Bushing blocks optimization for an external gear pump

MARIA PIA D'AMBROSIO - SixSigmaIn Team snc
MARCO MANARA - Casappa SpA

Summary

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- Case Study and Project
- Drawing Tolerances - statistical definition
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- Process Capability basic concepts
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- Responses scenario
- Ppk Risk model: step 2
- Ppk Risk model: final solution choice
- Results evaluation
- Why @Risk
- DoS Design of Simulations

Company profile - SixSigmaIn Team

SixSigmaIn Team - Lainate (Milan Area, Italy)

The distinguishing feature of SixSigmaIn Team consists in the merging of competencies related to Statistical Problem Solving, Adult Learning, Business Intelligence and Tools Development.

SixSigmaIn Team provides advanced and customized DMAIC, DFSS, Design of Experiments, Tolerance and Reliability Analysis trainings and solutions for an effective industrial application of statistical analysis with the best statistical tools.
SixSigmaIn Team's clients include the Italian locations of companies such as Siemens VDO (now Continental Automotive Italy), Osram Sylvania, Cabot , Rolls Royce, Philips, Reckitt-Benckiser, G.D Group, Zeiss Vision, Saes Getters, Diasorin, GSK, Solvay Pharma and others.

Some Decision Support Systems / Stat Tool developed by SixsigmaIn Team:

- MTBridge Engine © : Minitab Automation Tool
- Champion of Italy © : Monte Carlo Simulation and Tolerance Analysis add-in for Minitab
- R&M 2000 © : statistics application to analyze, target and control pharma products market share
- R&M Rules and Maps © : software tool and book for strategic marketing and position analysis.

International Collaboration Network

- Stat-Ease Inc
- BMG Breakthrough Management Group Inc

Company profile - Casappa S.p.A.

Casappa S.p.A. – HQ: Parma (Italy)

Casappa was founded in 1952.
Through the holding Finrel SpA controlled by the Casappa brothers, it groups 7 subsidiary companies and 5 associated companies.
The group has more than 1300 employees and had a turnover of 227 million euro in 2008.

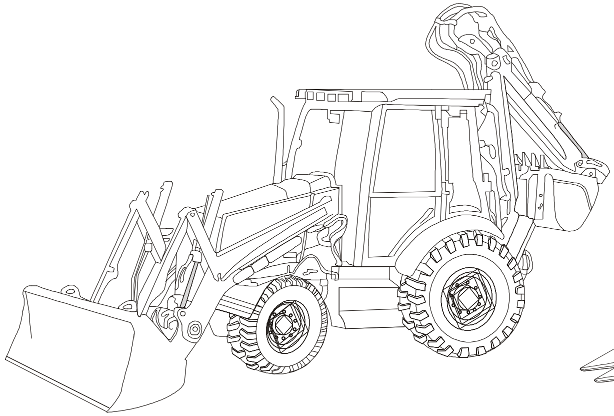
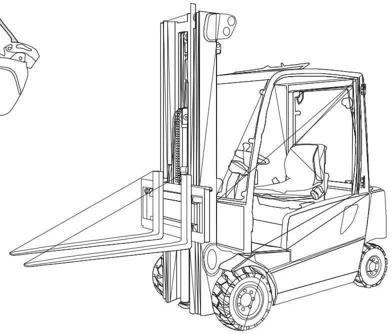
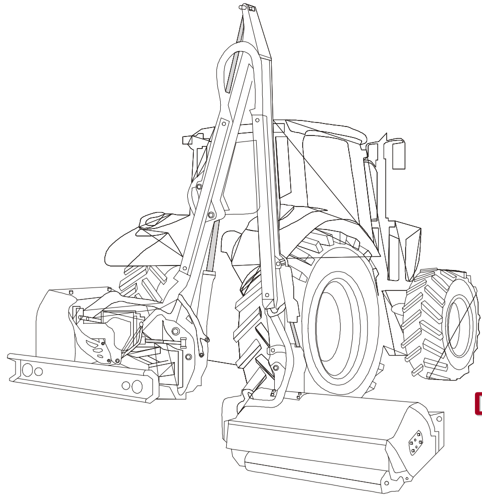
The core business of Casappa SpA is Hydraulics:
- external gear pumps and motors
- axial piston pumps and motors (fixed and variable displacement)
- filters

High technology and great attention to Research & Development are essential to the Company.

Highly customer-oriented, Casappa co-designs customized solution with the biggest world leader manufacturers of earthmoving and agricultural machines

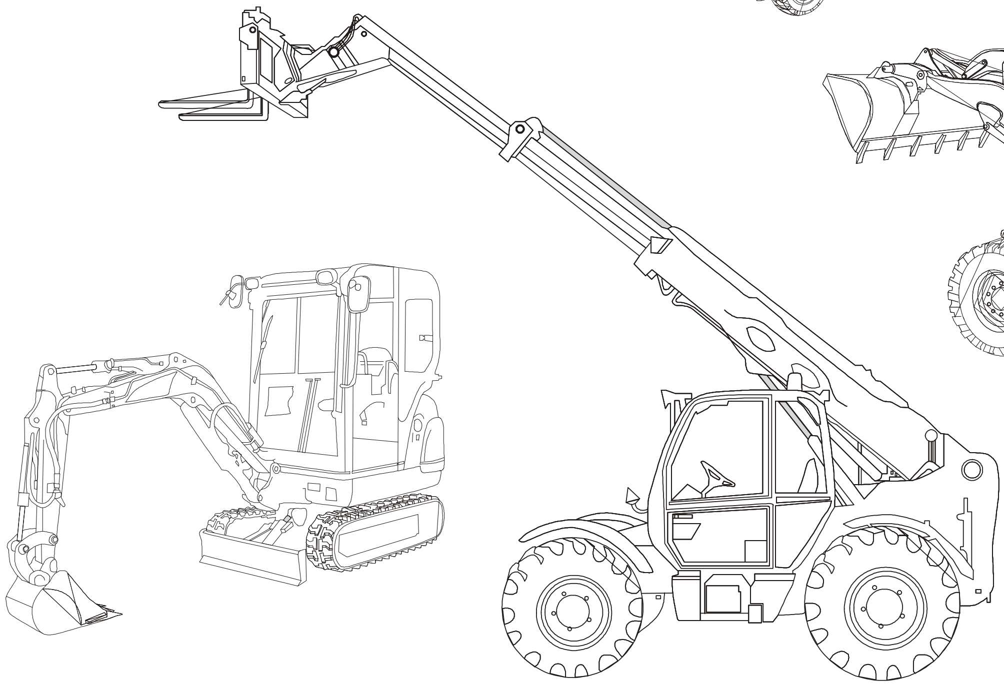
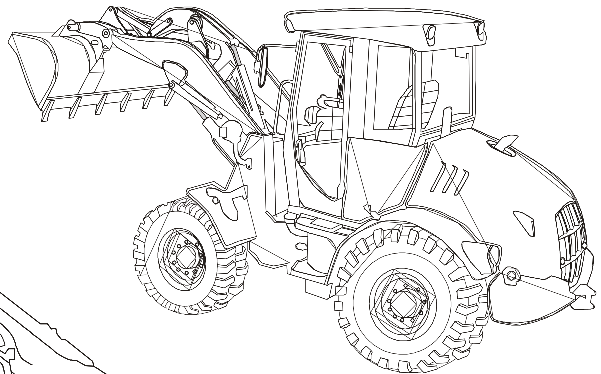
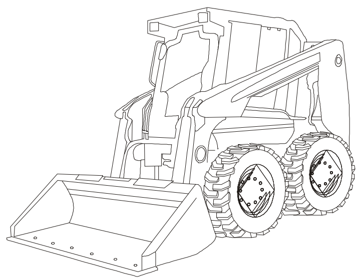
Company profile - Casappa S.p.A.

Applications

Some customers:

AGCO
AMMAN-YANMAR
ATLAS COPCO
CATERPILLAR
CNH
DOOSAN INFRACORE
DAIMLER CHRYSLER
GUIMA PALFINGER
HYUNDAI
HYVA INTERNATIONAL
IR-BOBCAT
JUNGHEINRICH
KOMATSU
MANITOU
MANITOWOC-GROVE
STILL WAGNER
TEREX
TEXTRON
TORO
TOYOTA
VOLVO

The presenters

Maria Pia D'Ambrosio - SixSigmaIn Team snc

Maria Pia works as Senior Trainer at her own Company – SixSigmaIn Team.
She studied Chemistry at University of Milan and she worked as Process Engineer for metallurgical Companies for about 15 years.
She has been involved in the Six Sigma activities and Statistic since 1997 and is a BMG Certified Master Black Belt.
Her main specialization knowledge is Design of Experiments, Tolerance and Reliability Analysis.
She is Design Expert and Minitab teacher / specialist.
Her main activities are coaching, tutoring and supporting people and Companies to get a major breakthrough in their processes.

Marco Manara - Casappa S.p.A.

Engineering Manager of the gear pumps and motors business unit at Casappa HQ.
Six Sigma Black Belt (certified by BMG - Breakthrough Management Group - in 2008).
Deeply involved in the Six Sigma deployment in Casappa, he has started a process of re-engineering and re-designing several company products, using statistical definition of the process tolerances and Design For Six Sigma concepts.
In the last two years, among other responsibilities, he has been working on developing several models for tolerance analysis application.

SixSigmaIn Team & Casappa S.p.A. collaboration

Our collaboration started in 2006

Main works together:

- **Six Sigma and Advanced Statistics Training**

  SixSigmaIn has been in charge of training Green and Black Belts during the Casappa Six Sigma program deployment

- **Optimization of measurement systems**

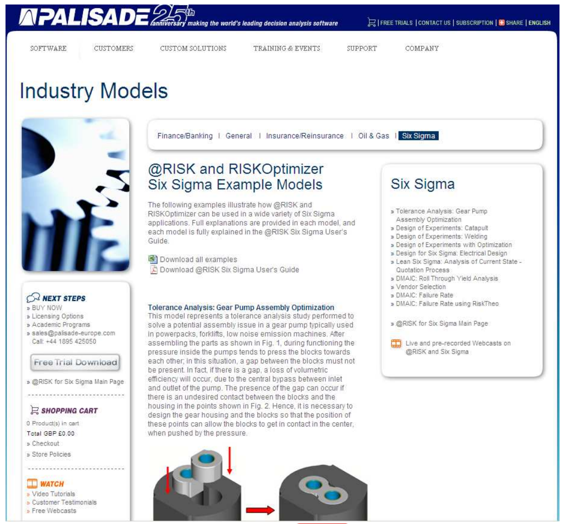
  This was the key project carried out during the first two years of Six Sigma deployment

< Casappa is using high-level competence in the analysis phase in order to apply pragmatic but reliable and robust solutions […]. A modern manufacturing company can not take the risk of not understanding if a discrepancy in the quality control depends on a not optimized process or on errors introduced by the measurement system ! >

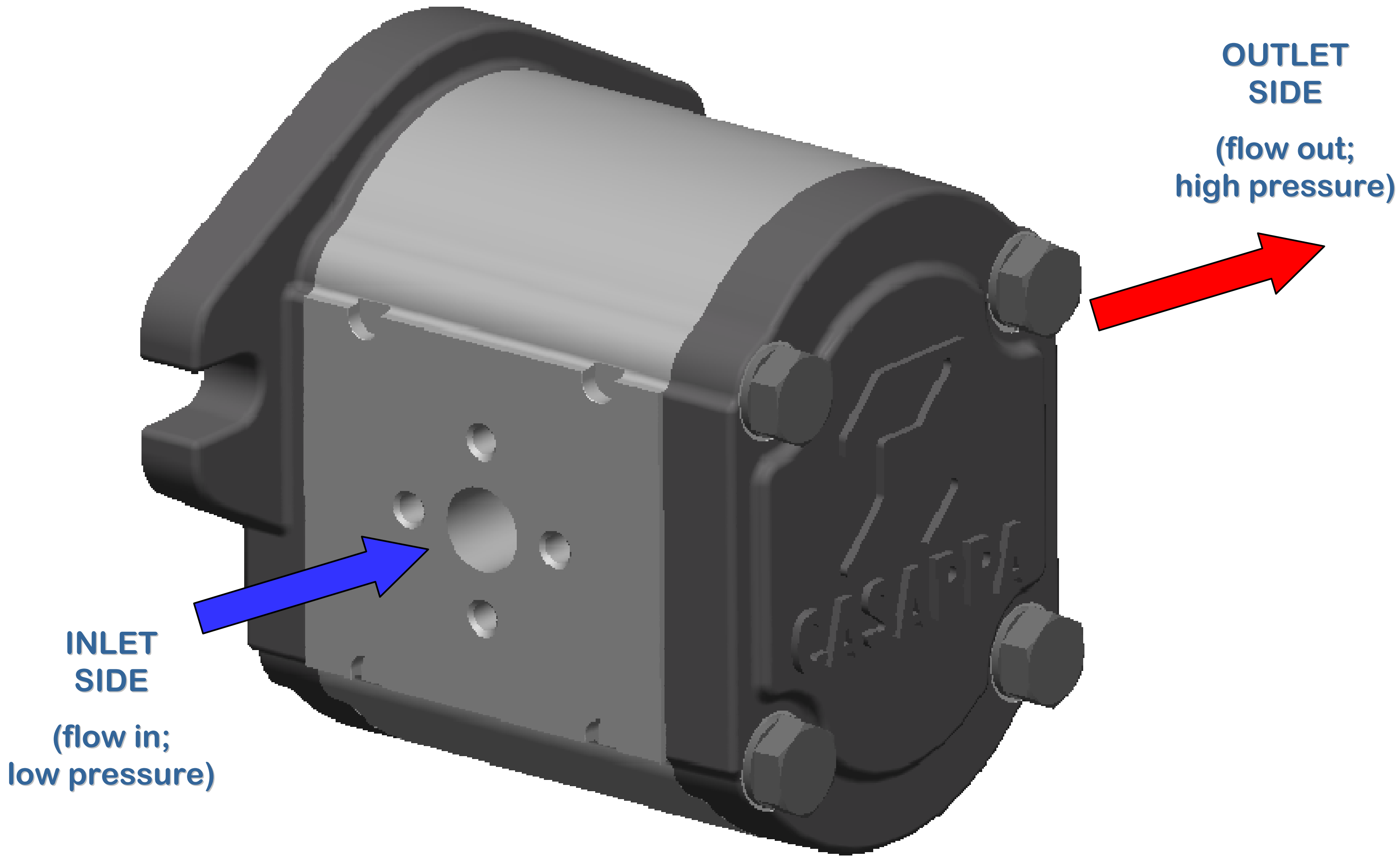
- **Tolerance analysis studies**

  The example published on Palisade website concerned the optimization of the assembly for a low noise gear pump

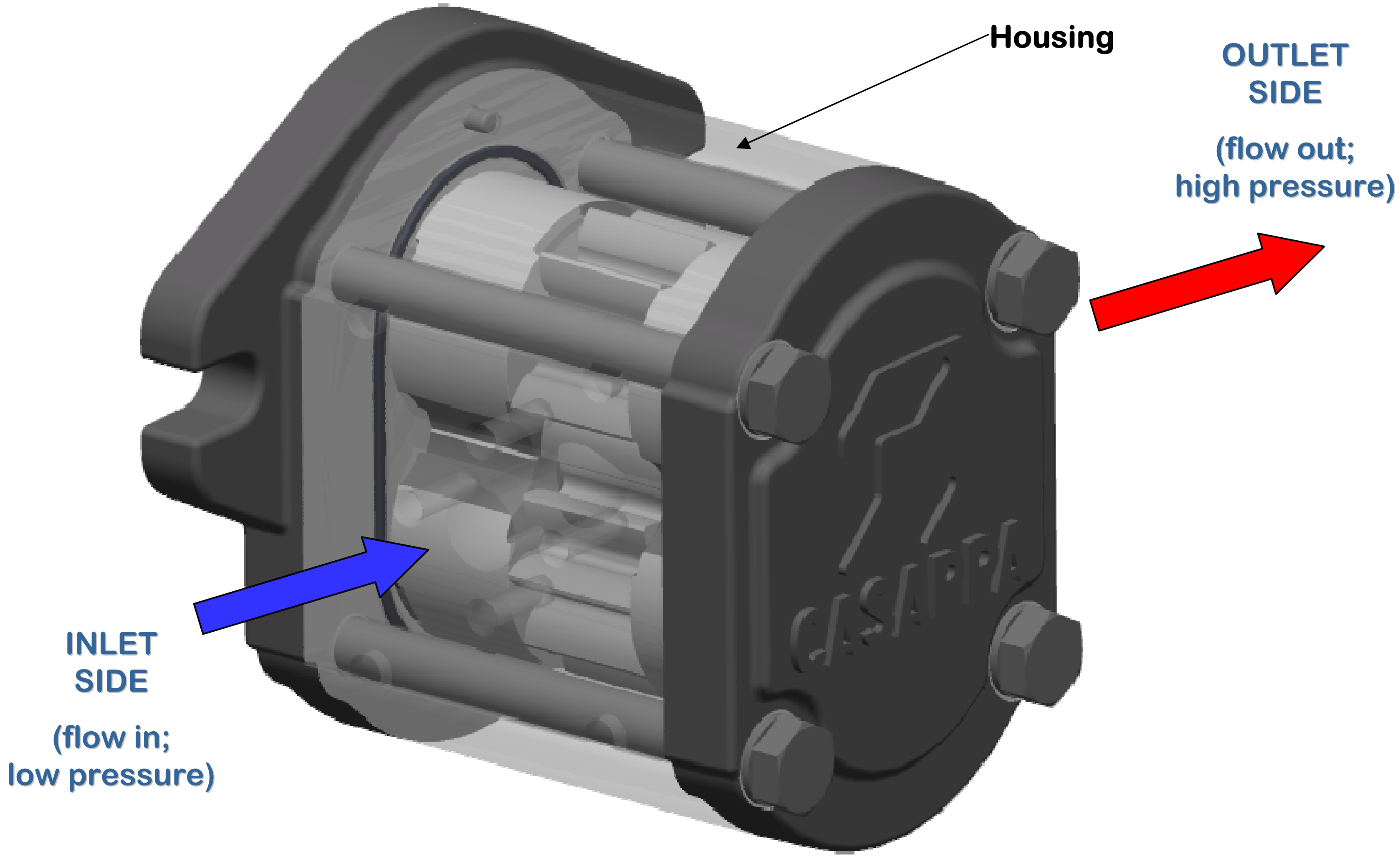
This article was published on the Italian journal "Macchine Utensili" in November 2008



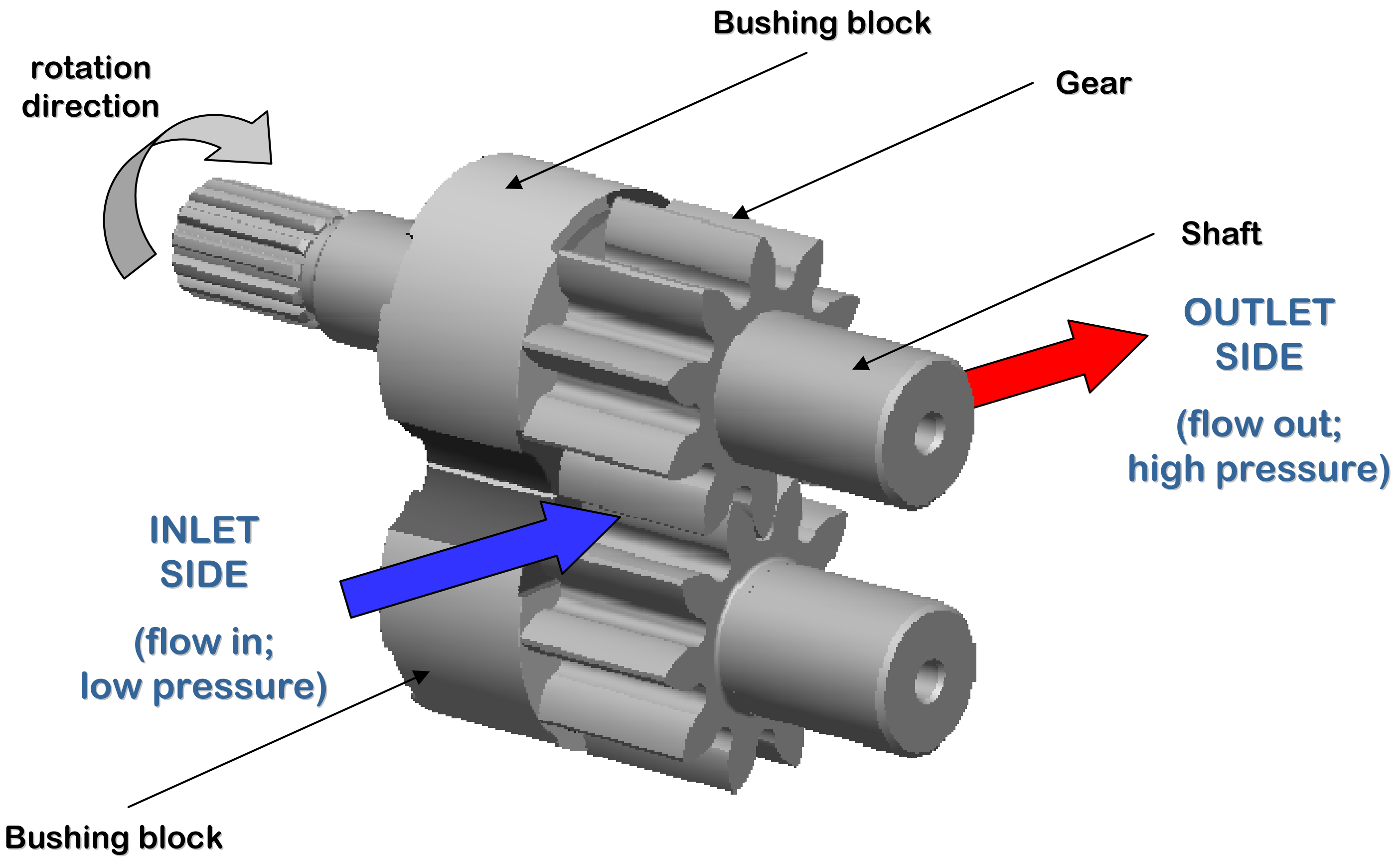
Hydraulic pumps - basic concepts



Hydraulic pumps - basic concepts



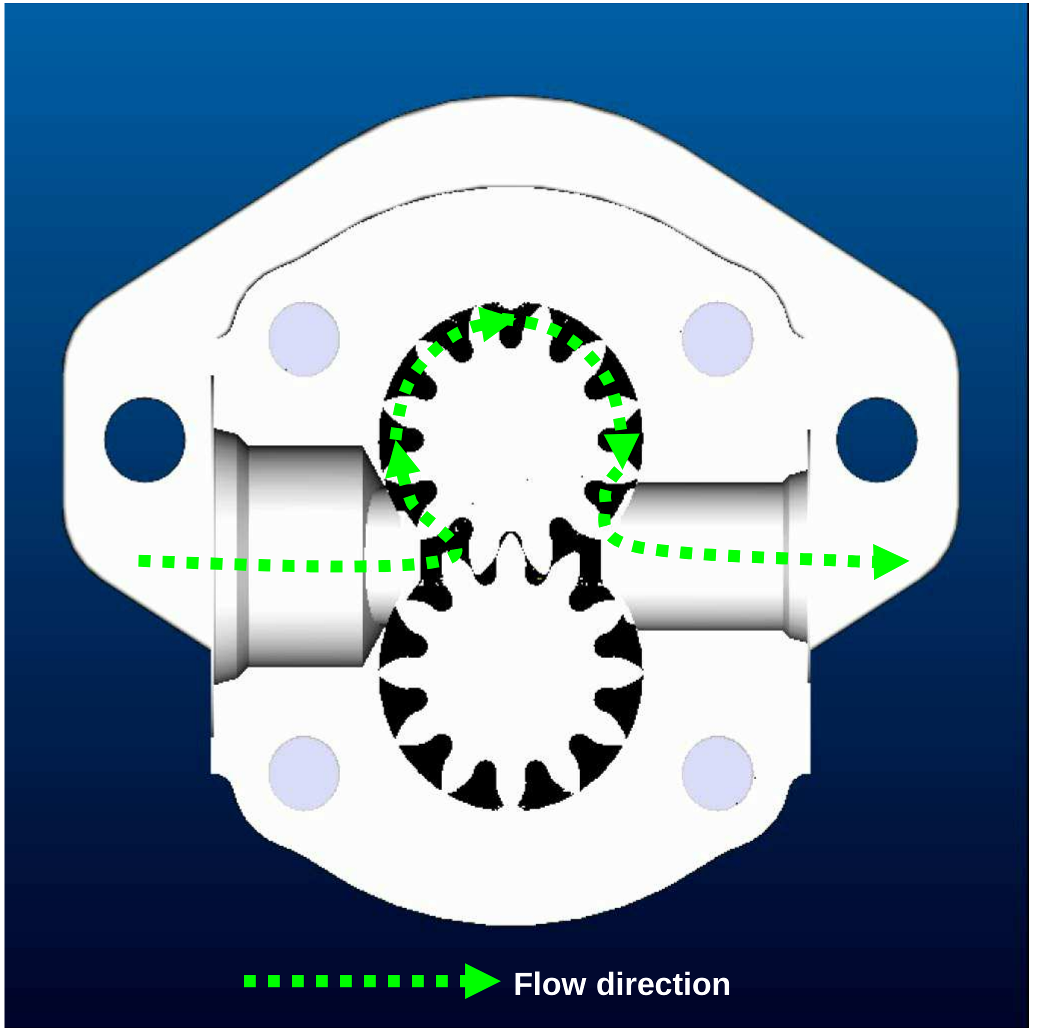
Hydraulic pumps - basic concepts



Hydraulic pumps - basic concepts

INLET
SIDE

(flow in;
low pressure)



