ROBUST DESIGN FROM COMPUTER SIMULATORS

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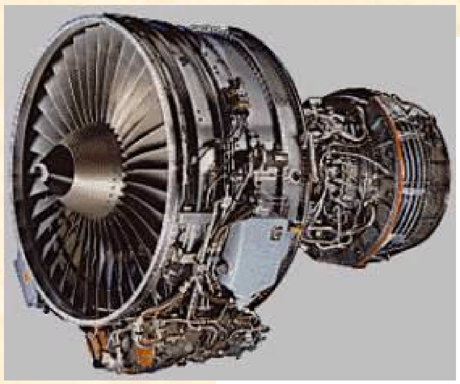
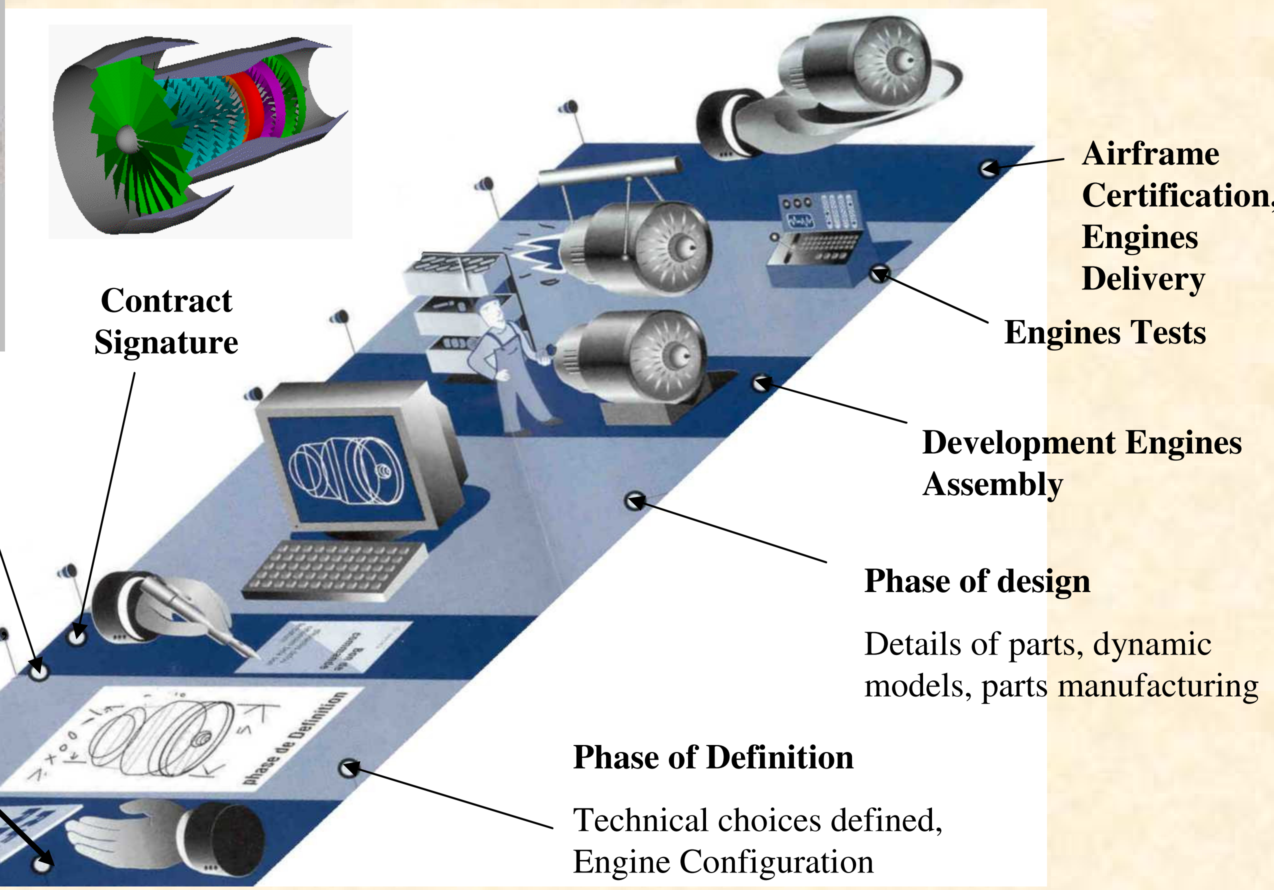
Challenges for Product Development





Challenges for Product Development

- Reducing time to market.
- Accelerating the development process.
- Improving product quality.
- Achieving robust products.

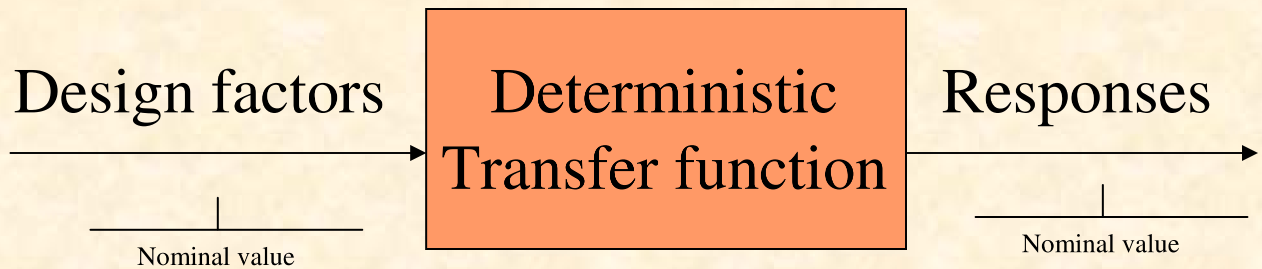
Is there a magic formula?

How can statistics help?

