Enhanced capability of metal forming simulation tools - a pioneering approach to simulate real process behavior

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Introduction

Both FEM simulation and statistical analysis are well known tools in metal forming industries. Accuracy and performance of FEM software have been improving significantly over the last 10 years, and users are able to model real processes in a very good accordance with measured data. However, there is mostly no consideration of input variances, which is the topic of this paper.

Basics

Among the many input parameters of a forging process (for a multi-stage process one can count more than 200 different inputs!) the following important inputs shall be mentioned:

- Forging Material characteristics (flow curve = f(temperature, strain, strain rate, micro-structure)
- Influence of heat coefficients
- Friction type and friction value as well as lubrication
- Heat transfer
- Ambient media and heat radiation
- Stock dimensions
- Initial temperatures and kind of heating device
- Process kinematics
- Set-up heights of process stages
- condition of dies (new, re-worked, worn)
- condition of forging device (stiffness, backlash, new guides, worn equipment)

Common problems to FEM simulation are:

a) some of the mentioned inputs are not well known or are very complex
b) most users of FEM simulation define such input values for a given condition as a fixed and constant value, but in reality all those values show a variance

Analogy: Shooting Exercise

Consider for example the following shooting exercise, where a person tries to hit the center of a target.

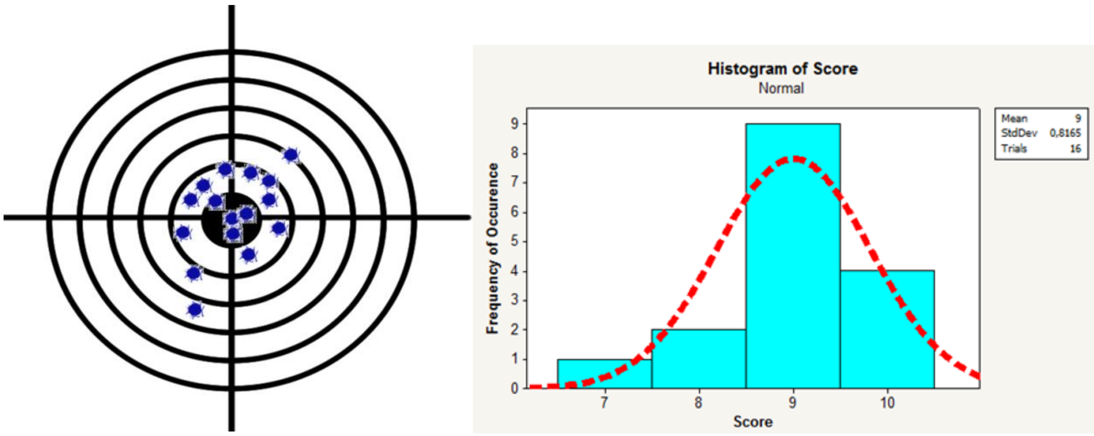


Figure 1: shows a typical sample of shoot pattern and its histogram

Everybody accepts that no one can score a "10" every time because of many reasons:

- breeze direction…
- air speed…
- pulling the trigger…
- shape of bullet…
- weight of bullet…
- current condition of gun muzzle
- bullet path…

None of these parameters are constant for every shot, but vary instead from shot to shot. Many processes show a so called "normal" distribution also known as a "Gaussian Curve", but in terms of a forging simulation we are often stating: *"simulation does not work properly if we don't find exact match between reality and simulation result"*.

The combination of statistical analysis with FEM simulation can help to overcome lacking process knowledge and will enhance accuracy and depth of simulation outputs. Therefore one needs to simulate different input-parameter variations and afterwards analyze (statistical) influence on the selected output values

A shop floor example from Milwaukee Forge

Now let us consider a typical shop floor example, and for this we reference a three stage hot forging process at Milwaukee Forge, of a round hub.