OUTLET
SIDE

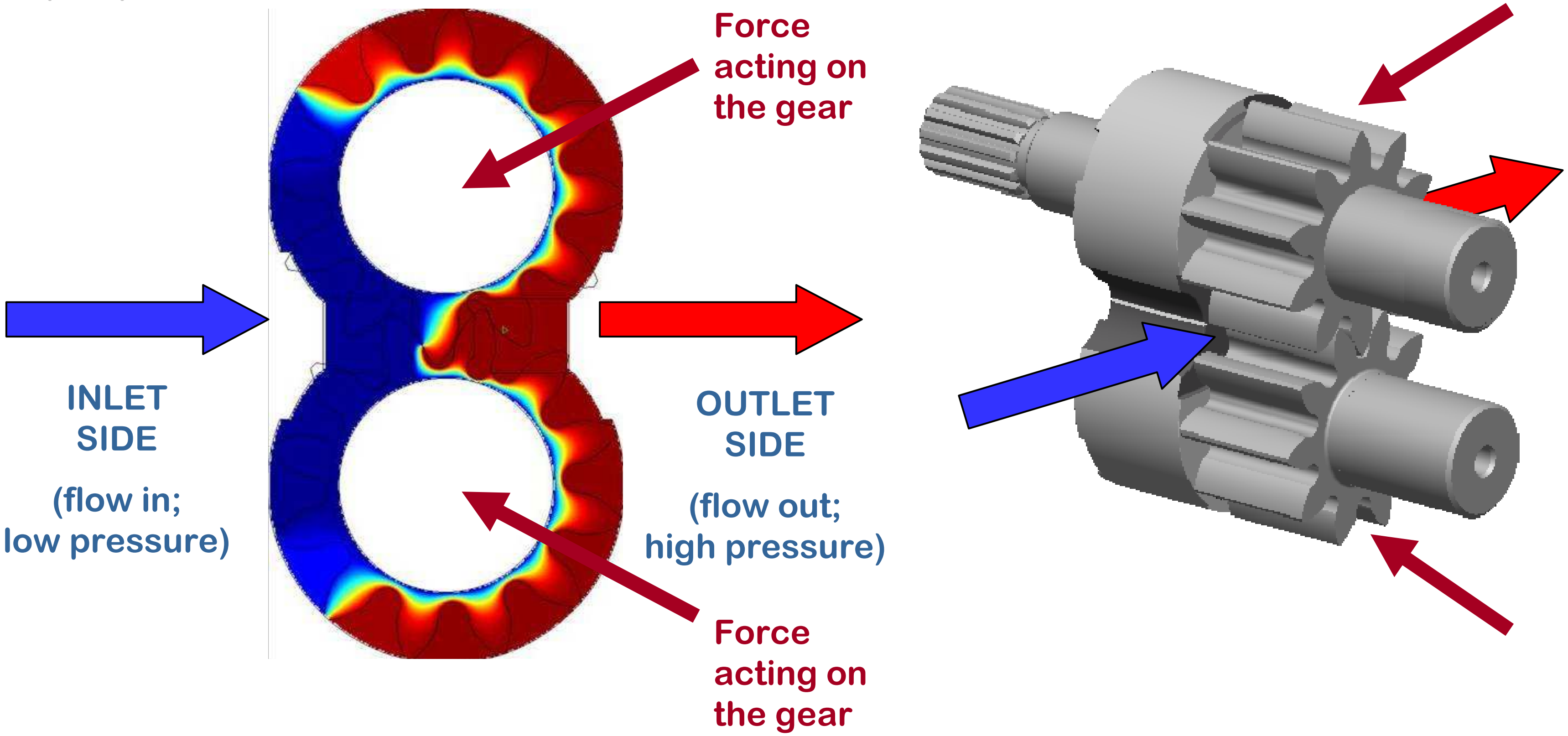
(flow out;
high pressure)

Hydraulic pumps - basic concepts

Pump internal pressure distribution

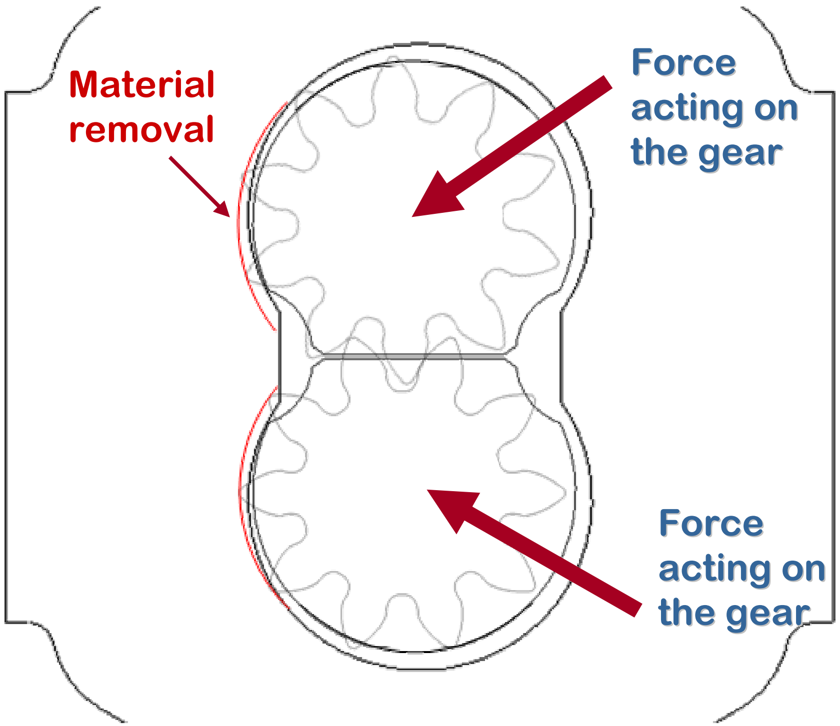
Due to the pressure distribution, a force acts on the gear and pushes it towards the inlet side of the housing.

This phenomenon is responsible for the material removal from the body produced during the initial break-in of the pump. The material removal is essential for the good performance (high efficiency) of the pump.

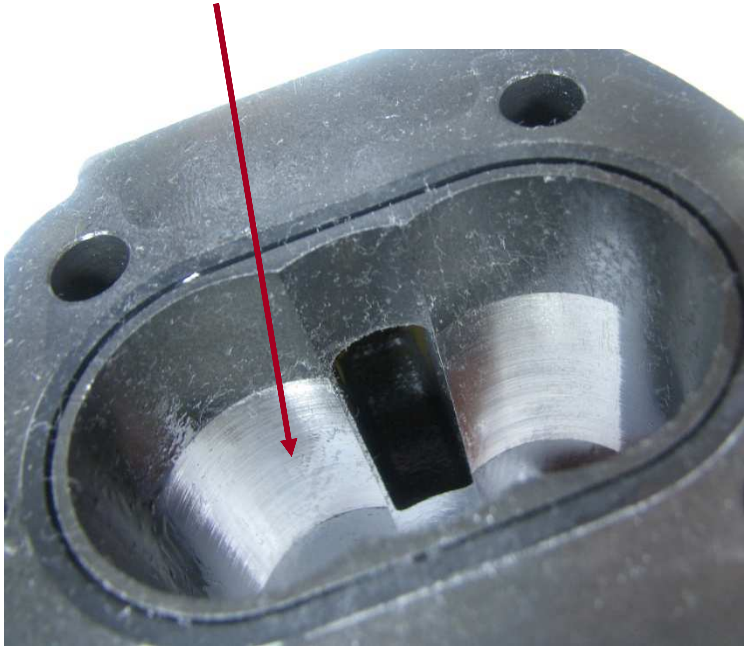


Hydraulic pumps - basic concepts

The **bushing blocks geometry** plays a key role in determining the material removal amount.



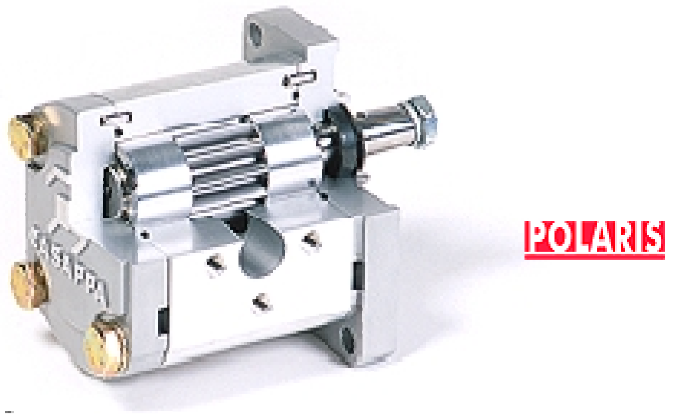
Material removal



Case Study: Polaris PLP30

The bushing blocks geometry plays a main role in the process of defining functional and mechanical parameters related to the performance of the pump (high efficiency, low noise level, assembly ability).

In this specific case (a pump of the series Polaris PLP30), a change in the supplier chain and the implementation of a different production technology have required a re-design both of the geometrical characteristics of the blocks and of some related dimensions of the housing where the blocks are installed.

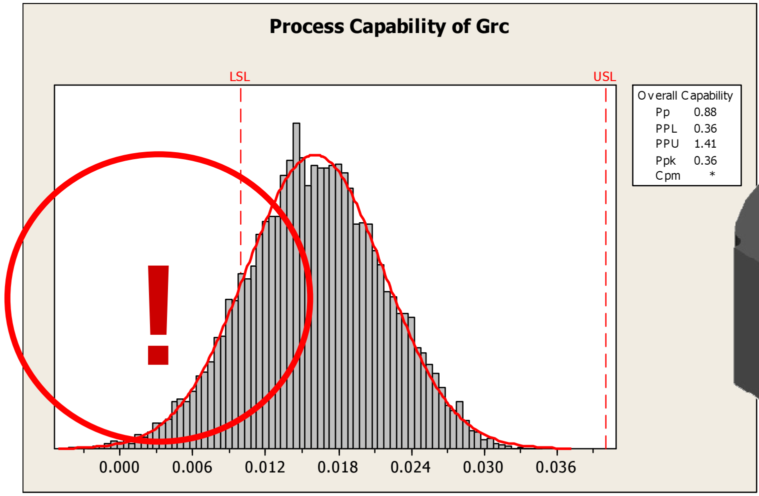


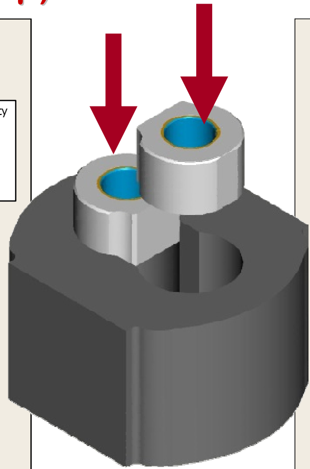
Let's take a look at the current situation…

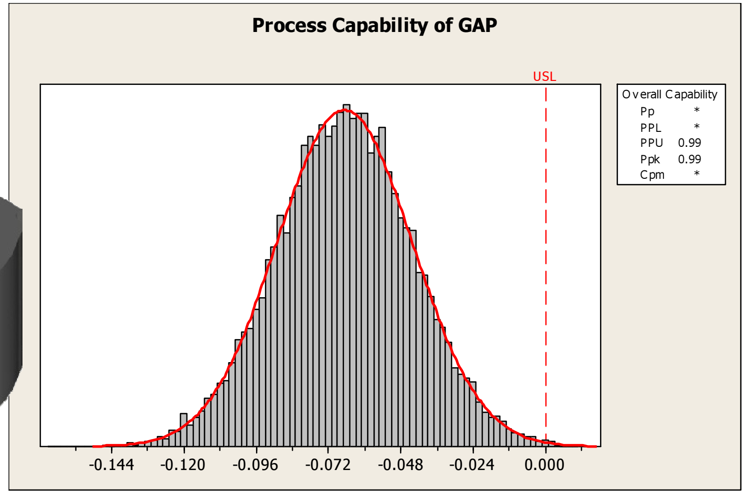
Case Study: Polaris PLP30

The Grc Ppk is only 0.36 and the GAP Ppk is 0.99… not enough!

(certainly, if GAP > 0, there will be a scrap)

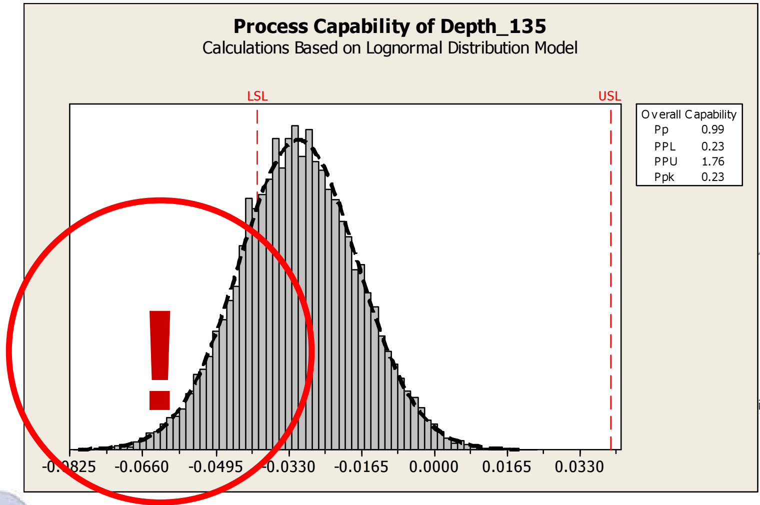


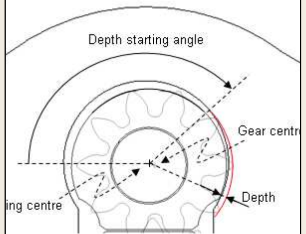


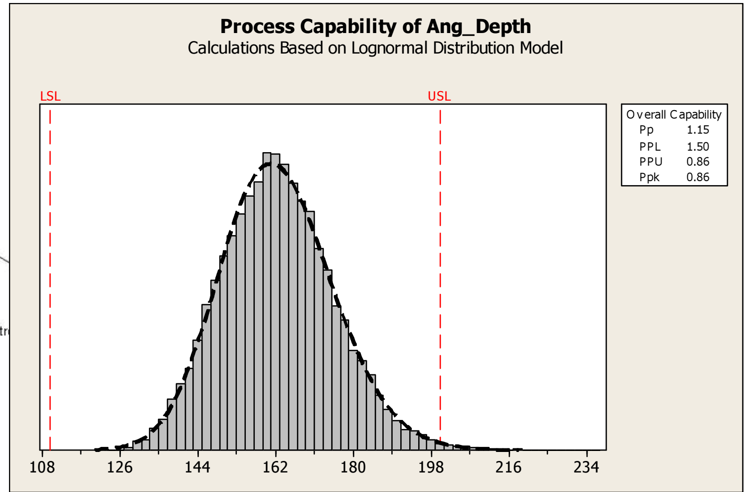


A couple of parameters related to the material removal:

The Depth_135 Ppk is 0.23 and the Ang_Depth Ppk is 0.86 …… definitely not enough!







Case Study: Polaris PLP30

We have acquired a strong experience between 2007 and 2009 working on Drawing Tolerances Statistical Analysis and Capability Analysis of our processes.
That was the starting-point of this new project, whose purpose is:

- to improve and optimize this pump performance to gain
  - economical benefits (reduction of internal scraps)
  - marketing advantages (higher quality and performance)

- AND to create and standardize an internal statistical procedure to design all our new pumps

How is it possible to solve the problem in an efficient and robust way?

To be robust, a Statistical Analysis of data is required.

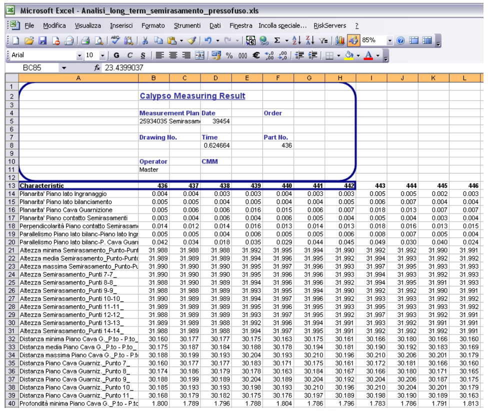
To be efficient, we have to Simulate.

To win, we need Discipline and Method.

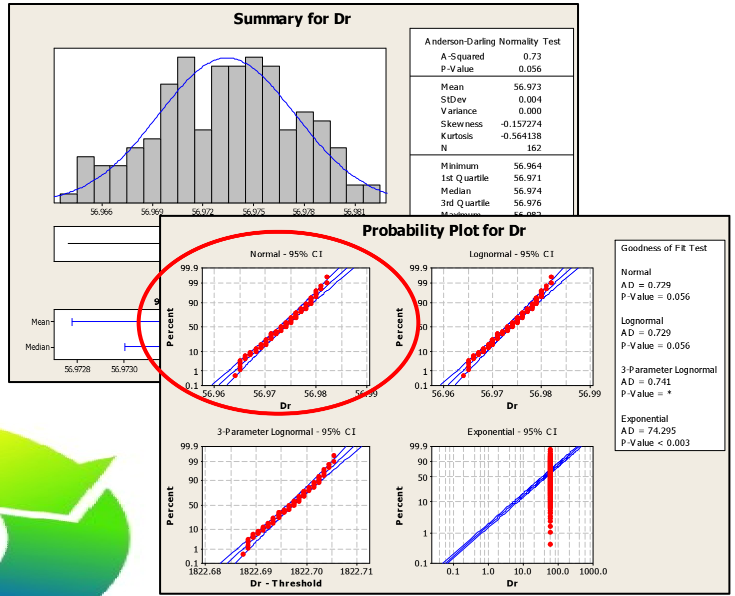
Drawing Tolerances - Robust definition using Statistics

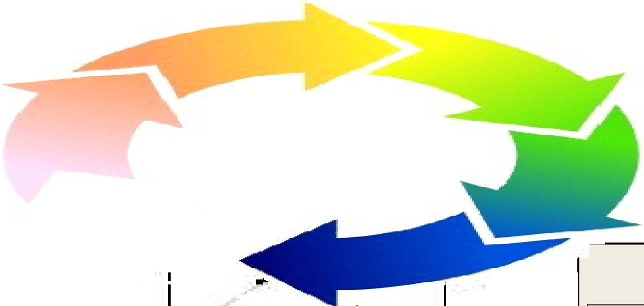
CMM measurements (SPC) after the process optimization carried out in 2007-2008

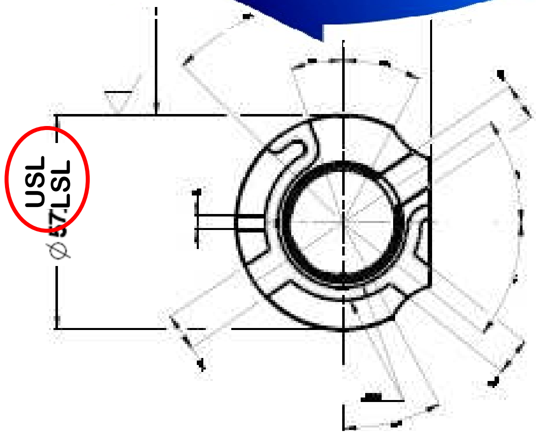
CMM data



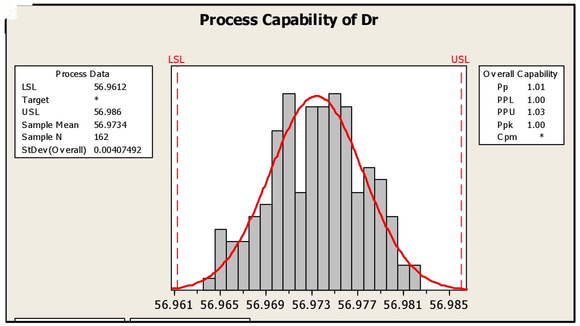
Acquired data analysis and best distribution identification







The determined tolerance range becomes the drawing tolerance



Long Term process capability and calculation of the tolerance range for Ppk = 1 (or 1.33)

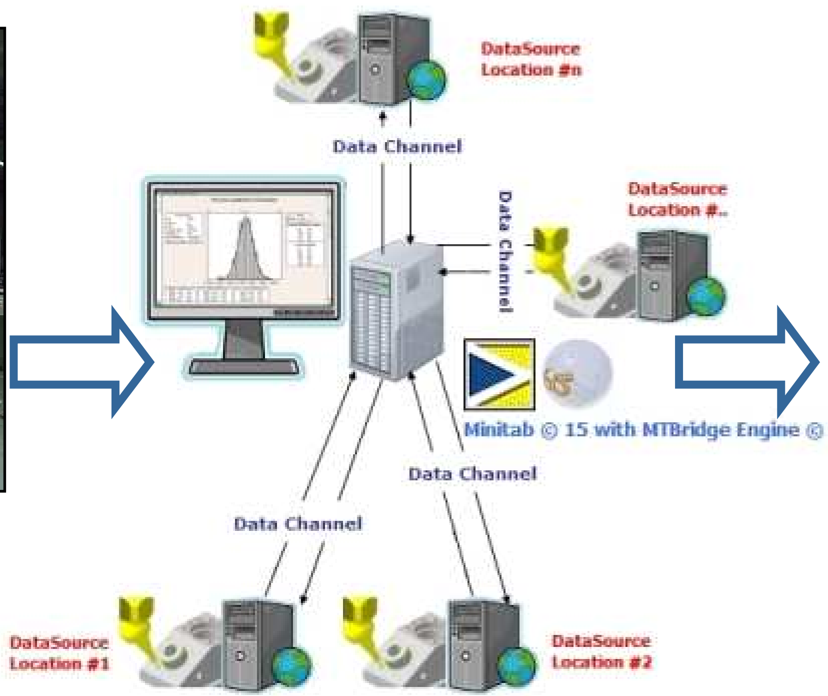
CASAPPA® FLUID POWER DESIGN

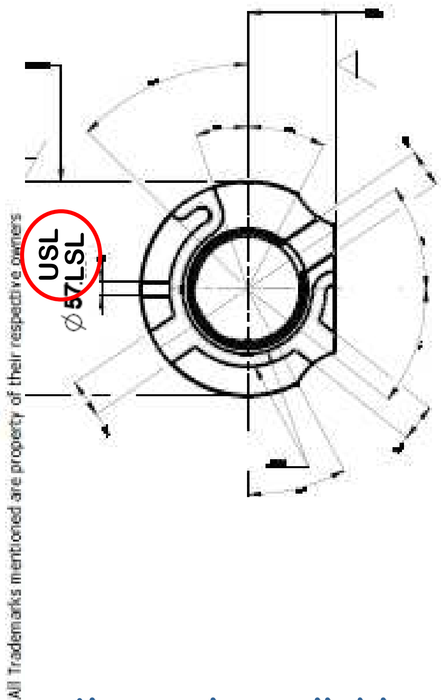
Drawing Tolerances - Robust definition using Statistics

Automation can be applied to the measurements (e.g. when using CMM data acquisition) and analysis of the parts dimensions to define the type of distribution better approximating the real data and the process natural variation and capability.

