Exactly What are Process Performance Models in the CMMI?

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Who Are We?

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Contents / Agenda

Introduction

The SEI and the CMMI community **seek to improve the consistency of interpretation** of CMMI High Maturity and Capability.

A primary source of inconsistency exists with the understanding and application of CMMI process performance models (QPM, OPP, OID)

The SEI is launching **several new courses** to address these inconsistencies, to include the “Understanding CMMI High Maturity Practices” and the “Measuring for Performance-Driven Improvement” course series.

This presentation provides a synopsis of the discussion, with examples, of **CMMI Process Performance Models**.

Foundational Concepts

CMMI References to Process Performance Models -1

OPP SP 1.5 Establish Process-Performance Models

Establish and maintain the process-performance models for the organization's set of standard processes

QPM SP 1.4 Manage Project Performance

Subpractice 4 Use process-performance models calibrated with obtained measures of critical attributes to estimate progress towards achieving the project’s quality and process-performance objectives

CAR SP 1.1 Select Defect Data for Analysis

PPBs and PPMs can be useful for both identifying defects or problems and for predicting the impact and ROI that prevention activities will have

CMMI References to Process Performance Models -2

CAR SP 2.2 Evaluate the Effects of Changes

Evaluate the effect of changes on process performance

OID SG 1 Select Improvements

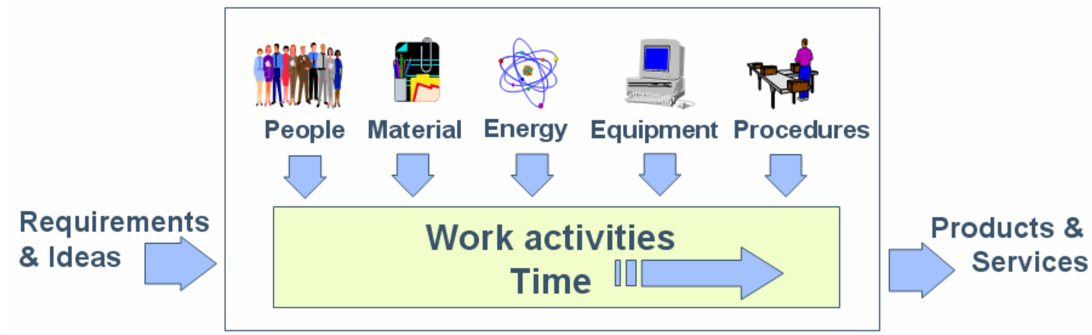
Analysis of process-performance baselines and models to identify sources of improvements

Process-performance models provide insight into the effect of process changes on process capability and performance.

More than just insight, PPMs can be used to predict performance of process changes, thus, facilitating cost benefit analysis

Essential Ingredients of Process Performance Models -1

They relate the behavior or circumstance of a process or sub-process to an outcome.



They predict future outcomes based on possible or actual changes to factors (e.g. support “what-if” analysis).

They use factors from one or more sub-processes to conduct the prediction.

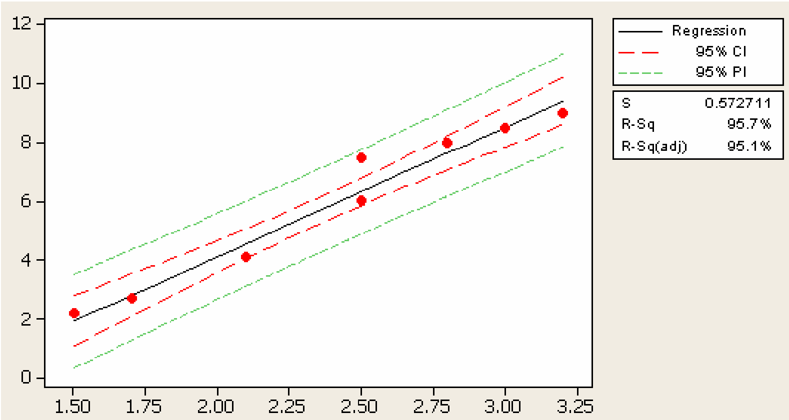
Reqts Defects

Interview Customer | Synthesize Req’ts | Create Usage Scenarios | Solicit Customer Response

Essential Ingredients of Process Performance Models -2

The factors used are preferably controllable so that projects may take action to influence outcomes.

They are statistical or probabilistic in nature rather than deterministic (e.g. they account for variation in a similar way that QPM statistically accounts for variation; they model uncertainty in the factors and predict the uncertainty or range of values in the outcome).



Essential Ingredients of Process Performance Models -3

High maturity organizations generally possess **a collection of process-performance models** that go beyond predicting cost and schedule variance, based on Earned Value measures, to include other performance outcomes.

- Quality
- Productivity
- Escaped Defects
- Interim & Final Outcomes
- Process Effectiveness
- Cycle Time
- Customer Satisfaction

Specifically, the models predict quality and performance outcomes **from factors related to one or more sub-processes** involved in the development, maintenance, service, or acquisition processes.

- Root causes of outcomes
- Factors correlated with outcomes
- Leading Indicators of outcomes

Process Performance Baselines vs Models

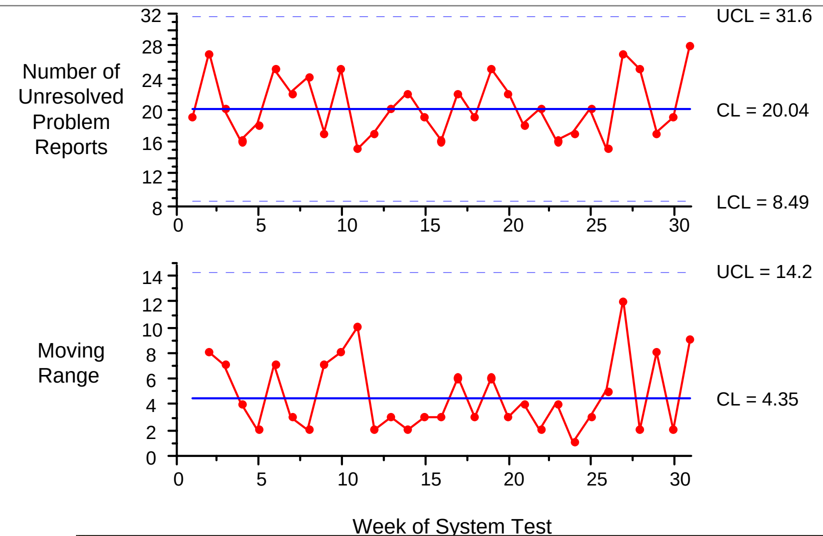
The organization's process-performance baselines may be used by the projects to estimate the natural bounds for process performance.

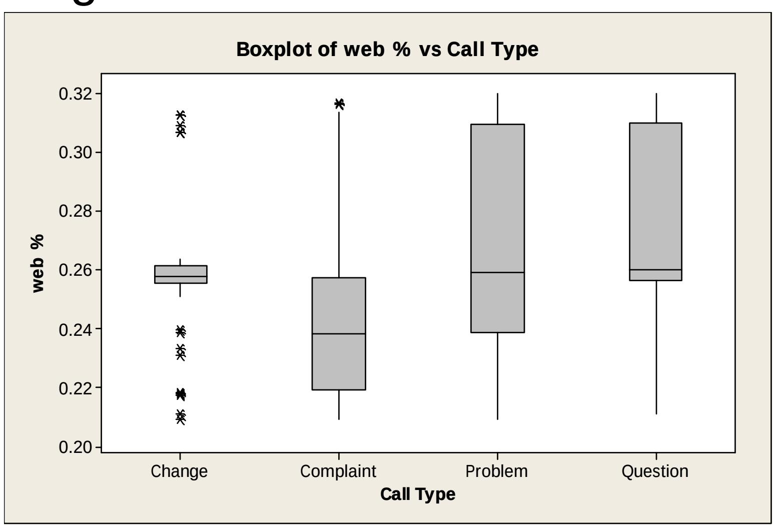
A process-performance baseline (e.g. control chart) may be used to provide an indication of future performance of itself - **if all other factors remain constant.**

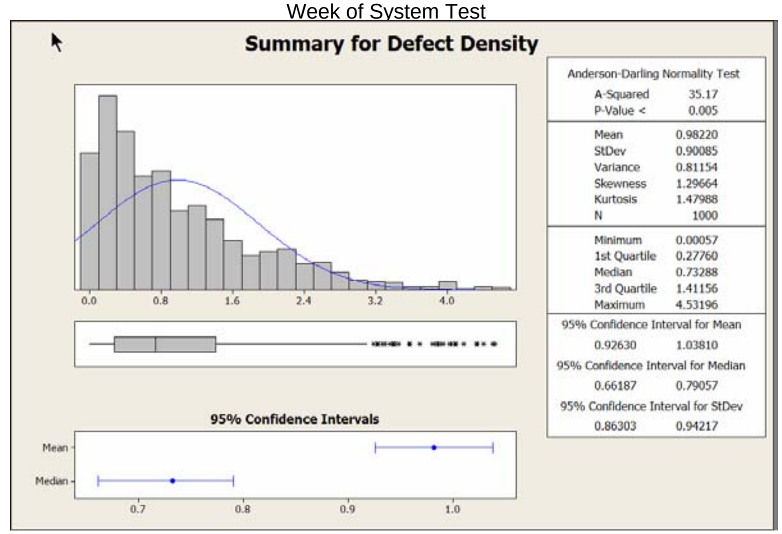
However, we will see that process-performance models exist to predict future performance based on other subprocess factors - **whether or not one or more subprocess factor changes!**

Process Performance Baselines

Process-performance baselines are derived by analyzing the collected measures to **establish a distribution and range of results** that characterize the expected performance for selected processes when used on any individual project in the organization.