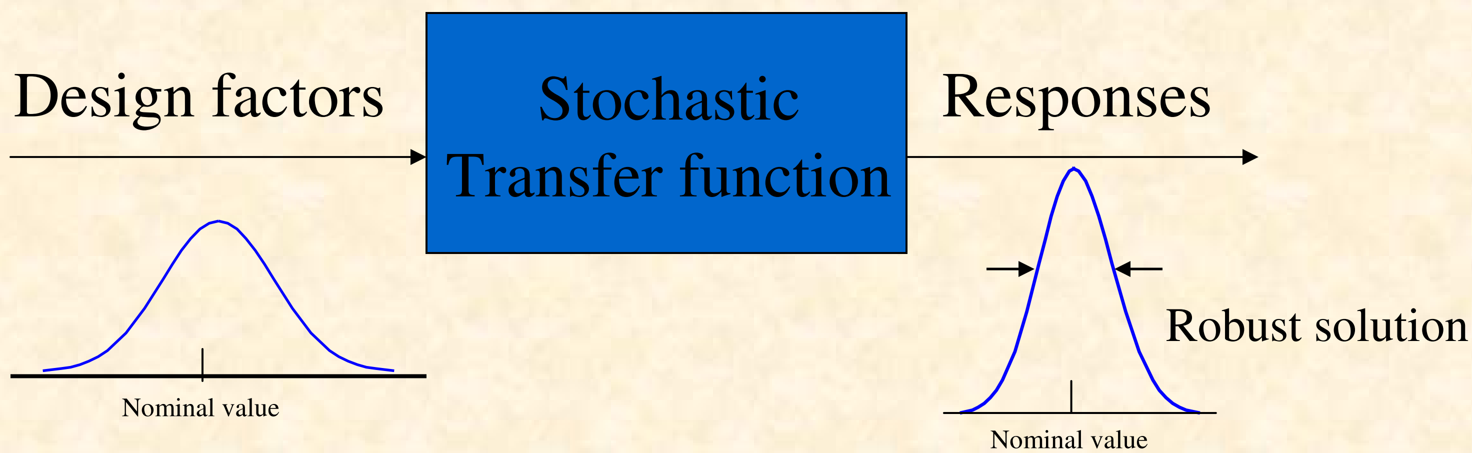
Experiments are an integral part of Product and Process Development (PD). **Designed experiments** help meet the PD challenge. They:

- Facilitate study of complex processes with many input factors.
- Provide solid evidence for decision making.
- Ramp up the learning curve and accelerate product development.

Classical engineering paradigm:



Modern engineering paradigm:



The focus of this talk:

Achieving robustness

in product and process design

from **computer experiments**.

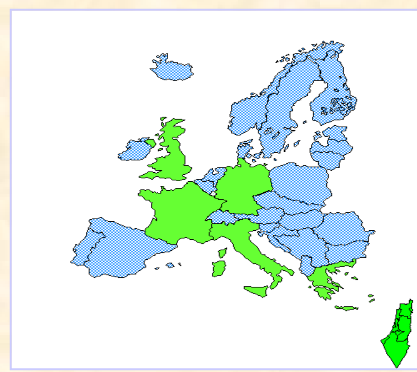
Computer Experiments:

Study the product or process on a computer simulator rather than in the laboratory or the field.

Once the simulator code is ready, it is possible to run much faster and less expensive experiments for complex products and processes.

TITOSIM (**Reducing Time to Market via Statistical Information Management**) a 5FP Growth EU project is developing tools and software for effective use of computer experiments and robust design to reduce time to market.

This EU project is coordinated by Fiat Research (CRF). Partners include industrial companies, consulting firms (*KPA Ltd.),* and universities *(*London School of Economics).



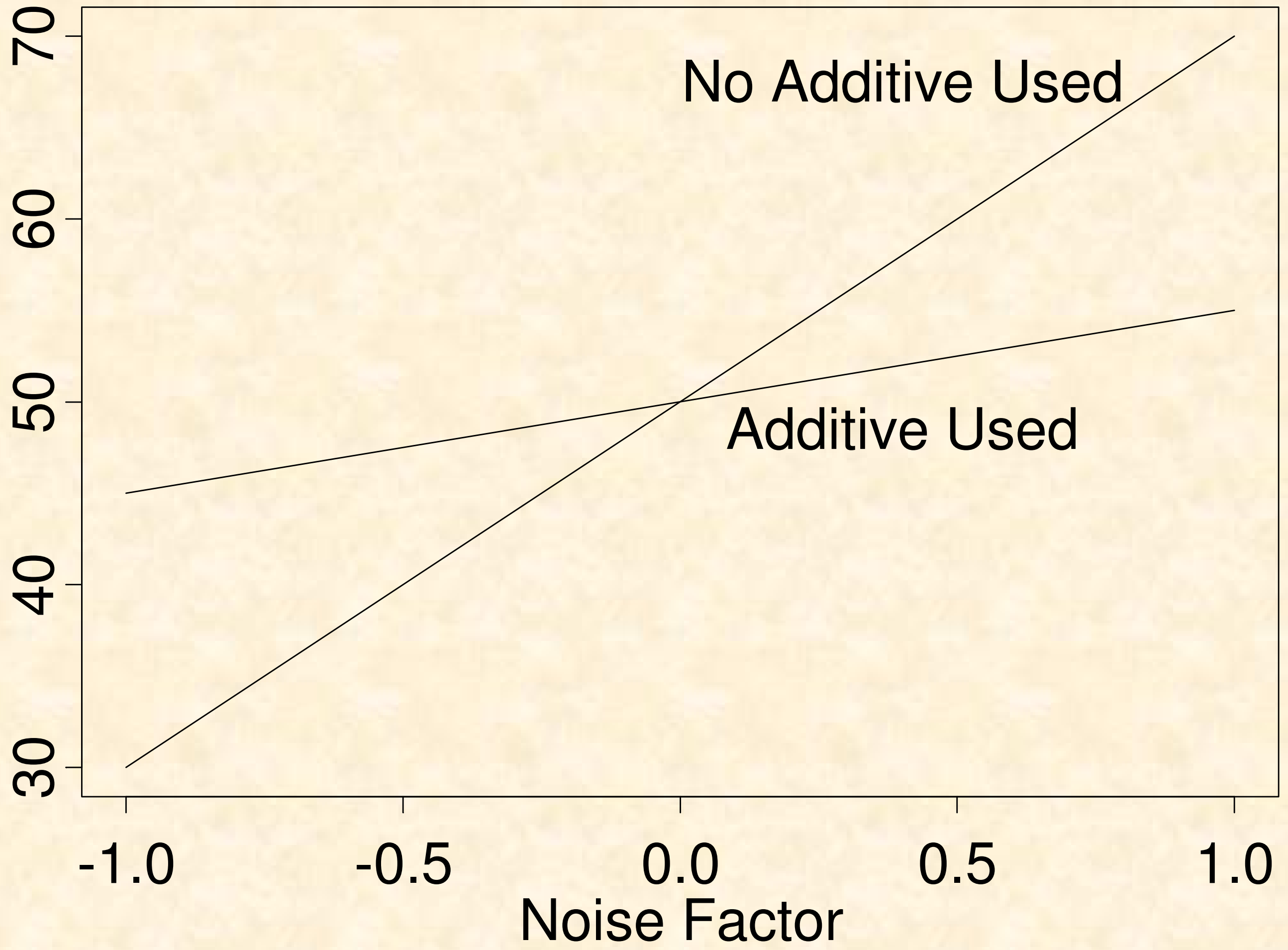
Some representative case studies from TITOSIM.