Industrial Statistics with MTBridge Engine

the real cost savings in your Six Sigma projects





In this way, the process variation and the type of distribution of the data are continuously available and updated and can be used for short term and long term capability analysis. The long term capability data are used to define the project tolerances or can be used as inputs in Monte Carlo simulations for tolerance analysis projects.

Tolerance Analysis: Monte Carlo Simulation

Before starting with a Monte Carlo Simulation, we need to define a model of the pump:

1. Definition of the responses we want to evaluate: $Y_1, Y_2, \ldots, Y_m$

Definition of the desired targets for all the responses (LSL and/or USL) in order to optimize the pump performance

2. Definition of the factors involved: $x_1, x_2, \ldots, x_n$; each factor x_i will be represented by:

- a Nominal Value x_i

- a Tolerance range $x_{i,USL} - x_{i,LSL}$

- a characteristic statistical Distribution (Normal, Weibull, ...)

In this specific project, what we want to optimize is the Nominal Value (using Ppk).

The Tolerance range and the data Distribution are given by the process (statistical definition of the tolerances)

3. Mathematical model of the pump: definition of the transfer functions

$Y_1 = f_1 (x_1, x_2, \ldots, x_n)$

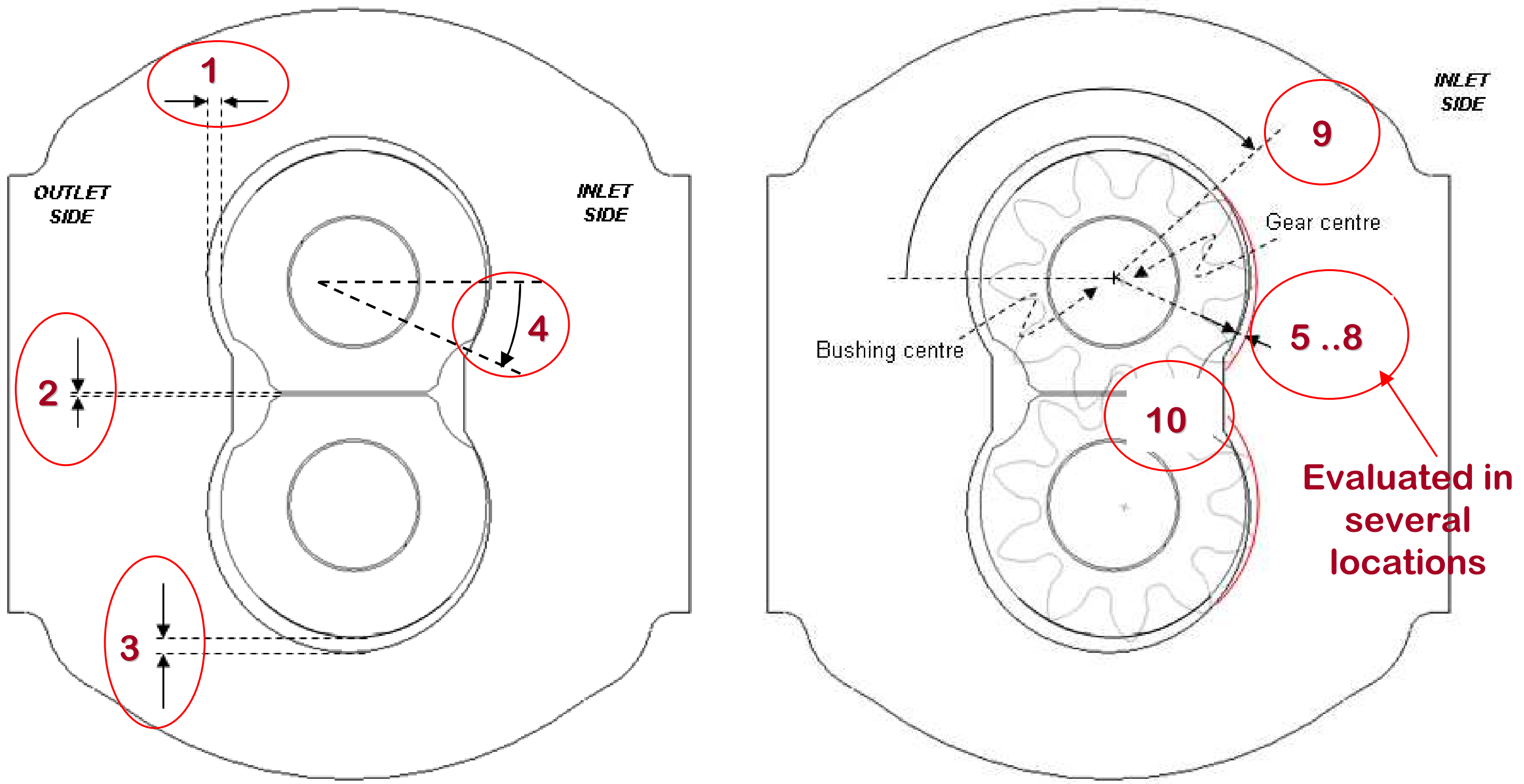
$Y_2 = f_2 (x_1, x_2, \ldots, x_n)$

...

$Y_m = f_m (x_1, x_2, \ldots, x_n)$

1. Responses

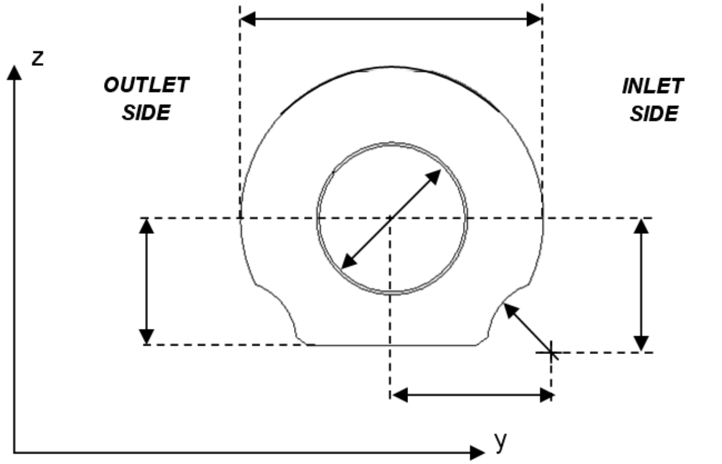
10 responses have to be optimized simultaneously



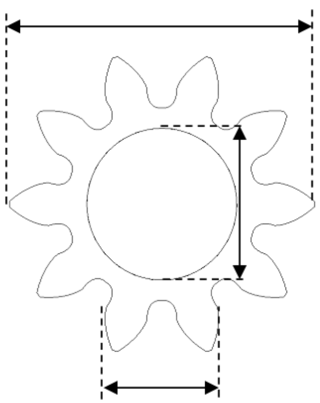
For all the responses, desired targets (LSL and/or USL, Ppk goal) are defined, in order to optimize the pump performance

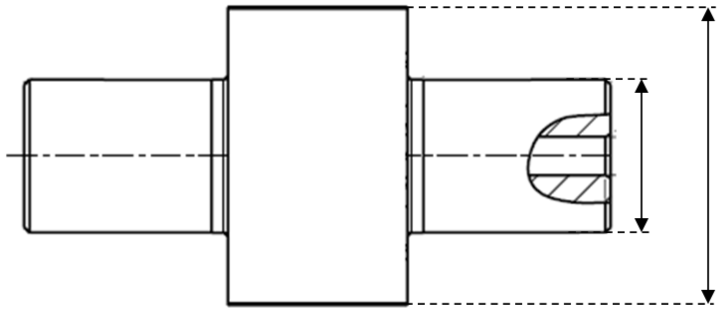
2. Factors of the model

The mathematical model presents 19 factors. Due to process constraints or economical reasons, some of them are not modifiable. Nevertheless, all of them must be taken into account in the model: they will affect the responses and their variance.

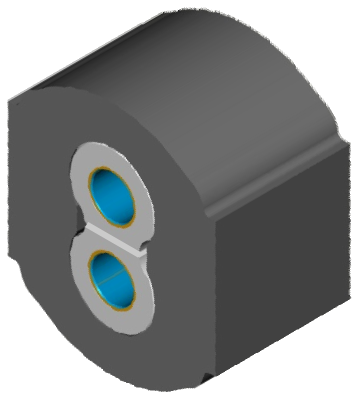


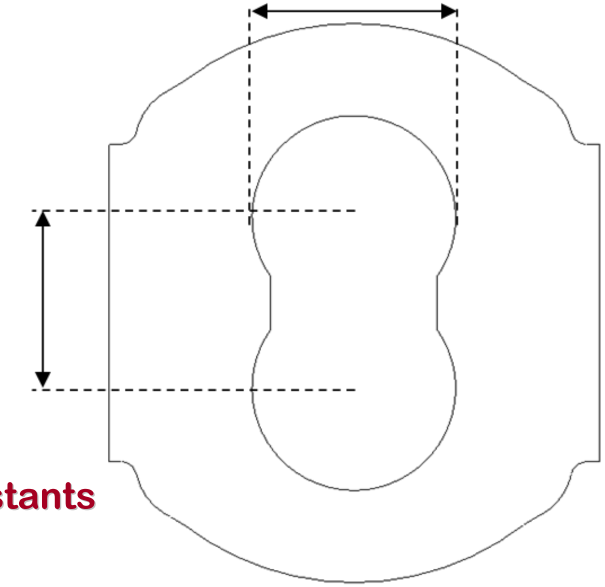
directions for evaluation of eccentricity between bushing centre and block centre





Since there is a combination of two bushing blocks and two gears in the modeled pump, each parameter involved in the single assembly of one block has to be considered twice.



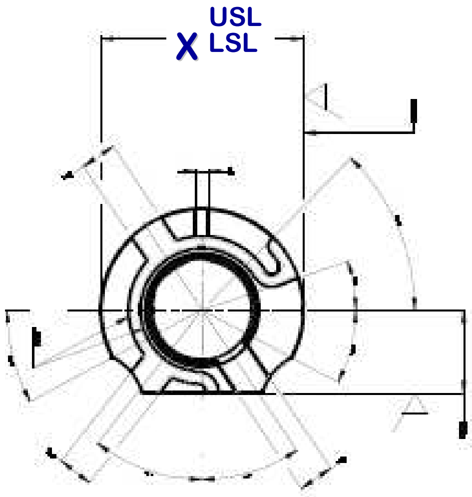


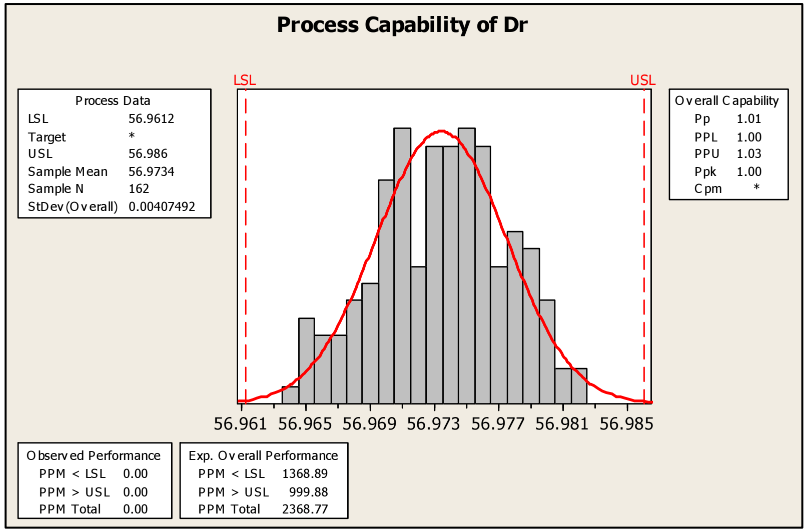
This gives 10 additional factors for a total of 29 factors and 2 constants in the final mathematical model.

2. Factors of the model

Each factor x_i is represented by:

- a **Nominal Value** x_i
- a **Tolerance range** $x_{i,USL} - x_{i,LSL}$
- a **statistical Distribution** (Normal, Weibull, …)





We want to optimize the Nominal Value (and consequently the relative Ppk Value) while the Tolerance range and the data Distribution are given by the process (statistical definition of the tolerances)

In this case study, we have focused on **8 factors** which are modifiable in terms of nominal value.

The space of possible variation of these 8 factors will be investigated using simulations.

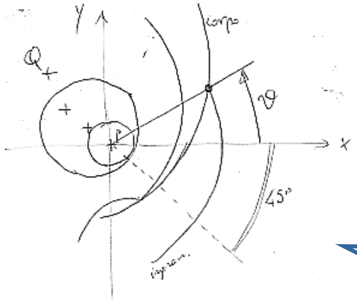
We will try to find the **optimal combination of the factors able to best fulfill the targets** (LSL and USL) we have defined for the responses.

3. Mathematical model

All the responses are expressed mathematically as a function of the factors.
The model is quite complex, as it can be seen in the equations showing the mathematical relationship between some of the responses and the input factors. An example:

SETTORE ANGOLARE ASPORTAZIONE

calcolo



$\begin{cases} x_Q = ecc_{pex} \\ y_Q = -ecc_{pey} \end{cases}$ $\begin{cases} x_P = 0 \\ y_P = 0 \end{cases}$

cf 1, cf 2: $\begin{cases} x^2 + y^2 = \left(\frac{OD}{2}\right)^2 \\ x^2 + y^2 - 2x x_Q - 2y y_Q + x_Q^2 + y_Q^2 - \left(\frac{Dc}{2}\right)^2 = 0 \end{cases}$

$$-2x x_Q - 2y y_Q + x_Q^2 + y_Q^2 - \left(\frac{Dc}{2}\right)^2 + \left(\frac{OD}{2}\right)^2 = 0$$

$$y = \frac{1}{2y_Q}\left[-2x_Q x + \left(x_Q^2 + y_Q^2 - \left(\frac{Dc}{2}\right)^2 + \left(\frac{OD}{2}\right)^2\right)\right]$$

$$x^2 + \frac{1}{4y_Q^2}\left[4x_Q^2 x^2 - 4x_Q(\dots)x + (\dots)^2\right] - \left(\frac{OD}{2}\right)^2 = 0$$

$$\left(1 + \frac{x_Q^2}{y_Q^2}\right)x^2 - \frac{x_Q}{y_Q^2}(\dots)x + \frac{1}{4y_Q^2}(\dots)^2 - \left(\frac{OD}{2}\right)^2 = 0$$

Ang Depth equations

2/4

cf. 1 $\quad x^2 + y^2 = \left(\frac{OD}{2}\right)^2$

cf. 2 $\quad (x - x_Q)^2 + (y - y_Q)^2 = \left(\frac{Dc}{2}\right)^2$

$$x^2 + y^2 - 2x x_Q - 2y y_Q + x_Q^2 + y_Q^2 - \left(\frac{Dc}{2}\right)^2 = 0$$

- Determinazione di $\overline{AB}$ per verifica (sarà anche un caso particolare di $\overline{CD}$ con $\varphi = \pi$)

$x_A = \frac{OD}{2}$

x_B : intersez. $\begin{cases} \text{cf. 2} \\ \text{retta } y = 0 \end{cases}$

$$x^2 - 2x x_Q + x_Q^2 + y_Q^2 - \left(\frac{Dc}{2}\right)^2 = 0$$

$$x = \frac{x_Q \pm \sqrt{x_Q^2 - x_Q^2 - y_Q^2 + \left(\frac{Dc}{2}\right)^2}}{1} = x_Q \pm \sqrt{-y_Q^2 + \left(\frac{Dc}{2}\right)^2} \Rightarrow x_B = x_Q + \sqrt{\left(\frac{Dc}{2}\right)^2 - y_Q^2}$$

segno (+)

$ax^2 + bx + c = 0$

$\Delta = b^2 - 4ac$

$x_{1,2} = \frac{-b \pm \sqrt{\Delta}}{2a}$

opp. $\frac{\Delta}{4} = \left(\frac{b}{2}\right)^2 - ac$

$x_{1,2} = \frac{-\frac{b}{2} \pm \sqrt{\frac{\Delta}{4}}}{a}$

$$\overline{AB} = \frac{OD}{2} - \left(x_Q + \sqrt{\left(\frac{Dc}{2}\right)^2 - y_Q^2}\right)$$

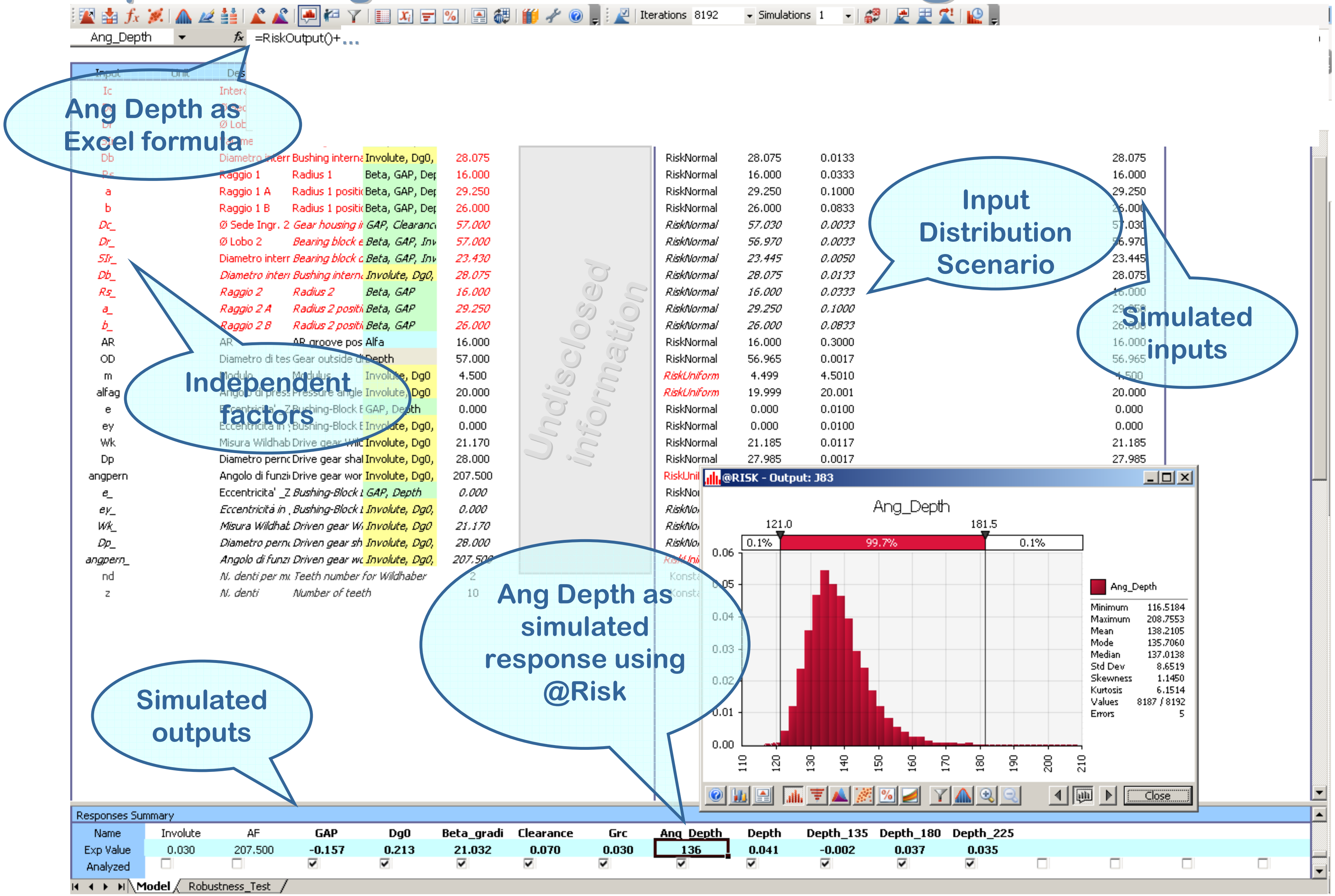
x_Q e y_Q sono f(angfunz) $\Rightarrow \overline{AB} = f$(angfunz)

$\overline{AB} > 0 \Rightarrow$ asportazione sì

$< 0 \Rightarrow$ asportazione no

$\overline{AB}$ = Depth_x

4. Implementing the model in Excel with @Risk



Some Process Capability basic concepts

The Overall Process Performance indices (Pp,Ppk) are an estimate of the Long Term Process Capability.

They are a measurable property of a process to the specification or the ability of a process to produce output within specification limits.
The Long Term Process Capability is an effective metric for communicating differences before and after an improvement.

If the upper and lower specification limits of the process are USL and LSL, the estimated mean of the process is μ (position measure) and the estimated variability of the process, expressed as a standard deviation (dispersion measure), is σ, then commonly-accepted Overall Process Performance indices include:

$$\hat{P}_p = \frac{USL - LSL}{6 \times \hat{\sigma}}$$

Pp estimates what the process would be capable of producing if the process could be centered. Assumes process output is approximately normally distributed.

$$\hat{P}_{pk} = \min\left[\frac{USL - \hat{\mu}}{3 \times \hat{\sigma}}, \frac{\hat{\mu} - LSL}{3 \times \hat{\sigma}}\right]$$

Some Process Capability basic concepts

Ppk is a metric that does not account for process performance that is not exactly centered between the specification limits, and therefore is interpreted as what the process would be capable of achieving if it could be centered and stabilized.