Examples of Process Performance Models

Basic Statistical Prediction Models

X \ Y	Continuous	Discrete
Discrete	ANOVA & MANOVA	Chi-Square & Logit
Continuous	Correlation & Regression	Logistic Regression

Example Scenarios of ANOVA

Using these factors…	To predict this outcome!
Type of Reviews Conducted; Type of Design Method; Language Chosen; Types of Testing	Delivered Defect Density
High-Medium-Low Domain Experience; Architecture Layer; Feature; Team; Lifecycle model; Primary communication method	Productivity
Estimation method employed; Estimator; Type of Project; High-Medium-Low Staff Turnover; High-Medium-Low Complexity; Customer; Product	Cost and Schedule Variance
Team; Product; High-Medium-Low Maturity of Platform; Maturity or Capability Level of Process; Decision-making level in organization; Release	Cycle Time or Time-to-Market
Iterations on Req'ts; Yes/No Prototype; Method of Req'ts Elicitation; Yes/No Beta Test; Yes/No On-Time; High-Medium-Low Customer Relationship	Customer Satisfaction (as a percentile result)

Example ANOVA Output

One-way ANOVA: Escaped Defect Density versus Quality Check

Source	DF	SS	MS	F	P
Quality Check	4	139.519	34.880	48.30	0.000
Error	330	238.306	0.722		
Total	334	377.825			

S = 0.8498   R-Sq = 36.93%   R-Sq(adj) = 36.16%

We predict a range of escaped defect density for each type of quality check.

Level	N	Mean	StDev
System Test	94	3.7298	0.6768
Inspection	10	4.5164	0.8615
Walkthrough	88	4.8568	0.8417
Informal w/Peer	37	5.6081	1.1186
Email Comments	6	6.6500	1.2755

```
Individual 95% CIs For Mean Based on
Pooled StDev
----+---------+---------+---------+-----
(*-)
        (*-)
           (-*)
                 (--*--)
                        (------*------)
----+---------+---------+---------+-----
   4.0       5.0       6.0       7.0
```

Example Scenarios of Regression

Using these factors…	To predict this outcome!
Req'ts Volatility; Design and Code Complexity; Test Coverage; Escaped Defect Rates	Delivered Defect Density
Staff Turnover %; Years of Domain Experience; Employee Morale Survey %; Volume of Interruptions or Task Switching	Productivity
Availability of Test Equipment %; Req'ts Volatility; Complexity; Staff Turnover Rates	Cost and Schedule Variance
Individual task durations in hrs; Staff availability %; Percentage of specs undefined; Defect arrival rates during inspections or testing	Cycle Time or Time-to-Market
Resolution time of customer inquiries; Resolution time of customer fixes; Percent of features delivered on-time; Face time per week	Customer Satisfaction (as a percentile result)

Example Regression Output

Regression Analysis: Defect Densi versus ReqtsVolatil, YearsDomainE

```
The regression equation is
Defect Density = 0.484 + 0.480 ReqtsVolatility - 0.0242 YearsDomainExperience

Predictor                   Coef    SE Coef       T      P
Constant                 0.48367    0.03957   12.22  0.000
ReqtsVolatility          0.47963    0.09511    5.04  0.000
YearsDomainExperience  -0.024215   0.001941  -12.48  0.000

S = 0.00893207   R-Sq = 85.9%   R-Sq(adj) = 84.8%

Analysis of Variance

Source          DF         SS         MS      F      P
Regression       2  0.0126076  0.0063038  79.01  0.000
Residual Error  26  0.0020743  0.0000798
Total           28  0.0146819
```

Example Scenarios of Chi Square & Logit

Using these factors…	To predict this outcome!
Programming Language; High-Medium-Low Schedule compression; Req'ts method; Design method; Coding method; Peer Review method	Types of Defects
Predicted Types of Defects; High-Medium-Low Schedule compression; Types of Features Implemented; Parts of Architecture Modified	Types of Testing Most Needed
Architecture Layers or components to be modified; Type of Product; Development Environment chosen; Types of Features	Types of Skills Needed
Types of Customer engagements; Type of Customer; Product involved; Culture; Region	Results of Multiple Choice Customer Surveys
Product; Lifecycle Model Chosen; High-Medium-Low Schedule compression; Previous High Risk Categories	Risk Categories of Highest Concern

Example Chi-Square Output

Tabulated statistics: ReviewType, Volatility

Rows: ReviewType   Columns: Volatility

	High	Low	Medium	All
Inspection	7	18	17	42
	16.67	42.86	40.48	100.00
	41.18	62.07	80.95	62.69
	10.45	26.87	25.37	62.69
	10.66	18.18	13.16	42.00
Walkthrough	10	11	4	25
	40.00	44.00	16.00	100.00
	58.82	37.93	19.05	37.31
	14.93	16.42	5.97	37.31
	6.34	10.82	7.84	25.00
All	17	29	21	67
	25.37	43.28	31.34	100.00
	100.00	100.00	100.00	100.00
	25.37	43.28	31.34	100.00
	17.00	29.00	21.00	67.00

Cell Contents:

Count
% of Row
% of Column
% of Total
Expected count

Pearson Chi-Square = 6.363, DF = 2, P-Value = 0.042
Likelihood Ratio Chi-Square = 6.540, DF = 2, P-Value = 0.038

Example Scenarios of Logistic Regression

Using these factors…	To predict this outcome!
Inspection Preparation Rates; Inspection Review Rates; Test Case Coverage %; Staff Turnover Rates; Previous Escape Defect Rates	Types of Defects
Escape Defect Rates; Predicted Defect Density entering test; Available Test Staff Hours; Test Equipment or Test Software Availability	Types of Testing Most Needed
Defect Rates in the Field; Defect rates in previous release or product; Turnover Rates; Complexity of Issues Expected or Actual	Types of Skills Needed
Time (in Hours) spent with Customers; Defect rates of products or releases; Response times	Results of Multiple Choice Customer Surveys
Defect densities during inspections and test; Time to execute tasks normalized to work product size	Risk Categories of Highest Concern

Example Logistic Regression Output -1

Logistic Regression Table

Predictor	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)			
Const(2)			
CodeType			
2	1.22	0.46	3.23
Complexity	1.13	1.06	1.21

We are using two x factors:

Code Type (New vs. Reused) and Complexity information of modules to predict the Y outcome of future productivity of modules (High, Medium, Low LOC per hour).

Log-Likelihood = -59.290

Test that all slopes are zero: G = 14.713, DF = 2, P-Value = 0.001

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	122.799	122	0.463
Deviance	100.898	122	0.918

Example Logistic Regression Output -2

Logistic Regression Table

Predictor	Coef	SE Coef	Z				
Const(1)	-7.04343	1.68017	-4.19	0.			
Const(2)	-3.52273	1.47108	-2.39	0.			
CodeType							
2	0.201456	0.496153	0.41	0.685	1.22	0.46	3.23
Complexity	0.121289	0.0340510	3.56	0.000	1.13	1.06	1.21

This p value tells us that the type of code (new vs. reused) is insignificant in predicting future productivity.

Log-Likelihood = -59.290

Test that all slopes are zero: G = 14.713, DF = 2, P-Value = 0.001

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	122.799	122	0.463
Deviance	100.898	122	0.918

These p values tell us that we should accept the Null Hypothesis that the model fits the data.

Example Logistic Regression Output -3

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	-7.04343	1.68017	-4.19	0.000			
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2	0.201456	0.496153	0.41	0.685	1.22	0.46	3.23
Complexity	0.121289	0.0340510	3.56	0.000	1.13	1.06	1.21

Log-Likelihood = -59.290

Test that all slopes are zero: G

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	122.799	122	0.463
Deviance	100.898	122	0.918

The positive coefficient for Complexity <u>and</u> the Odds Ratio greater than 1.0 indicate that complexity increases are associated with lower productivity – specifically for each increase of 1 in complexity, the odds increase by 13% of Low Productivity vs. Medium Productivity, and increase by 13% of Medium Productivity vs. High Productivity.

Advanced Prediction Models

Monte Carlo Simulation

Discrete Event Process Modeling and Simulation

Bayesian Belief Networks (BBNs)

Software Reliability Growth Models

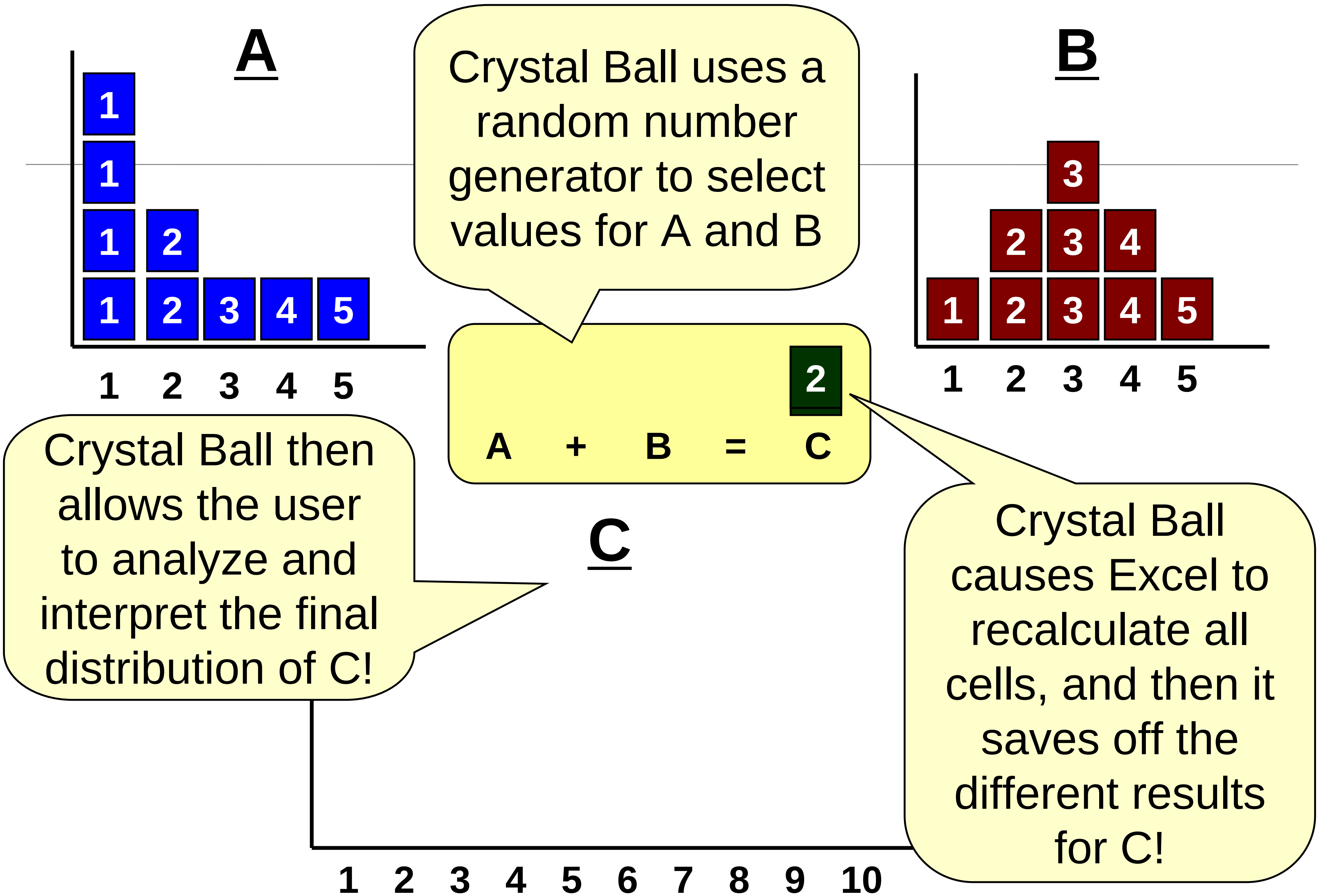
Time Series Analysis

Rayleigh Curves

Weibull Analysis

Why Use Monte Carlo Simulation?