- Improve the design of a highway barrier.
- Identify optimal electronic injection parameters in order to minimize engine fuel consumption and noise.
- Optimize the design of a turbine vane.
- Minimize the effects of micro-vibrations on satellite performance.
- Improve the performance of a turbofan in a jet engine.
- Maximize the throughput of a production cell

Robustness Design Experiments

- Variation is not desirable.
- Variation is often caused by specific factors that vary during production or use -- noise factors.
- Study the effects of noise factors by including them explicitly in an experiment.
- Neutralize their effects by exploiting interactions between noise factors and design factors.

When the additive is used, the slope is "flatter" so that the noise factor transmits less variance to the response.



Computer experiments are different from physical experiments.

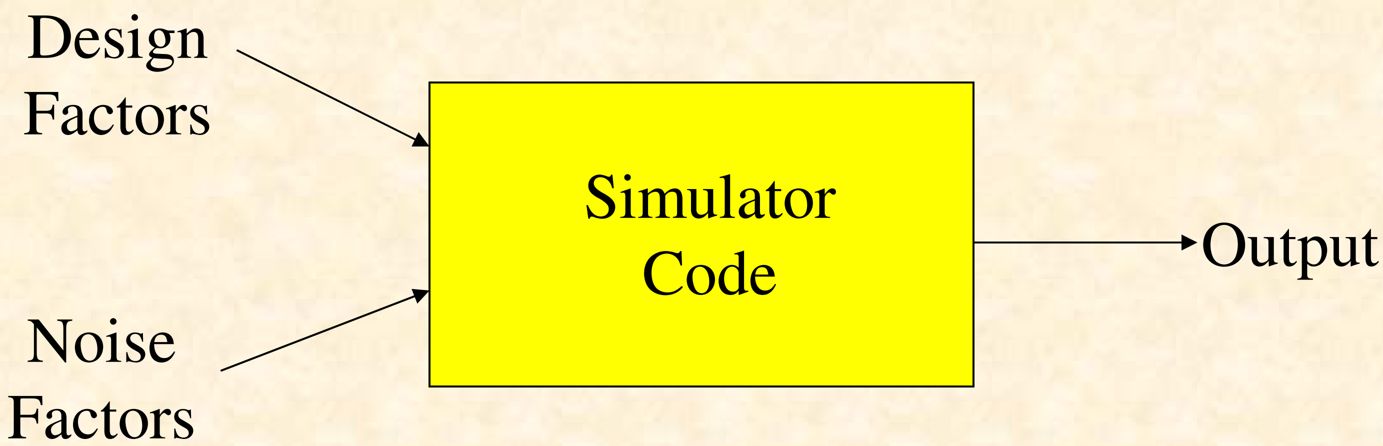
- No random error.
- Repeating inputs gives same output.
- Easy to use many factor levels.

Should the same methods be used for robust design?

Sources of variability in computer experiments.

- Tolerances about nominal levels.
- Environmental factors.
- Construction of finite element grids.
- Ability of simulator to match reality.

A schematic view of a computer experiment for robust product design.

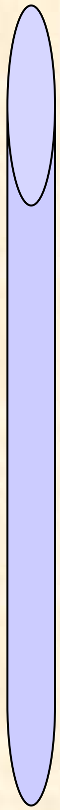


All response variation is a result of input (noise factor) variation.

So careful definition of noise factor distributions is essential.

- Shape.
- Spread.
- Are these properties dependent on the nominal level?
- Complexity – does a single noise factor capture all the input variation?

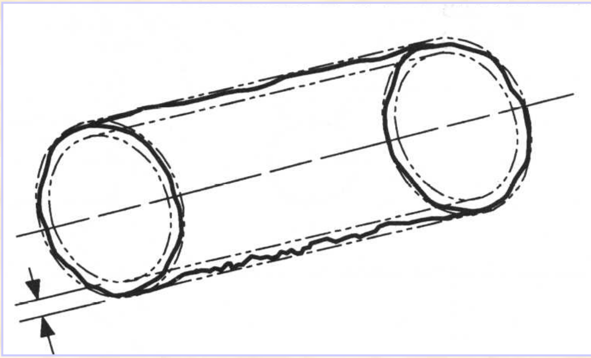
Consider a metal rod used in an automobile frame.

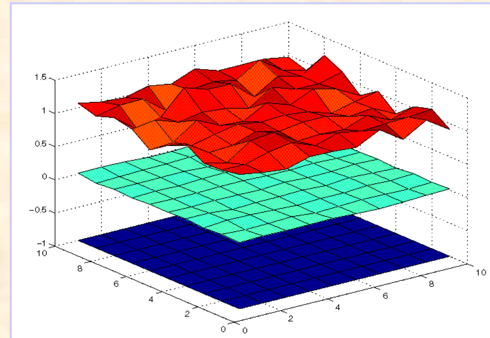


What is the thickness of the rod?

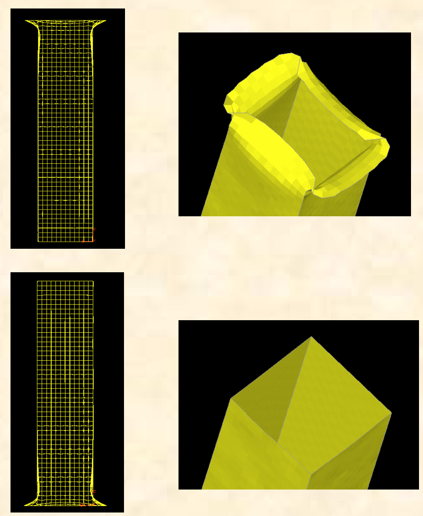
- Nominal thickness.
- Global deviation from nominal.
- Local deviations from global.

ST-ORM, a stochastic simulation manager, uses random fields based on extensive data analysis to model the local deviations and include them as part of the noise description. This can mean *thousands* of noise variables.





Simulations with random fields produce two bifurcating phenomena



Four strategies for robust design experimentation with computer simulators.

1. Cross-product design with SN analysis (Taguchi's strategy).
2. Cross-product design with response model analysis.
3. Simulate by random sampling and model the variability.
4. Emulate the response function and simulate the variability from emulator.

1. The Taguchi Paradigm

1. Set up a cross-product design, with separate designs for the design and noise factors.
2. Summarize the variability at each design factor setting by the SN ratio
3. Analyze how SN depends on the design factors and set them to maximize SN.
4. Analyze how the mean output depends on the design factors.