Formulating this the most generally, estimation of a process performance boils to a comparison of the process variability (it is so-called "process voice") with client's expectations defined through specification limits (it is so-called "customer voice").

Pp and Ppk are based on total variability. They use an "inflated" standard deviation to account for changes over time.
These definitions are motivated by the fact that for a normally distributed process, 6σ is the actual process spread covering 99.73% of the parts; if the specified process tolerance USL- LSL = 6σ, then Pp = 1 and the process is said to be 'just capable'.

If Pp is greater than 1 then the process is meeting the specifications as long as the mean is centered.
If Ppk is greater than 1 then the process mean is sufficiently far from the specification limit. The higher the number, the better the data looks within the spec limits.
If the process is stable and in control the estimate of Pp is similar to the estimate of Cp (Short Term Process Capability, based on inherent common cause or within subgroup variation from Statistical Process Control (SPC) chart methods).

The above formulas for Pp, Ppk all assume that the data is Normally distributed. If the data is not Normally distributed, the above formulas do not work (i.e. give gibberish numbers).

Some Process Capability basic concepts

What happens if the process is not approximately normally distributed?

The indices that we considered thus far are based on normality of the process distribution. This poses a problem when the process distribution is not normal.

One should note that there are an infinite number of distributions which may show the familiar bell-shaped curve, but are not Normally distributed.
This is particularly important to remember when performing capability analyses.
We therefore need to determine whether the underlying distribution can indeed be modeled well by a Normal distribution.

If the Normal distribution assumption is not appropriate, yet capability indices are recorded, one may seriously misrepresent the true capability of a process.

Some Process Capability basic concepts

The most common methods for handling non-normal data are:

- Non-parametric Approach Using the Empirical Distribution.

- Transform the data so that they become approximately normal. Transformations do not always work. Many a time, it will be also difficult to identify and use the correct transformation.

- Identifying the distribution of the data. Based on probability plots and goodness-of-fit tests, you can choose a distribution that best fits the data prior to conducting a capability analysis.
In this last case there are two methods of calculation of ppk index

  - ISO / Quantile / Clements Method
  - Bothe / Z-scores method

Why the Bothe / Z-scores Method is Better

For any distribution, the Z-scores method takes the actual risk level and calculates the metric value corresponding to a normal distribution with the same risk level.
Using this method, any given metric value always means the same level of risk.

Some Process Capability and DoE basic concepts

Why Not Use the Normal Formulas Always?

Expert opinions and statistical softwares vary on this practice, some recommend and use it, many are opposed, some others are undocumented.

The procedure we use (and suggest) to evaluate the Response Capability in a Simulation

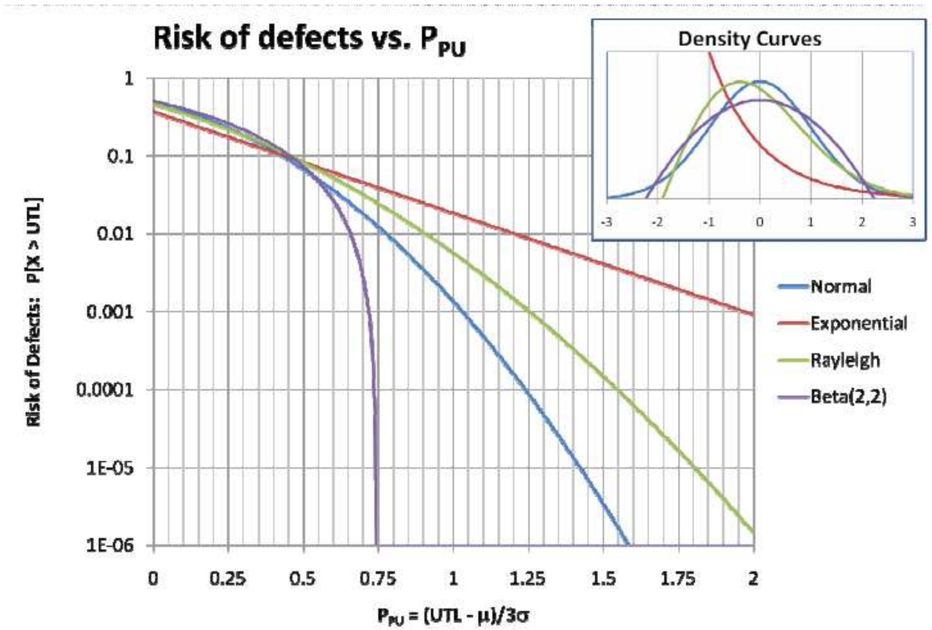
- **Distribution Identification to evaluate the optimal distribution for the simulated data based on the probability plots and goodness-of-fit tests, prior to conducting a capability analysis study.**
- **Bothe / Z-scores method for Ppk calculation.**


MARIA PIA D'AMBROSIO, FRANCO ANZANI, SERGIO VENTURINI

DFSS E SIMULAZIONE MONTE CARLO: PROBLEMATICHE DI IMPLEMENTAZIONE NELLA TOLERANCE ANALYSIS

La prassi abitualmente seguita di simulare poche migliaia di valori e da questi estrapolare conclusioni circa l'ottimalità del processo (in termini di difettosità dello stesso), consenta di ottenere solo risposte approssimate e parziali. Per arrivare a risultati corretti è necessario disporre di strumenti che possano gestire con facilità simulazioni di milioni di dati

economia & management 3 | 2005



See our 2005 Economia & Management paper or 2009 ASQ, Andrew Sleeper's paper for more info

Ppk Risk model - Resuming … we use …

The procedure we use (and suggest) to evaluate the Response Capability in a Simulation

- Distribution Identification to evaluate the optimal distribution for the simulated data based on the probability plots and goodness-of-fit tests, prior to conducting a capability analysis study. (*)
- Bothe / Z-scores method for Ppk calculation.

Why ? (Plus)

- Capability metric is a measure of risk;
- We use capability metrics to make decisions risk optimization;
- Applying the normal formulas always means that any particular value of capability metric could represent much less risk or much more risk, depending on the shape of the distribution;
- A good capability metric means the same thing to management, regardless of the process simulation;
- Using this method, any given metric value always means the same level of risk.
- Incorrect Ppk values in a Solver context could be problematic if Ppk metrics are not robust.

Problems (Minus)

- Requires long time for elaboration;
- Not available as standard SixSigma command / function in @Risk or Crystal Ball.

(*) When automation is necessary, the distribution with the smallest GoF test statistics is chosen, even if it does not indicate that the distribution best fits the data.

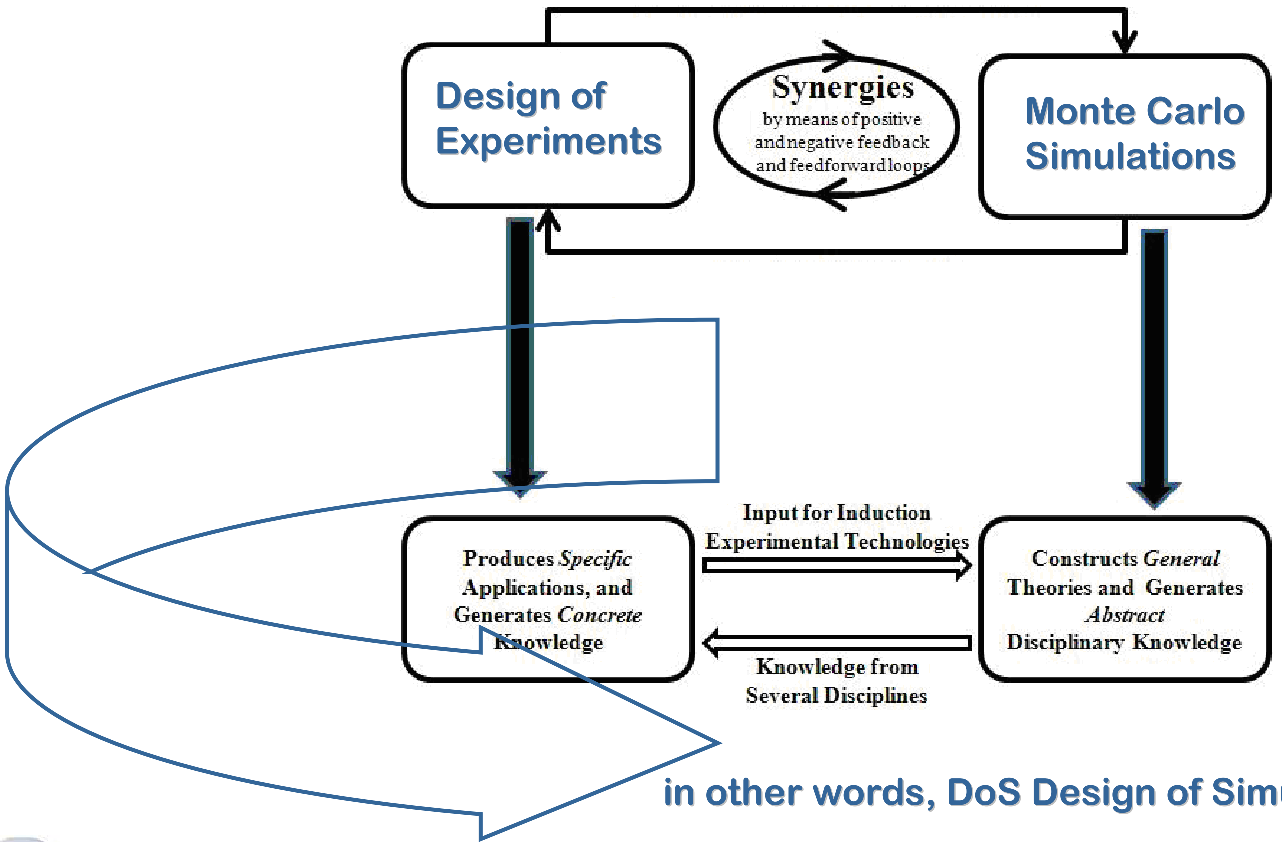
Ppk Risk model - How to simulate our data input scenario ?

[engineering point of view] **OFAT driven or**

[mathematics point of view] **Solver driven or**

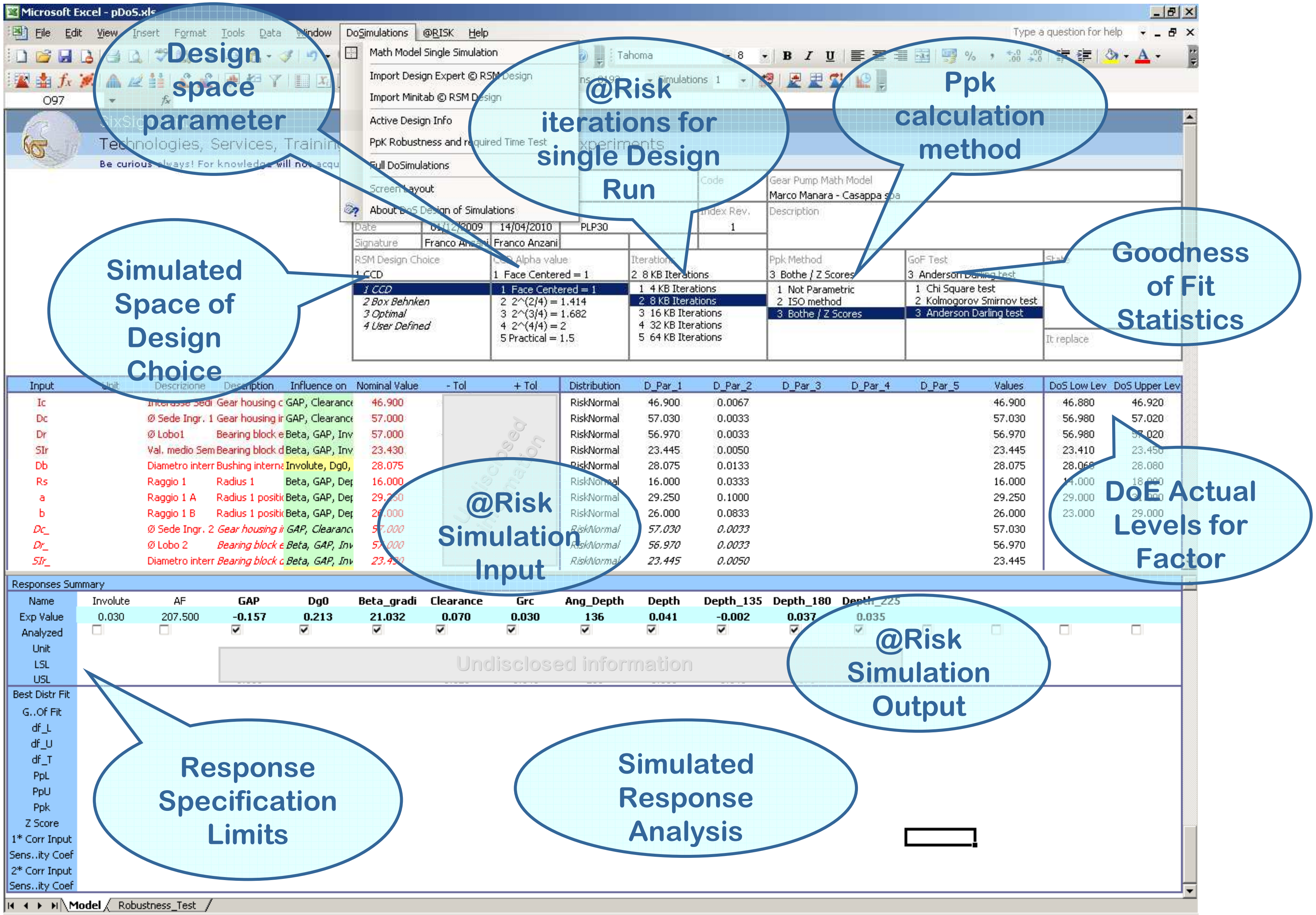
[statistists point of view] **DoE design driven ?**

No doubts in this complex case study: Design of (Simulated) Experiments driven !

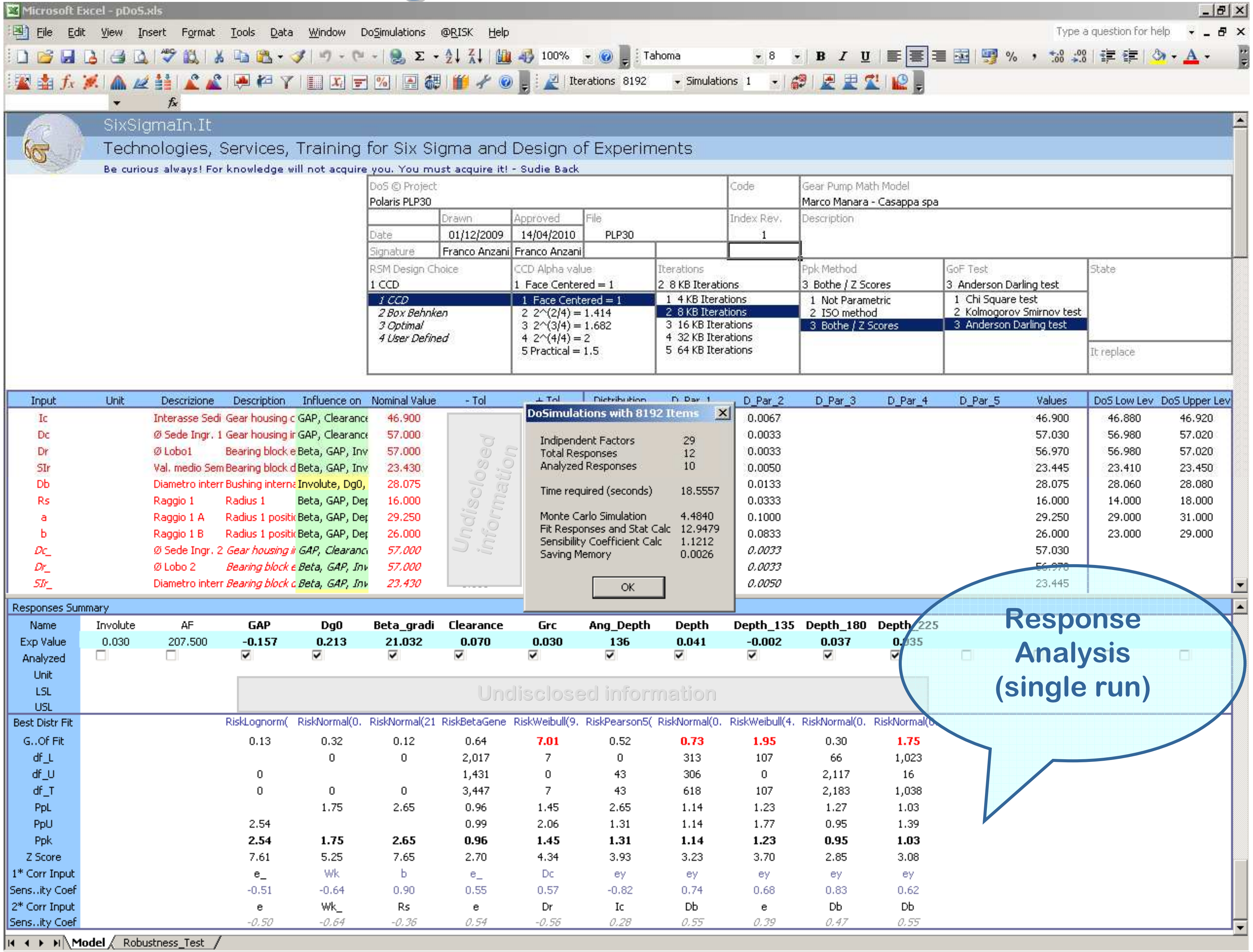


in other words, DoS Design of Simulations (for @Risk) driven !

Adding DoS to our @Risk model



Ppk Risk model - Single Run



Microsoft Excel - pDoS.xls

SixSigmaIn.It

Technologies, Services, Training for Six Sigma and Design of Experiments

Be curious always! For knowledge will not acquire you. You must acquire it! - Sudie Back

DoS © Project: Polaris PLP30				Code	Gear Pump Math Model: Marco Manara - Casappa spa
	Drawn	Approved	File	Index Rev.	Description
Date	01/12/2009	14/04/2010	PLP30	1	
Signature	Franco Anzani	Franco Anzani			

RSM Design Choice	CCD Alpha value	Iterations	Ppk Method	GoF Test	State
1 CCD	1 Face Centered = 1	2 8 KB Iterations	3 Bothe / Z Scores	3 Anderson Darling test	
1 CCD	1 Face Centered = 1	1 4 KB Iterations	1 Not Parametric	1 Chi Square test	
2 Box Behnken	2 2^(2/4) = 1.414	2 8 KB Iterations	2 ISO method	2 Kolmogorov Smirnov test	
3 Optimal	3 2^(3/4) = 1.682	3 16 KB Iterations	3 Bothe / Z Scores	3 Anderson Darling test	
4 User Defined	4 2^(4/4) = 2	4 32 KB Iterations			It replace
	5 Practical = 1.5	5 64 KB Iterations			

Input	Unit	Descrizione	Description	Influence on	Nominal Value	- Tol	+ Tol	Distribution	D_Par_1	D_Par_2	D_Par_3	D_Par_4	D_Par_5	Values	DoS Low Lev	DoS Upper Lev
Ic		Interasse Sedi	Gear housing c	GAP, Clearance	46.900					0.0067				46.900	46.880	46.920
Dc		Ø Sede Ingr. 1	Gear housing ir	GAP, Clearance	57.000					0.0033				57.030	56.980	57.020
Dr		Ø Lobo1	Bearing block e	Beta, GAP, Inv	57.000					0.0033				56.970	56.980	57.020
SIr		Val. medio Sem	Bearing block d	Beta, GAP, Inv	23.430					0.0050				23.445	23.410	23.450
Db		Diametro interr	Bushing interna	Involute, Dg0,	28.075					0.0133				28.075	28.060	28.080
Rs		Raggio 1	Radius 1	Beta, GAP, Dep	16.000					0.0333				16.000	14.000	18.000
a		Raggio 1 A	Radius 1 positi	Beta, GAP, Dep	29.250					0.1000				29.250	29.000	31.000
b		Raggio 1 B	Radius 1 positi	Beta, GAP, Dep	26.000					0.0833				26.000	23.000	29.000
Dc_		Ø Sede Ingr. 2	Gear housing ii	GAP, Clearanc	57.000					0.0033				57.030		
Dr_		Ø Lobo 2	Bearing block e	Beta, GAP, Inv	57.000					0.0033				56.970		
SIr_		Diametro interr	Bearing block c	Beta, GAP, Inv	23.430					0.0050				23.445		

Undisclosed information

DoSimulations with 8192 Items

Indipendent Factors	29
Total Responses	12
Analyzed Responses	10
Time required (seconds)	18.5557
Monte Carlo Simulation	4.4840
Fit Responses and Stat Calc	12.9479
Sensibility Coefficient Calc	1.1212
Saving Memory	0.0026

OK

Responses Summary

Name	Involute	AF	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Exp Value	0.030	207.500	**-0.157**	**0.213**	**21.032**	**0.070**	**0.030**	**136**	**0.041**	**-0.002**	**0.037**	**0.035**
Analyzed	☐	☐	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Unit												
LSL												
USL												
Best Distr Fit			RiskLognorm(	RiskNormal(0.	RiskNormal(21	RiskBetaGene	RiskWeibull(9.	RiskPearson5(	RiskNormal(0.	RiskWeibull(4.	RiskNormal(0.	RiskNormal(
G..Of Fit			0.13	0.32	0.12	0.64	7.01	0.52	0.73	1.95	0.30	1.75
df_L				0	0	2,017	7	0	313	107	66	1,023
df_U			0			1,431	0	43	306	0	2,117	16
df_T			0	0	0	3,447	7	43	618	107	2,183	1,038
PpL				1.75	2.65	0.96	1.45	2.65	1.14	1.23	1.27	1.03
PpU			2.54			0.99	2.06	1.31	1.14	1.77	0.95	1.39
Ppk			**2.54**	**1.75**	**2.65**	**0.96**	**1.45**	**1.31**	**1.14**	**1.23**	**0.95**	**1.03**
Z Score			7.61	5.25	7.65	2.70	4.34	3.93	3.23	3.70	2.85	3.08
1* Corr Input			e_	Wk	b	e_	Dc	ey	ey	ey	ey	ey
Sens..ity Coef			-0.51	-0.64	0.90	0.55	0.57	-0.82	0.74	0.68	0.83	0.62
2* Corr Input			e	Wk_	Rs	e	Dr	Ic	Db	e	Db	Db
Sens..ity Coef			-0.50	-0.64	-0.36	0.54	-0.56	0.28	0.55	0.39	0.47	0.55