- Allows modeling of variables that are uncertain (e.g. put in a range of values instead of single value)
- Enables more accurate sensitivity analysis
- Analyzes simultaneous effects of many different uncertain variables (e.g. more realistic)
- Eases audience buy-in and acceptance of modeling because their values for the uncertain variables are included in the analysis
- Provides a basis for confidence in a model output (e.g. supports risk management)


A
1 1 1 1
2 2
3
4
5
1 2 3 4 5
Crystal Ball uses a random number generator to select values for A and B
B
3
2 3 4
1 2 3 4 5
1 2 3 4 5
2
A + B = C
Crystal Ball then allows the user to analyze and interpret the final distribution of C!
C
Crystal Ball causes Excel to recalculate all cells, and then it saves off the different results for C!
1 2 3 4 5 6 7 8 9 10

Why Use Optimization Modeling?

Partners with Monte Carlo simulation to automate tens of thousands of "what-ifs" to determine the best or optimal solution

Best solution determined via model guidance on what decisions to make

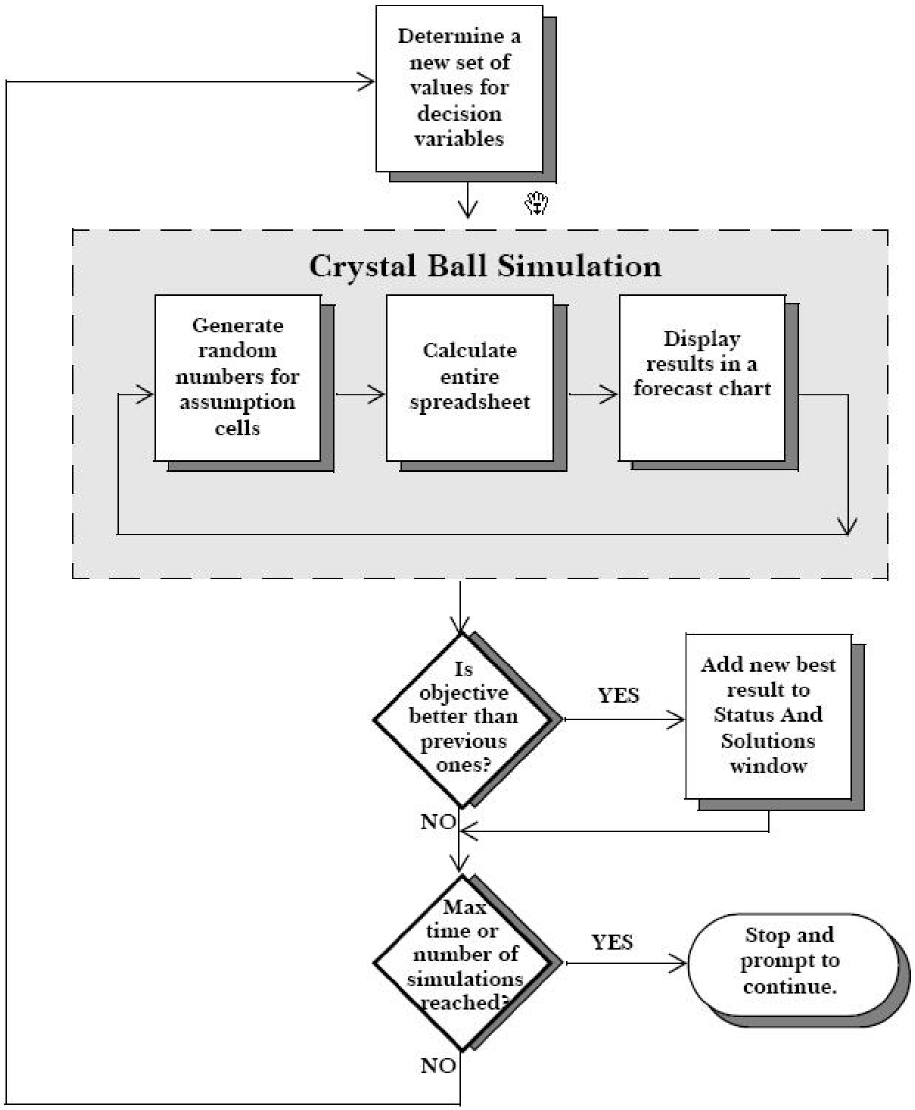
Easy to use by practitioners without tedious hours using analytical methods

Uses state-of-the-art algorithms for confidently finding optimal solutions

Supports decision making in situations in which significant resources, costs, or revenues are at stake

What Is Optimization Modeling?

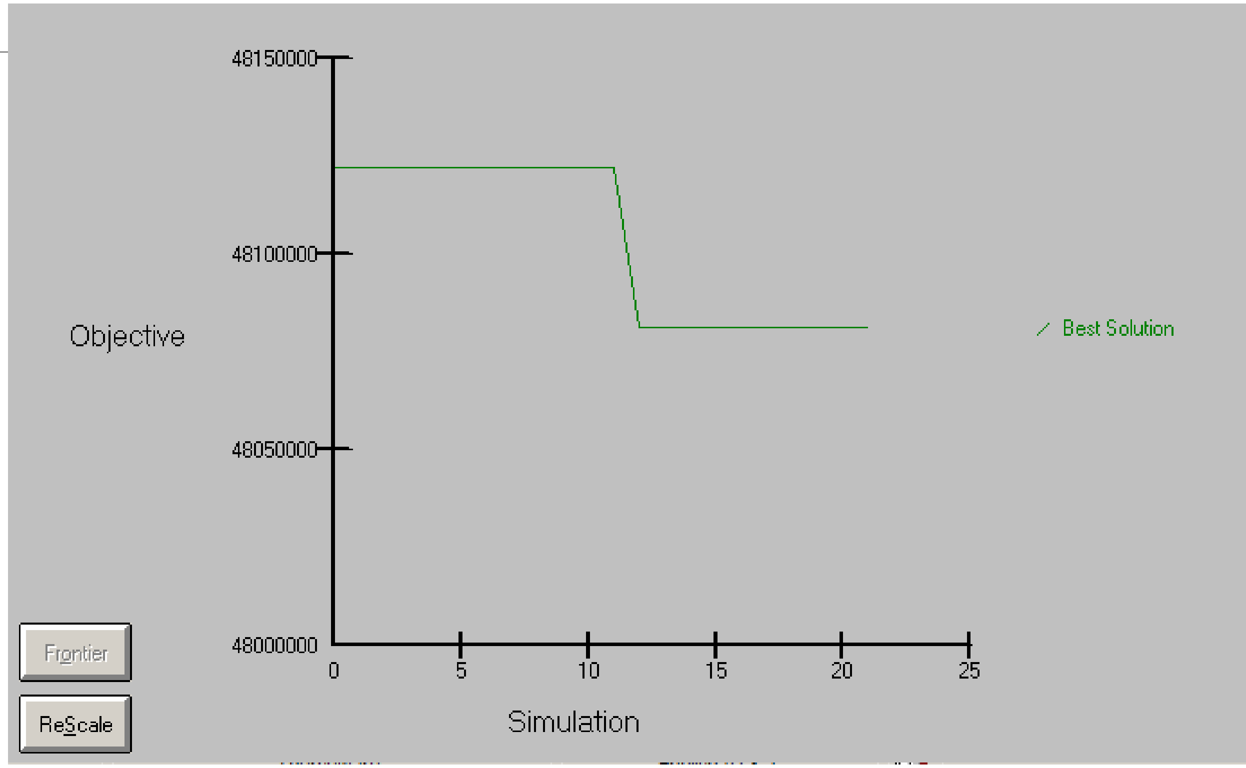
Allows you to optimize one or more decisions within a model that can also contain uncertain variables



"Portions of the Monte Carlo input and output contained in this presentation are printed with permission of Decisioneering, inc..“