Note that the same basic input to the simulator code may occur as a design factor (nominal level) and as a noise factor (tolerance about nominal).

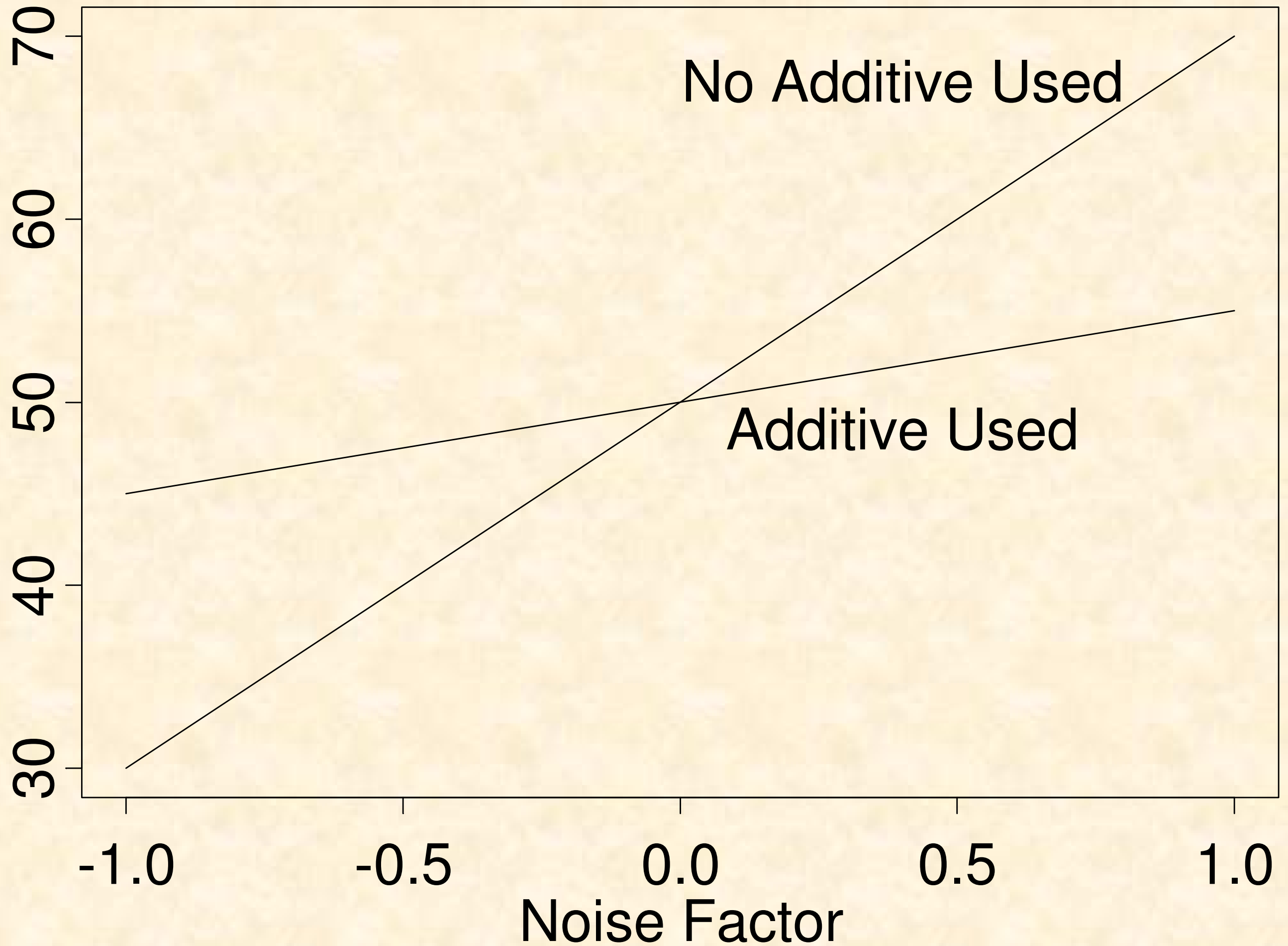
A single value is input to the simulator for each run, based on both factors in the design.

For example, the design factor level for the weight of an input is 300 grams and the noise factor level is –2%. The simulator is run with a weight of 294 grams.

