and gas, insurance, manufacturing, healthcare, pharmaceuticals, science and other fields, @RISK is as flexible as Excel itself. Every day tens of thousands of professionals use @RISK to estimate costs, analyze NPV and IRR, study real options, determine pricing, explore for oil and resources, and much more.

A key application of @RISK is Six Sigma and quality analysis. Whether it's in DMAIC, Design for Six Sigma (DFSS), Lean projects, Design of Experiments (DOE), or other areas, uncertainty and variable lies at the core of any Six Sigma analysis. @RISK uses Monte Carlo simulation to identify, measure, and root out the causes of variability in your production and service processes. A full suite of capability metrics gives you the calculations you need to step through any Six Sigma method quickly and accurately. Charts and tables clearly show Six Sigma statistics, making it easy and effective to illustrate this powerful technique to management. The Industrial edition of @RISK adds RISKOptimizer to your Six Sigma analyses for optimization of project selection, resource allocation, and more.

Industries ranging from engine manufacturing to precious metals to airlines and consumer goods are using @RISK every day to improve their processes, enhance the quality of their products and services, and save millions. This guide will walk you through the @RISK Six Sigma functions, statistics, charts and reports to show you how @RISK can be put to work at any stage of a Six Sigma project. Example case studies round out the guide, giving you pre-built models you can adapt to your own analyses.

The standard features of @RISK, such as entering distribution functions, fitting distributions to data, running simulations and performing sensitivity analyses, are also applicable to Six Sigma models. When using @RISK for Six Sigma modeling you should also familiarize yourself with these features by reviewing the @RISK for Excel Users Guide and on-line training materials.

Table of Contents

Chapter 1: Overview of @RISK and Six Sigma Methodologies 1
Introduction3
Six Sigma Methodologies7
@RISK and Six Sigma9
Chapter 2: Using @RISK for Six Sigma 13
Introduction15
RiskSixSigma Property Function17
Six Sigma Statistics Functions21
Six Sigma and the Results Summary Window35
Six Sigma Markers on Graphs37
Case Studies 39
Example 1 – Design of Experiments: Catapult41
Example 2 – Design of Experiments: Welding47
Example 3 – Design of Experiments with Optimization53
Example 4 – DFSS: Electrical Design61
Example 5 – Lean Six Sigma: Analysis of Current State – Quotation Process
Example 6 – DMAIC: Roll Through Yield Analysis73
Example 7 – Six Sigma DMAIC Failure Rate77

Chapter 1: Overview of @RISK and Six Sigma Methodologies

Introduction	3
What is Six Sigma?	3
The Importance of Variation	5
Six Sigma Methodologies	7
Six Sigma / DMAIC	7
Design for Six Sigma (DFSS)	7
Lean or Lean Six Sigma	8
@RISK and Six Sigma	9
@RISK and DMAIC	9
@RISK and Design for Six Sigma (DFSS)	10
@RISK and Lean Six Sigma	11
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Introduction

In today's competitive business environment, quality is more important than ever. Enter @RISK, the perfect companion for any Six Sigma or quality professional. This powerful solution allows you to quickly analyze the effect of variation within processes and designs.

In addition to Six Sigma and quality analysis, @RISK can be used to analyze any situation in which there is uncertainty. Applications include analysis of NPV, IRR, and real options, cost estimation, portfolio analysis, oil and gas exploration, insurance reserves, pricing, and much more. To learn more about @RISK in other applications, and the use of @RISK in general, refer to the @RISK User's Guide included with your software.

What is Six Sigma?

Six Sigma is a set of practices to systematically improve processes by **reducing process variation** and thereby eliminating **defects**. A defect is defined as **nonconformity of a product or service to its specifications**. While the particulars of the methodology were originally formulated by Motorola in the mid-1980s, Six Sigma was heavily inspired by six preceding decades of quality improvement methodologies such as quality control, TQM, and Zero Defects. Like its predecessors, Six Sigma asserts the following:

- Continuous efforts to reduce variation in process outputs is key to business success
- Manufacturing and business processes can be measured, analyzed, improved and controlled
- Succeeding at achieving sustained quality improvement requires commitment from the entire organization, particularly from top-level management

Six Sigma is driven by data, and frequently refers to "X" and "Y" variables. X variables are simply independent input variables that affect the dependent output variables, Y. Six Sigma focuses on identifying and controlling variation in X variables to maximize quality and minimize variation in Y variables.

The term Six Sigma or 60 is very descriptive. The Greek letter sigma (o) signifies standard deviation, an important measure of variation. The variation of a process refers to how tightly all outcomes are clustered around the mean. The probability of creating a defect can be estimated and translated into a "Sigma level." The higher the Sigma level, the better the performance. Six Sigma refers to having six standard deviations between the average of the process center and the closest specification limit or service level. That translates to fewer than 3.4 defects per one million opportunities (DPMO). The chart below illustrates Six Sigma graphically.



Six sigmas – or standard deviations – from the mean.

The cost savings and quality improvements that have resulted from Six Sigma corporate implementations are significant. Motorola has reported \$17 billion in savings since implementation in the mid 1980s. Lockheed Martin, GE, Honeywell, and many others have experienced tremendous benefits from Six Sigma.

The Importance of Variation

Too many Six Sigma practitioners rely on static models that don't account for inherent uncertainty and variability in their processes or designs. In the quest to maximize quality, it's vital to consider as many scenarios as possible.

That's where @RISK comes in. @RISK uses Monte Carlo simulation to analyze thousands of different possible outcomes, showing you the likelihood of each occurring. Uncertain factors are defined using over 35 probability distribution functions, which accurately describe the possible range of values your inputs could take. What's more, @RISK allows you to define Upper and Lower Specification Limits and Target values for each output, and comes complete with a wide range of Six Sigma statistics and capability metrics on those outputs.

@RISK Industrial edition also includes RISKOptimizer, which combine the power of Monte Carlo simulation with genetic algorithmbased optimization. This gives you the ability to tackle optimization problems like that have inherent uncertainty, such as:

- resource allocation to minimize cost
- project selection to maximize profit
- optimize process settings to maximize yield or minimize cost
- optimize tolerance allocation to maximize quality
- optimize staffing schedules to maximize service

The figure here illustrates how @RISK helps to identify, quantify, and hone in on variation in your processes.



Six Sigma Methodologies

@RISK can be used in a variety of Six Sigma and related analyses. The three principal areas of analysis are:

- Six Sigma / DMAIC / DOE
- Design for Six Sigma (DFSS)
- Lean or Lean Six Sigma

Six Sigma / DMAIC

When most people refer to Six Sigma, they are in fact referring to the DMAIC methodology. The DMAIC methodology should be used when a product or process is in existence but is not meeting customer specification or is not performing adequately.

DMAIC focuses on evolutionary and continuous improvement in manufacturing and services processes, and is almost universally defined as comprising of the following five phases: **Define, Measure, Analyze, Improve and Control:**

- 1) **Define** the project goals and customer (internal and external Voice of Customer or VOC) requirements
- 2) Measure the process to determine current performance
- 3) Analyze and determine the root cause(s) of the defects
- 4) **Improve** the process by eliminating defect root causes
- 5) Control future process performance

Design for Six Sigma (DFSS)

DFSS is used to design or re-design a product or service from the ground up. The expected process Sigma level for a DFSS product or service is at least 4.5 (no more than approximately 1 defect per thousand opportunities), but can be 6 Sigma or higher depending on the product. Producing such a low defect level from product or service launch means that customer expectations and needs (Critical-To-Qualities or CTQs) must be completely understood before a design can be completed and implemented. Successful DFSS programs can reduce unnecessary waste at the planning stage and bring products to market more quickly.