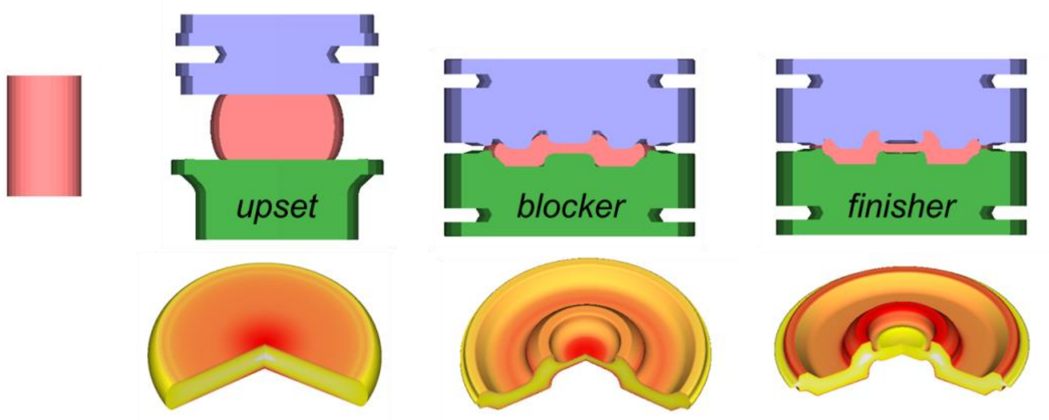


Figure 2: Investigated three stage forging process of a hub.

The process is characterized as:

- three stages (upset, blocker, finisher)
- 4000t crank press
- nominal cut height of billet: appr. 8 inch (203 mm)
- nominal initial temperature: appr. 2250 °F (1235°C)
- nominal finisher stroke: appr. 14.99 inch (380.75 mm)

The problem encountered was that the simulated force does not correspond to the actual measured values on the press.

- Force finisher measured = 3,700t;
- Force finisher simulated = 4,570t

Due to steep increase of force vs. stroke even marginal change in stroke leads to major changes in force. In order to get the variance of the force (or the distribution of the force) one need to define inputs (design variables) and create different combinations of these inputs to get information on their influence on the objective value (force)

Classical Design of Experiment (DoE)

DoE is a statistical tool that helps to find out significant (statistical) influences between inputs and outputs. Compared to the classic OFAT- approach ("One Factor at a time") during DoE inputs are changed systematically and simultaneously. Hence not only main effects but also interactions of several inputs can be investigated and assessed. DoE approach is used also to minimize number of experimental runs.

The idea is to set parameter combinations whereas for each parameter a minimum and a maximum possible value have to be defined – the so called corner points of the 2^k-Design. DoE combines every corner point of a parameter with corner points of every other parameter – last but not least a so called centre point is formed = combination of mean of {min; max}of every parameter.

The Classical DoE has two dis-advantages:

- Delivers accurate results only for linear interrelations
- Does not give any information about variance -> need to take additional steps to calculate variance

Design- Parameter Optimization "DesParO"

Advanced "DesParO"- approach of Fraunhofer- Gesellschaft is a new, non-linear design-parameter optimization based on radial basis functions with non-linear de-trending. It allows for maximum information (including variance of the objective value) by minimizing number of parameter combinations for every non-linear relation. Compared to DoE the parameter combinations are distributed across the parameter space. The difference between the DoE and DesParO approach is visualized in Figure 3.

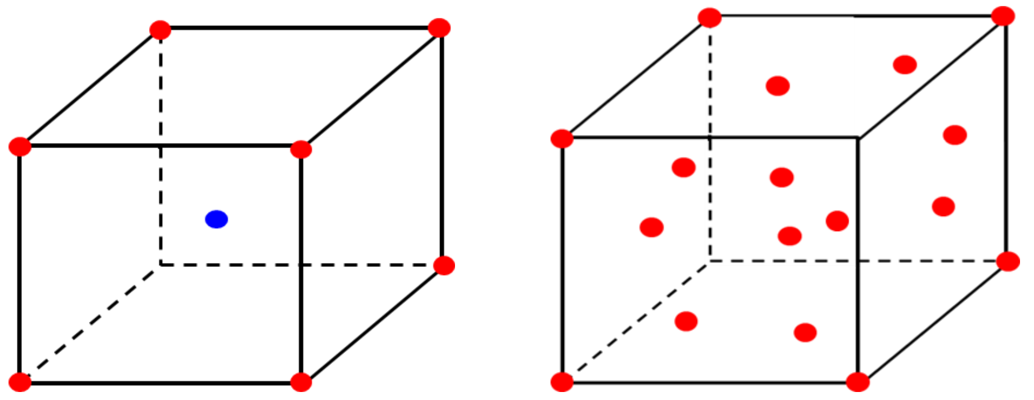


Figure 3: parameter combinations through the parameter space of left) Classic DoE and right) Non-linear DesParO- approach

For the selected hot forging example the following input parameters where varied:

- Cut height of the stock material: 8 inch +/- 0.098 inch
- Initial temperature: 2255°F +/- 45°F
- Shear friction: 0.4 +/- 0.1
- Finisher stroke: 15 inch +/- 0.02 inch

The selected objective functions for output is the finisher force.