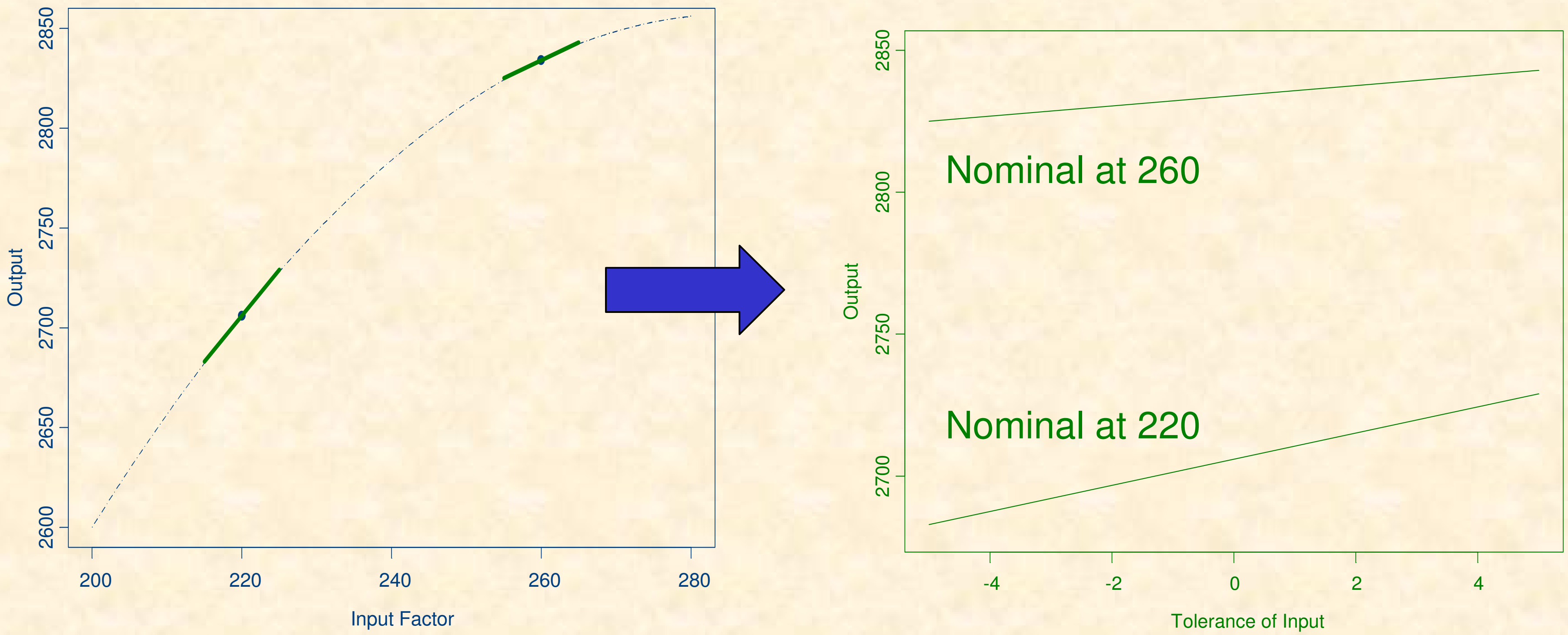
2. The Response Model Paradigm

1. Set up a cross-product design or a combined array.
2. Analyze how the output depends on both the design and the noise factors.
3. Exploit design by noise factor interactions to reduce sensitivity to noise factor variations.

The use of interactions follows that in physical robust design experiments.



There is an analogous picture for noise factors that represent tolerances of design factors.



The experiment actually uses four levels for the basic input to the simulator.

The “design factor” version of the input models “macro” variation in the output.

The “noise factor” version of the input models “micro” variation in the output.

A change in the derivative could also be related to one of the other design factors.

3. Simulate and Model the Variability

1. Set up a design using the design factors only.
2. At each design factor setting, simulate noise factor levels from their distributions.
3. Summarize the variability at each design factor setting.
4. Model how the variability depends on the design factors.

4. Emulate the Output and Simulate the Variation

1. Generate a design with the fundamental inputs to the simulator.
2. Model how the output is related to the inputs, constructing an emulator of the simulator.
3. For a given design factor setting, randomly generate noise settings and emulate the output.
4. Summarize the emulated variability.
5. Model how the emulated variability is related to the design factors.

Where do the different strategies spend their simulator budget?

	Design Settings	Noise Settings	Total
1. Cross-product	n	m	nm
2. Response Model	n	m	nm
3. Simulate	p	q	$pq=nm$
4. Emulate	nm		nm

The emulator approach can provide a much wider picture of the "macro" variation related to the inputs.

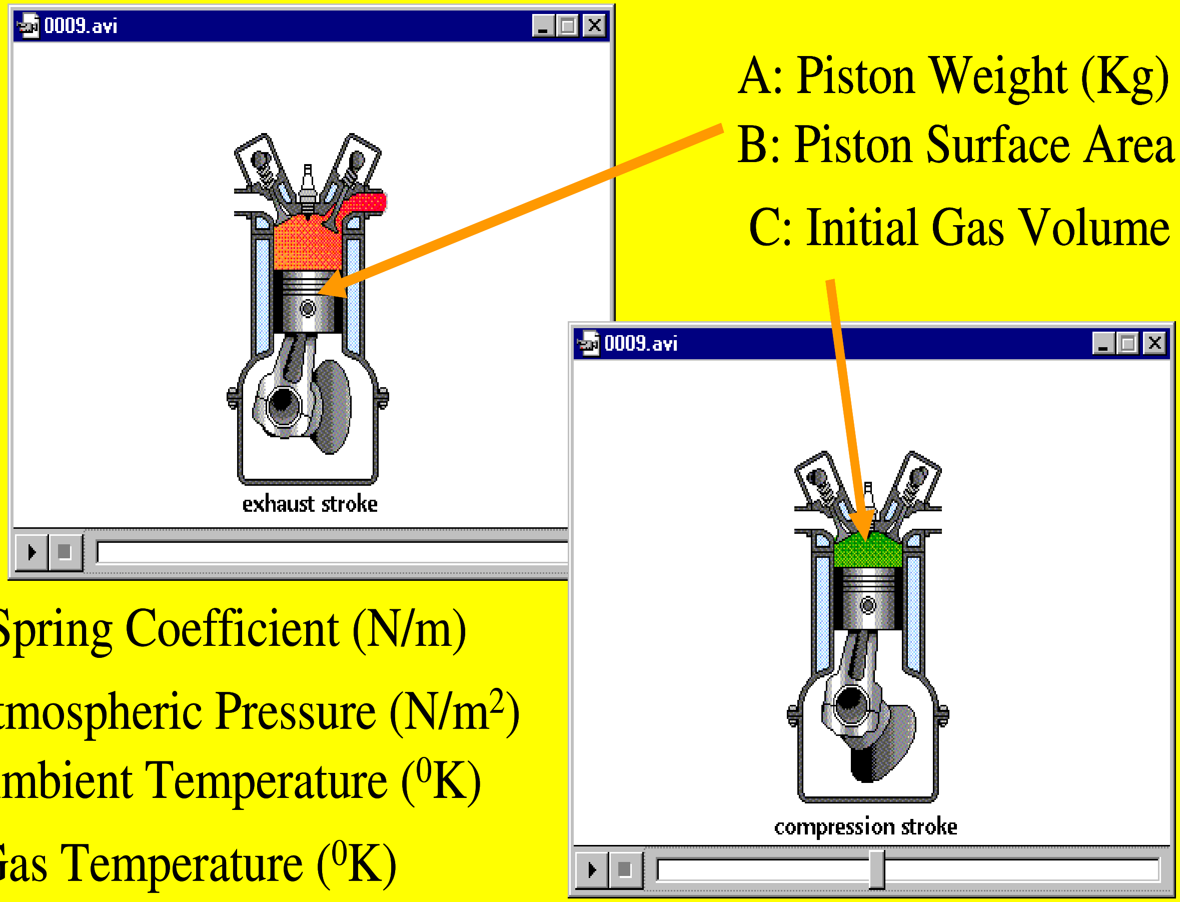
The macro variation is used to emulate the micro variation.

Provided this scheme accurately represents the micro variation, the emulator approach may enjoy a real advantage for a fixed sample size. This should be the case when the output is essentially a "smooth" function of the basic inputs.

Case Study: The Piston Simulator

Simple simulator of the cycle time of a piston developed by Kenett and Zacks for their book ***Modern Industrial Statistics*** *(Duxbury Press, 1998)*.

The simulator uses a basic random field model on seven factors with randomness introduced directly in the values of the factors.



A: Piston Weight (Kg)

B: Piston Surface Area (m^2)

C: Initial Gas Volume (m^3)

D: Spring Coefficient (N/m)

E: Atmospheric Pressure (N/m^2)

F: Ambient Temperature (^0K)

G: Gas Temperature (^0K)

Each of the input factors can be treated as both a

design factor (nominal level)

and a

noise factor (tolerance about the nominal).