Unlike the DMAIC methodology, the phases or steps of DFSS are not universally recognized or defined -- almost every company or training organization will define DFSS differently. One popular Design for Six Sigma methodology is called **DMADV**, and retains the same number of letters, number of phases, and general feel as the DMAIC acronym. The five phases of DMADV are defined as: **Define**, **Measure**, **Analyze**, **Design and Verify**:

- 1) **Define** the project goals and customer (internal and external VOC) requirements
- 2) **Measure** and determine customer needs and specifications; benchmark competitors and industry
- 3) Analyze the process options to meet the customer needs
- 4) **Design** (detailed) the process to meet the customer needs
- 5) **Verify** the design performance and ability to meet customer needs

Lean or Lean Six Sigma

"Lean Six Sigma" is the combination of Lean manufacturing (originally developed by Toyota) and Six Sigma statistical methodologies in a synergistic tool. Lean deals with improving the speed of a process by reducing waste and eliminating non-value added steps. Lean focuses on a customer "pull" strategy, producing only those products demanded with "just in time" delivery. Six Sigma improves performance by focusing on those aspects of a process that are critical to quality from the customer perspective and eliminating variation in that process. Many service organizations, for example, have already begun to blend the higher quality of Six Sigma with the efficiency of Lean into Lean Six Sigma.

Lean utilizes "Kaizen events" -- intensive, typically week-long improvement sessions -- to quickly identify improvement opportunities and goes one step further than a tradition process map in its use of value stream mapping. Six Sigma uses the formal DMAIC methodology to bring measurable and repeatable results.

Both Lean and Six Sigma are built around the view that businesses are composed of processes that start with customer needs and should end with satisfied customers using your product or service.

@RISK and Six Sigma

Whether it's in DMIAC, Design of Experiments or Lean Six Sigma, uncertainty and variability lie at the core of any Six Sigma analysis. @RISK uses Monte Carlo simulation to identify, measure, and root out the causes of variability in your production and service processes. Each of the Six Sigma methodologies can benefit from @RISK throughout the stages of analysis.

@RISK and DMAIC

@RISK is useful at each stage of the DMAIC process to account for variation and hone in on problem areas in existing products.

- Define. Define your process improvement goals, incorporating customer demand and business strategy. Value-stream mapping, cost estimation, and identification of CTQs (Critical-To-Qualities) are all areas where @RISK can help narrow the focus and set goals. Sensitivity analysis in @RISK zooms in on CTQs that affect your bottom-line profitability.
- 2) Measure. Measure current performance levels and their variations. Distribution fitting and over 35 probability distributions make defining performance variation accurate. Statistics from @RISK simulations can provide data for comparison against requirements in the Analyze phase.
- 3) Analyze. Analyze to verify relationship and cause of defects, and attempt to ensure that all factors have been considered. Through @RISK simulation, you can be sure all input factors have been considered and all outcomes presented. You can pinpoint the causes of variability and risk with sensitivity and scenario analysis, and analyze tolerance. Use @RISK's Six Sigma statistics functions to calculate capability metrics which identify gaps between measurements and requirements. Here we see how often products or processes fail and get a sense of reliability.

- 4) Improve. Improve or optimize the process based upon the analysis using techniques like Design of Experiments. Design of Experiments includes the design of all information-gathering exercises where variation is present, whether under the full control of the experimenter or not. Using @RISK simulation, you can test different alternative designs and process changes. @RISK is also used for reliability analysis and using RISKOptimizer resource optimization at this stage.
- 5) Control. Control to ensure that any variances are corrected before they result in defects. In the Control stage, you can set up pilot runs to establish process capability, transition to production and thereafter continuously measure the process and institute control mechanisms. @RISK automatically calculates process capability and validates models to make sure that quality standards and customer demands are met.

@RISK and Design for Six Sigma (DFSS)

One of @RISK's main uses in Six Sigma is with DFSS at the planning stage of a new project. Testing different processes on physical manufacturing or service models or prototypes can be cost prohibitive. @RISK allows engineers to simulate thousands of different outcomes on models without the cost and time associated with physical simulation. @RISK is helpful at each stage of a DFSS implementation in the same way as the DMAIC steps. Using @RISK for DFSS gives engineers the following benefits:

- Experiment with different designs / Design of Experiments
- Identify CTQs
- Predict process capability
- Reveal product design constraints
- Cost estimation
- Project selection using RISKOptimizer to find the optimal portfolio
- Statistical tolerance analysis
- Resource allocation using RISKOptimizer to maximize efficiency

@RISK and Lean Six Sigma

@RISK is the perfect companion for the synergy of Lean manufacturing and Six Sigma. "Quality only" Six Sigma models may fail when applied to reducing variation in a single process step, or to processes which do not add value to the customer. For example, an extra inspection during the manufacturing process to catch defective units may be recommended by a Six Sigma analysis. The waste of processing defective units is eliminated, but at the expense of adding inspection which is in itself waste. In a Lean Six Sigma analysis, @RISK identifies the causes of these failures. Furthermore, @RISK can account for uncertainty in both quality (ppm) and speed (cycle time) metrics.

@RISK provides the following benefits in Lean Six Sigma analysis:

- Project selection using RISKOptimizer to find the optimal portfolio
- Value stream mapping
- Identification of CTQs that drive variation
- Process optimization
- Uncover and reduce wasteful process steps
- Inventory optimization using RISKOptimizer to minimize costs
- Resource allocation using RISKOptimizer to maximize efficiency

Chapter 2: Using @RISK for Six Sigma

Introduction	15
RiskSixSigma Property Function	17
Entering a RiskSixSigma Property Function	18
Six Sigma Statistics Functions	21
RiskCp	23
RiskCpm	23
RiskCok	24
RiskCpkLower	25
RiskCpkUpper	25
RiskDPM	
RiskK	
RiskLowerXBound	
RiskPNC	
RiskPNCLower	
RiskPNCUpper	
RiskPPMLower	
RiskPPMUpper	
RiskSigmalLevel	
RiskUpperXBound	
RiskYV	
RiskZlower	
RiskZMin	
RiskZUpper	
Six Sigma and the Results Summary Window	35
Six Sigma Markers on Graphs	37

Introduction

@RISK's standard simulation capabilities have been enhanced for use in Six Sigma modeling through the addition of four key features. These are:

- 1) The **RiskSixSigma** property function for entering specification limits and target values for simulation outputs
- 2) Six Sigma statistics functions, including process capability indices such as RiskCpk, RiskCpm and others which return Six Sigma statistics on simulation results directly in spreadsheet cells
- 3) New columns in the Results Summary window which give Six Sigma statistics on simulation results in table form
- 4) **Markers** on graphs of simulation results which display specification limits and the target value

The standard features of @RISK, such as entering distribution functions, fitting distributions to data, running simulations and performing sensitivity analyses, are also applicable to Six Sigma models. When using @RISK for Six Sigma modeling you should also familiarize yourself with these features by reviewing the @RISK for Excel Users Guide and on-line training materials.

RiskSixSigma Property Function

In an @RISK simulation the **RiskOutput** function identifies a cell in a spreadsheet as a simulation output. A distribution of possible outcomes is generated for every output cell selected. These probability distributions are created by collecting the values calculated for a cell for each iteration of a simulation.

When Six Sigma statistics are to be calculated for an output, the **RiskSixSigma** property function is entered as an argument to the RiskOutput function. This property function specifies the lower specification limit, upper specification limit, target value, long term shift, and the number of standard deviations for the six sigma calculations for an output. These values are used in calculating six sigma statistics displayed in the Results window and on graphs for the output. For example:

RiskOutput("Part Height",,RiskSixSigma(.88,.95,.915,1.5,6))

specifies an LSL of .88, a USL of .95, target value of .915, long term shift of 1.5, and a number of standard deviations of 6 for the output Part Height. You can also use cell referencing in the RiskSixSigma property function.

These values are used in calculating Six Sigma statistics displayed in the Results window and as markers on graphs for the output.

When @RISK detects a RiskSixSigma property function in an output, it automatically displays the available Six Sigma statistics on the simulation results for the output in the Results Summary window and adds markers for the entered LSL, USL and Target values to graphs of simulation results for the output.

Entering a RiskSixSigma Property Function

The RiskSixSigma property function can be typed directly into a cell's formula as an argument to a RiskOutput function. Alternatively the **Excel Function Wizard** can be used to assist in entering the function directly in a cell formula.