DoE results

Table 1 shows experimental 2^k- design of a classical DoE- generator ("2" = number of levels per parameter – high and low – "k" = number of parameters). The total number of experiments without "centre points = 2^k

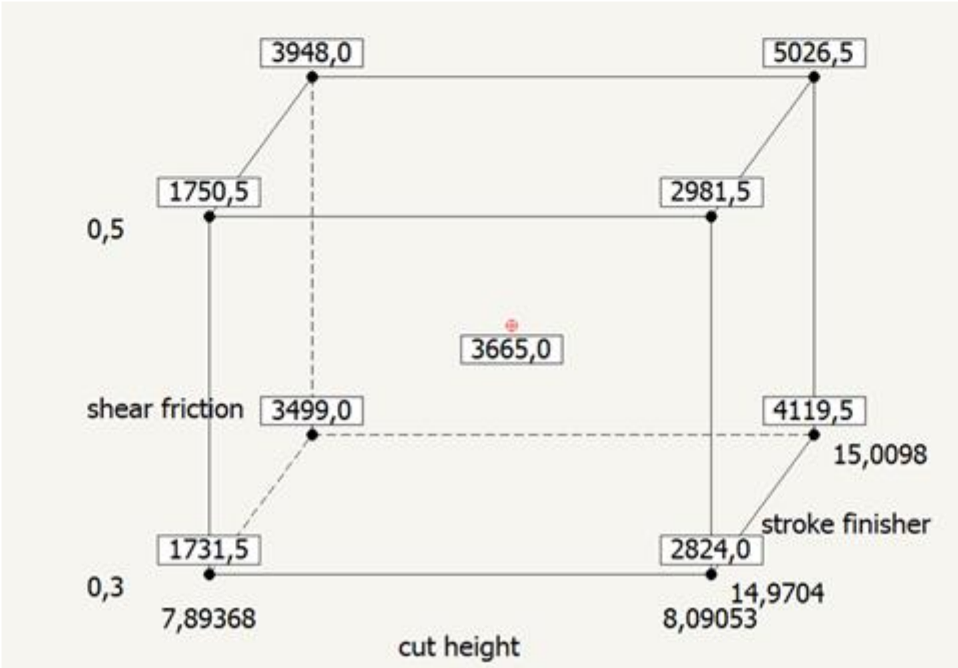
For the selected 4 parameters hence $2^4 = 16$ runs (+ centre points)

run	Centre point	cut height [inch]	initial temperature [°F]	shear friction	stroke finisher [inch]
1	1	7.893685	2210	0.3	14.970443
2	1	8.090535	2210	0.3	14.970443
3	1	7.893685	2300	0.3	14.970443
4	1	8.090535	2300	0.3	14.970443
5	1	7.893685	2210	0.5	14.970443
6	1	8.090535	2210	0.5	14.970443
7	1	7.893685	2300	0.5	14.970443
8	1	8.090535	2300	0.5	14.970443
9	1	7.893685	2210	0.3	15.009813
10	1	8.090535	2210	0.3	15.009813
11	1	7.893685	2300	0.3	15.009813
12	1	8.090535	2300	0.3	15.009813
13	1	7.893685	2210	0.5	15.009813
14	1	8.090535	2210	0.5	15.009813
15	1	7.893685	2300	0.5	15.009813
16	1	8.090535	2300	0.5	15.009813
17	0	7.992110	2255	0.4	14.990128

Table 1: Experimental plan with 4 parameters and one centre point (run 17)

After simulating these 17 runs with shown parameter combinations one can start a statistical analysis. This analysis brought first cognition: in a statistical sense the initial temperature with its selected corner points has no significant influence compared to the other input (design) parameters.