Design Goals

1. **Average cycle time of 0.7 sec.**
2. **Minimal variation.**

The Piston Simulator

1. The Taguchi Paradigm

Experimental plan uses each input as both a design factor and a noise factor.

Separate 2^{7-4} arrays are crossed to generate the design.

Nominal settings and tolerances for the input factors in the cross-product design.

Factor	Low	High	Tolerance
Weight	35	55	.2
Surface Area	.0075	.0175	.002
Init Gas Vol	.0181	.0837	.0005
Spring Coef	1667	4333	100
Atmos Pres	93333	106666	200
Amb Temp	291	295	.26
Fill Gas Temp	343.3	356.7	.26

The nominal settings are at –2/3 and +2/3 of the factor ranges given by Kenett and Zacks.

Overall average: 0.729.

Factor effects on the SN ratio and the Average.

Factor	Effect on SN	Effect on Average
Weight	1.39	0.054
Surface Area	-3.05	-0.045
Init Gas Vol	8.97	0.065
Spring Coef	6.95	-0.138
Atmos Pres	0.62	-0.024
Amb Temp	-1.57	-0.041
Fill Gas Temp	-1.61	0.034

Recommendations.

Set Initial Gas Volume and Spring Coefficient to high nominal values to reduce variation.

Set Weight high to move mean toward target.

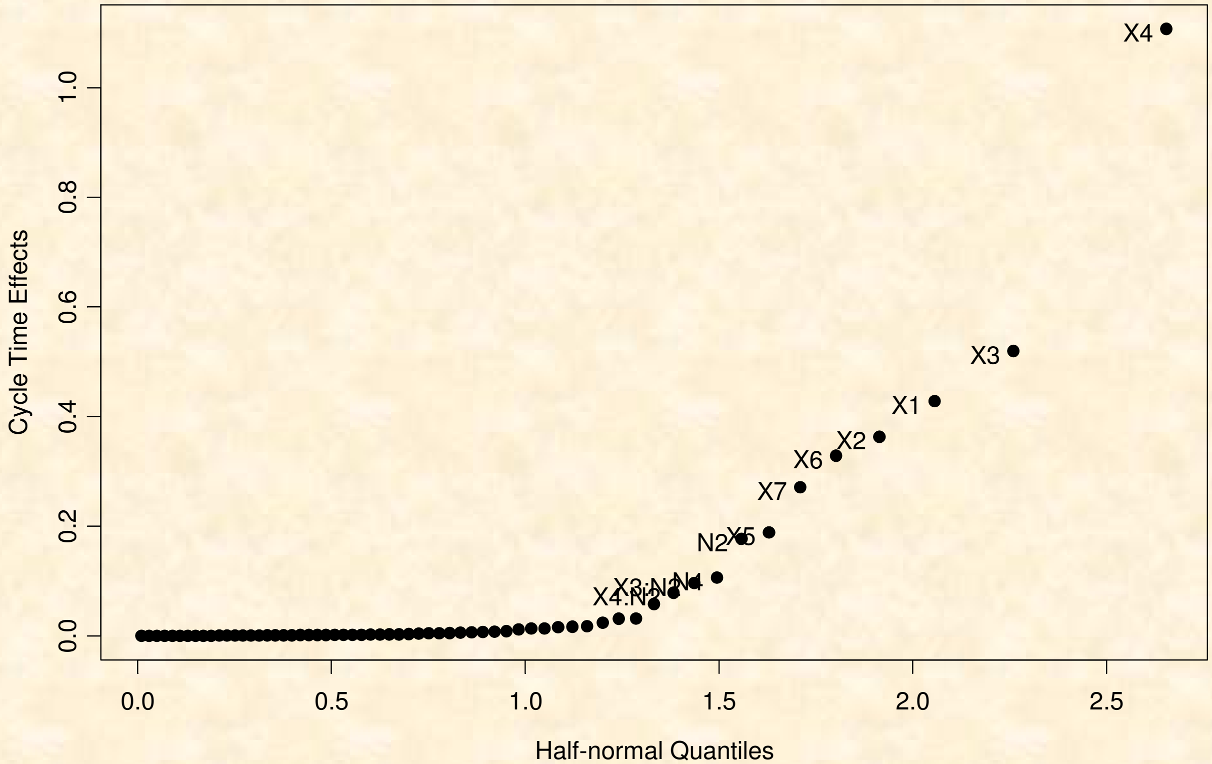
Estimated mean: 0.71.

The Piston Simulator

2. The Response Model Paradigm

Analyze the same data, but with explicit modeling of effects for the noise factors and design by noise interactions.

Half-normal plot of the factor effects.



X's refer to design factors, N's to noise factors.

Effects of the design factors do not change.

The table lists the effect of each input as a noise factor.

Noise Factor	Effect on Average
Weight	0.001
Surface Area	-0.022
Init Gas Vol	0.002
Spring Coef	-0.013
Atmos Pres	0.000
Amb Temp	0.000
Fill Gas Temp	0.000

The two main noise factors can be largely neutralized through their interactions with design factors.

Surf Area	-0.022	Spr Coef	-0.013
x In G Vol	0.012	x Spr Coef	0.007
x Spr Coef	0.010		

Thus setting the Initial Gas Volume and the Spring Coefficient to high levels will substantially reduce the transmitted variation.

Recommendations

As before.

This analysis also shows us which tolerances make an important contribution to the variance and thus might suggest further effective engineering actions to neutralize their effects.

The Piston Simulator

3 & 4. Simulate and Model the SD

Design 1: four replicates of a 2^{7-3} in the design factors.

Design 2: two replicates of a 32-run LHC.

Design 1: Average 0.831; Average SD 0.0085.

Factor effects on the SN ratio and the Average.

Factor	Effect on SD (*100)	Effect on Average
Weight	-0.9	0.091
Surface Area	2.2	0.000
Init Gas Vol	0.6	0.000
Spring Coef	-4.4	-0.194
Atmos Pres	-1.6	-0.001
Amb Temp	-0.1	-0.001
Fill Gas Temp	0.3	0.001

Recommendations

To reduce the SD, increase Spring Coef and decrease Surface Area and Atmospheric Pressure.