@RISK's **Insert Function command** allows you to quickly insert a RiskOutput function with an added RiskSixSigma property function. Simply select the **Output** menu **RiskOutput (Six Sigma Format)** command from @RISK's Insert Function menu and the appropriate function will be added to the formula in the active cell.



Output Properties – Six Sigma Tab

@RISK also provides a Function Properties window which can be used to enter a RiskSixSigma property function into a RiskOutput function. This window has a tab titled Six Sigma that has entries for the arguments to the RiskSixSigma function. Access the RiskOutput Function Properties window by clicking on the properties button in the @RISK Add Output window.

Output Properties: C82			×
Options Convergence	Six Sigma		
Calculate Capability	Metrics For This	Output	
Specification Limits			
LSL	85		
USL	125		
<u>T</u> arget	105		
Other			
Use Long-Term S	hift		
S <u>h</u> ift	1.5		
Upper/Lower X Boun	d		
# St <u>d</u> Dev	1		
<u> </u>		ОК	Cancel

The default settings for an output to be used in Six Sigma calculations are set on the Six Sigma tab. These properties include:

- **Calculate Capability Metrics for This Output**. Specifies that capability metrics will be displayed in reports and graphs for the output. These metrics will use the entered LSL, USL and Target values.
- LSL, USL and Target. Sets the LSL (Lower Specification Limit), USL (Upper Specification Limit) and Target values for the output.
- **Use Long Term Shift and Shift.** Specifies an optional shift for calculation of long-term capability metrics.
- **Upper/Lower X Bound.** The number of standard deviations to the right or the left of the mean for calculating the upper or lower X-axis values.

Entered Six Sigma settings result in a **RiskSixSigma** property function being added to the RiskOutput function. Only outputs which contain a RiskSixSigma property function will display Six Sigma markers and statistics in graphs and reports. @RISK Six Sigma statistics functions in Excel worksheets can reference any output cell that contains a RiskSixSigma property function.

Note: All graphs and reports in @RISK use the LSL, USL, Target, Long Term Shift and the Number of Standard Deviations values from RiskSixSigma property functions that existed at the start of a simulation. If you change the specification limits for an output (and its associated RiskSixSigma property function), you need to re-run the simulation to view changed graphs and reports.

Six Sigma Statistics Functions

A set of @RISK statistics functions return a desired **Six Sigma statistic** on a simulation output. For example, the function *RiskCPK(A10)* returns the CPK value for the simulation output in Cell A10. These functions are updated real-time as a simulation is running. These functions are similar to the standard @RISK statistics functions (such as RiskMean) in that they calculate statistics on simulation results; however, these functions calculate statistics commonly required in Six Sigma models. These functions can be used anywhere in spreadsheet cells and formulas in your model.

Some important items to note about @RISK's Six Sigma statistics functions are as follows:

- If a cell reference is entered as the first argument to the statistics function and that cell has a **RiskOutput function with a RiskSixSigma property function**, @RISK will use the LSL, USL, Target, Long Term Shift and Number of Standard Deviation values from that output when calculating the desired statistic.
- If a cell reference is entered as the first argument, the cell <u>does not</u> have to be a simulation output identified with a RiskOutput function. However, if it is not an output, **an optional RiskSixSigma property function needs to be added to the statistic function itself** so @RISK will have the necessary settings for calculating the desired statistic.
- Entering an optional RiskSixSigma property function directly in a statistics function causes **@RISK to override any Six Sigma settings specified in the RiskSixSigma property function in a referenced simulation output.** This allows you to calculate Six Sigma statistics at differing LSL, USL, Target, Long Term Shift and Number of Standard Deviation values for the same output.
- If a **name is entered instead of cellref**, @RISK first checks for an output with the entered name, and the reads its RiskSixSigma property function settings. It is up to the user to ensure that unique names are given to outputs referenced in statistics functions.
- The **Sim#** argument entered selects the simulation for which a statistic will be returned when multiple simulations are run. This argument is optional and can be omitted for single simulation runs.

- When an optional RiskSixSigma property function is entered directly in a Six Sigma statistics function, different arguments from the property function are used depending on the calculation being performed.
- Statistics functions located in template sheets used for creating custom reports on simulation results are only updated when a simulation is completed.

Entering Six Sigma Statistics Functions

@RISK's **Insert Function command** allows you to quickly insert a Six Sigma Statistics Function. Simply select the **Six Sigma command** in the **Statistics function category** on the @RISK's Insert Function menu, then select the desired function. The selected function will be added to the formula in the active cell.



RiskCp

Description	RiskCp (<i>cellref or output name, Sim#, RiskSixSigma</i> (<i>LSL,USL, Target,LongTerm Shift,Number of Standard Deviations</i>)) calculates the Process Capability for cellref or output name in Sim#, optionally using the LSL and USL in the included RiskSixSigma property function. This function will calculate the quality level of the specified output and what it is potentially capable of producing.
Examples	RiskCP(A10) returns the Process Capability for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskCP(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the Process Capability for the output cell A10, using an LSL of 100 and a USL of 120.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskCpm

Description	RiskCpm (<i>cellref or output name, Sim#, RiskSixSigma</i> (<i>LSL,USL, Target,LongTerm Shift,Number of Standard Deviations</i>)) returns the Taguchi capability index for cellref or output name in Sim #, optionally using the USL, LSL, and the Target in the RiskSixSigma property function. This function is essentially the same as the Cpk but incorporates the target value which in some cases may or may not be within the specification limits.
Examples	RiskCpm(A10) returns the Taguchi capability index for cell A10. RiskCpm(A10,, RiskSixSigma(100, 120, 110, 0, 6)) returns the Taguchi capability index for cell A10, using an USL of 120, LSL of 100, and a Target of 110.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskCpk

Description	RiskCpk(<i>cellref or output name, Sim#, RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of Standard Deviations)</i>) calculates the Process Capability Index for cellref or output name in Sim# optionally using the LSL and USL in the included RiskSixSigma property function. This function is similar to the Cp but takes into account an adjustment of the Cp for the effect of an off-centered distribution. As a formula, Cpk = either (USL-Mean) / (3 x sigma) or (Mean-LSL) / (3 x sigma) whichever is the smaller.
Examples	RiskCpk(A10) returns the Process Capability Index for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskCpk(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the Process Capability Index for the output cell A10, using an LSL of 100 and a USL of 120.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

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RiskCpkLower

Description	RiskCpkLower(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the one-sided capability index based on the Lower Specification limit for cellref or output name in Sim# optionally using the LSL in the RiskSixSigma property function.
Examples	RiskCpkLower(A10) returns the one-sided capability index based on the Lower Specification limit for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskCpkLower(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the one-sided capability index for the output cell A10, using an LSL of 100.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskCpkUpper

Description	RiskCpkUpper(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the one-sided capability index based on the Upper Specification limit for cellref or output name in Sim# optionally using the USL in the included RiskSixSigma property function.
Examples	RiskCpkUpper(A10) returns the one-sided capability index based on the Upper Specification limit for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskCpkUpper(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the Process Capability Index for the output cell A10, using an LSL of 100.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskDPM

Description	RiskDPM(<i>cellref</i> or <i>output</i> name, Sim#, RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of Standard Deviations)) calculates the defective parts per million for cellref or output name in Sim# optionally using the LSL and USL in the included RiskSixSigma property function.
Examples	 RiskDPM(A10) returns the defective parts per million for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10. RiskDPM(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the defective parts per million for the output cell A10, using an LSL of 100 and USL of 120.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskK

Description	RiskK(<i>cellref or output name, Sim#, RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of Standard Deviations)</i>) calculates a measure of process center for cellref or output name in Sim# optionally using the LSL and USL in the included RiskSixSigma property function.
Examples	 RiskK(A10) returns a measure of process center for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10. RiskK(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns a measure of process center for the output cell A10, using an LSL of 100 and USL of 120.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskLowerXBound

Description	RiskLowerXBound (<i>cellref or output name, Sim#,</i> <i>RiskSixSigma</i> (<i>LSL, USL, Target, Long Term Shift, Number of</i> <i>Standard Deviations</i>)) returns the lower X-value for a specified number of standard deviations from the mean for cellref or output name in Sim #, optionally using the Number of Standard Deviations in the RiskSixSigma property function.
Examples	 RiskLowerXBound(A10) returns the lower X-value for a specified number of standard deviations from the mean for cell A10. RiskLowerXBound(A10,, RiskSixSigma(100, 120, 110, 1.5, 6)) returns the lower X-value for -6 standard deviations from the mean for cell A10, using a Number of Standard Deviations of 6.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskPNC

Description	RiskPNC(<i>cellref or output name, Sim#, RiskSixSigma(LSL,USL, Target, Long Term Shift, Number of Standard Deviations))</i> calculates the total probability of defect outside the lower and upper specification limits for cellref or output name in Sim# optionally using the LSL, USL and Long Term Shift in the included RiskSixSigma property function.
Examples	RiskPNC(A10) returns the probability of defect outside the lower and upper specification limits for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskPNC(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the probability of defect outside the lower and upper specification limits for the output cell A10, using an LSL of 100, USL of 120 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskPNCLower

Description	RiskPNCLower(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL, USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the probability of defect outside the lower specification limits for cellref or output name in Sim# optionally using the LSL, USL and LongTerm Shift in the included RiskSixSigma property function.
Examples	RiskPNCLower (A10) returns the probability of defect outside the lower specification limits for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskPNCLower(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the probability of defect outside the lower specification limits for the output cell A10, using an LSL of 100, USL of 120 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskPNCUpper

Description	RiskPNCUpper(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the probability of defect outside the upper specification limits for cellref or output name in Sim# optionally using the LSL, USL and LongTerm Shift in the included RiskSixSigma property function.
Examples	RiskPNCUpper(A10) returns the probability of defect outside the upper specification limits for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskPNCUpper(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the probability of defect outside the upper specification limits for the output cell A10, using an LSL of 100, USL of 120 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskPPMLower

Description	RiskPPMLower (<i>cellref or output name, Sim#,</i> <i>RiskSixSigma</i> (<i>LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations</i>)) calculates the number of defects below the lower specification limit for cellref or output name in Sim# optionally using the LSL and LongTerm Shift in the included RiskSixSigma property function.
Examples	 RiskPPMLower(A10) returns the number of defects below the lower specification limit for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10. RiskPPMLower(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the number of defects below the lower specification limit for the output cell A10, using an LSL of 100 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskPPMUpper

Description	RiskPPMUpper(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the number of defects above the upper specification limit for cellref or output name in Sim# optionally using the USL and LongTerm Shift in the included RiskSixSigma property function.
Examples	RiskPPMUpper(A10) returns the number of defects above the upper specification limit for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskPPMUpper(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the number of defects above the upper specification limit for the output cell A10, using an USL of 120 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskSigmalLevel

Description	RiskSigmaLevel (<i>cellref or output name, Sim#,</i> <i>RiskSixSigma</i> (<i>LSL, USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates the Process Sigma level for cellref or output name in Sim# optionally using the USL and LSL and Long Term Shift in the included RiskSixSigma property function. (Note: This function assumes that the output is normally distributed and centered within the specification limits.)
Examples	RiskSigmaLevel(A10) returns the Process Sigma level for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskSigmaLevel(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the Process Sigma level for the output cell A10, using an USL of 120, LSL of 100, and a Long Term Shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included
RiskUpperXBound

Description	RiskUpperXBound (<i>cellref or output name, Sim#,</i> <i>RiskSixSigma</i> (<i>LSL, USL, Target, Long Term Shift, Number of</i> <i>Standard Deviations</i>)) returns the upper X-value for a specified number of standard deviations from the mean for cellref or output name in Sim #, optionally using the Number of Standard Deviations in the RiskSixSigma property function.
Examples	 RiskUpperXBound(A10) returns the upper X-value for a specified number of standard deviations from the mean for cell A10. RiskUpperXBound(A10,, RiskSixSigma(100, 120, 110, 1.5, 6)) returns the upper X-value for -6 standard deviations from the mean for cell A10, using a Number of Standard Deviations of 6.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskYV

Description	RiskYV(<i>cellref or output name, Sim#, RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of Standard Deviations)</i>) calculates the yield or the percentage of percentage of the process that is free of defects for cellref or output name in Sim# optionally using the LSL, USL and LongTerm Shift in the included RiskSixSigma property function.
Examples	RiskYV(A10) returns the yield or the percentage of the process that is free of defects for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskYV(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the yield or the percentage of the process that is free of defects for the output cell A10, using an LSL of 100, USL of 120 and LongTerm shift of 1.5.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskZlower

Description	RiskZlower(<i>cellref or output name, Sim#, RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of Standard Deviations)</i>) calculates how many standard deviations the Lower Specification Limit is from the mean for cellref or output name in Sim# optionally using the LSL in the included RiskSixSigma property function.
Examples	RiskZlower(A10) returns how many standard deviations the Lower Specification Limit is from the mean for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskZlower(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns how many standard deviations the Lower Specification Limit is from the mean for the output cell A10, using an LSL of 100.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskZMin

Description	RiskZMin (<i>cellref or output name, Sim#, RiskSixSigma</i> (<i>LSL, USL, Target, LongTerm Shift, Number of Standard Deviations</i>) calculates the minimum of Z-Lower and Z-Upper for cellref or output name in Sim# optionally using the USL and LSL in the included RiskSixSigma property function.
Examples	RiskZMin(A10) returns the minimum of Z-Lower and Z-Upper for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskZMin(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns the minimum of Z-Lower and Z-Upper for the output cell A10, using a USL of 120 and LSL of 100.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

RiskZUpper

Description	RiskZUpper(<i>cellref or output name, Sim#,</i> <i>RiskSixSigma(LSL,USL, Target,LongTerm Shift,Number of</i> <i>Standard Deviations)</i>) calculates how many standard deviations the Upper Specification Limit is from the mean for cellref or output name in Sim# optionally using the USL in the included RiskSixSigma property function.
Examples	RiskZUpper(A10) returns how many standard deviations the Upper Specification Limit is from the mean for the output cell A10. A RiskSixSigma property function needs to be entered in the RiskOutput function in Cell A10.
	RiskZUpper(A10, ,RiskSixSigma(100,120,110,1.5,6)) returns how many standard deviations the Upper Specification Limit is from the mean for the output cell A10, using a USL of 120.
Guidelines	A RiskSixSigma property function needs to be entered for <i>cellref</i> or output name, or a RiskSixSigma property function needs to be included

Six Sigma and the Results Summary Window

The **@RISK Results Summary** window summarizes the results of your model and displays thumbnail graphs and summary statistics for your simulated output cells and input distributions.

When @RISK detects a **RiskSixSigma** property function in an output, it automatically displays the available Six Sigma statistics on the simulation results for the output in the table. These columns may be hidden or displayed as desired.



Customizing the Displayed Statistics

The Results Summary window columns can be customized to select which statistics you want to display on your results. The Columns icon, at the bottom of the window, displays the **Columns for Table** dialog.

ŵ s	elect Columns f	for Table: Results Summary	×
	Column Name	Description	
	Graph	Graph for input/output	
	Min	Minimum possible value of distribution	
	Mean	Mean value	
	Max	Maximum possible value	
	Cpk	Process Capability	
	CpkUpper	Process Capability - Upper Spec	
	CpkLower	Process Capability - Lower Spec	
	Ср	Process Potential	
	Zupper	Z-score for Upper Limit	
	Zlower	Z-score for Lower Limit	
	DPM	Defective Parts Per Million	
	Sigma Level	Process Sigma Level	
	PNC	Total Percent Non-Conforming	
	PNC Honer	Percent Non-Conforming Above Unner Limit	<u> </u>
0		OK Cancel	

If you select to show Percentile values in the table, the actual percentile is entered in the rows **Value at Entered Percentile**.