Decisioneering company web page is http://www.decisioneering.com

Example Output of Optimization Modeling



****BEST SOLUTION****

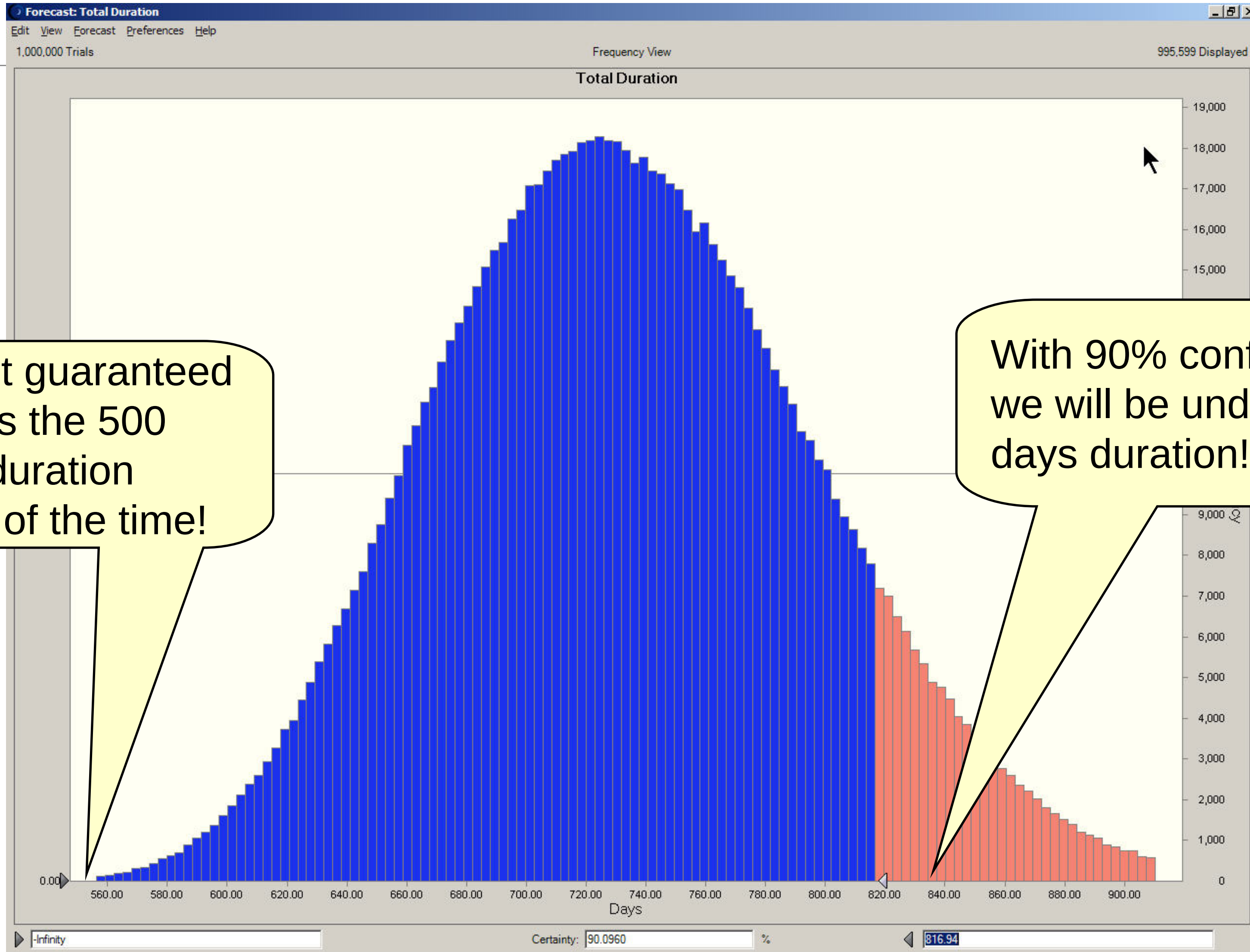
Values of Variables:
AdditionalSQAstaff: 2.5
Objective: Total Costs Including Extra SQA Staff: Mean: 48080751.0001639
Additional details may be found below...

Example 1: Adding Reality to Schedules -1

Process	**Durations**		
Step	Best	Expected	Worst
1	27	30	75
2	45	50	125
3	72	80	200
4	45	50	125
5	81	90	225
6	23	25	63
7	32	35	88
8	41	45	113
9	63	70	175
10	23	25	63
		500	

What would you forecast the schedule duration to be?

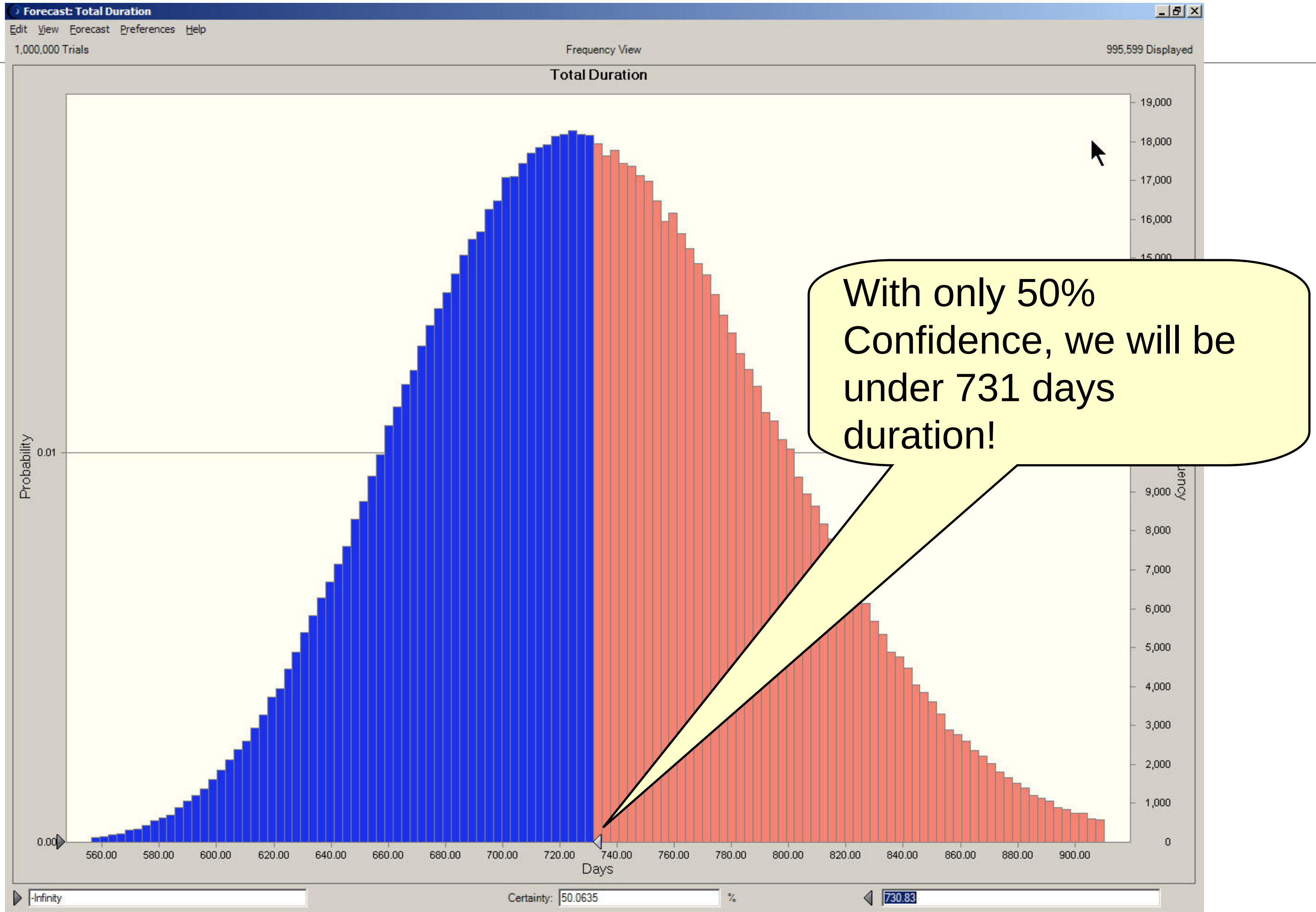
Example 1: Adding Reality to Schedules -2



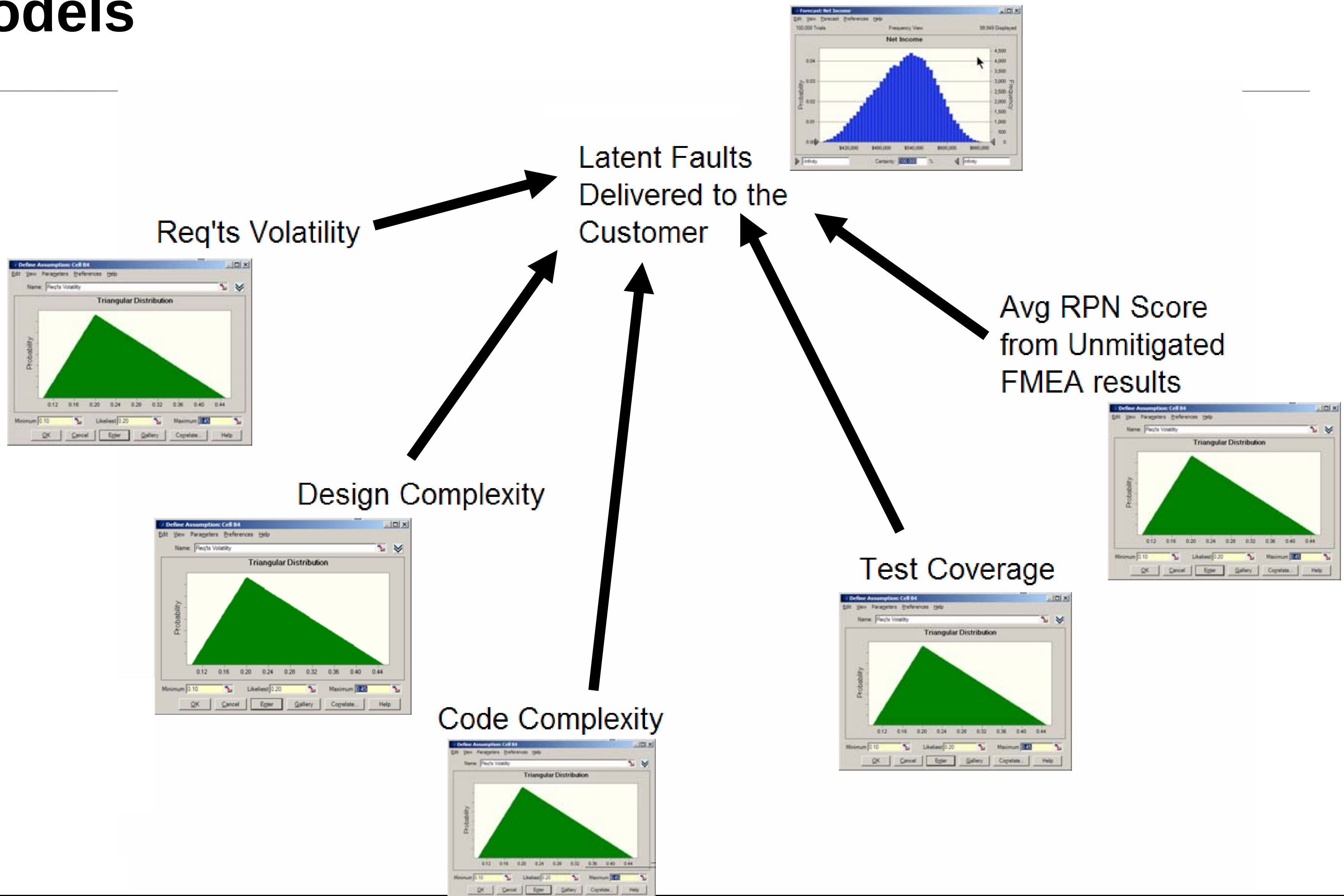
Almost guaranteed to miss the 500 days duration 100% of the time!