For selected corner points the following diagram shows the calculated forces:



With the remaining 3 input parameters that are significant in a statistical sense, one can form now the linear equation:

Finisher Force [S/T] = -733727
+ 5108*CutHeight [inch]
+ 1915.63*ShearFriction [-]
+ 46390*StrokeFinisher [inch]

Within the boundaries of the given parameters (say within the cube) one can now calculate any desired parameter combination, whereas not every combination must be reasonable necessarily.

To get information on variance of the objective value (Finisher Force) one need to proceed with a Monte Carlo simulation. Therefore one creates an estimated and randomized distribution of all the input parameters using their mean and a known or estimated standard deviation. Doing so, for instance 100,000 times, one can create 100,000 randomized combinations of the three input parameters. With the help of the above mentioned formula one calculates for every combination the Finisher Force and … that’s it. It takes one a few seconds to run this…

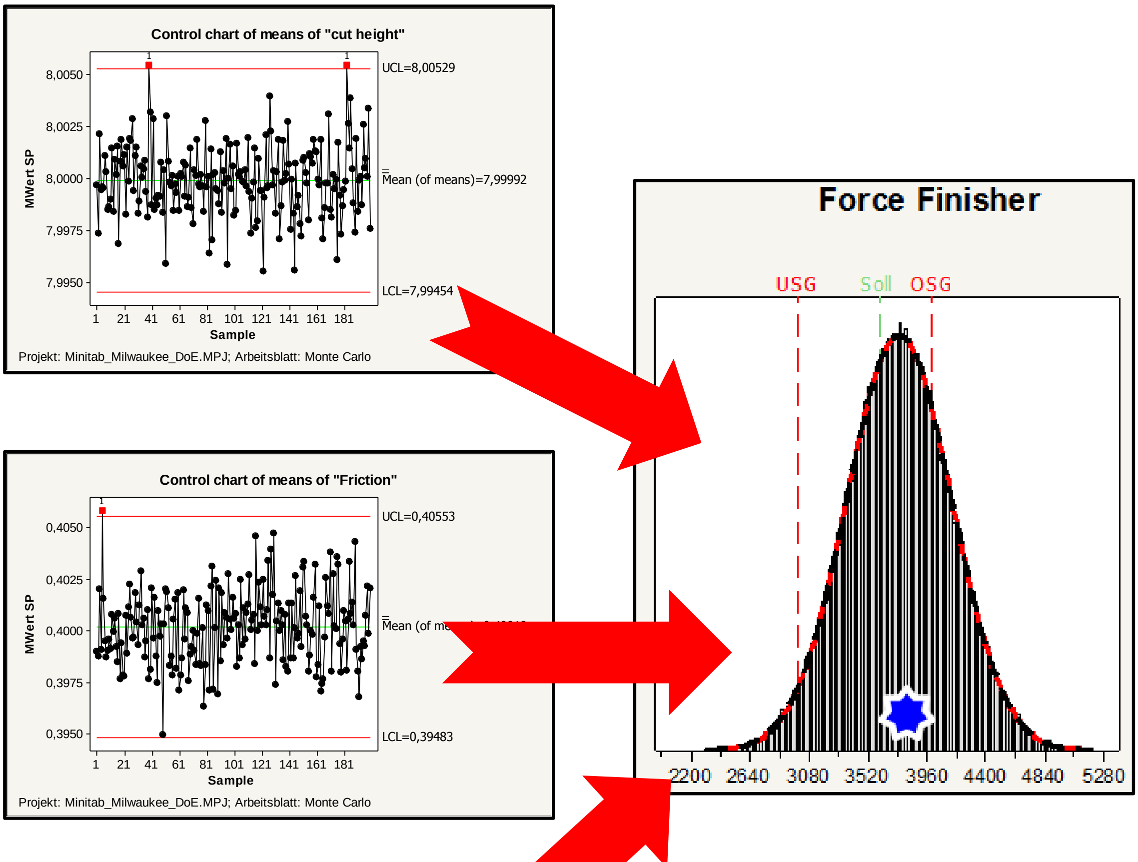
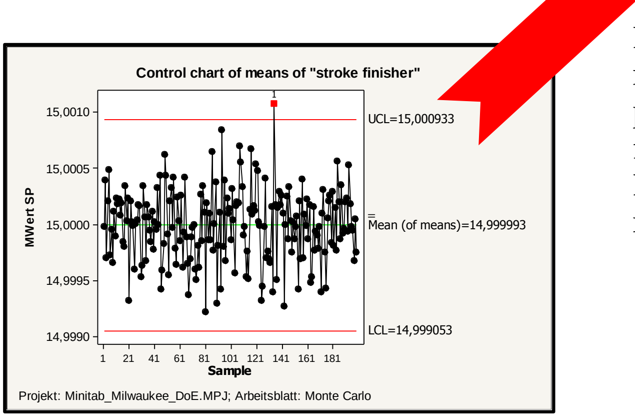