đ٩ s	elect Columns fo	r Table: Results Summary	×		
	Column Name	Description]		
	Mode	Mode or most likely value			
	Std Dev	Standard deviation of distribution			
	Variance	Variance of distribution			
	Skewness	Skewness of distribution			
	Kurtosis	Kurtosis of distribution			
	1%	Value at entered percentile			
	99%	Value at entered percentile			
	p1,x1	iditable p1,x1 values			
	p2,x2	ditable p1,x2 values			
	x2-x1	Difference between x2 and x1 values			
	p2-p1	ofference between p2 and p1 values			
	Errors	lumber of errors for input/output			
	Filtered	Number of filtered values for input/output			
ſ					
0		OK Cancel			

Generating a Report in Excel

The Results Summary window can be exported to Excel to get a report containing the displayed statistics and graphs. To do this, click the **Copy and Export** icon at the bottom of the window and select **Report in Excel**.

2	Home Inset Page Layout	Pornulas	Data Review	Book2 - Microso	oft Excel				×
Dist	Define Add Inset Define Litutions Output Function - Correlations Fit	bution Distri	bution Model Window	Iterations 1000 · Simulations 1 · 2 2 2 2 2 2 2 Simulations	Start Advanced Simulation Analyses	Browse Results Results	ne filters Excel Report	Swap Swap Functions Tealt	Library * P Utilites * § Help *
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6	Weld Strength (74)	C82	10 83.35	\$ 111.00	138.31	93.63	132.53	0.\$520009	0.5520009
8 9									
10									
11 12									

Six Sigma Markers on Graphs

When @RISK detects a **RiskSixSigma** property function in an output, it automatically adds markers for the entered LSL, USL and Target values to graphs of simulation results for the output.



These markers can be removed if desired using the **Markers** tab of the **Graph Options** dialog. Additional markers may also be added. The Graph Options dialog is displayed by right-clicking on the graph or by clicking the Graph Options icon (the second icon from the left on the bottom of the graph window).

🚹 Graph Option	าร		×
Distribution Title	X-Axis Y-Axis C	urves Legend Delimiters	Markers Other
🔽 <u>D</u> isplay Marke	ers		,
	<u>R</u> edefine # <u>M</u> arked Curves	Mean +/-1 Std Deviation 5% 5% X1 X2 Distribution SplicePoint USL (Six Sigma) USL (Six Sigma) Target (Six Sigma)	
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<u>B</u> ackground C	olor		~
<u>F</u> ont		Tahoma 7	>
0		ОК	Cancel

Case Studies

Example 1 – Design of Experiments: Catapult	41
Example 2 – Design of Experiments: Welding	.47
Example 3 – Design of Experiments with Optimization	53
Example 4 – DFSS: Electrical Design	61
Example 5 – Lean Six Sigma: Analysis of Current State – Quotation Process	.63
Example 6 – DMAIC: Roll Through Yield Analysis	73
Example 7 – Six Sigma DMAIC Failure Rate	77
Example 8 – Six Sigma DMAIC Failure Rate using RiskTheo	81

Example 1 – Design of Experiments: Catapult

Example Model: Six Sigma DOE Catapult.xls

The catapult or trebuchet model is a classic example used to teach **Design of Experiments**. It illustrates Monte Carlo simulation and tolerance analysis.

Suppose you are manufacturing catapults and customers demand the distance the catapult throws a standard ball is 25 meters, plus or minus 1 meter. There are many design specifications involved in producing your catapults, such as:

- Angle of Launch
- Mass of the Ball
- Distance Pulled
- Spring Constant



Entering a Distribution

Each of the design factors contains an @RISK probability distribution to represent different possible values each factor could take. @RISK probability distributions can be entered directly as formulas, using @RISK's **Insert Function** command or by using the **Define Distribution** icon on the @RISK toolbar. For example, a Uniform distribution represents the possible values for **Distance Pulled**.



Entering RiskSixSigma Properties

The output is **Distance Thrown**, and contains a RiskSixSigma property function defining Lower Specification Limit, Upper Specification Limit, and Target for Distance Thrown. Like inputs, an @RISK output can be typed into the formula bar or defined via dialog box using the Add Output button on the @RISK toolbar.

Output Properties: C33			X
Options Convergence	Six Sigma		
Calculate Capability	Metrics For This	Output	
Specification Limits			
			- MEEL
Loc.	24		B
USL	26		
<u>T</u> arget	25		
Other			
Use Long-Term Sł	hift		
S <u>h</u> ift	1.5		
Upper/Lower X Bound			
# St <u>d</u> Dev	1		
<u> </u>		ОК	Cancel

Capability metrics Cpk, Cpk Upper, Cpk Lower, Sigma Level, and DPM are calculated for the catapult, enabling you to determine whether it is ready for production.

34	
35	Six Sigma Results
36	Cpk 0.1325
37	Cpk Upper 0.2686
38	Cpk Lower 0.1325
39	Sigma Level 0.5029
40	DPM 615000.00
41	

Graphing the Results

The resulting distribution of **Distance Thrown** shows that about 60% of the time the distance is outside of specification limits.



Sensitivity analysis identifies the most important design factors affecting Distance Thrown as the Distance Pulled, followed by the Mass of the Ball.



This model can help explore the theory of **Taguchi or Robust Parameter Design**. Taguchi theory states that there are two types of variables which define a system – those whose levels affect the process variation, and those whose levels do not. The idea behind Taguchi Design is to set variables of the first type at a level which minimizes total process variation. Variables which don't affect process variation are used to control and/or adjust the process.

In the catapult model, you can adjust various design parameters – such as **Pull Distance** and **Mass of Ball** – to try to minimize the variation in the output **Distance Thrown**. Considering that 60% of the time the Distance Thrown is outside the specification limits of 24 to 26 meters, there is room for improvement.

Example 2 – Design of Experiments: Welding

Example Model: Six Sigma DOE.xls

Suppose you are analyzing a metallic burst cup manufactured by welding a disk onto a ring (see below). The product functions as a seal and a safety device, so it must hold pressure in normal use, and it must separate if the internal pressure exceeds the safety limit.



The model relates the weld strength to process and design factors, models the variation for each factor, and forecasts the product performance in relation to the engineering specifications. Modeling a response based on multiple factors can often be accomplished by generating a statistically significant function through experimental design or multiple regression analysis.



In this example, @RISK simulates the variation using Normal distributions for each factor. @RISK distributions support cell referencing so that you can easily set-up a tabular model that can be updated throughout a product and process development lifecycle.

The uncertain factors are:

Design Variables

- Disk thickness
- Horn wall thickness
- Horn length

Process Variables

- Weld pressure
- Weld time
- Trigger point
- Amplitude
- Frequency

Adding Distributions

Adding a distribution to each factor is as easy as clicking on the Define Distribution icon on the @RISK toolbar. From there you can select a Normal distribution and input its parameters or cell references, as shown below. You could also type the formula directly into Excel's formula bar for each input. For example, the cell for Well Pressure contains the formula

=RiskNormal(D73,E73)



The Six Sigma Output

The output is **Weld Strength (N)** in the Design & Process Performance section, and contains a RiskSixSigma property function that includes the Lower Specification Limit (LSL), Upper Specification Limit (USL), and Target value specified. As with defining input distributions, you can type the output formula directly in the output cell or use the Add Output dialog. The formula would be:

=*RiskOutput*("*Weld Strength* (*N*)",,,*RiskSixSigma*(*D82*,*E82*,105,0,1))+ [*the mathematical calculation*] The Add Output dialog appears below:

@RISK -	×			
<u>N</u> ame:	Weld Streng	th (N)		f#
	<u>R</u> emove		ОК	Cancel

Clicking on the properties button (*fx*) brings up the **Output Properties** dialog with the Six Sigma tab. Here you can enter LSL, USL, Target value, and other Six Sigma properties for your output. These are used to calculate Six Sigma statistics.