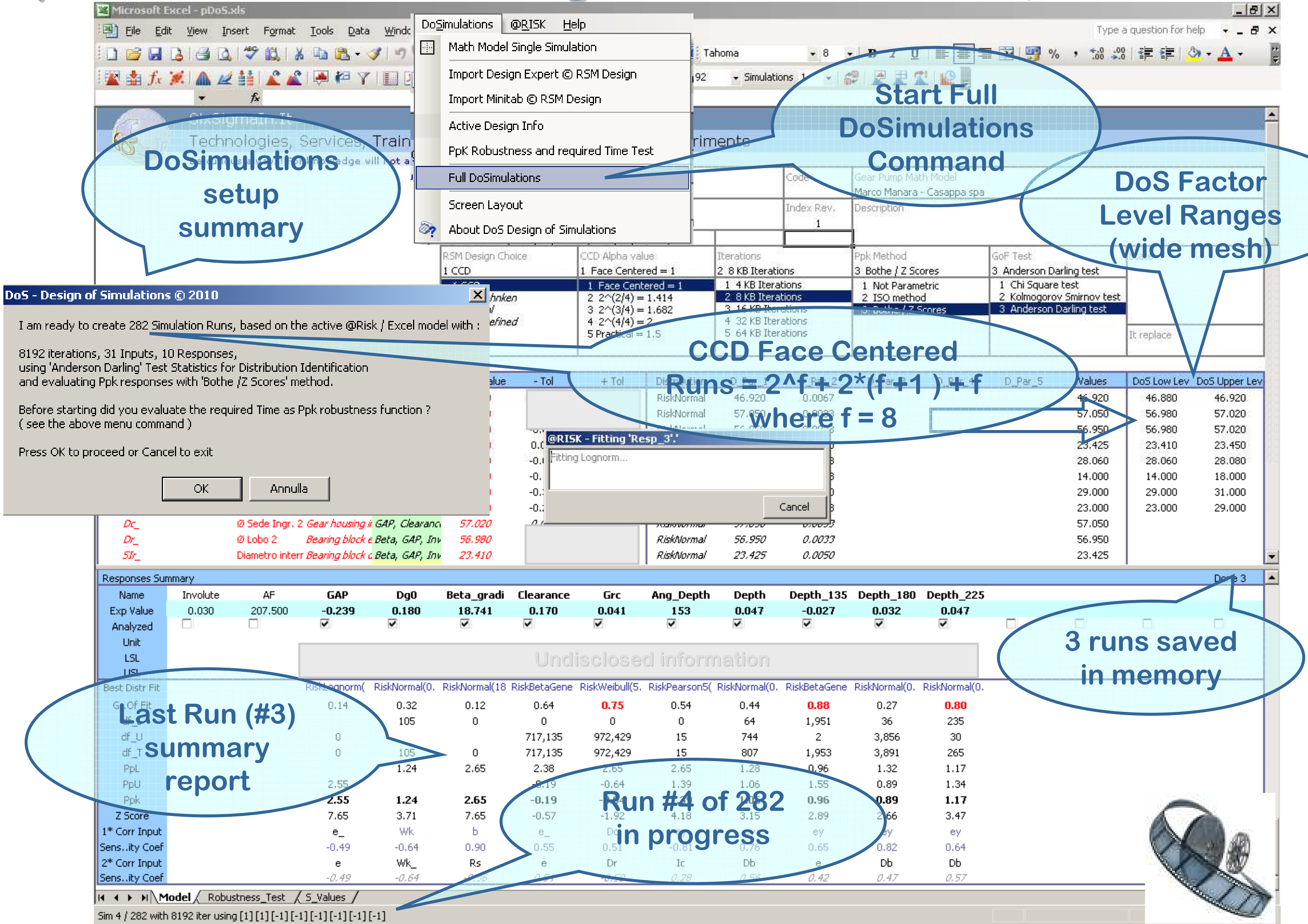
Undisclosed information

Model / Robustness_Test

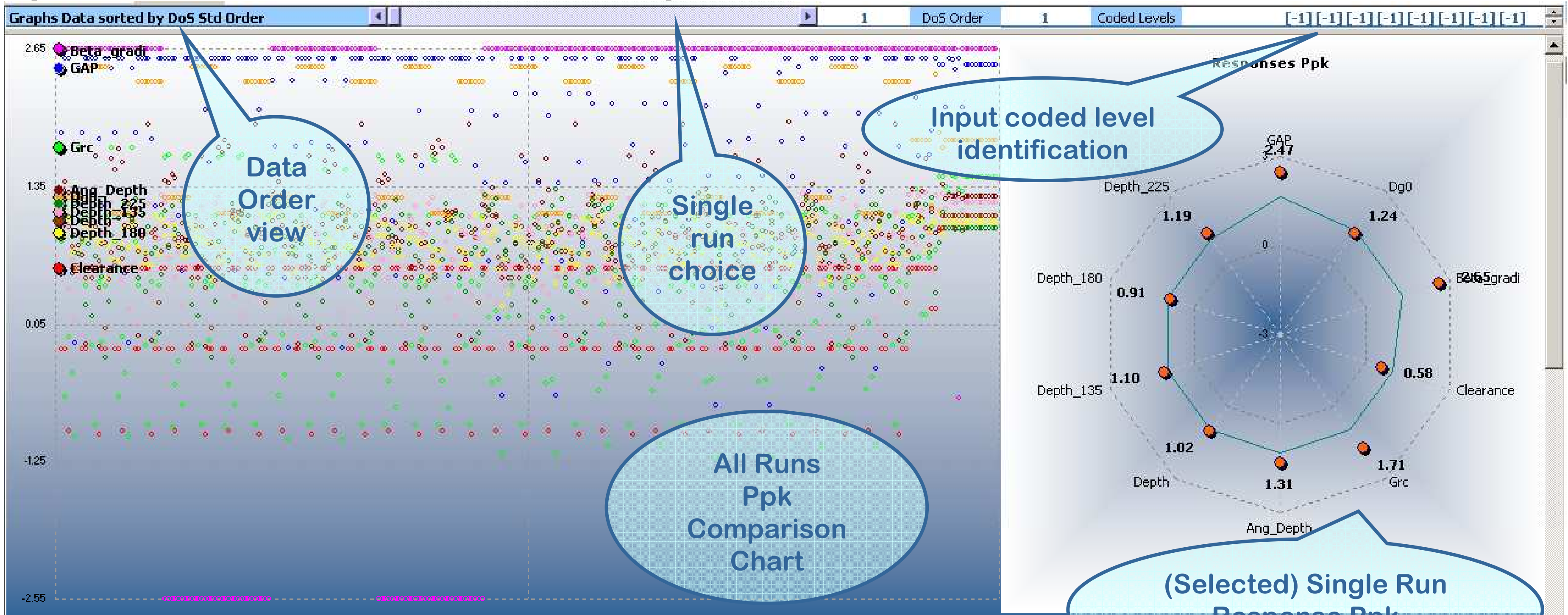
Response Analysis (single run)

CASAPPA® FLUID POWER DESIGN

Ppk Risk model - Running the DoS [First Step Simulation]



Ppk Risk model - First Step Simulation Results Scenario

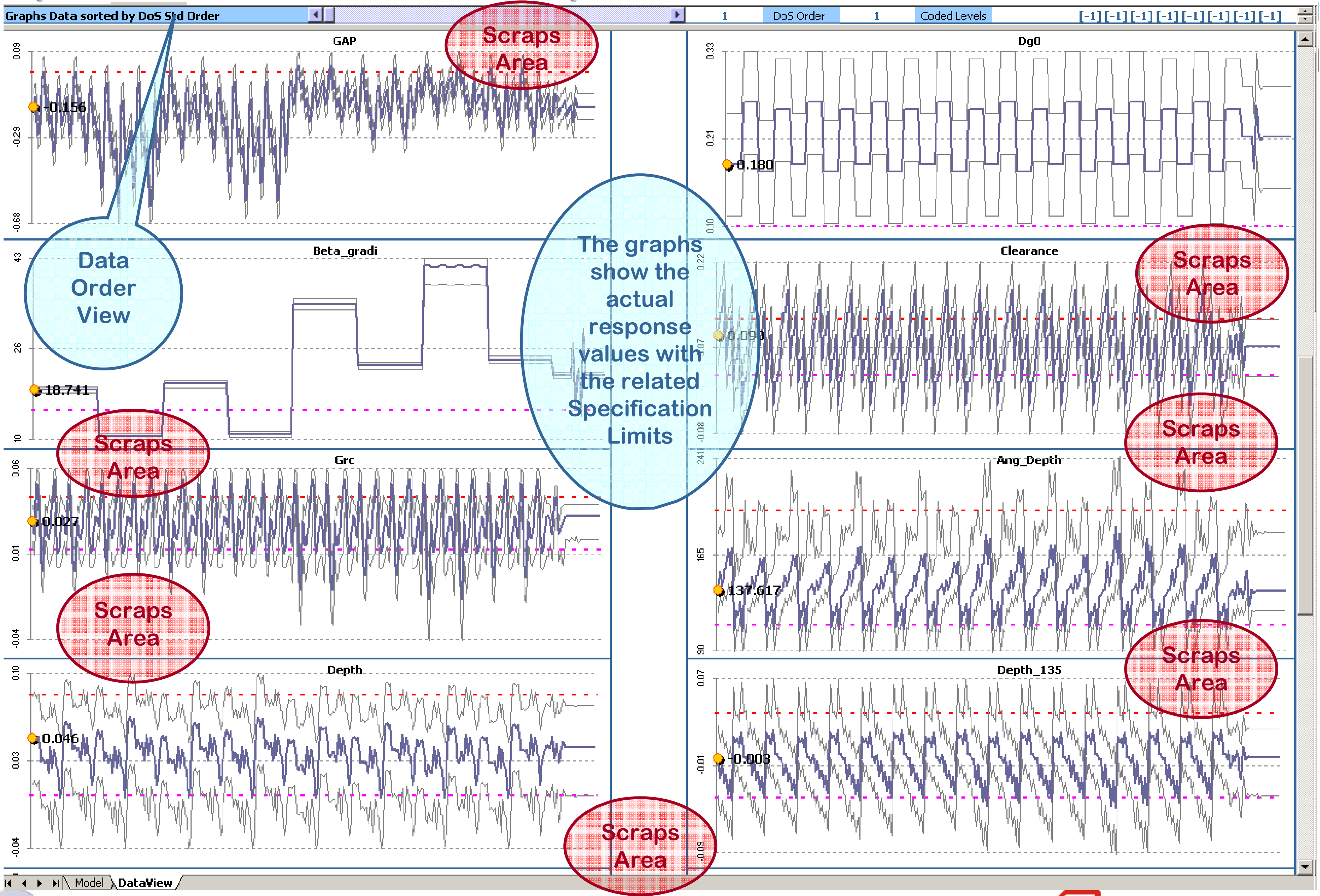


Responses	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Unit	Undisclosed information									
LSL										
USL										
Exp Values	**-0.156**	**0.180**	**18.741**	**0.090**	**0.027**	**137.617**	**0.046**	**-0.003**	**0.037**	**0.043**
Best_Fit	RiskLognorm(	RiskNormal(0.	RiskNormal(18	RiskBetaGene	RiskWeibull(5.	RiskPearson5(	RiskNormal(0.	RiskBetaGene	RiskNormal(0.	RiskNormal(0.
AD value	0.13	0.32	0.12	0.64	**1.25**	0.38	0.39	0.25	0.24	**0.73**
df_L		0	0	19	0	0	34	498	52	28
df_U	0			41,644	0	41	1,116	10	3,264	188
df_T	0	105	0	41,663	0	41	1,150	508	3,315	217
PpL		1.24	2.65	1.37	1.71	2.17	1.33	1.10	1.29	1.34
PpU	2.47			0.58	1.71	1.31	1.02	1.42	0.91	1.19
Ppk	**2.47**	**1.24**	**2.65**	**0.58**	**1.71**	**1.31**	**1.02**	**1.10**	**0.91**	**1.19**
Z Score	7.40	3.71	7.65	1.73	5.01	3.94	3.05	3.29	2.71	3.52
1* Sens_F	e_	Wk	b	e_	Dc	ey	ey	ey	ey	ey
Coef	-0.49	-0.64	0.90	0.55	0.47	-0.79	0.76	0.64	0.82	0.65
2* Sens_F	e	Wk_	Rs	e	Dr	Ic	Db	e	Db	Db
Coef	-0.49	-0.64	-0.36	0.54	-0.46	0.31	0.56	0.42	0.46	0.58
Ppk goal (1-3)	**1.66**	**1.33**	**1.33**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Weight (0-1)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

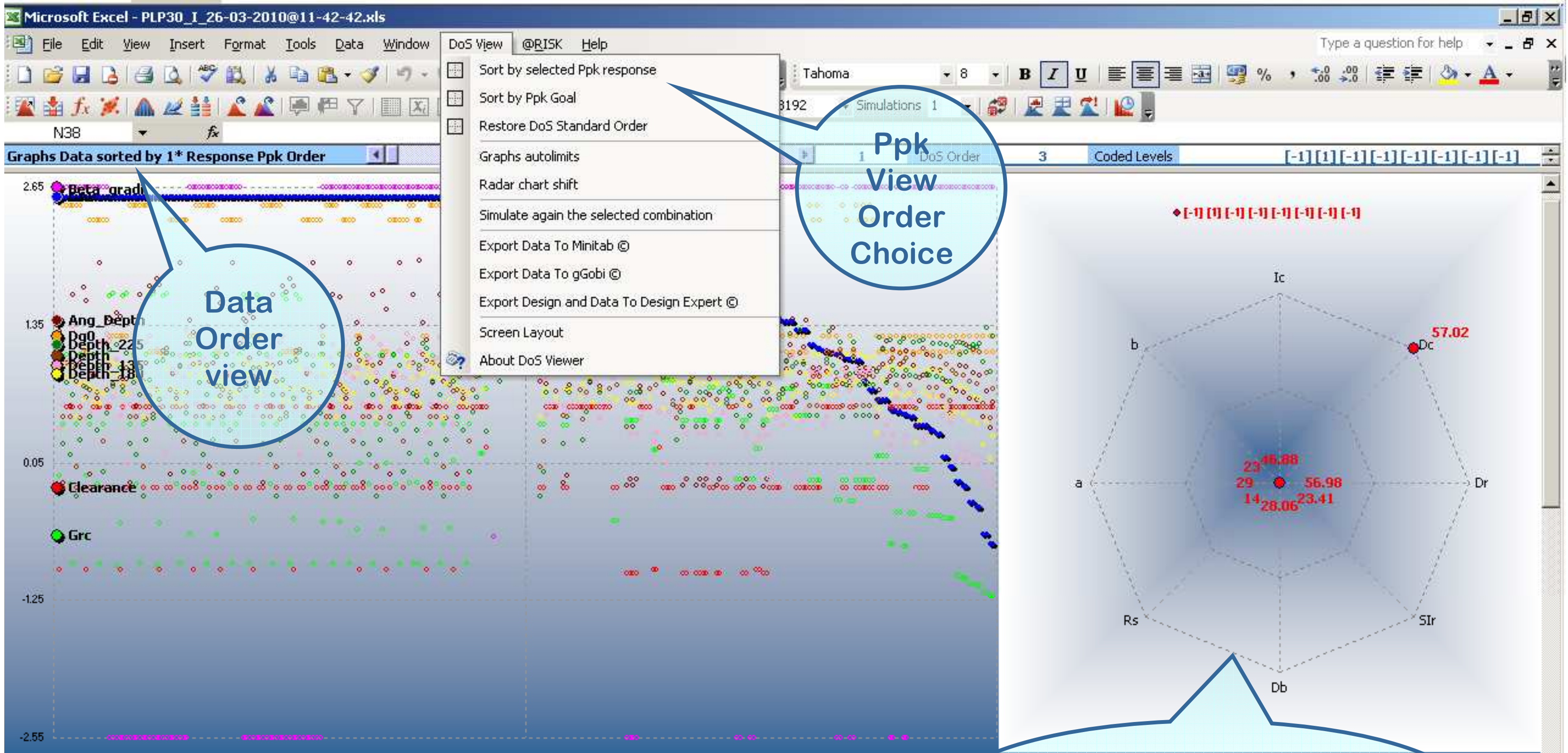
(Selected) Single Run Response Statistics Summary

Model | DataView

Ppk Risk model - First Step Simulation Results Scenario



Ppk Risk model - First Step Simulation Results Scenario

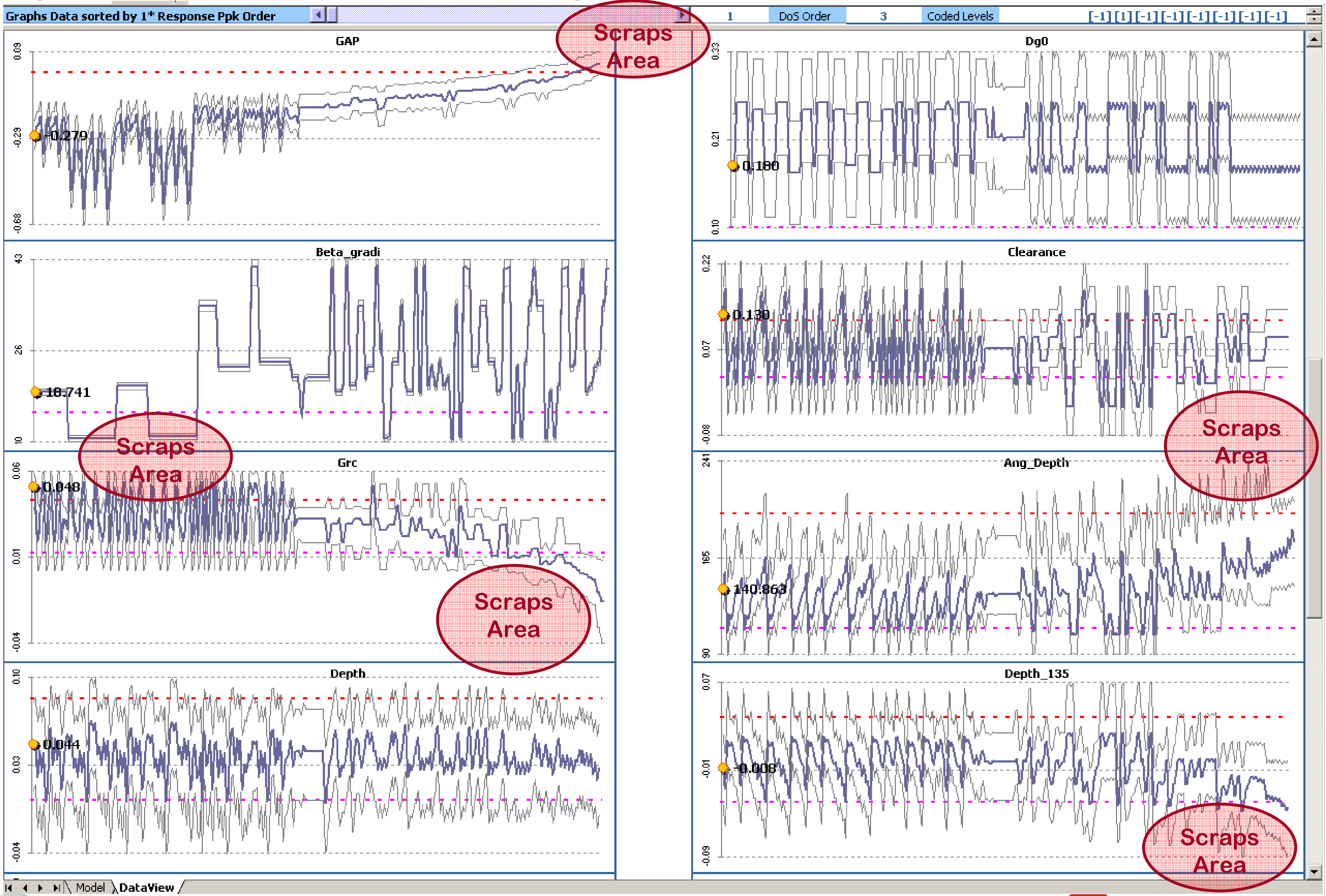


Responses	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Unit	Undisclosed information									
LSL										
USL										
Exp Values	**-0.279**	**0.180**	**18.741**	**0.130**	**0.048**	**140.863**	**0.044**	**-0.008**	**0.038**	**0.038**
Best_Fit	RiskLognorm(	RiskNormal(0.	RiskNormal(18	RiskBetaGene	RiskWeibull(5.	RiskPearson5(	RiskNormal(0.	RiskBetaGene	RiskNormal(0.	RiskNormal(0.
AD value	0.14	0.32	0.12	0.64	**0.75**	0.54	0.44	**0.88**	0.27	**0.80**
df_L		0	0	0	0	0	64	1,951	36	235
df_U	0			717,135	972,429	15	744	2	3,856	30
df_T	0	105	0	717,135	972,429	15	807	1,953	3,891	265
PpL		1.24	2.65	2.38	2.65	2.65	1.28	0.96	1.32	1.17
PpU	2.55			-0.19	-0.64	1.39	1.06	1.55	0.89	1.34
Ppk	**2.55**	**1.24**	**2.65**	**-0.19**	**-0.64**	**1.39**	**1.06**	**0.96**	**0.89**	**1.1**[illegible]
Z Score	7.65	3.71	7.65	-0.57	-1.92	4.18	3.15	2.89	2.66	3.[illegible]7
1* Sens_F	e_	Wk	b	e_	Dc	ey	ey	ey	ey	ey
Coef	-0.49	-0.64	0.90	0.55	0.51	-0.81	0.76	0.65	0.82	0.64
2* Sens_F	e	Wk_	Rs	e	Dr	Ic	Db	e	Db	Db
Coef	*-0.49*	*-0.64*	*-0.36*	*0.54*	*-0.50*	*0.28*	*0.56*	*0.42*	*0.47*	*0.57*
Ppk goal (1-3)	**1.66**	**1.33**	**1.33**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Weight (0-1)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

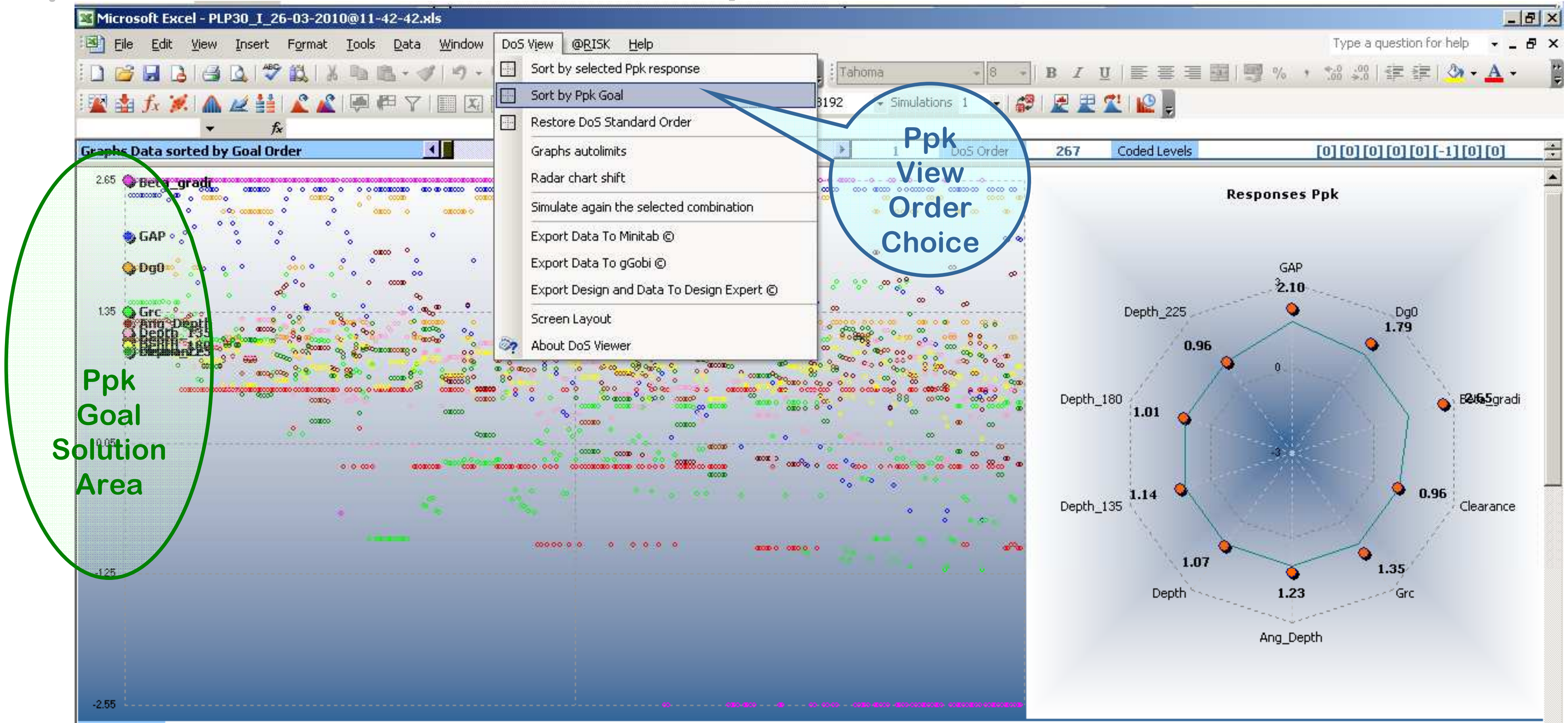
(Selected) Single Run Response Statistics Summary