With 90% confidence, we will be under 817 days duration!

Example 1: Adding Reality to Schedules -3



Example 2: Building Process-Performance Models



Several Example Tools

http://www.palisade.com/trials.asp

@RISK

The world's most powerful risk analysis tool. Take into account all possible scenarios using Monte Carlo simulation. Work directly in Excel, create presentation-quality graphs, use distribution fitting, and more!

@RISK for Project

Analyze cost and schedule risks in Microsoft Project using Monte Carlo simulation.

- STANDARD
- PROFESSIONAL

http://www.decisioneering.com/

DECISIONEERING

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Crystal Ball®

Risk analysis, simulation and optimization software

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Purchase

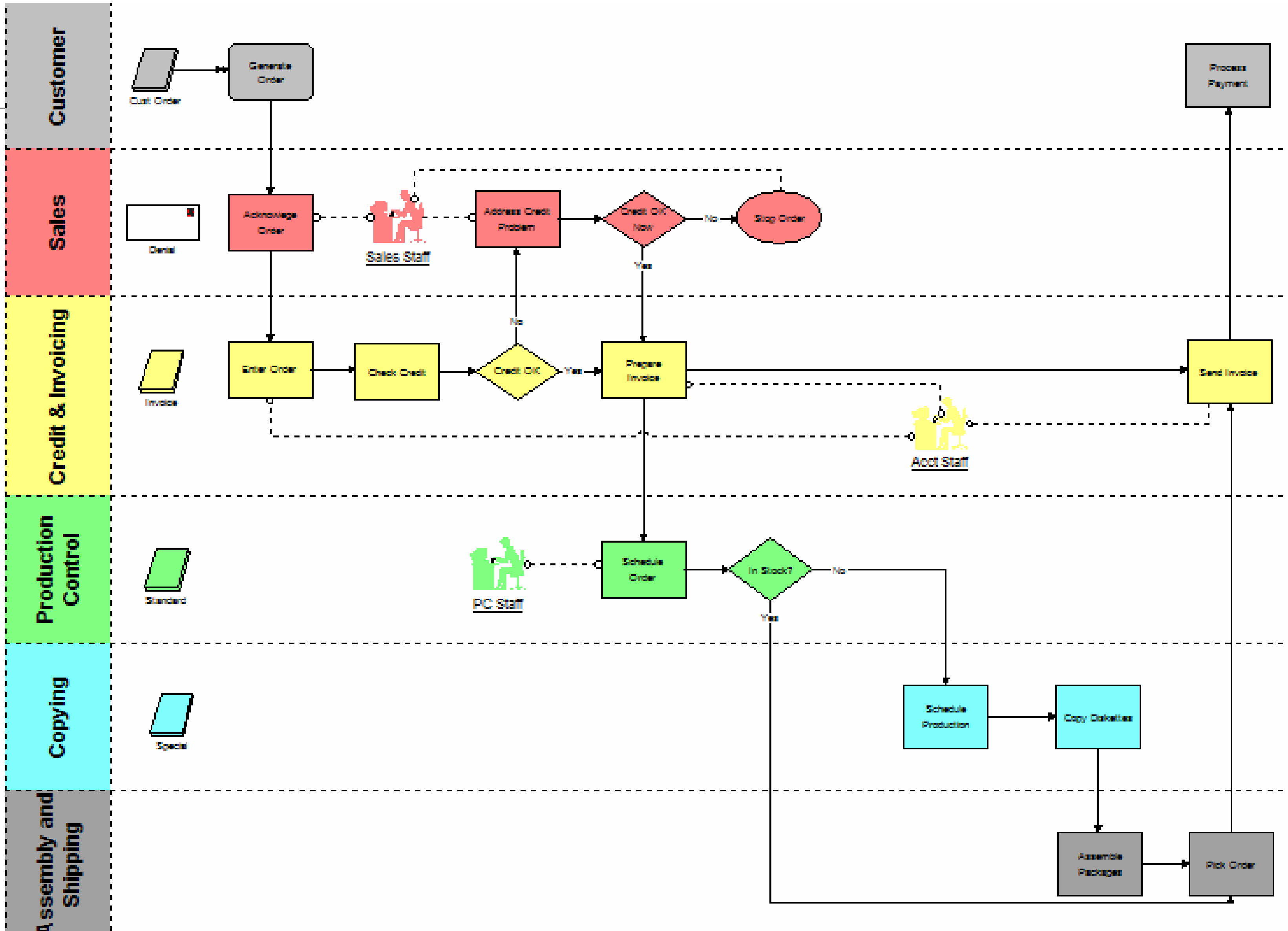
Why Use Discrete Event Process Modeling and Simulation?

Discrete event simulation is one way of building up models to observe the time-based behavior of a system.

The key benefits of simulation include the ability to:

- model the behavior of a system as time progresses,
- give you the power to understand where bottlenecks are, and
- verify that your proposed changes will, in fact, work.

An Example Model with Output-1



An Example Model with Output-2

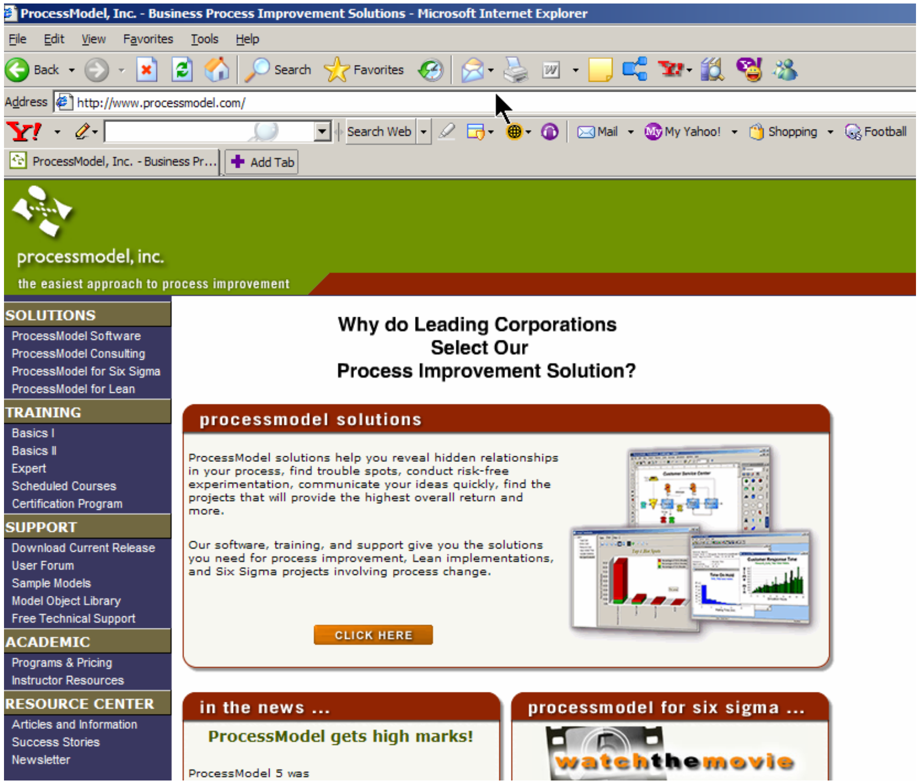
ACTIVITY STATES BY PERCENTAGE (Multiple Capacity)

Activity Name	Scheduled Hours	% Empty	% Partially Occupied	% Full
Generate Order inQ	36.79	100.00	0.0	0.0
Acknowlege Order inQ	36.79	95.94	4.06	0.0
Acknowlege Order				
Enter Order inQ				
Enter Order				
Check Credit				
Address Credit Probl				
Address Credit Probl				
Stop Order inQ				
Stop Order				