Output Properties: C82			X					
Options Convergence Six Sigma								
Calculate Capability Metrics For This Output								
ĿSL	85							
USL	125							
<u>T</u> arget	arget 105							
Other								
Use Long-Term S	Use Long-Term Shift							
S <u>h</u> ift	1.5							
Upper/Lower X Bound	ł							
# St <u>d</u> Dev								
0		ОК	Cancel					

Simulation Results

After you run the simulation, Six Sigma statistics were generated using @RISK Six Sigma functions for Cpk-Upper, Cpk-Lower, Cpk, and PPM Defects (or DPM). Standard @RISK statistics functions (like RiskMean) were also used.

D	Design & Process Performance									
		LSL	USL	Mean	StdDev					
Weld Strength (N)	110.96	85	125	111.01	8.57					
Cpk-Upper	0.54									
Cpk-Lower	1.01									
Cpk	0.54		Co	st & Volun	ne					
PPM Defects	62,000	Part Cost:		\$0.28	ea.					
Annual Defect Cost	\$21,700	Annual Vo	lume:	1.25	MM					

The @RISK output distribution displays the expected performance based on the design and process input variation and shows LSL, USL, and Target value with markers. You can easily access the output statistics using the reporting features or through @RISK functions.



The @RISK Sensitivity Analysis clearly shows that the Weld Time and Amplitude parameters are driving the Weld Strength variation.



The next steps for this problem could include two options: The engineer can attempt to reduce or better control the variation within the Weld Time and Amplitude, or use RISKOptimizer to find the optimal process and design targets to maximize yield or reduce scrap cost.

Example 3 – Design of Experiments with Optimization

Example Model: Six Sigma DOE Opt.xls

This model demonstrates the use of RISKOptimizer in experimental design. RISKOptimizer combines Monte Carlo simulation with genetic algorithm-based optimization. Using these two techniques, RISKOptimizer is uniquely capable of solving complex optimization problems that involve uncertainty.

With RISKOptimizer, you can choose to maximize, minimize, or approach a target value for any given output in your model. RISKOptimizer tries many different combinations of controllable inputs that you specify in an effort to reach its goal. Each combination is called a "solution," and the total group of solutions tried is called the "population." "Mutation" refers to the process of randomly trying new solutions unrelated to previous trials. You can also set constraints that RISKOptimizer must abide by during the optimization.

For uncertain, uncontrollable factors in your model, you define @RISK probability distribution functions. For each trial combination of inputs, RISKOptimizer also runs a Monte Carlo simulation, sampling from those @RISK functions and recording the output for that particular trial. RISKOptimizer can run thousands of trials to get you the best possible answer. By accounting for uncertainty, RISKOptimizer is far more accurate than standard optimization programs.

In this example, as above, the part under investigation is a metallic burst cup manufactured by welding a disk onto a ring. The product functions as a seal and a safety device, so it must hold pressure in normal use, and it must separate if the internal pressure exceeds the safety limit.

The model relates the weld strength to process and design factors, models the variation for each factor, and forecasts the product performance. RISKOptimizer was used to search for the optimal combination of process settings and nominal design values to minimize scrap cost, called **Annual Defect Cost** in the model. This is the same as maximizing yield. The process and design variables RISKOptimizer will adjust are:

Design Variables

- Disk thickness
- Horn wall thickness
- Horn length

Process Variables

- Weld pressure
- Weld time
- Trigger point
- Amplitude
- Frequency

All in an effort to minimize the output Annual Defect Cost.



The RISKOptimizer toolbar added to Excel 2000-2003 appears below:



The RISKOptimizer toolbar in Excel 2007 appears as follows:



Toolbar

The Optimization Model

Clicking on the **Model Definition** icon brings up the following dialog where you define which cells to adjust, what your output is, and what constraints to use. In addition to the inputs and outputs described above, we will also define a constraint where the Trigger Point must always be less than or equal to Weld Time.

🕏 RISKOptimiz	zer- N	Nodel							×
Optimization Goal Cell Statistic			imum 71 Je			<u>[</u>	• 1		
Adj <u>u</u> stable Cell Ra	nges								
Minimum		Ra	nge		Maximum	Values	-	<u>A</u> dd	
Recipe: Disk The Provide America Content of the Provide Ame	nicknes	s						Delete	
1	<=		=D49	<=	5	Any			
- Recipe: Ring W	/all Thi	ckness							
2	<=		=D50	<=	10	Any			
- Recipe: Horn L	ength								
100	<=		=D51	<=	200	Integer			
- Recipe: Weld P	ressur	e							
40	<=		=D57	<=	1500	Integer	-	<u>G</u> roup	
Co <u>n</u> straints									_
Description			Form	ula		Туре		A <u>d</u> d	
					=\$D\$59<=\$D\$58	Ha	ard	<u>E</u> dit	
								Dele <u>t</u> e	
0						OK		Cancel	

Optimization Settings

Clicking on **Optimization Settings** icon brings up the following dialog where you can set a variety of conditions for how the optimization and simulations will run.

🕏 RISKOptimizer - Optimization Settings		
General Runtime View Macros		
Optimization Parameters		
Population Size 50		
Random Number Generator Seed Automatic	~	
Sampling		
Sampling Type	•	
☑ Use Same Random Number Generator Seed Each Simulation		
When a Simulation is Not Running, Distributions Return		
C Random Values (Monte Carlo)		
Static Values Expected Values	•	
	ОК	Cancel

Running the Optimization

When you click Start Optimization, the **RISKOptimizer Progress** window appears, showing you a summary status of the analysis.

RISKOptimizer Progress						
Iteration:	1000 of 1000					
Simulation:	12 (7 Valid)					
Runtime:	00:00:06 of 00:03:00					
Original:	15408.0000					
Best:	12840					
B						

The magnifying glass button opens the RISKOptimizer Watcher dialog, which displays more detailed information about the optimization and simulations being run. Below you can see a chart of simulations run and best values obtained.



The Summary tab displays **Best**, **Original**, **and Last** values calculated, as well as parameters for the optimization like Crossover and Mutation Rates.

RISKOptimizer Watcher										
Progress Summary Log Population Diversity Stopping Options										
Adjustable Ce	Adjustable Cell Values									
	Simul.	Result	D49	D50	D51	D57	D58			
Best	65	8988.0000	2.1802	3.4188	156	437	0.50			
Original	1	15408.0000	2.1322	3.5468	162	432	0.52			
Last	107	1284000	2.2077	7.7738	156	443	0.90			
•										
Adjustable Ce	I Group Settings									
Group Sho	wn	D49 (Disk	Thickness}			•				
		je is generi								
Crossover	Rate	•			• 0.50	000				
Mutation R	ate				• 0.10	000				

The Diversity tab visually shows the different cells being calculated and the various possible solutions.

RISKOptimizer Watcher									
Progress Summary Log Population Diversity Stopping Options									
	_								
_									
			-						
			-						
	_								
			_						
			-						
Cells (Across) vs. Solutions (Up)									
				,					

After simulation and optimization, RISKOptimizer efficiently found a solution that reduced the Annual Defect Cost to under \$8,000.

Using RISKOptimizer can save time and resources in a quality improvement and cost reduction effort. The next steps for this problem would be to validate the model and optimized solution through experimentation.

Example 4 – DFSS: Electrical Design

Example Model: Six Sigma Electrical Design.xls

This simple DC circuit consists of two voltage sources - one independent and one dependent - and two resistors. The independent source specified by the design engineer has an operational power range of 5,550 W + 300 W. If the power draw on the independent voltage source is outside of the specification, the circuit will be defective. The design performance results clearly indicate that the design is not capable of performance with a percentage of the circuits failing on both the high and low end of the limits. The PNC values identify the Percent of Nonconforming units expected on the upper and lower ends of the specification.

The basic model logic follows:



The model calculates the standard deviation for each component based on known information and the following assumptions within this model:

- 1) The mean of the component values are centered within the tolerance limits.
- The component values are normally distributed. Note that @RISK can be used to fit a probability distribution to a data set or to model other types of probability distributions, if needed.