Model | DataView

Ppk Risk model - First Step Simulation Results Scenario



Ppk Risk model - First Step Simulation Results Scenario

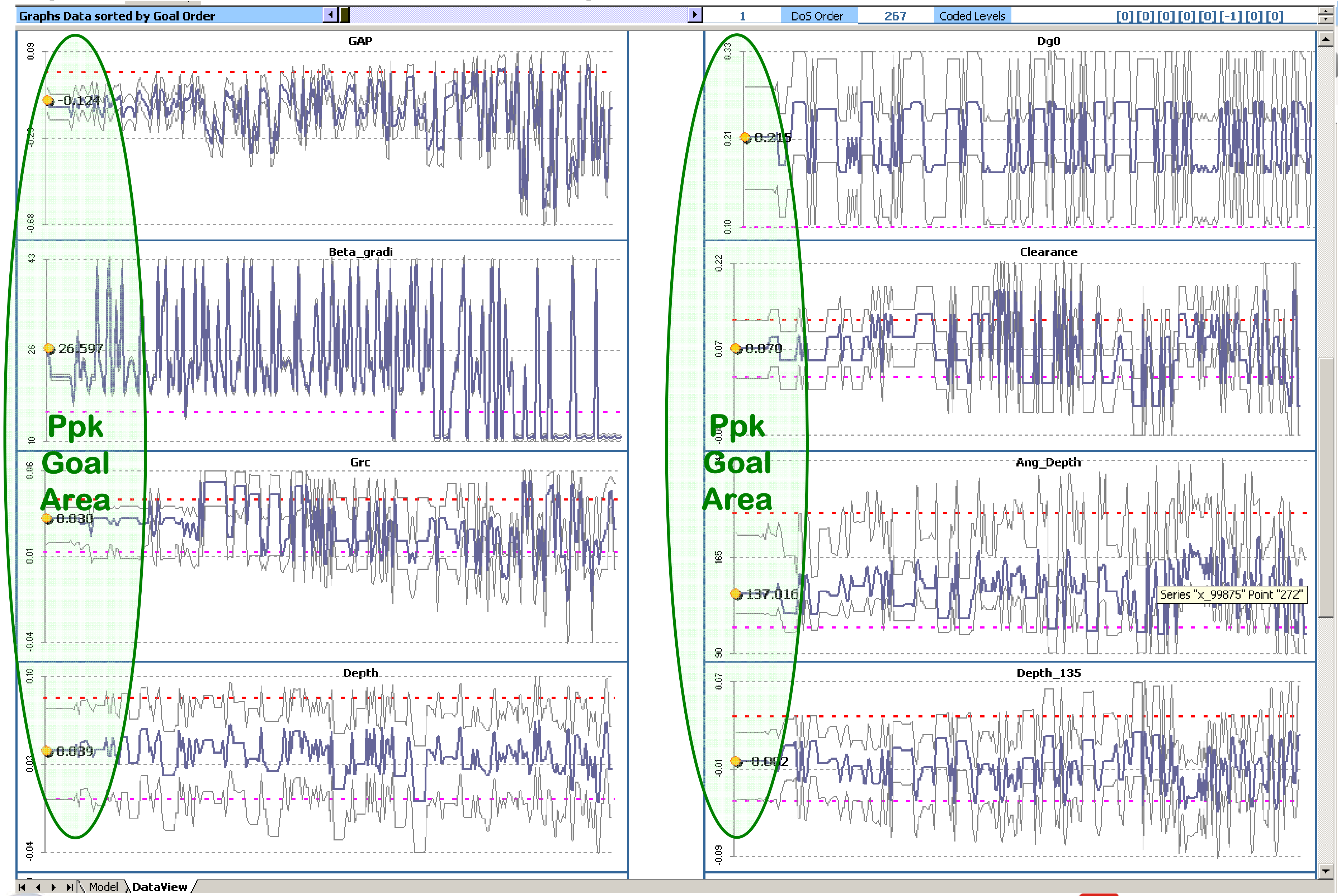


Responses	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Unit	Undisclosed information									
LSL										
USL										
Exp Values	-0.124	0.215	26.597	0.070	0.030	137.016	0.039	-0.002	0.035	0.033
Best_Fit	RiskLognorm(	RiskNormal(0.	RiskLognorm(	RiskBetaGene	RiskWeibull(10	RiskPearson5(	RiskNormal(0.	RiskWeibull(5.	RiskNormal(0.	RiskNormal(0.
AD value	0.16	0.32	0.21	0.64	3.94	0.45	0.72	1.97	0.31	1.88
df_L		0	0	2,017	26	0	680	320	153	2,024
df_U	0			1,431	0	110	127	0	1,175	5
df_T	0	0	0	3,447	26	110	807	320	1,329	2,029
PpL		1.79	2.65	0.96	1.35	2.65	1.07	1.14	1.20	0.96
PpU	2.10			0.99	2.01	1.23	1.22	1.82	1.01	1.47
Ppk	**2.10**	**1.79**	**2.65**	**0.96**	**1.35**	**1.23**	**1.07**	**1.14**	**1.01**	**0.96**
Z Score	6.29	5.36	7.65	2.70	4.05	3.69	3.15	3.41	3.00	2.87
1* Sens_F	e_	Wk	b	e_	Dc	ey	ey	ey	ey	ey
Coef	-0.53	-0.64	0.85	0.55	0.55	-0.82	0.74	0.68	0.82	0.62
2* Sens_F	e	Wk_	Rs	e	Dr	Ic	Db	e	Db	Db
Coef	-0.52	-0.64	-0.35	0.54	-0.55	0.27	0.55	0.40	0.47	0.56
Ppk goal (1-3)	1.66	1.33	1.33	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Weight (0-1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

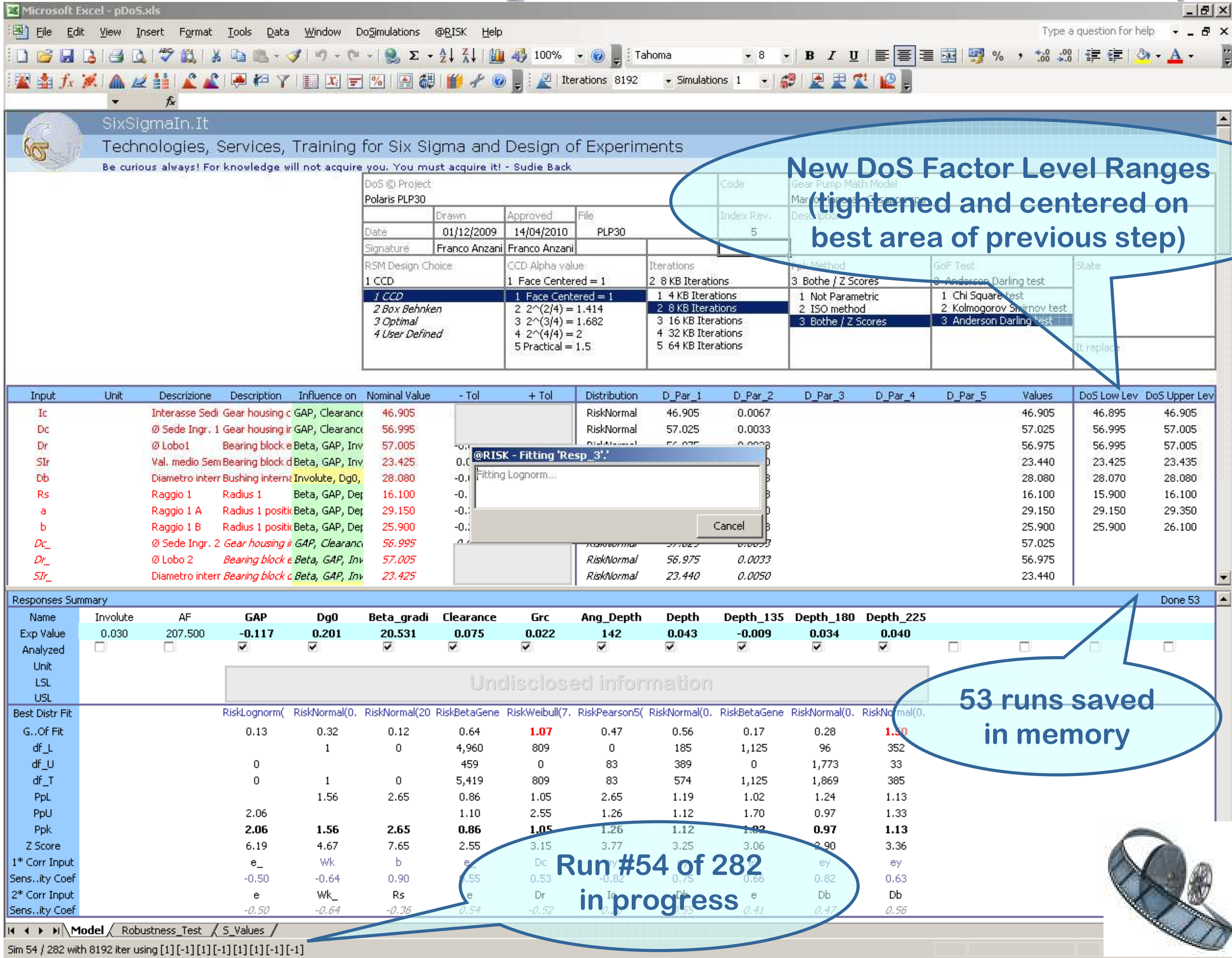
Ppk Goal Criteria

Model DataView

Ppk Risk model - First Step Simulation Results Scenario

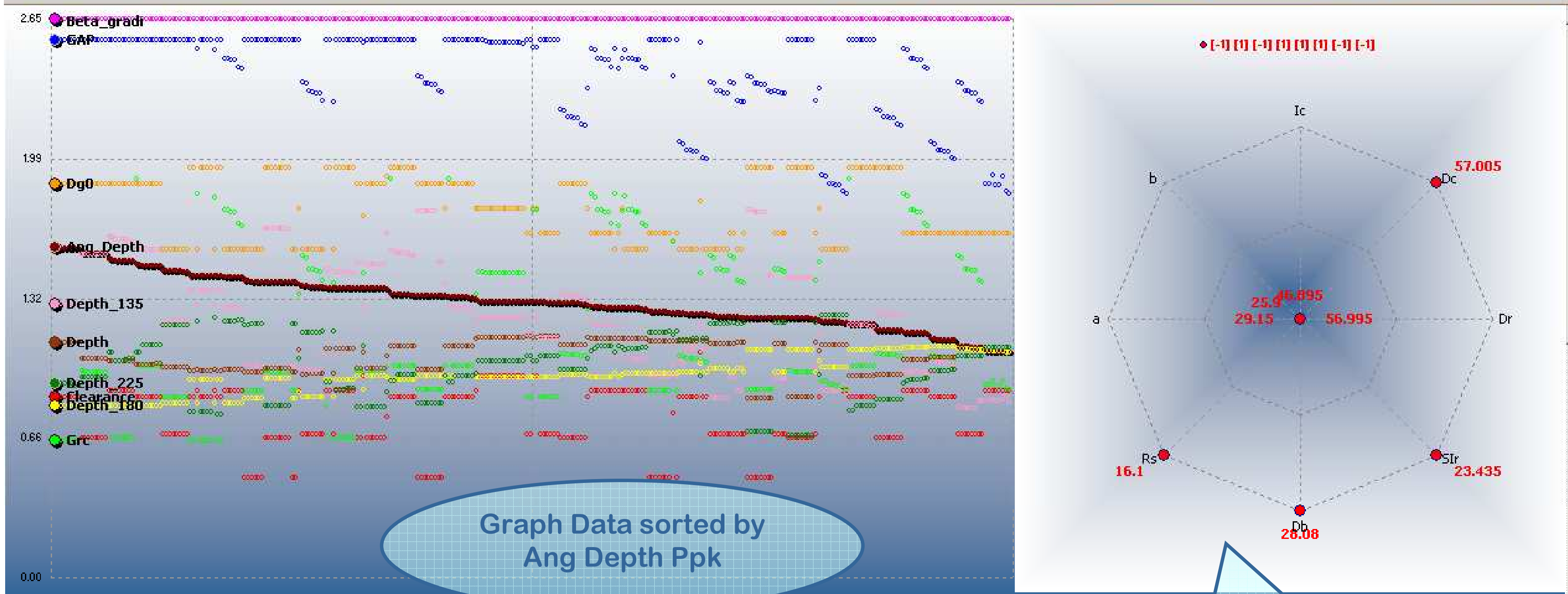


Ppk Risk model - Running the Second Simulation Step



Ppk Risk model - Second Step Simulation Results Scenario

Graphs Data sorted by 6* Response Ppk Order | 1 | DoS Order | 59 | Coded Levels | [-1][1][-1][1][1][1][-1][-1]



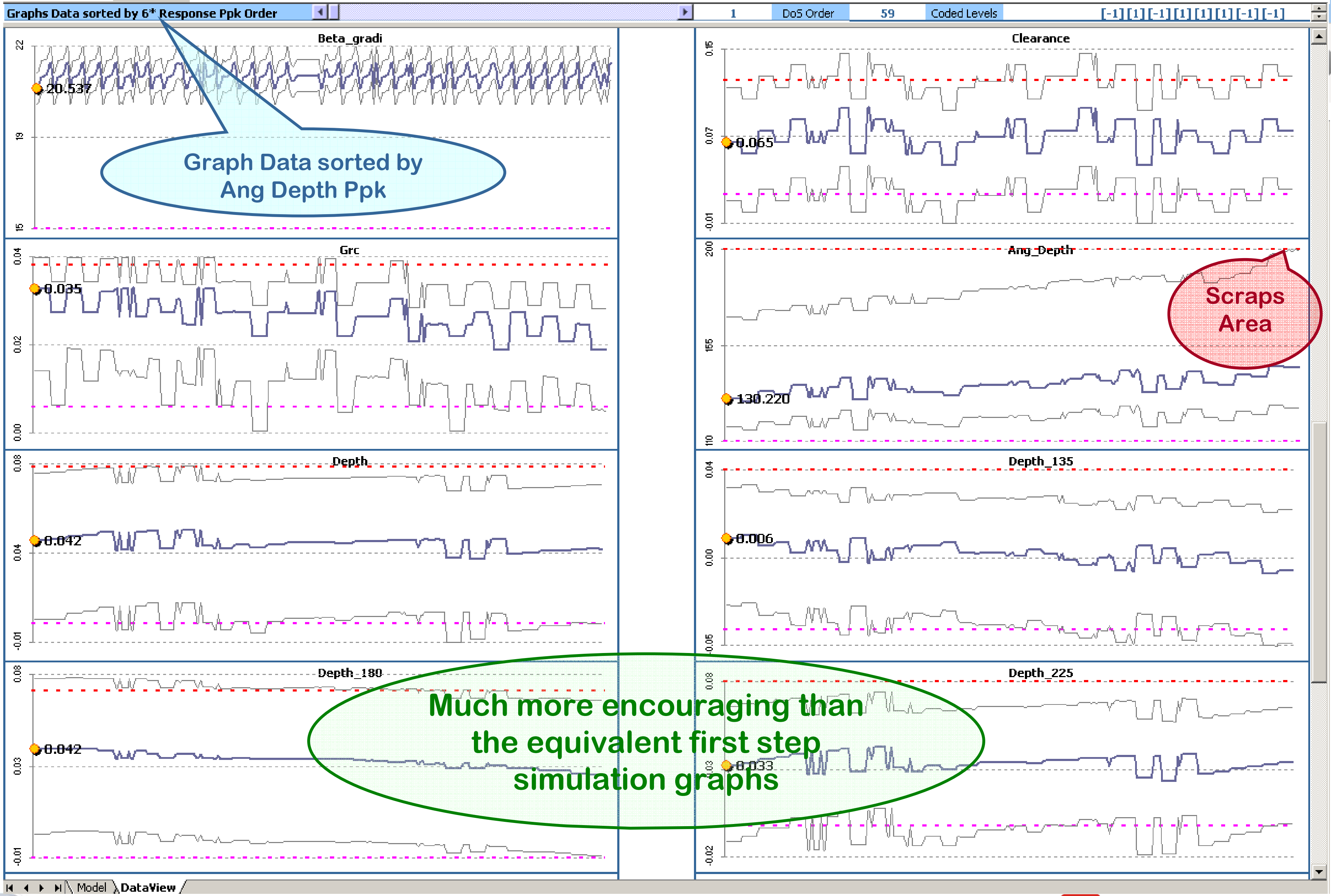
Graph Data sorted by Ang Depth Ppk

(Selected) Single Run Input factor Radar Chart

Responses	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Unit	Undisclosed Information									
LSL										
USL										
Exp Values	-0.204	0.221	20.537	0.065	0.035	130.220	0.042	0.006	0.042	0.033
Best_Fit	RiskLognorm(	RiskNormal(0.	RiskNormal(20	RiskBetaGene	RiskLogistic(0.	RiskPearson5(	RiskBetaGene	RiskBetaGene	RiskNormal(0.	RiskNormal(0.
AD value	0.13	0.32	0.12	0.64	9.18	0.64	0.99	2.57	0.36	2.60
df_L		0	0	4,960	1	0	396	1	10	2,899
df_U	0			459	25,023	1	420	50	7,187	25
df_T	0	0	0	5,419	25,024	1	816	51	7,198	2,924
PpL		1.87	2.65	0.86	1.61	2.07	1.12	1.63	1.42	0.92
PpU	2.55			1.10	0.65	1.56	1.11	1.30	0.82	1.35
Ppk	**2.55**	**1.87**	**2.65**	**0.86**	**0.65**	**1.56**	**1.11**	**1.30**	**0.82**	**0.92**
Z Score	7.65	5.61	7.65	2.55	1.96	4.69	3.15	3.89	2.45	2.76
1* Sens_F	e_	Wk	b	e_	Dr	ey	ey	ey	ey	ey
Coef	-0.50	-0.64	0.90	0.55	-0.60	-0.83	0.71	0.74	0.83	0.58
2* Sens_F	e	Wk_	Rs	e	Dc	Ic	Db	e	Db	Db
Coef	*-0.50*	*-0.64*	*-0.36*	*0.54*	*0.60*	*0.28*	*0.52*	*0.35*	*0.47*	*0.52*
Ppk goal (1-3)	1.66	1.33	1.33	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Weight (0-1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