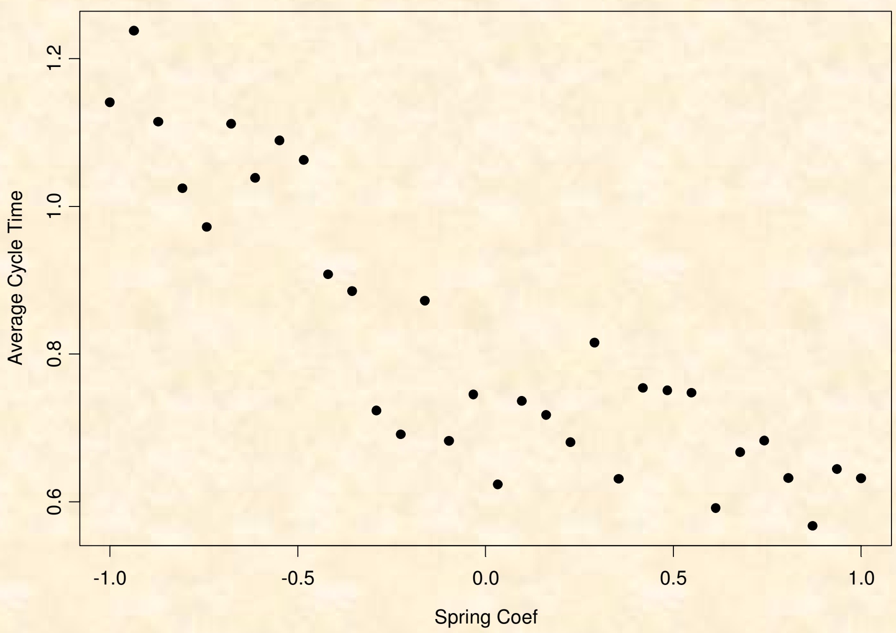
To move the mean closer to target, increase the Weight to about 52.5 (0.5 in standardized units).

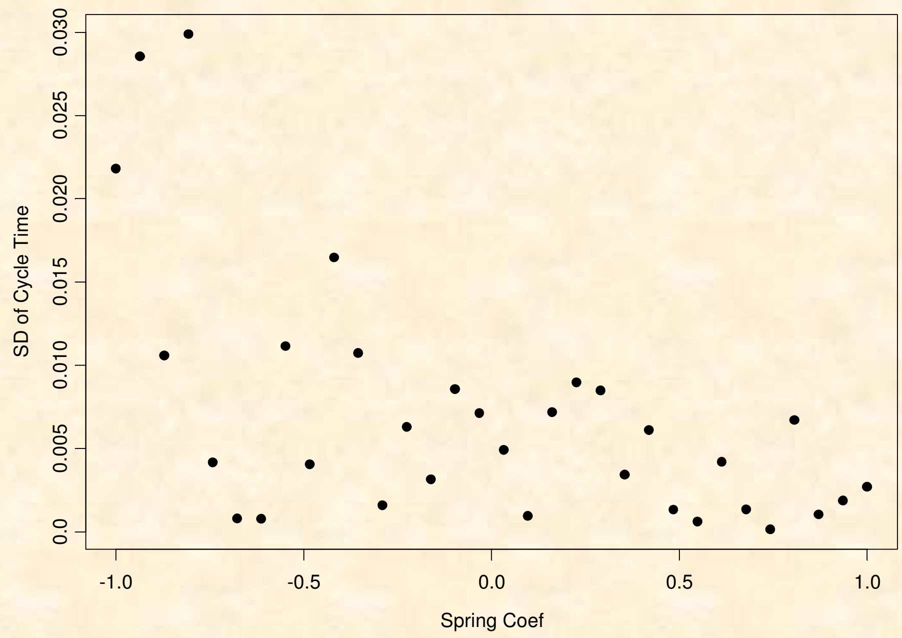
Design 2: Average 0.818; Average SD 0.0070.

Factor effects on the SN ratio and the Average.

Factor	Effect on SD (*100)	Effect on Average
Weight	-0.2	0.125
Surface Area	-0.1	-0.010
Init Gas Vol	-0.1	0.003
Spring Coef	-0.7	-0.312
Atmos Pres	-0.2	0.001
Amb Temp	0.2	0.029
Fill Gas Temp	-0.1	0.025