A RiskSixSigma property function in the Output cell **PowerDEP** defines Upper Limit, Lower Limit, and Target that are used for Six Sigma results calculations. @RISK Six Sigma functions are used to calculate Cpk Lower, Cpk Upper, Cpk, Cp, DPM, PNC Upper and PNC Lower.

Sensitivity Analysis

The **@RISK Sensitivity Analysis** identifies the input variables driving variation in the output. The sensitivity shows that the two voltage sources are the main contributors to the variation in power consumption. Armed this information, the engineering team can focus their improvement efforts on the voltage sources instead of the resistors.



The model can be used to test different components and tolerances, performances and yields can be compared, and the optimal solution can be selected to maximize yield and reduce cost.

Example 5 – Lean Six Sigma: Analysis of Current State – Quotation Process

Example Model: Six Sigma Quotation Process.xls

In both **Lean** and **Six Sigma** approaches to continuous improvement, one of the key requirements is to understand the current state of the process under review. This is initially done in the Value Stream Mapping phase of a Lean Implementation or in the Define and Measure phases of the DMAIC Six Sigma process. Most practitioners put the process together in one or more sessions and, after a cursory review, the team moves on to generating solutions. There is significant benefit, however to taking the time to model the process and prove that the data and assumptions that were made are accurate. This becomes vitally important when one or more of the following are true:

- The process is critical to the success of the enterprise (Mission Critical)
- There is significant denial that the process needs improvement
- Improvement costs will be significant
- The results of the continuous improvement effort may come under significant scrutiny at a later date
- The process is subject to the **Hawthorne Effect** the more we study it, the better it gets

Simulation has the ability to prove the initial analysis of the current state and show the true situation that the analysis team encountered. There are three often very different processes at work in every area: the process that we think exists; the process we have documented; and the process that really is being carried out on a daily basis. A carefully constructed @RISK simulation can document the actual process and model the impact of improvements later in the Continuous Improvement cycle. And the model is straightforward to construct.

Developing the Model and Collecting Data

This example focuses on the process flow of an organization's internal sales quotation process, and was taken from an actual company. There are many tools used to graphically show the process. The one we will use here is a **Swimlane Chart**.



The entire quotation process had over 36 individual steps and was impacted by ten individuals or departments. Cursory data indicated that it took up to four weeks to get the quote through the system, yet for critical issues, quotes could be expedited through the system in less than one week. Long quote cycletimes prevented the company from effective bidding in often lucrative emergency orders for their products and services. Because of the fact that expedited quotes could be done in one quarter of the time, management thought that the issue resided in the personnel, not the process. The analysis team needed a tool to prove the process was at fault.

After developing the chart, the team had a question: How long does it take to process a quotation from the receipt of the request to the release of the quote package to the Engineering department? This is the first part of the process and had data that was relatively easy to acquire, and findings here could be applied throughout the process. This portion of the quotation process has four steps. First, the data is collected and entered (Step A). Next, it goes into a queue for Customer Service review (Step B). Here, corrections and additional data are entered onto the form and tracking number assigned (Step C). Finally the packet is put into a queue for the Engineering department to perform the quotation activity (Step D).



The team developed a simple time sheet that captured the times that the paperwork went from area to area, and how long it was worked on in each step of the process. From this data, the team performed some initial analysis of the four steps in this portion of the process.

Building the Distributions and Defining the Output

A simple distribution of the data, for our purposes, means that the data follows a single curve. Complex distributions are made up of several separate distributions and are typically more difficult to define. The data that the team gathered has both types.

@RISK can find the distribution behind the data through the **Fit Distributions** button on the toolbar. A fitted distribution can then be entered as a distribution function in the spreadsheet. With your data in Excel, select the Fit Distributions button and follow the prompts. @RISK will analyze the data and check its fit to a series of distribution functions.

For the team's data on Step C (Review), the result from @RISK's distribution fitting is shown below. The resulting distribution was then placed directly into the spreadsheet cell below the "C-Review" heading using the Write to Cell button. (The team selected the Normal distribution over the slightly better fitting Weibull because, with a small dataset, the difference between the two curves was acceptable.)


The team continued to do this for all the distributions for each of the four steps. Finally they set the Total Time for the four Steps A-D as the @RISK output and ran the simulation.

The results of the simulation were revealing. The mean Total Time to process a quote was about 1700 minutes, which is over one calendar day. It could take anywhere from 350 minutes (almost 6 hours) to well over 2 calendar days.

The only value-added portion of the time is the Review step. This step took an average of 35 minutes to complete, with a range of from 6 to 64 minutes. This was reviewed with the area affected and management, though surprised, agreed with the findings.

Statistics on Simulation Results @RISK also allowed the team to generate basic statistics that interact with the output cell. As an example, the team wanted to add the mean, maximum, minimum and standard deviation of the Total Time output cell to a table in the spreadsheet. From @RISK's Insert
Function menu, the team selected Simulation Result in the Statistics section. From this set, the RiskMean function was chosen. Finally the output cell "Total Time" was selected as the argument. Now every time the simulation is run, this cell is updated with the mean of the Total Time.



The team repeated this for the maximum, minimum, and standard deviation selections.

Entering Six Sigma Functions

Next the team wanted to add the Cpk analysis of the output cell using the @RISK Six Sigma functions. In the output cell Total Time, they entered a **RiskSixSigma** function, where:

- a cell reference identified the the header cell where the name of the output was taken
- a cell reference identified the **Lower Specification Limit** for the expected result
- a cell reference identified the **Upper Specification Limit** for the expected result
- a cell reference identified the **Target** value for the expected result

The RiskSixSigma function was easily set up using the **Output Properties** dialog (accessed by clicking the **Function Properties fx** icon in @RISK's **Add/Edit Output dialog**).

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With the output now configured, the team wanted the simulation to calculate the @RISK Six Sigma functions of **Cp, CpkUpper**, **CpkLower and Cpk**. This is done by inserting the correct function (such as RiskCp, RiskCpkUpper, etc) from **Six Sigma** in the Statistics section of @RISK's **Insert Function** menu or by typing them into the formula bar. These will be recalculated for every simulation.



Graphing the Simulation Output

Through @RISK's results graphs and Six Sigma markers showing LSL, USL, and Target values directly on the graph, management was surprised to see that it took, on average, over a full day to complete 35 minutes of work. The simulation results for the Total Time output, and for the values sampled from the input distribution fo Step C – Review are shown below.





The team could, based on the simulation, document the actual flows and detail what happens when the quotes are not expedited. Management saw the potential improvement if the entire process were tracked and improved. This management buy-in at the project onset proved to be key to the long term success of the project.

From this initial model, the team constructed the full model for the entire process. With this model in hand, the team was able to model improvement efforts at various stages of the project and verify that the improvements were making positive gains. The total time to generate the initial simulation and results using @RISK was less than one hour after the original data was entered into Excel.

Example 6 – DMAIC: Roll Through Yield Analysis

Example Model: Six Sigma DMAIC RTY.xls

DMAIC - or **Define**, **Measure**, **Analyze**, **Improve**, **and Control** - is used to improve existing products or processes. Imagine you are a costume jewelry manufacturer, coating inexpensive silver with thin layers of gold. You import materials and components from China. A small number of components are always defective, but you don't know how many or how much it is costing.

You've gathered data on the number of components that are defective or become defective at various points in the manufacturing process. On the surface, it seems like defective parts are not a major problem. Upwards of 99% of components are acceptable at each stage of the process. However, the combined effect of the defective parts leads to 15-20% waste of final products, which can translate into 200,000 defective units per million produced. If materials are \$.50 per unit, that is \$100,000 in waste before counting labor, machine time, and other expenses.