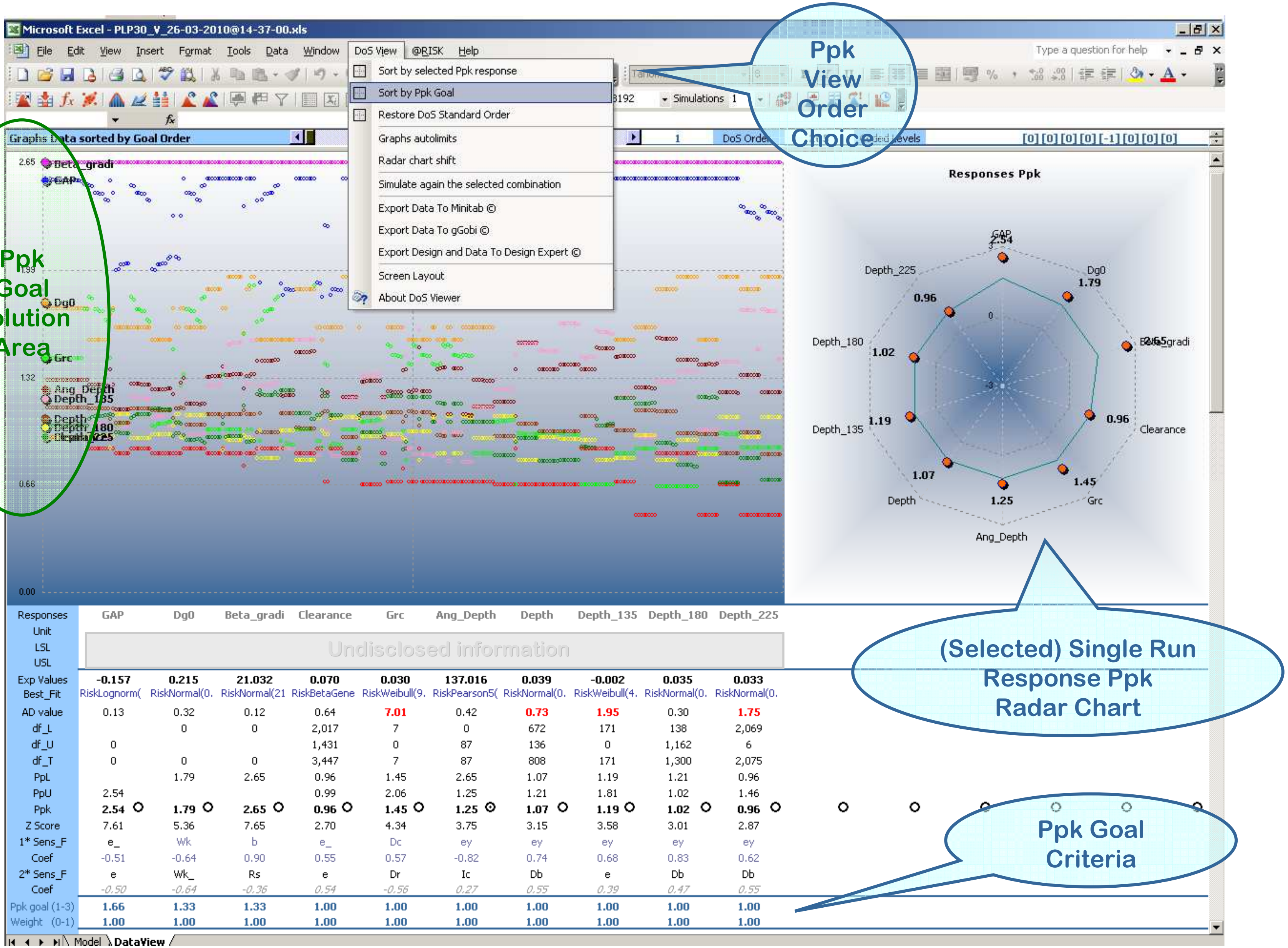
Model | DataView

Ppk Risk model - Second Step Simulation Results Scenario



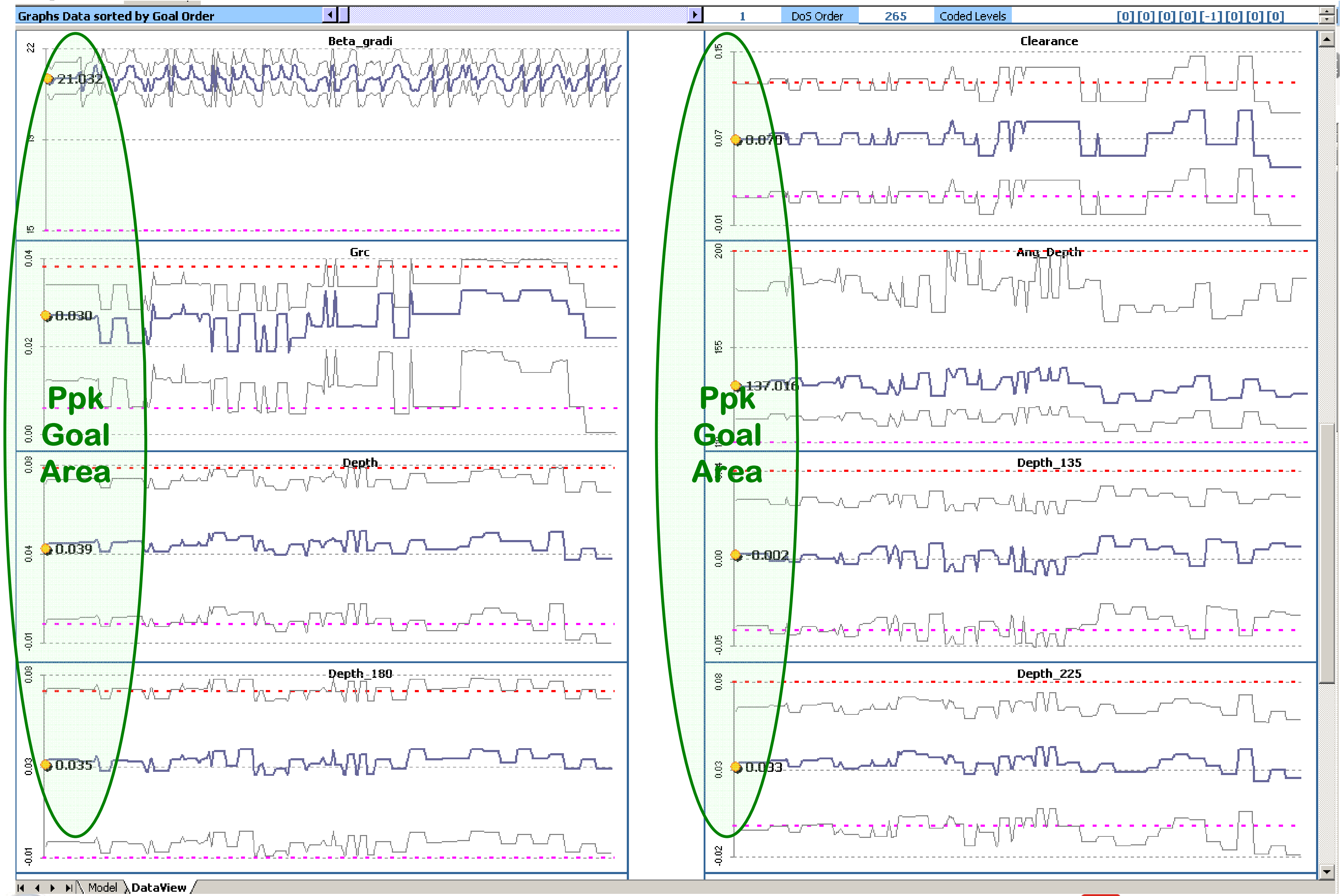
CASAPPA FLUID POWER DESIGN

Ppk Risk model - Final Solution Choice

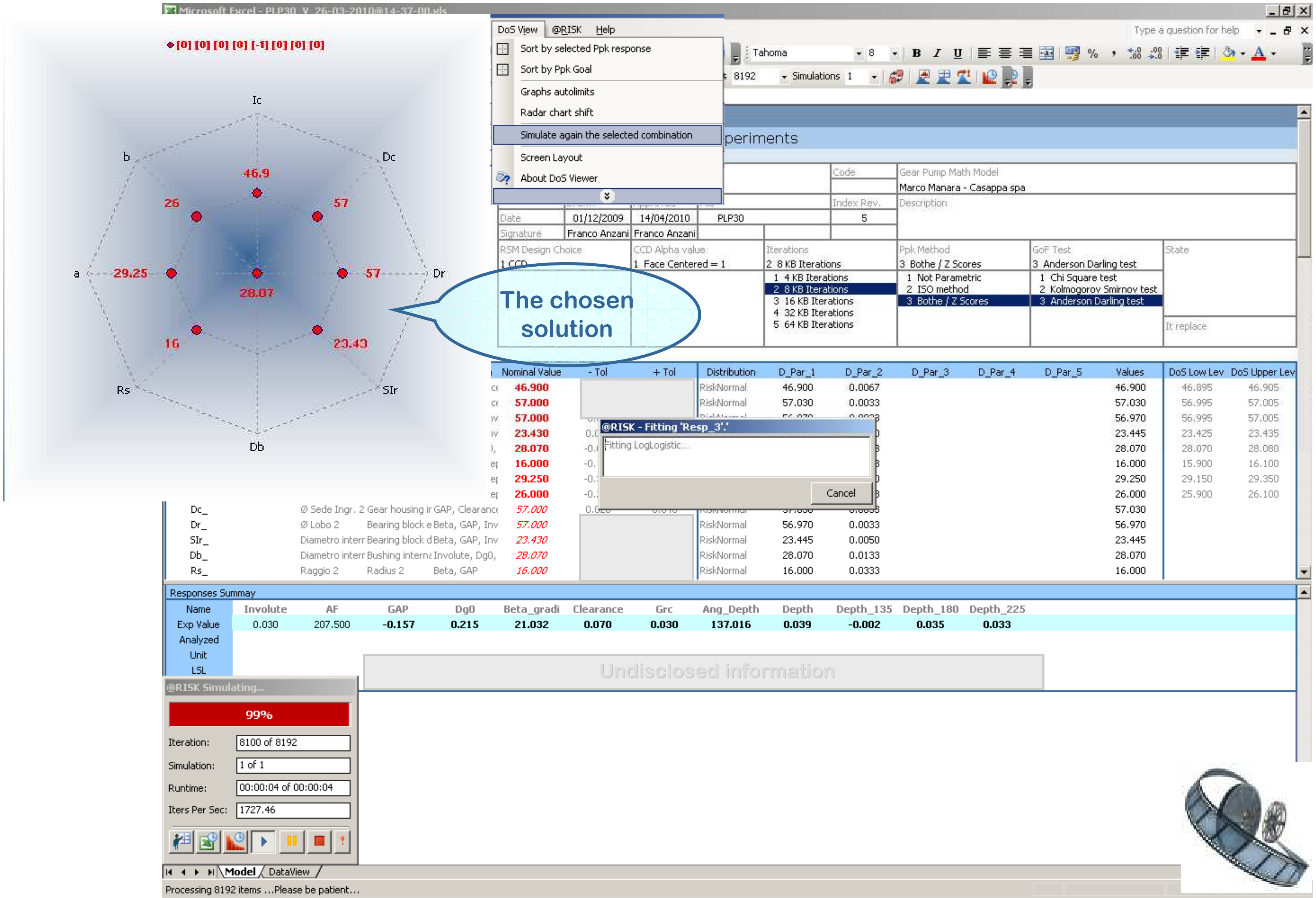


Responses	GAP	Dg0	Beta_gradi	Clearance	Grc	Ang_Depth	Depth	Depth_135	Depth_180	Depth_225
Unit	Undisclosed information									
LSL										
USL										
Exp Values	-0.157	0.215	21.032	0.070	0.030	137.016	0.039	-0.002	0.035	0.033
Best_Fit	RiskLognorm(	RiskNormal(0.	RiskNormal(21	RiskBetaGene	RiskWeibull(9.	RiskPearson5(	RiskNormal(0.	RiskWeibull(4.	RiskNormal(0.	RiskNormal(0.
AD value	0.13	0.32	0.12	0.64	7.01	0.42	0.73	1.95	0.30	1.75
df_L		0	0	2,017	7	0	672	171	138	2,069
df_U	0			1,431	0	87	136	0	1,162	6
df_T	0	0	0	3,447	7	87	808	171	1,300	2,075
PpL		1.79	2.65	0.96	1.45	2.65	1.07	1.19	1.21	0.96
PpU	2.54			0.99	2.06	1.25	1.21	1.81	1.02	1.46
Ppk	2.54	1.79	2.65	0.96	1.45	1.25	1.07	1.19	1.02	0.96
Z Score	7.61	5.36	7.65	2.70	4.34	3.75	3.15	3.58	3.01	2.87
1* Sens_F	e_	Wk	b	e_	Dc	ey	ey	ey	ey	ey
Coef	-0.51	-0.64	0.90	0.55	0.57	-0.82	0.74	0.68	0.83	0.62
2* Sens_F	e	Wk_	Rs	e	Dr	Ic	Db	e	Db	Db
Coef	-0.50	-0.64	-0.36	0.54	-0.56	0.27	0.55	0.39	0.47	0.55
Ppk goal (1-3)	1.66	1.33	1.33	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Weight (0-1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

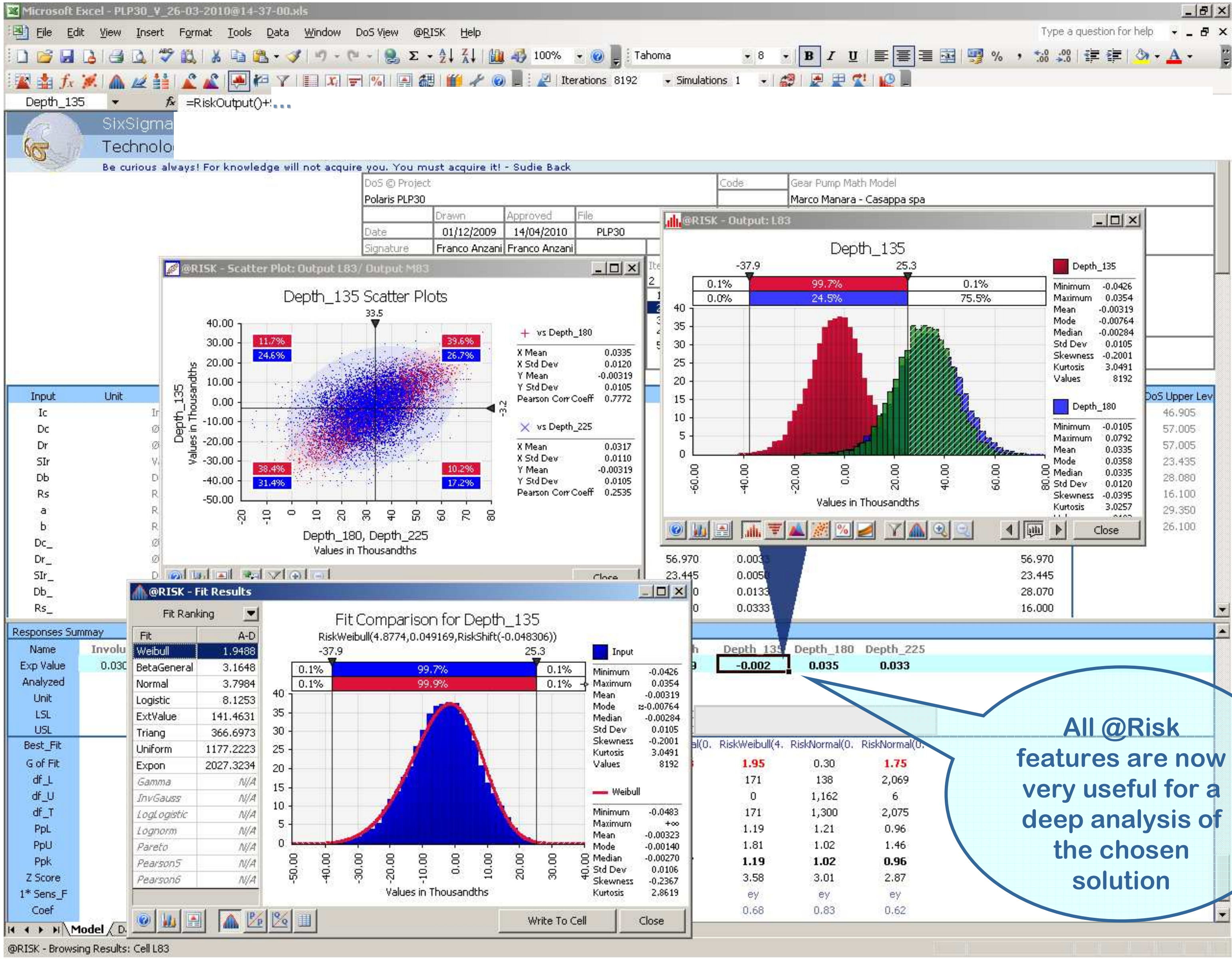
Ppk Risk model - Final Solution Choice



Ppk Risk model validation: Final simulation of the chosen solution

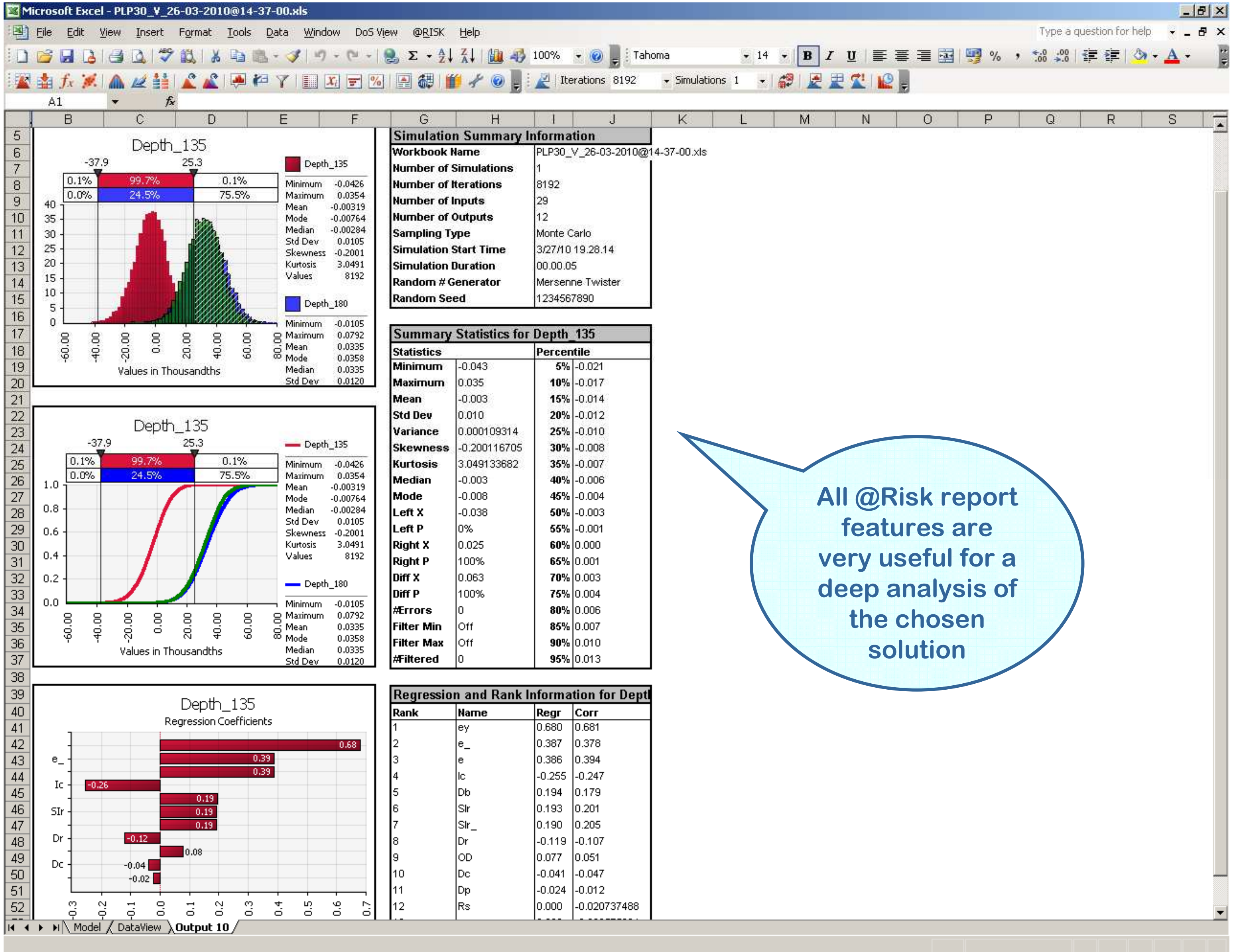


Ppk Risk model - Final Solution Analysis



All @Risk features are now very useful for a deep analysis of the chosen solution

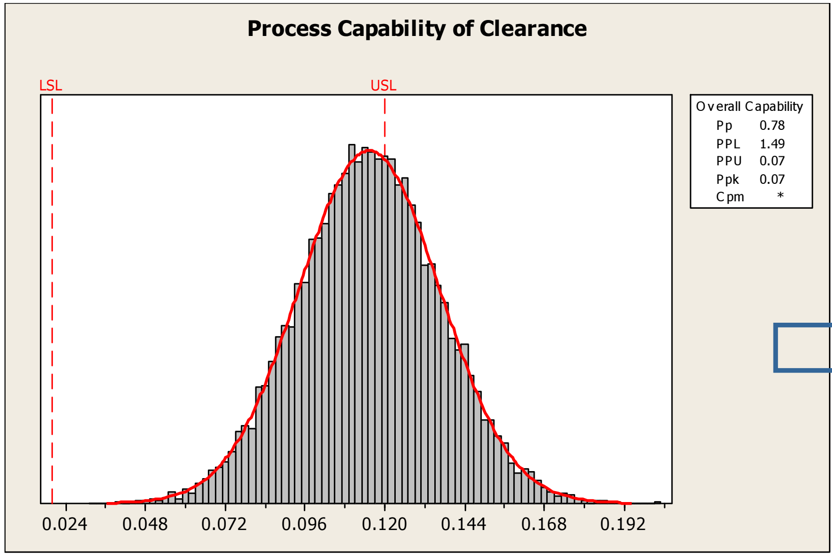
Ppk Risk model - Final Solution Analysis

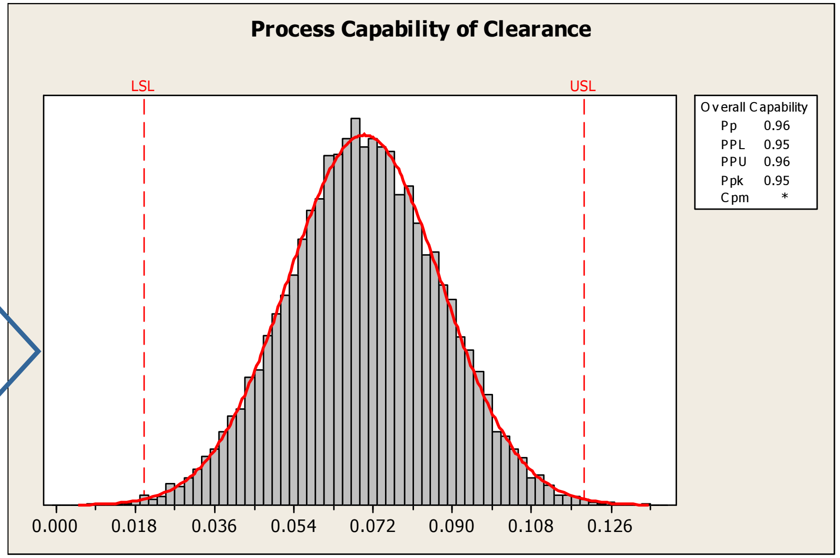


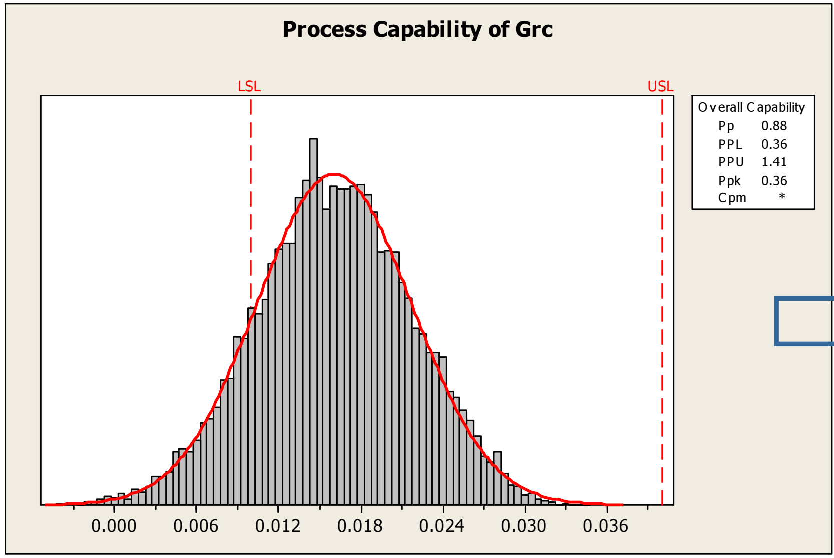
All @Risk report features are very useful for a deep analysis of the chosen solution

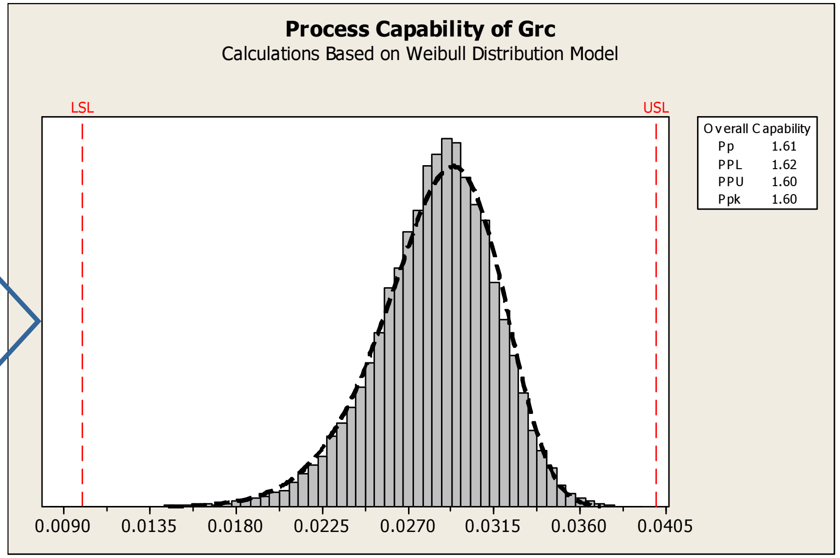
Polaris PLP30 - Results evaluation using Minitab