Figure 5: Monte Carlo-simulation uses randomized distributions of input parameters and statistical evaluated formula to calculate distribution of Force Finisher (✸ shows measured real value of finisher force)



This exercise demonstrates how DoE combined with Monte Carlo Simulation provides a first rough approximation. DoE can provide only linear relations – but for first quick and deeper insight of the process it is a good and suitable tool.

DesParO results

As mentioned before, DesParO uses a different kind of non-linear generator to create an experimental design with sample points through the whole "space" of the available parameters.

run	Cut height [inch]	Initial Temperature [°F]	Shear Friction	Stroke Finisher [inch]
run1	8.0590308	2246.0	0.46	15.0019
run2	8.0708418	2228.0	0.37	15.0007
run3	7.9645429	2256.8	0.49	15.0066
run4	8.0196609	2274.8	0.33	14.9944
run5	7.9251729	2246.0	0.33	14.9748
run6	7.9921019	2298.2	0.35	15.0007
run7	7.9094250	2294.6	0.41	14.9740
run8	7.9330469	2269.4	0.48	14.9842
run9	7.9054880	2211.8	0.39	14.9728
run10	7.9448579	2258.6	0.37	15.0003
run11	7.9960389	2269.4	0.41	14.9720
run12	7.9802909	2294.6	0.49	14.9988
run13	7.9212360	2289.2	0.43	14.9874
run14	8.0157239	2235.2	0.46	14.9826
run15	7.9802909	2229.8	0.34	14.9815
run16	8.0039129	2247.8	0.33	15.0063
run17	7.9133620	2220.8	0.40	15.0003
run18	8.0865898	2294.6	0.44	14.9854
run19	8.0393458	2242.4	0.39	14.9795

Table 2: Experimental plan with 4 parameters generated with DesParO

After simulating the 19 different runs and handing over results to DesParO one has immediately available all possible information including variances.

There is no need for any other simulation, the internal DesParO metamodel calculates the required statistical information automatically in real-time.