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52	Cutting	0	0	0	0	0	0	0	0				
53	Cleaning	0	0		0	1	1	0	0				
54	Electroplating	0.00	0.10	0 10	0.77	0	0	0	0				ш
20	Total	0.00	0.40	0.40	0.11	1.52	1.19	2.32	1.19				
57		Data			1								
58	Unpackaging / Inspection	Cutting	Cleaning	Electroplating									
59	236.1622343	901.964	962.8937382	601.9177653	1								
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61	215.4454857	831.609	1088.748251	447.085089									
62	234.5399238	400.6967	1005.431237	640.763609									
64	205.1656081	888.4106	913.7734386	573.0917982									
65	232.8379071	822.0953	1052.650674	611.0135421									
66	216.4401231	987.5231	1002.298515	564.7300577									
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73	199.6920514	910.6343	1015.523847	575.932403									
74	229.5699606	729.1365	926.5063694	508.5643563									
75	223.3430953	1084.297	985.7020412	623.2414152									
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You need to reduce the number of defective units produced. However, the process is long and complicated, and you don't know which stage to begin with. Using @RISK, you can simulate many different outcomes and pinpoint the manufacturing stage that is the worst offender. You can also get key process capability metrics for each stage as well as the entire process that will help you improve quality and reduce waste. In this way, @RISK is being used in the Measure and Analyze phases of the DMAIC method. @RISK is used to measure the existing state of the process (with capability metrics) and analyze how it might be improved (with sensitivity analysis).

Distribution Fitting

Using the data gathered from the manufacturing process, @RISK's distribution fitting feature was used to define distribution functions describing the number of defective parts at each stage of the process - **Unpackaging/Inspection, Cutting, Cleaning, and Electroplating**. The distribution fit for the Electroplating phase – Weibull distribution - is shown below.



These fitted distributions were added directly to the model. The Electroplating distribution is shown below.



Simulation Results

The **Defective Parts per Million (DPPM)** for each stage, and the process as a whole, were defined as @RISK outputs with Six Sigma specifications for Upper Specification Limit, Lower Specification Limit, and Target values. After the simulation run, a variety of Six Sigma metrics were calculated for each stage and the process as a whole.

	Process	Process Capability			Sigma Level (using Normal			(Min of Z Lower and Z
	Ср	Cpk	Cpk Lower	Cpk Upper	approximati	Z Lower	Z Upper	Upper)
Unpackaging / Inspection	0.637608	0.410619884	0.864597066	0.410619884	1.584851844	2.593791	1.23186	1.23186
Cutting	0.101803	0.089003251	0.089003251	0.114602388	0.302855481	0.26701	0.343807	0.26701
Cleaning	0.156284	0.096422506	0.216146266	0.096422506	0.530161445	0.648439	0.289268	0.289268
Electroplating	0.108775	0.069824459	0.14772538	0.069824459	0.353117972	0.443176	0.209473	0.209473
Total	0.577882	0.398831514	0.398831514	0.756932214	1.538198859	1.196495	2.270797	1.196495



The distribution of outcomes for DPPM is shown below.

Finally, sensitivity analysis and a Tornado graph revealed that the **Cutting stage** was the most to blame for overall product defects, despite the fact that another stage - Cleaning - had a lower First Time Yield (fewer defects). Even though the FTY of Cutting was higher, the Cutting process itself is less consistent and has more variation than the other processes.



Example 7 – Six Sigma DMAIC Failure Rate

Example Model: Six Sigma DMAIC Failure.xls

This is a failure rate model for use in quality control and planning. You are a manufacturer and need to calculate the likely % of defective products. In the DMAIC method - Define Measure, Analyze, Improve, Control - this is the Measure and Analyze phases, where you wish to measure the current state of quality and analyze the causes of problems or defects.

A product is defective when any one of its components does not meet its required tolerance level. Each component is deemed to be satisfactory if some property of its finished state (e.g. its width) lies within the defined tolerance bands.

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Modeling Component Width

This property of each finished component (e.g. its width) is modeled with a Normal distribution in the Sample column.

Sample	
10.00	
5.00	
8.00	
12.00	
6.00	



Those cells have also been added as @RISK outputs with RiskSixSigma property functions defining LSL, USL, and Target values for each component. The formula for Component1 appears below:

=RiskOutput(,,,RiskSixSigma(F26,G26,C26,0,0))+RiskNormal(C26,D26)

In this way we'll be able to see graphs of the components' quality, and calculate Six Sigma statistics on each component.

Using the RiskMean Function to Get Failure Rate

The component and aggregate **Failure Rate** is calculated from the **RiskMean** function, which is an @RISK Statistics function, and therefore applicable only after the simulation has been run. After simulation we can also see component and aggregate Six Sigma statistics Z score and DPM.

Z Min	Failure frequency	DPM
2.999060375	One in 334 will fail	3000
2.99523275	One in 334 will fail	3000
2.990852805	One in 334 will fail	3000
3.492267357	One in 1000 will fail	1000
3.002125568	One in 1000 will fail	1000
2.945880756	One in 91 will fail	11000

The graph for the samples of Component1 appears below, with markers for USL, LSL, and Target.



Example 8 – Six Sigma DMAIC Failure Rate using RiskTheo

Example Model: Six Sigma DMAIC Failure RiskTheo.xls

This is an extension of the DMAIC Failure model for use in quality control and planning. It includes the use of RiskTheo functions (in this case RiskTheoXtoP) for determining failure rate without actually running a simulation. RiskTheo functions return theoretical statistics on input distributions or formulas rather than returning the statistics on the data from a simulation run.

You are a manufacturer and need to calculate the likely % of defective products. In the DMAIC method - Define Measure, Analyze, Improve, Control - this is the Measure and Analyze phases, where you wish to measure the current state of quality and analyze the causes of problems or defects.

A product is defective when any one of its components does not meet its required tolerance level. Each component is deemed to be satisfactory if some property of its finished state (e.g. its width) lies within the defined tolerance bands.

					U	Ŧ	E	D	C	8
I from sim	Z Min from Sim	Failure rate from RiskTheo (%)	Failure rate (%) from sim (%)	OK7	Tolerance: Upper (USL)	Tolerance: Lower (LSL)	Sample	Std Dev	Mean (Target)	
3000	3.0019569	0.270%	0.300%	1	10.6	9.4	10	0.2	10	Component1
2000	3 00420087	0.158%	0.200%	-	5.15	4.825	5	0.05	5	Component2
0	3 503591776	0.047%	0.000%	1	12.875	11 125	12	0.25	12	Component4
1000	2.995848512	0.136%	0.100%	1	6.5	5.7	6	0.1	6	Component5
9000		0 746%	0.900%	1						Total
	3 00420087 2 994884973 3 503591776 2 995848512	0.158% 0.138% 0.047% 0.135% 0.135%	0.200% 0.300% 0.000% 0.500%	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	5 15 8 3 12 875 6 5	4.825 7.6 11.125 5.7	5 8 12 6	0.05 0.1 0.25 0.1	5 8 12 6	Component2 Component3 Component4 Component5 Total

Modeling Component Width

This property of each finished component (e.g. its width) is modeled with a Normal distribution in the Sample column.

Sample	
10.00	
5.00	
8.00	
12.00	
6.00	



Those cells have also been added as @RISK outputs with RiskSixSigma property functions defining LSL, USL, and Target values for each component. The formula for Component1 appears below:

=RiskOutput(,,,RiskSixSigma(F26,G26,C26,0,0))+RiskNormal(C26,D26)

In this way we'll be able to see graphs of the components' quality and calculate Six Sigma statistics on each component if we choose to run a simulation.

Using the RiskTheoXtoP Function to Get Failure Rate

The component and aggregate Failure Rate is calculated from the **RiskTheoXtoP**, which draws on the Normal distributions in the Sample column. The Failure Rate from simulation is also calculated using the RiskMean function if you choose to run a simulation. In this way you can compare simulated Failure Rate with RiskTheo Failure Rate.

Failure rate (%) from sim (%)	Failure rate from RiskTheo (%)
0.30%	0.270%
0.20%	0.158%
0.20%	0.138%
0.00%	0.047%
0.10%	0.135%
1%	

After simulation we can also see component and aggregate Six Sigma statistics Z score and DPM.

Z Min from sim	DPM from sim
2.998616548	3000
2.997415317	2000
2.997730848	2000
3.49840855	0
3.004560454	1000
3.146403741	8000