Radial clearances (Old design pump vs new Optimized design pump)



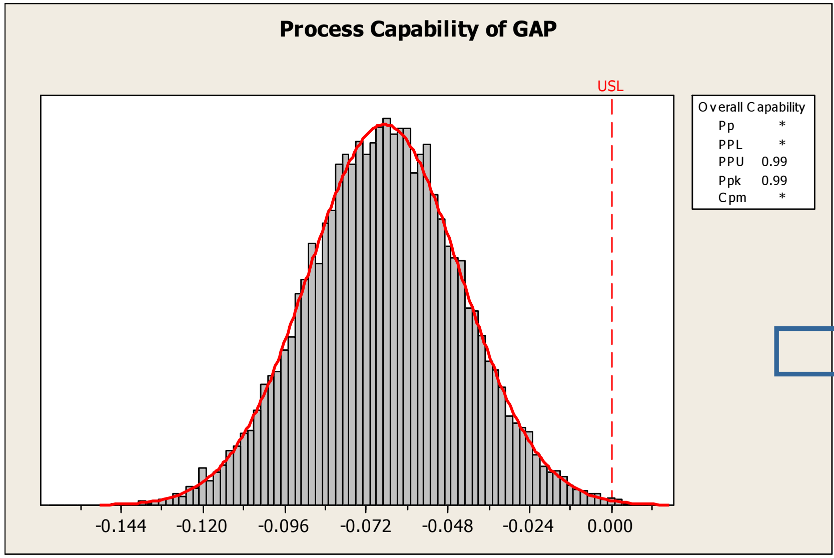


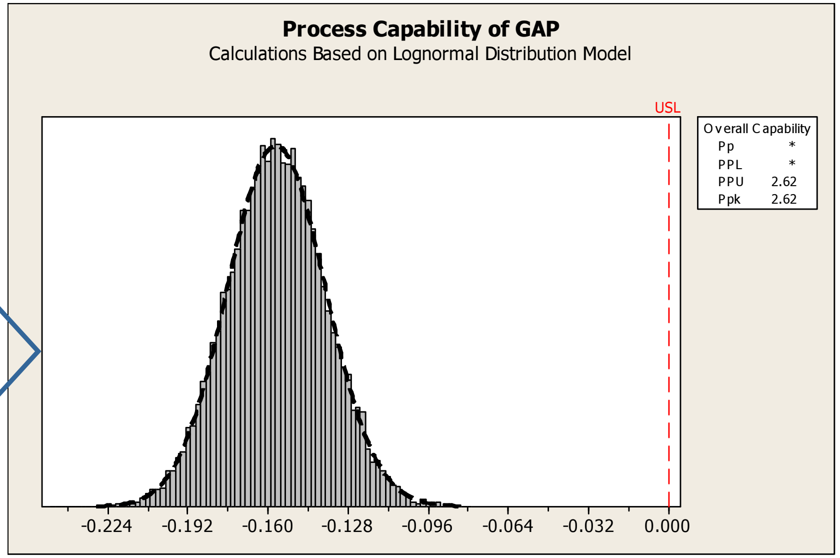


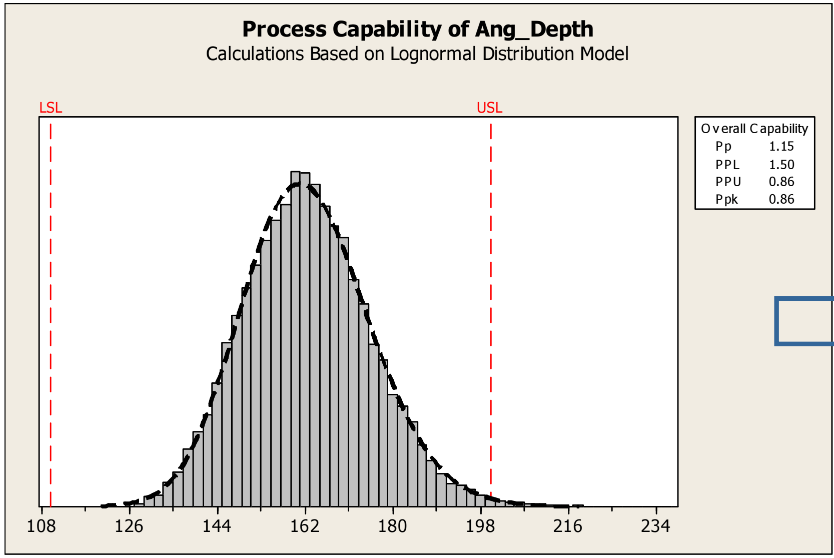


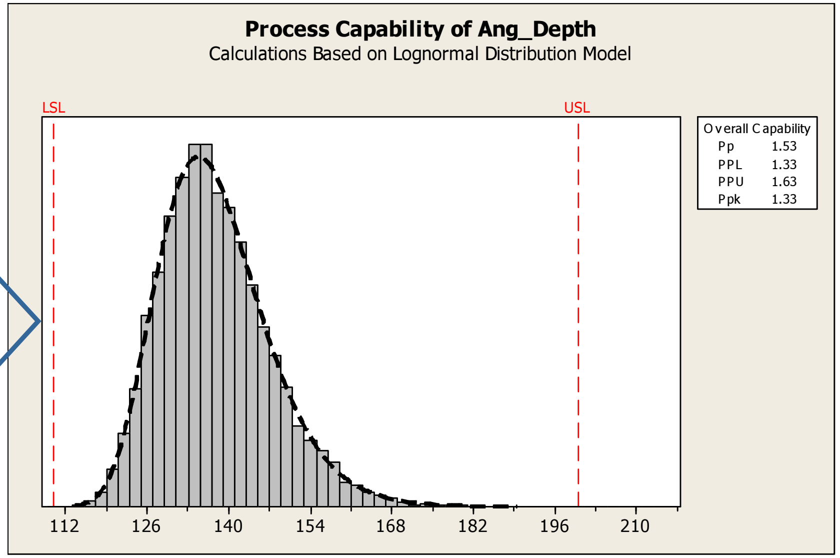
Polaris PLP30 - Results evaluation using Minitab

GAP & Material removal depth starting angle (Old pump vs Optimized design pump)



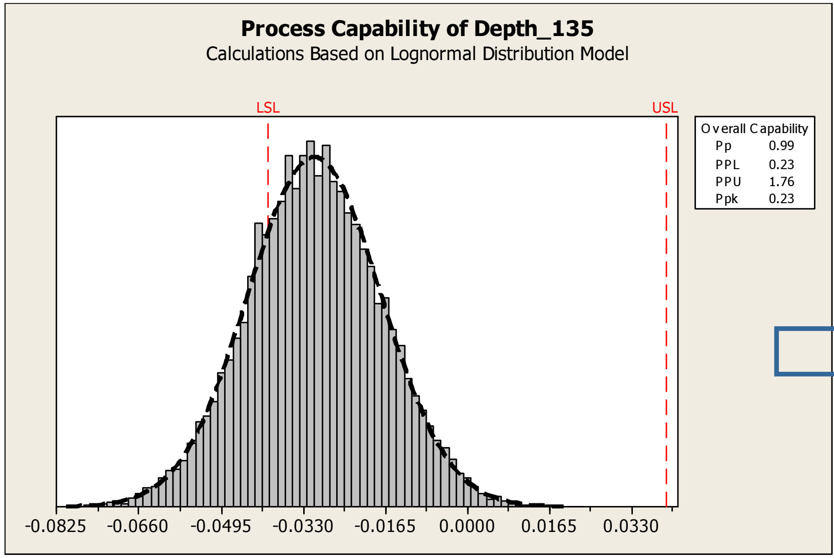


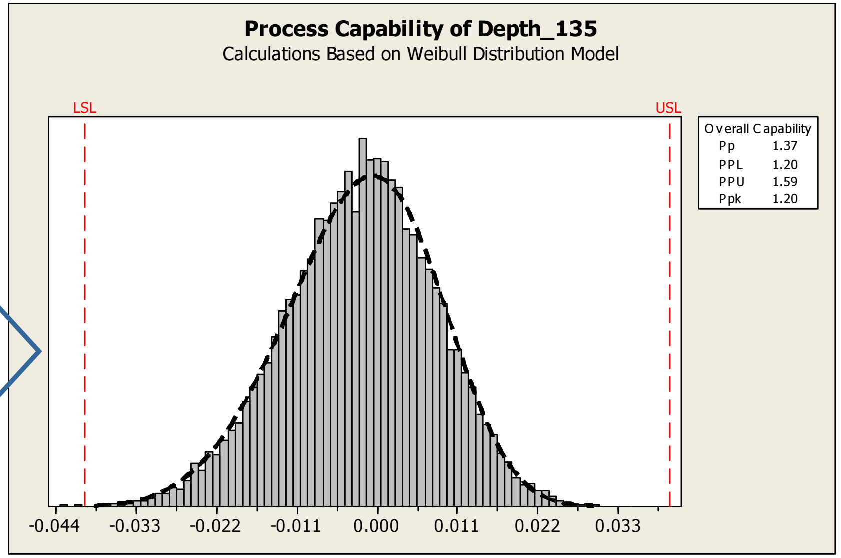


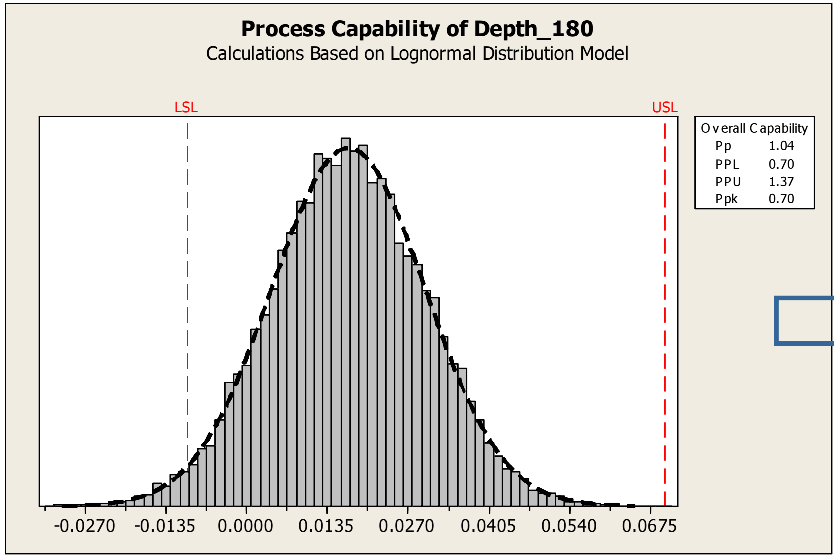


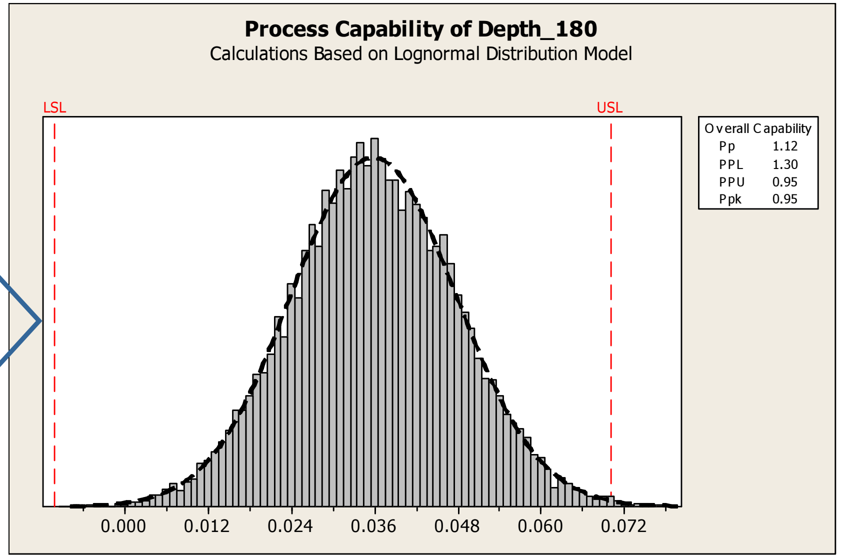
Polaris PLP30 - Results evaluation using Minitab

Material removal depth amount (Old pump vs Optimized design pump)



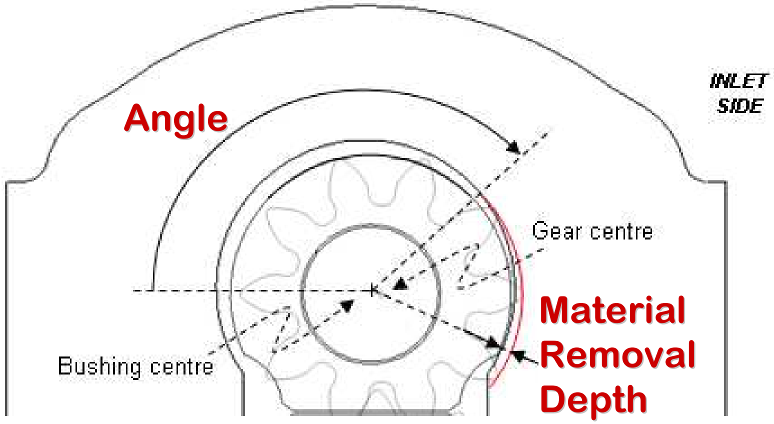


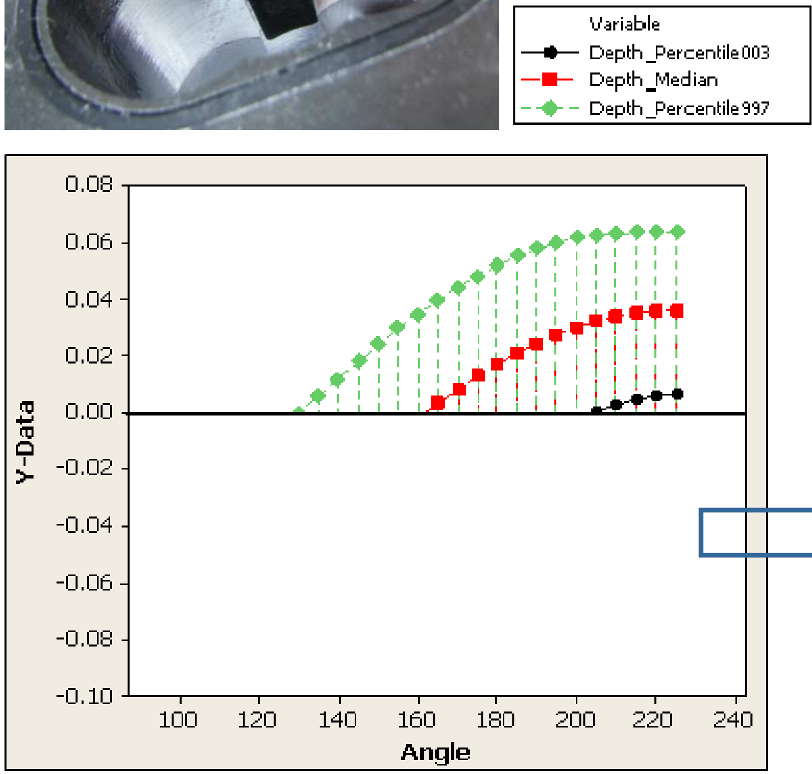


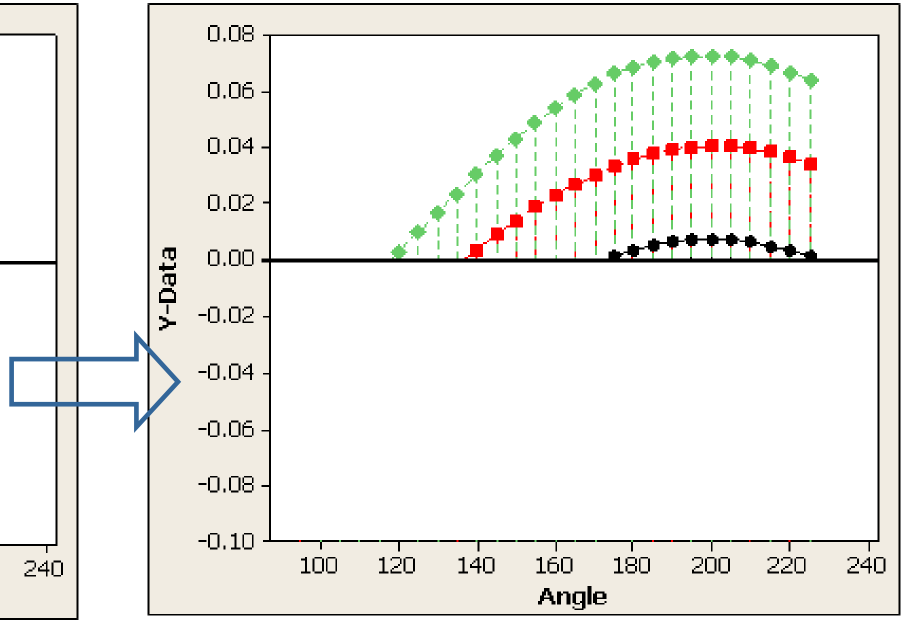


Polaris PLP30 - Results evaluation

Material removal depth vs angle (Old pump vs Optimized design pump)

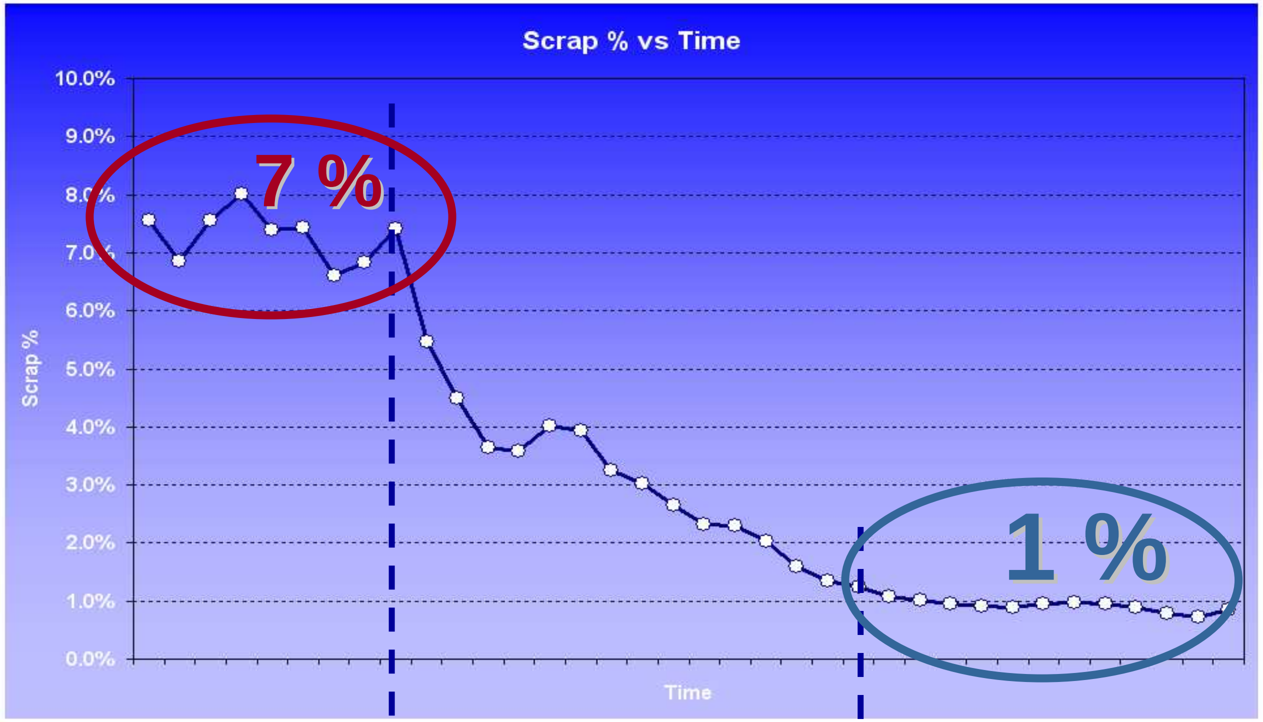






Scraps after the use of Statistical Simulation in Casappa

Scrap percentage at the end of line volumetric efficiency evaluation: from 7 % to 1 % !



Target 0.2 %

Introduction of the new optimized parts in production

2008 - 2009

Old parts completely out of production

2010 →

2008 / 09 Simplified simulation models
(Two responses simulation, the example shown on Palisade website)

2010 → Current advanced simulation models
(More responses and advanced analysis)

Why Palisade @Risk ?

Compared to its main competitors in Six Sigma applications (i.e. Crystal Ball):

- **@Risk5.x has the most complete, documented, stable and maintainable VBA / COM interface. This is the key factor of our choice.**
- **Simulation speed is secondary (CB is faster only if PSA formulas are usable).**
- **As shown on this page, the true bottleneck of our Ppk Risk model (and all robust Ppk models) is the time required to identify the Response Distributions.**

	DoSimulations with 8192 Items	DoSimulations with 16384 Items	DoSimulations with 32768 Items	DoSimulations with 65526 Items
Indipendent Factors	29	29	29	29
Total Responses	12	12	12	12
Analyzed Responses	10	10	10	10
Time required (seconds)	19.6720	35.6947	79.2844	154.0499
Monte Carlo Simulation	5.4537	7.7227	14.5967	28.1611
Fit Responses and Stat Calc	13.0303	25.6558	59.8628	115.4435
Sensibility Coefficient Calc	1.1791	2.3137	4.8224	10.4427
Saving Memory	0.0089	0.0025	0.0025	0.0026

- **In addition, generally speaking @Risk has more additional advantages / features if compared to Crystal Ball (*).**

(*) Franco Anzani's (DoS creator and designer) opinion

DoS Design of Simulations © : Technical Info

- Excel / @Risk5.x blank template (in other words it is an add-in of an add-in)

- Design Space of Simulations:
  - internal engine: CCD and Box Behnken
  - external (importing Design Expert XML definition file): Optimal and User Defined
  - up to 64 Input Factors [standard template] or unlimited (*) [advanced template]
  - among which up to 16 [Excel 2003] or 20 [Excel 2007] as factor levels
  - 3 to 16 Responses [standard template], 3 to 250 (*) [advanced template]

- Export Simulated Data to:
  - Design Expert: DoE Simulated Data analysis and/or additional optimization
  - Minitab: generic statistics analysis (**)
  - gGobi: data visualization software (freeware)

- Fully Customizable on request

- Work in progress: DLL callable version based on Champion of Italy structure
  - it does NOT use Excel formulas / parser / interface
  - fast simulation of millions of data
  - Excel is used only as a final report / graph tool

(*) limited by RAM memory, processor speed or available simulation time
(**) not suggested for DoE analysis (Minitab does not support robust transformation in DoE and - for a PpK Risk model - the transformation is a MUST)

Bushing blocks optimization for an external gear pump

If you require any further information, please contact:

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Marco Manara - Casappa S.p.A., manaram@casappa.com - www.casappa.com

The videos shown during this presentation are available @ this web address:

http://www.sixsigmain.it/palisade_london.html

Acknowledgements

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Thank you for your attention

Q & A