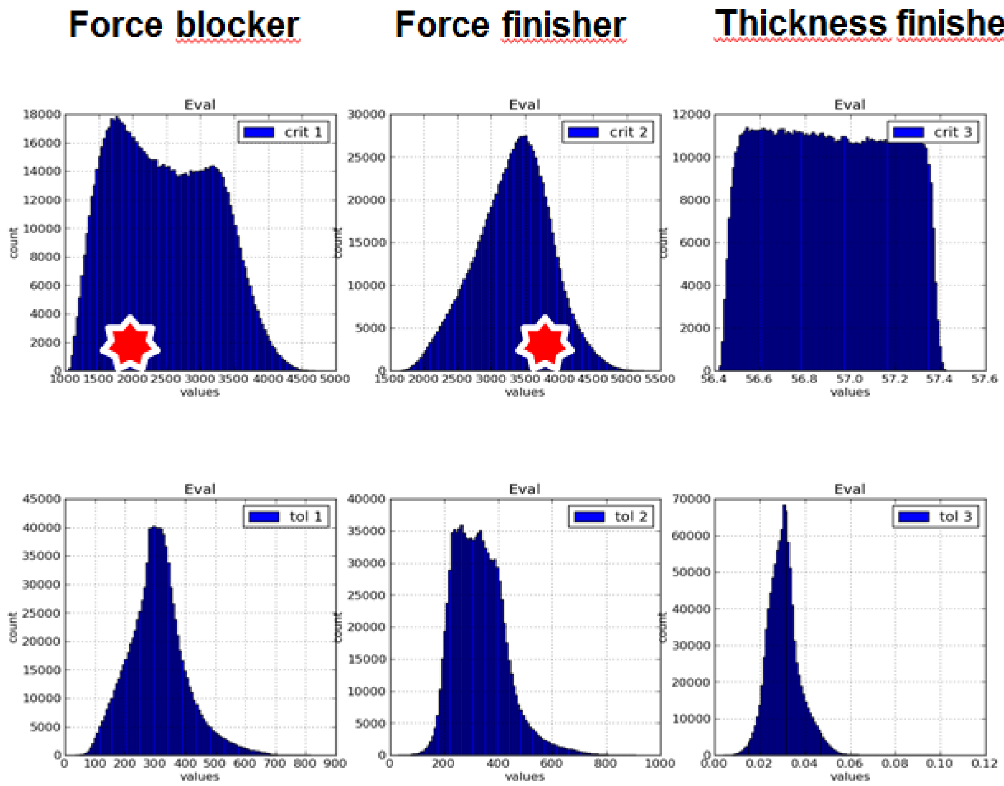


Figure 6: shows calculated distribution of three different objective values (upper row) and their calculated model tolerances (lower row); represents measured values (shop floor)

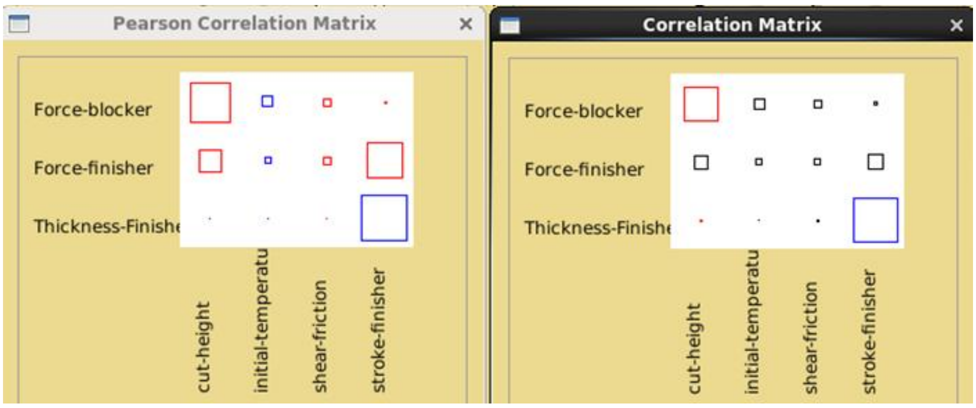


Figure 7: shows comparison of correlation (between parameters and objective values) between left) classical linear estimation and right) non-linear DesParO estimator

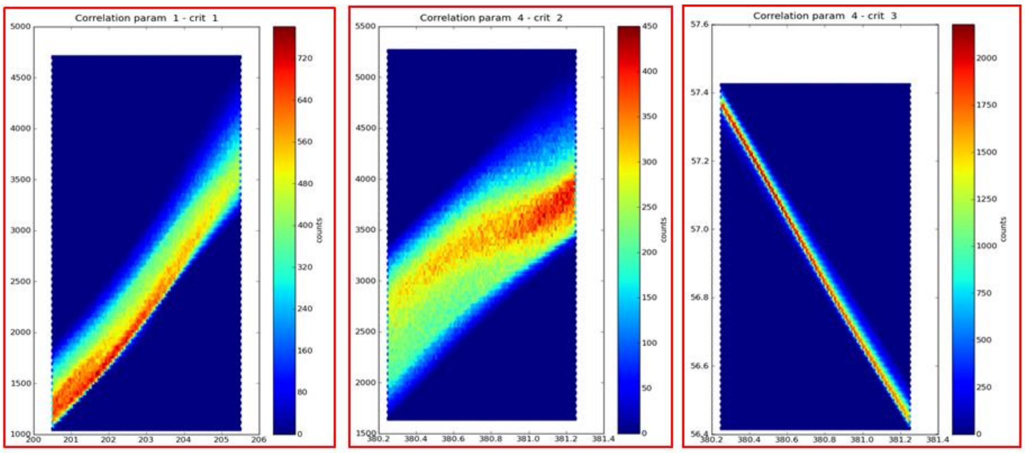
The correlation between parameters and criteria are shown in Figure 7, and the following information is needed to interpret the data:

- Different results in Pearson and correlation matrix show <u>non-linear dependencies</u>!
- Size of the squares represents strength of the influence
- □ = monotonic increasing
- □ = monotonic decreasing
- □ = non-linear (non-monotonic) dependencies

It can be seen that the "force-blocker" is mainly influenced by "cut-height", while the "thickness-finisher" is mainly influenced by "stroke-finisher".