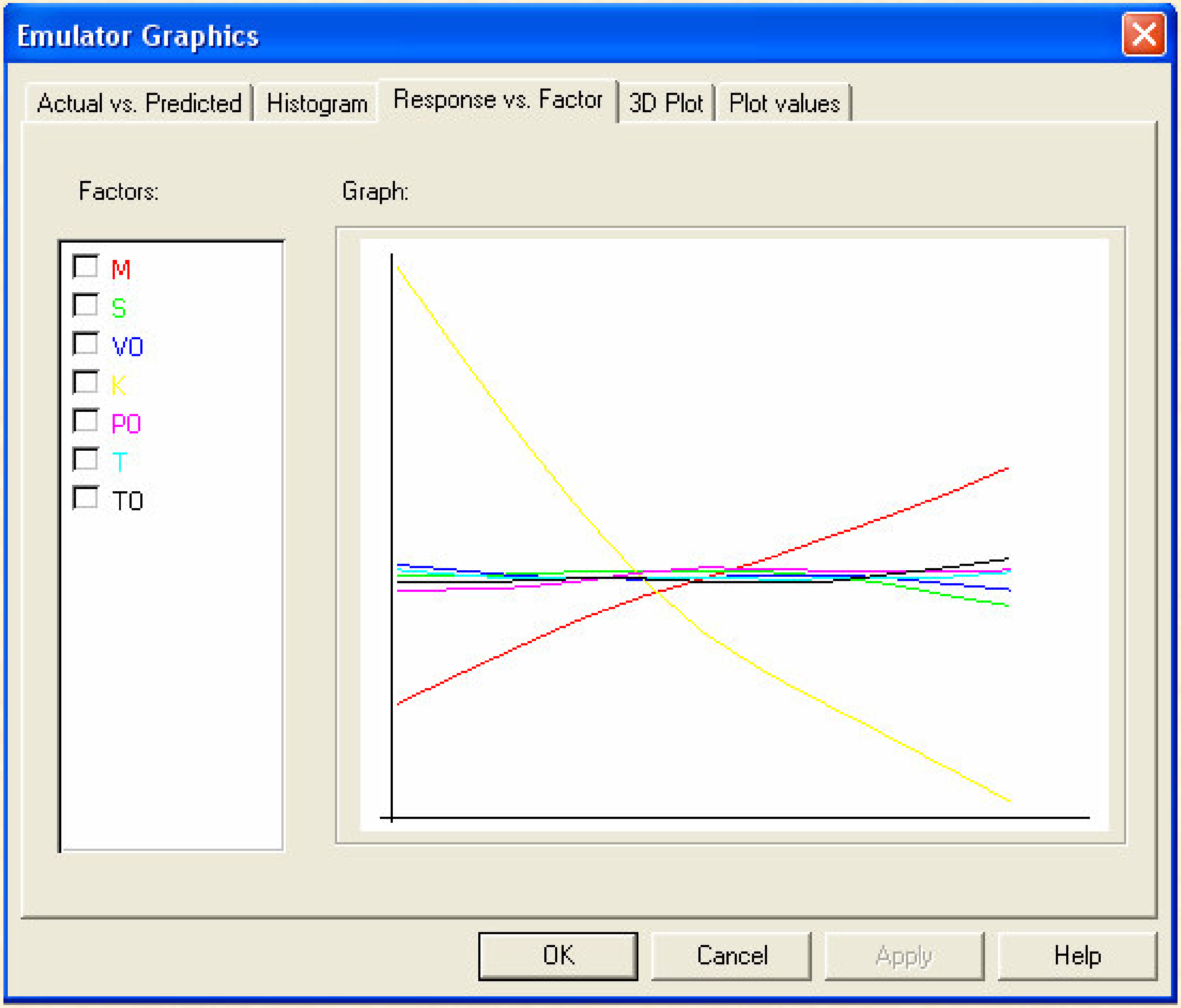
Effects of the Spring Coefficient





The TITOSIM prototype was used to fit a kriging type model to the data.

The model for the mean picks up the clear nonlinear effect of the Spring Coefficient and a weaker, linear effect for the Weight. The other factors all have very small effects


Emulator Graphics
Actual vs. Predicted
Histogram
Response vs. Factor
3D Plot
Plot values
Factors:
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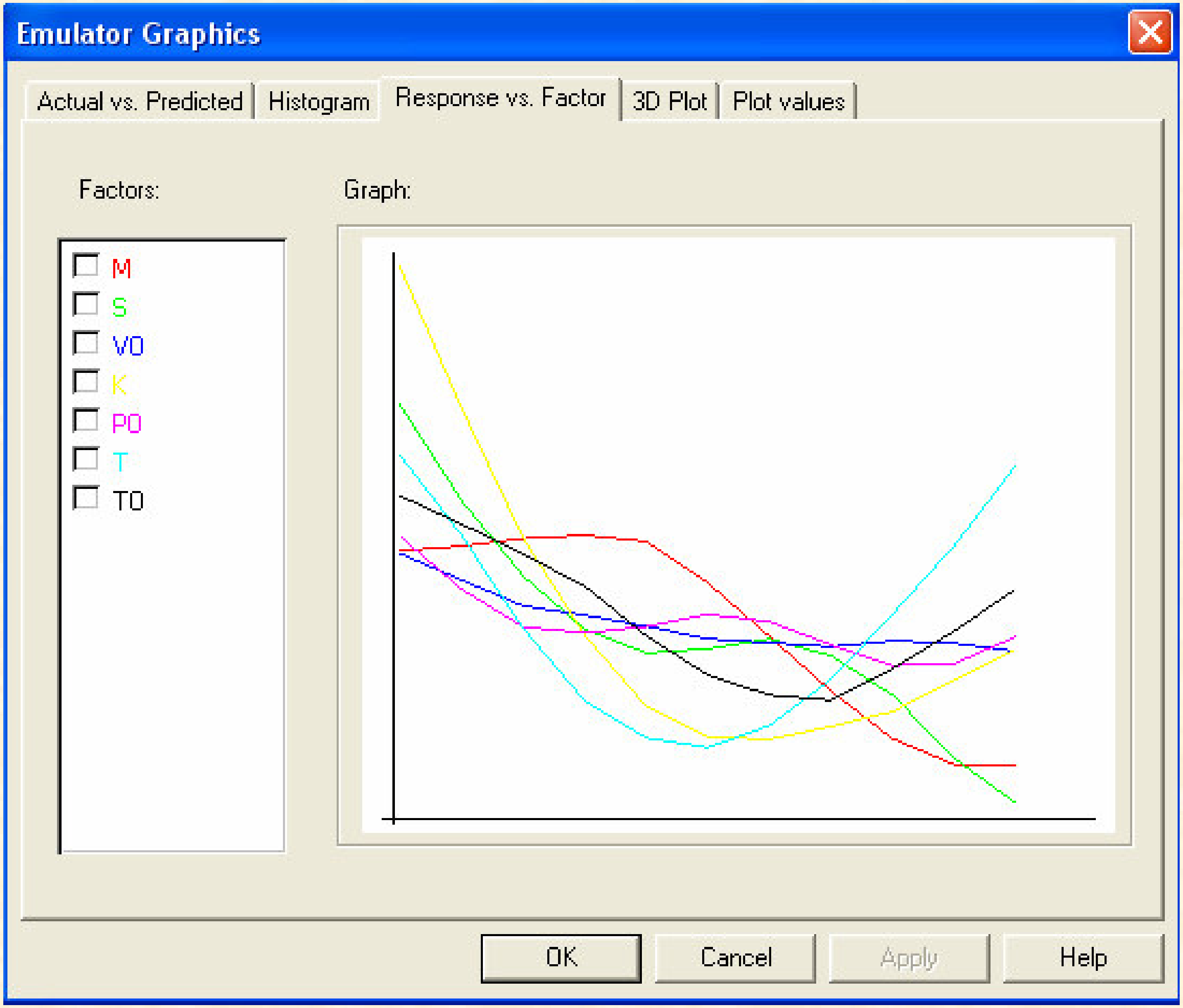
The model for the SD shows weak correlation between the factors and the SD.

Several factors are shown to have non-linear effects on the SD, including the Spring Coefficient, the Surface Area, the Weight and the Ambient Temperature.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Recommendations

To reduce the SD, set the Spring Coefficient in the top half of its range, the Weight and Surface Area to maximal values, and the Ambient Temperature to the middle of its range.

To move the mean closer to target, set the Spring Coefficient about 20% below the top of its range.

Comparison of the recommended settings, using random samples of 50 cycle times.

Method	Average	SD
Taguchi & Response Model	0.708	0.0048
Design 1 (2^{7-3})	0.692	0.0041
Design 2 (LHC)	0.750	0.0048

Conclusions

1. Computer experiments have great potential for **rapid robust design**.
2. Several methods are available for achieving **robustness with computer experiments**.
3. Our example does not indicate a clearly preferable method – **more research is needed**.
4. It does suggest that **effective modeling of the mean is necessary**, to ensure the ability to set the process on target.
5. Computer experiments open up **new paradigms in experimental designs** (Random fields, implementation effects,…).