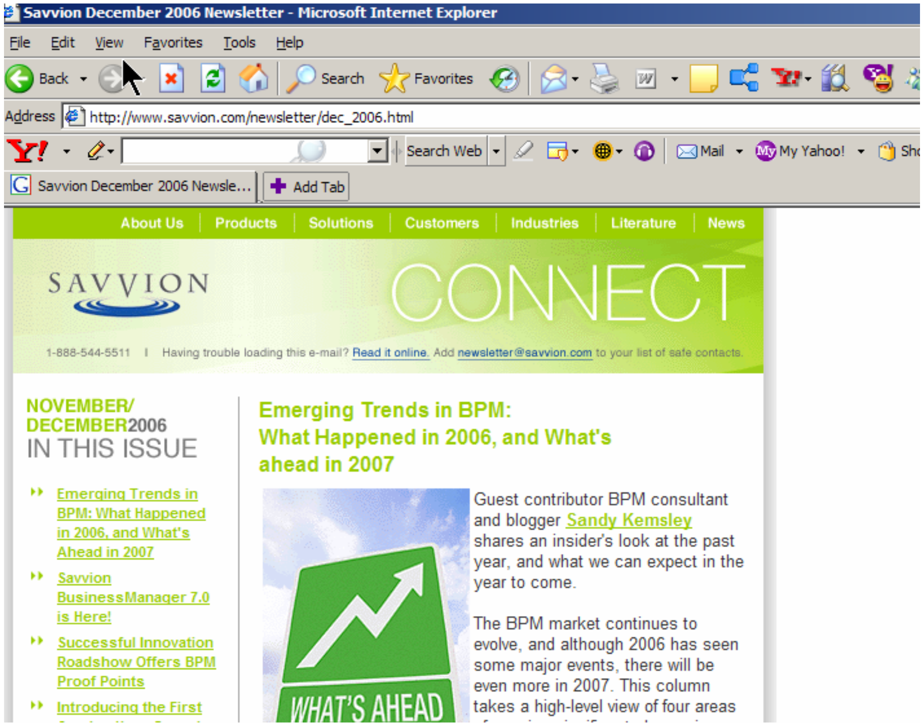
Resource Name	Units	Scheduled Hours	Number Of Times Used	Average Hours Per Usage	% Util
Sales Staff.1	1	36.79	4	2.00	21.74
Sales Staff.2	1	36.79	6	1.83	29.91
Sales Staff.3	1	36.79	5	2.00	27.17
Sales Staff	3	110.39	15	1.93	26.27
Acct Staff.1	1	36.79	4	0.55	6.07
Acct Staff.2	1	36.79	5	0.45	6.17
Acct Staff.3	1	36.79	6	0.40	6.53
Acct Staff.4	1	36.79	6	0.38	6.33
Acct Staff.5	1	36.79	4	1.02	11.12
Acct Staff	5	183.99	25	0.53	7.24
PC Staff.1	1	36.79	3	1.00	8.15
PC Staff.2	1	36.79	3	1.00	8.15
PC Staff	2	73.59	6	1.00	8.15

Examples of Process Modeling Simulation Tools

http://www.processmodel.com



http://www.savvion.com



Why Use Bayesian Belief Network (BBNs)?

BBNs are more flexible because probabilistic modeling does not require adherence to all standard statistical assumptions

BBNs enable modeling of both objective and subjective data

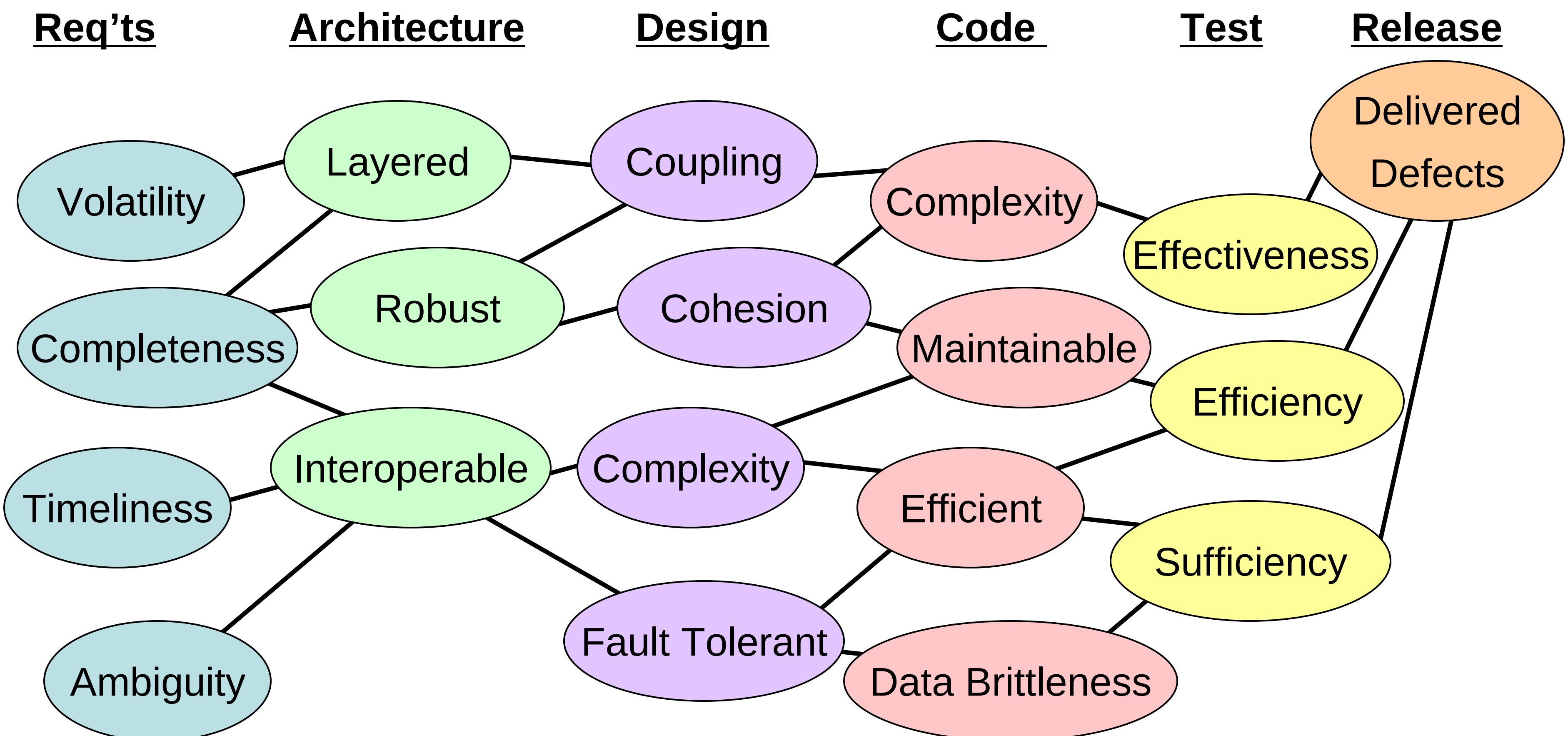
BBNs perform both forecasts of future performance and diagnosis of root causes of today's process performance issues

BBNs can operate with incomplete information whereas statistical modeling requires that all factors have data collected and reported

BBNs may be setup to have learning mechanisms from real-time project data

A BBN is a Collection of Performance Models

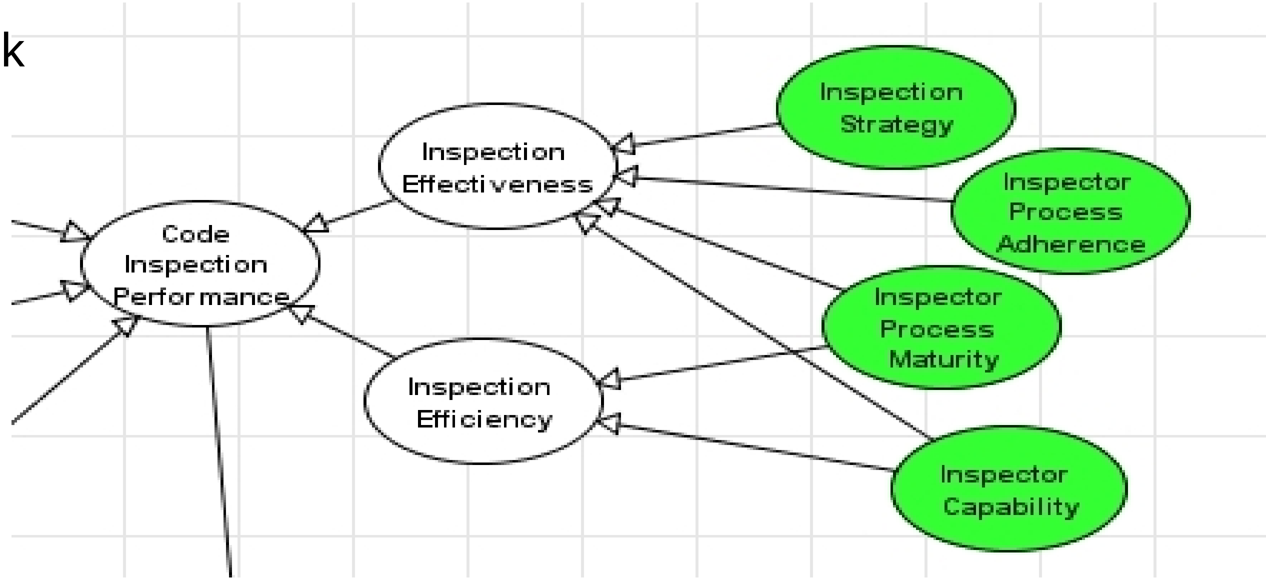
Identify critical factors by sub-process, within each phase of development, and populate a probabilistic table such as a BBN below: (Also Regression and ANOVA are needed to populate this table.)