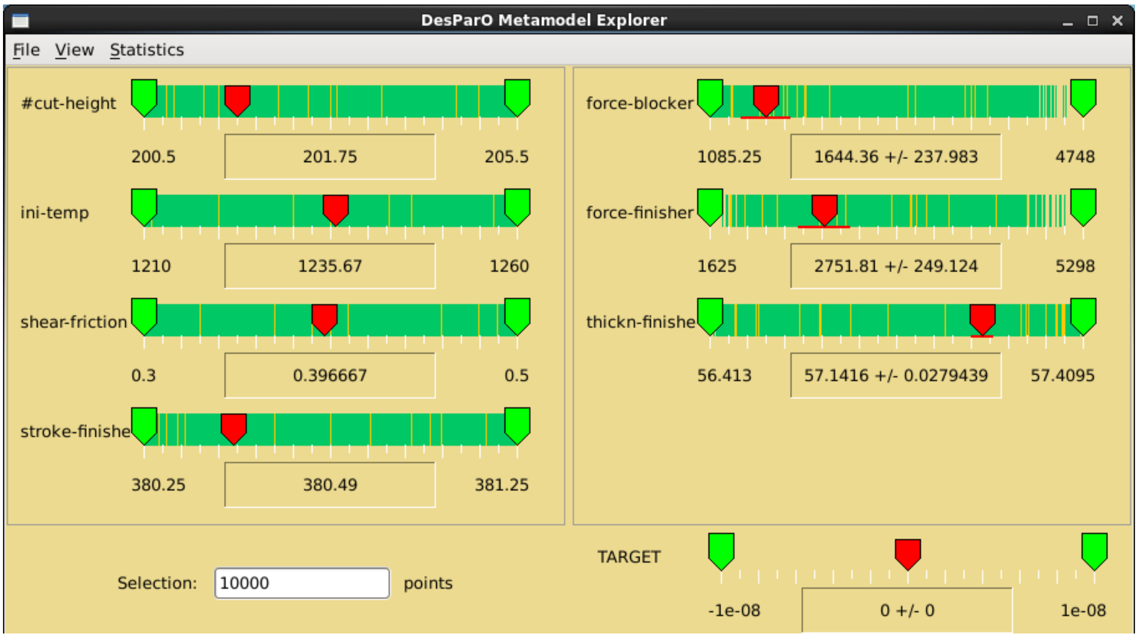
The correlation matrix clearly shows non-linear dependencies (black squares).

Visualization as 2D histogram plots also shows these several linear and non-linear trends.



Influence of cut-height on force-blocker **Influence of stroke-finisher on force-finisher** **Influence of stroke-finisher on thickness-finisher**

Last but not least there is an interactive explorer to investigate the relationships between inputs and outputs.



By changing input values or their boundaries by simply moving the sliders the internal "Metamodel" calculates immediately the effects on the output values. Target feature can be used to find automatically the right combination of settings for a desired objective function.

Conclusion

All natural and technical processes have a variance. This is one of the reasons why simulation results (usually using only one combination of input parameters) sometimes do not match with reality. This paper demonstrates how one can combine existing statistical tools with existing FEM software to take into account the variance in the process parameters, and study the relationships between input parameter variance and outputs. Non-linear dependencies can be described by using the pioneering DesParO approach of Fraunhofer Gesellschaft in Germany.

Aim of herein described way is not to give user of simulation package an excuse why in some cases their virtual processes do not behave like reality.

Early knowledge and insight of manufacturing processes including extremely important information on process variances help to save money by avoiding costly physical try-outs, frequent set-up changes, scrap, rework and claims (rejected parts).

Processes don't know tolerances but variances. Tolerances are "artificial" requirements. To know even for new processes an (estimated) variance can help decision makers to discuss and confirm (or not) on new tolerance requirements with customers based on facts.

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