Ericsson Quality Factor Model

Bayesian Belief Network

- Phases
- Quality Factors
- Expert opinion
- Prediction of Quality Impact



Managerial: Line, project & Process Management

Technical: Requirements, Design, Implementation, Inspection, Test

Examples of BBN Tools

“AGENARISK” http://www.agena.co.uk/

“NETICA” http://www.norsys.com/

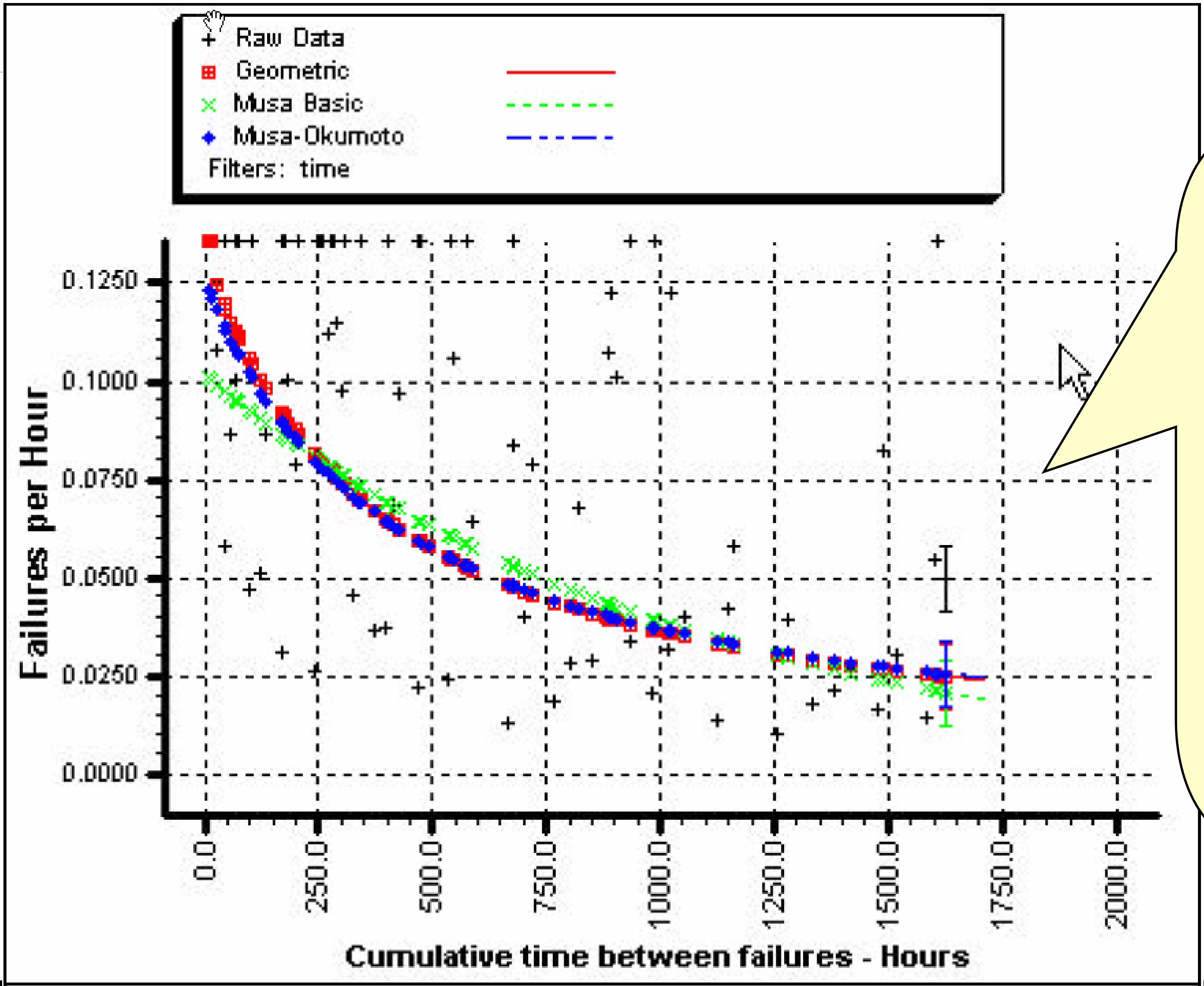
“HUGIN” http://www.hugin.com/

Why Use Software Reliability Growth Models?

The objective of most reliability growth models is to account for corrective actions in order to estimate the current and future reliability and other metrics of interest (e.g. Test-Analyze-And-Fix (TAAF) test cycles).

Reliability growth can be quantified by looking at various metrics of interest such as the increase in the MTBF, the decrease in the failure intensity, or the increase in the mission success probability.

Example Reliability Growth Model Output



We can predict future rates from software testing from previous failure rates using SRE models.

With this, we can conclude remaining test time to reach a required low failure rate!

Example of an SRE Modeling Tool

http://www.openchannelfoundation.org/projects/CASRE_3.0/

Not Logged In | Secure Login | New User

OPEN CHANNEL FOUNDATION

PUBLISHING SOFTWARE FROM ACADEMIC & RESEARCH INSTITUTIONS

Quick Application Search:

Search

CASRE 3.0

Foundation :: Reliability Analysis :: CASRE 3.0

Get this title!

- Get CASRE 3.0
- Monitor new releases

Basic information

- CASRE 3.0 Forum
- Contributors
- History
- Support

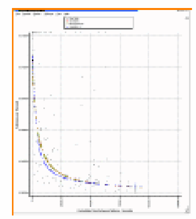
Additional resources

- Sample output
- System requirements and installation instructions

CASRE 3.0 GET IT!

Computer Aided Software, Version 3

Total downloads from Open Channel to date: 737



Moderators:
Allen Nikora

CASRE (Computer Aided Software Reliability Estimation) was developed as a software reliability measurement tool that is easier for nonspecialists in software reliability engineering to use than many other currently-available tools. CASRE incorporates the mathematical modeling capabilities of the public domain tool SMERFS (Statistical Modeling and Estimation of Reliability Functions for Software), and runs in a Microsoft Windows environment.

The command interface is menu driven; enabling and disabling of menu options guides users through the selection of a set of failure data, execution of a model, and analysis of model results. Input to the models is simultaneously displayed as text and as a high-resolution display that can be controlled to let users view the data in several different ways (e.g., time between successive failures, cumulative number of failures). Model predictions and statistical evaluations of a model's applicability (e.g., prequential likelihood ratio, model bias, bias trend) may be superimposed on the plot of the data used as input to the model. CASRE also incorporates earlier findings - that prediction accuracy may be increased by combining the results of several models in a linear fashion. Users can define their own model combinations, store them as part of the tool's configuration, and execute them in the same way as any other model.

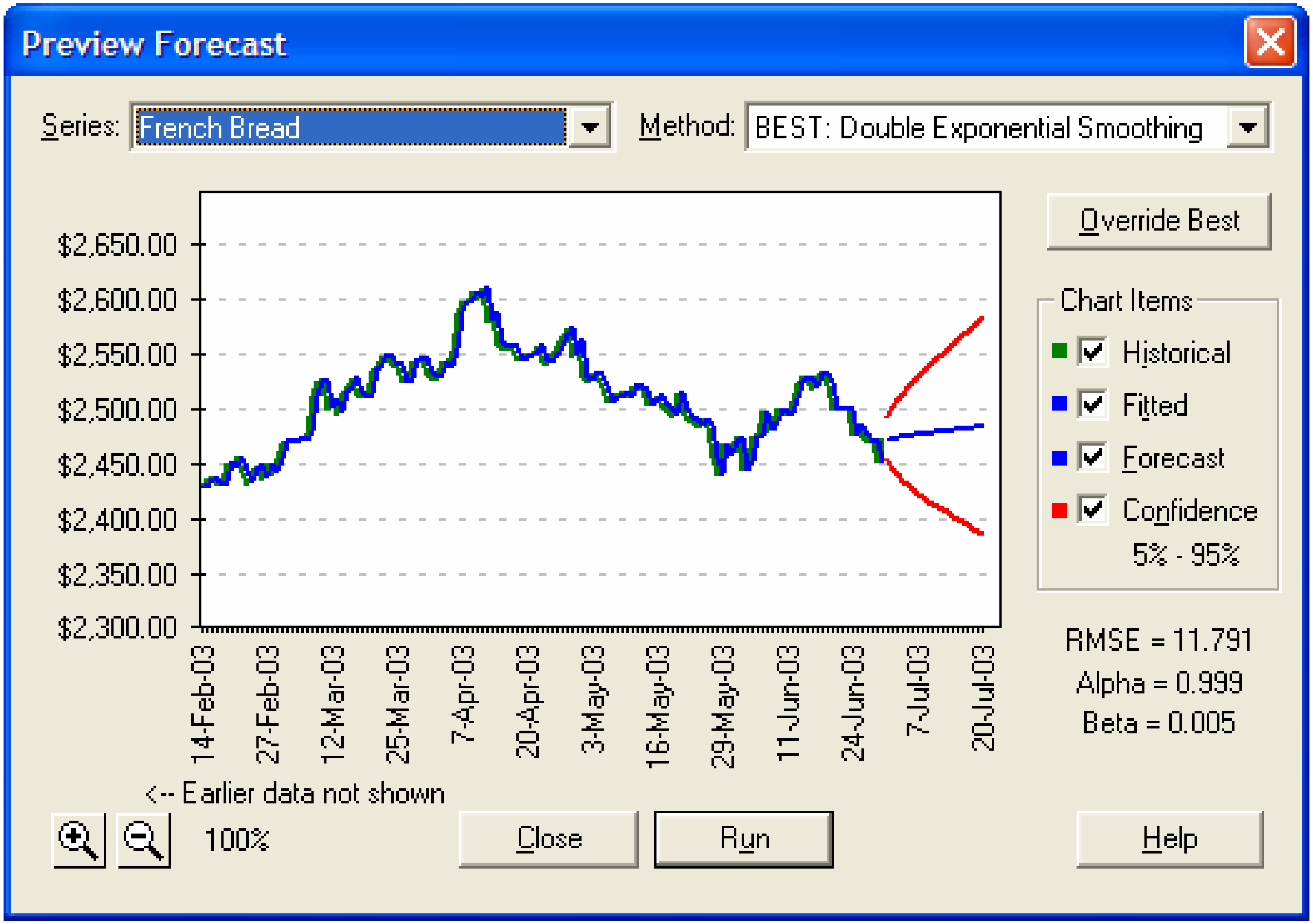
Why Use Time Series Analysis?

When our process performance data trends or cycles across time

When process performance does not follow a constant central tendency

When process owners suspect time-dependent changes in process performance

Example Output of Time Series Analysis

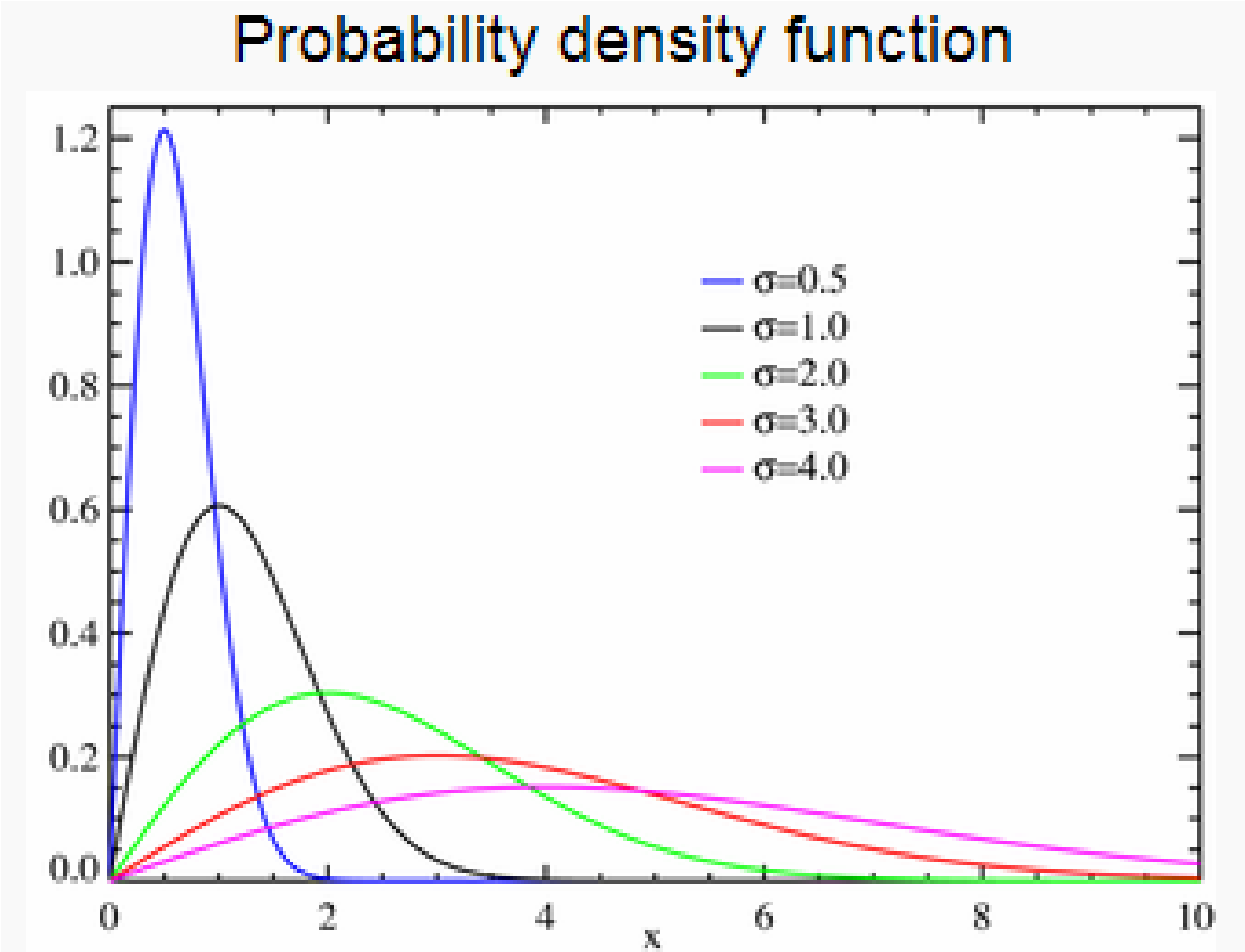


Why Use Rayleigh Curves?

This distribution often used to model the arrival of defects across a lifecycle

By fitting a Rayleigh curve to historical data on defect arrivals, one may use the curve to predict future defect arrivals with prediction intervals

An Example Use of a Rayleigh Curve



Why Use Weibull Analysis?

The Weibull distribution is a general form of many distributions (using the beta parameter - b)

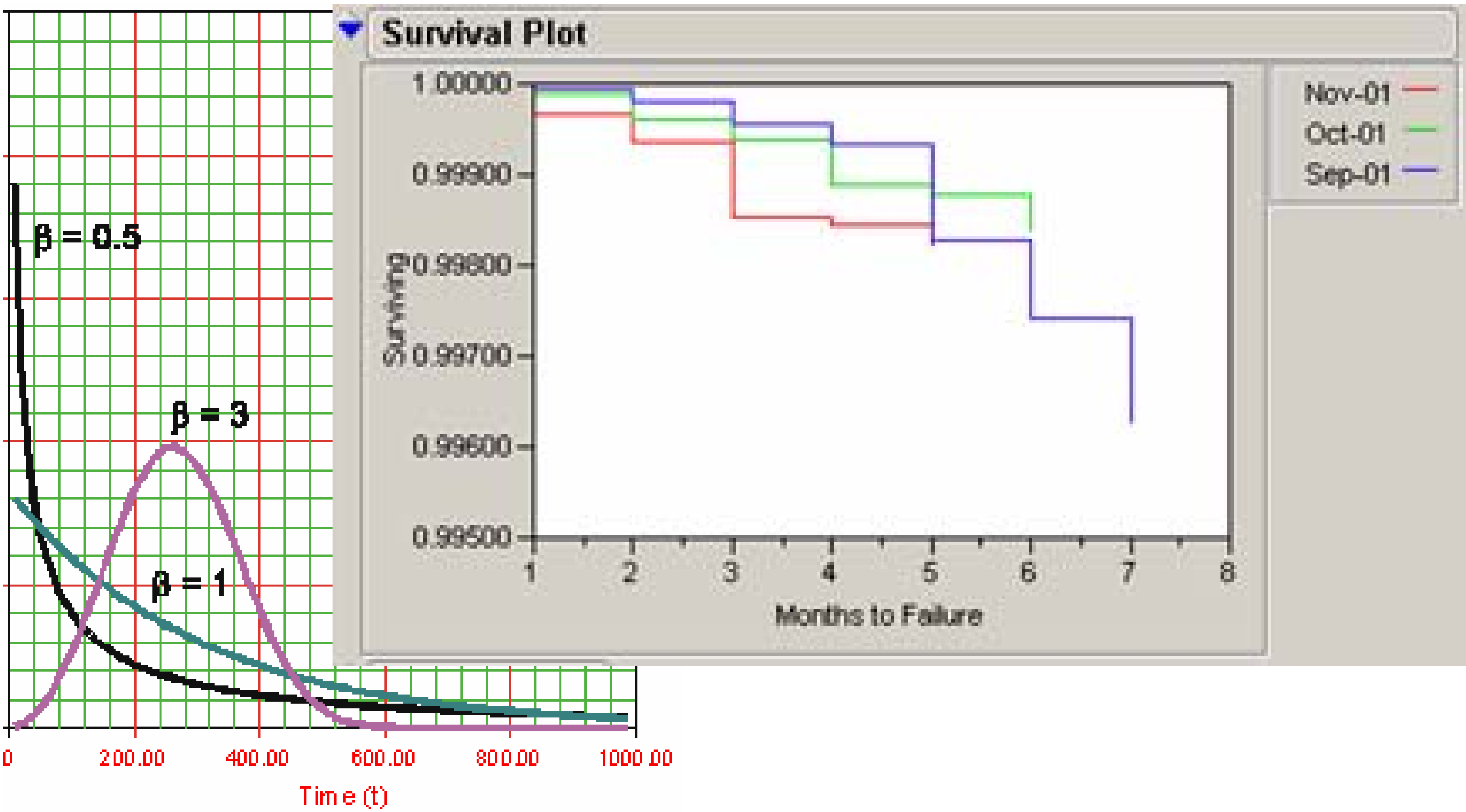
- b = 1, you have the Exponential distribution
- b = 2, you have the Rayleigh distribution
- b = 2.5, you have the Lognormal distribution
- b = 3.6, you have the Normal distribution
- b = 5, you have the peaked Normal distribution

Thus, fitting historical performance data using a Weibull distribution takes some of the guess work out of deciding what distribution to use

The Weibull distribution used most often to model reliability, learning curves, error rates, etc…

Probably the most popular, modern distribution to use in modeling performance data

Example Output of Weibull Analysis



Deployment Lessons Learned

Getting Started with Models

Decide what performance outcome to predict

Decide what sub-process factors to use in the model

Understand what type of data each of the factors and outcome are (Nominal, Ordinal, Interval, Ratio)

Decide which modeling technique to use (refer to SEI job aids)

Remember that multiple modeling approaches probably exist for any situation

Also remember that all models are wrong, some are useful!

Progress Tracking Matrix

Rating Criteria (Red=Not Attempted, Yellow=Completed and Fully Documented, Green=Approved by SEPG)

	Focus Project 1	Focus Project 2	Focus Project 3	Focus Project 4	Focus Project 5	Focus Project 6	Focus Project 7	Focus Project 8	Focus Project 9	Focus Project 10
QPM										
Achieve Statistical Training and SAS JMP training	G	Y	R	G	R	R	Y	R	R	R
Project Goal Matrix	R	R	R	R	R	R	R	R	R	R
Project Quality and Process Performance Objectives (SMART)	R	R	R	R	R	R	R	R	R	R
Select 1-3 QPM Indicators that will be statistically managed	R	R	R	R	R	R	R	R	R	R
Decide on Statistical Method: Control Chart, Intervals, Regression	R	R	R	R	R	R	R	R	R	R
Indicator Template Populated	R	R	R	R	R	R	R	R	R	R
Initial Data Collected; Data integrity checked	R	R	R	R	R	R	R	R	R	R
Indicator(s) Reviewed in Meetings with Minutes	R	R	R	R	R	R	R	R	R	R
Notes on reaction to special causes of variation	R	R	R	R	R	R	R	R	R	R
OPP										
Achieve Statistical Training and SAS JMP training	R	R	R	R	R	R	R	R	R	R
Identify outcomes to predict: cost, schedule, quality	R	R	R	R	R	R	R	R	R	R
Identify factors within the project to predict outcomes	R	R	R	R	R	R	R	R	R	R
Identify and collect initial data; ensure data integrity	R	R	R	R	R	R	R	R	R	R
Conduct ANOVA, regression, or logistic regression models	R	R	R	R	R	R	R	R	R	R
Attain Adj-Rsquared > 0.70 and p values < 0.05	R	R	R	R	R	R	R	R	R	R
Develop prediction or confidence intervals to gauge performance	R	R	R	R	R	R	R	R	R	R
Record notes on model including rationale and factors used	R	R	R	R	R	R	R	R	R	R
Prediction models reviewed in meetings with minutes	R	R	R	R	R	R	R	R	R	R

Aligning Models with Objectives and Processes

Process Step	Goal 1	Goal 2	Goal 3	Goal 4	Goal 5	Goal 6	Goal 7
Req'ts Elicitation	X			X			
Prototype		X					
Architecture Modification						X	
High level Design			X				
Low level Design			X				
Coding							X
Unit Test							
Integration Test						X	
System Test	X			X			
Alpha Test							
Beta Test		X					

Each **X** receives a S.M.A.R.T. objective statement and is a candidate for a prediction model.

Conclusion

Questions?