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Effective Run-In and Optimization of an Injection Molding Process

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1. Introduction

This chapter is written to give developers and machine operators a better idea how to install robust processes or how to review and optimize these. The clear structure moves from basic introduction to in-depth application of the methods and tools, thus guiding readers through these processes. While this paper cannot replace a further deepening in this matter, it can assess its usefulness.

Since the publication of my article "Effective Run-In of an Injection Molding Process", (Moser & Madl, 08/2009) I have noticed that both the start phase of an optimization process and the end phase ("verification / validation") are the most critical parts. Due to this problem, I have decided to extend the upcoming article with the following chapters. Increasingly, "Processes Capability" is a necessary basis for accomplishing design transfer with the customer on a valid foundation. Also "Quality by Design" and "Design Space Estimations" are no longer foreign words within the injection molding business. Especially, the medical and automotive businesses call for process validation. This new chapter will, therefore, be divided into the following sections:

- Familiarization
- Screening
- Optimization
- Robustness
- Validation
- Summary

This procedure will help process' manager move through the setup or optimization process. Most students who joined, for instance, a "Process Capability Statistics"- or a "Design of Experiments" course, have difficulties finding the fulcrum or lever to complete the first steps. Consequently, they often just invest in "trial and error methods" to get their process to work. Also, common paradigms like "change one parameter at a time" will not help accelerate optimization or enable the improvement team to map the whole process, including interactions or nonlinear behaviours. Therefore, this chapter will outline tools to collect the main process factors, identify the disturbance factors and also some more special tools to interpret the impact of these on the process. The best way to get a run in or on optimization process started is to get a "complementary" team of experts at the table. Within in this team, it

is important to lift the members into a mode where they are willing and motivated to work on the problem in an open, cooperative, and productive atmosphere. Beside this, because of its rules and structure, "team leading", "mediation skills", and "creativity tools" comprise an indispensable base to build up a mutual attitude towards the improvement process. Furthermore, these tools will lead the team from reflecting to describing a problem and to joint agreement on supported decisions, work-methods and actions. An additional advantage will be a clear structure, such as, for instance, the "DMAIC Cycle".

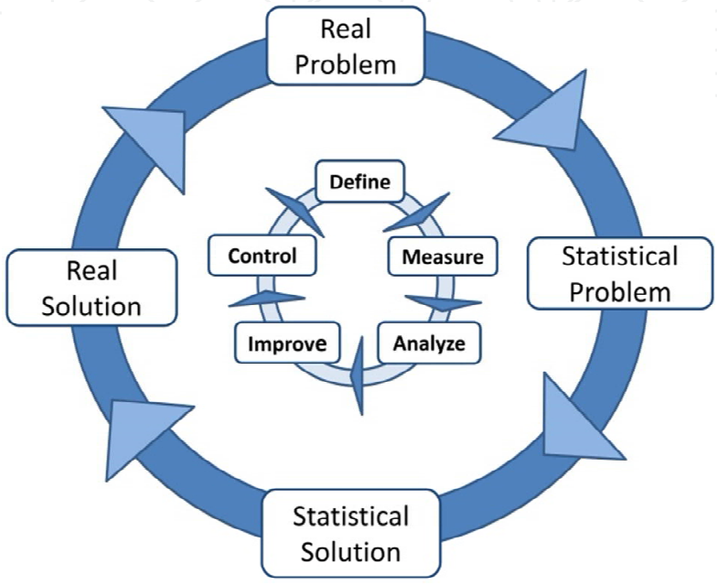


Fig. 1. DMAIC Cycle (Lunau, 2006, 2007).

The DMAIC Cycle „which as a logical further development of the Deming cycle, provides a good structure to get into the "problem solving process". Within this approach, the question "what is the 'real problem'?" is asked. Two different symptoms form cause and effect, so it is helpful to discuss this in the team of experts, for instance, with the following tools and methods. After the "Real Problem" has been defined, it is necessary to find a way to measure cause and effect of the problem. This might sound straight forward and logical, but in most cases, it is not done. This means, for instance, that a check of the capability of the measuring equipment is often not requested for measuring the whole process variation range of the "Process working space". Measurement methods and also the equipment calibration and capability should be validated *(each time)* prior to execution of the experiments. Otherwise, it may happen that a lot expensive, time- consuming experiments are preformed and also a lot of measurements are taken, but these are not adequate to describe cause and effect. (Process space)

The next step to get factor settings and systems- or product-attributes measurably defined is to analyze their correlation with a structured approach. Design of Experiments is a very powerful tool to do this. During the experiments, it is recommended to request every step in planning, such as:

- It has to be verified whether the latest setup (factor variation) of the worksheet is adequate for focusing on the desired responses of the targets (Fig. 18)

- if some responses are not measurable or quantifiable, continuing without adaption leads to fuzziness, respectively to bad "goodness of prediction models"
- It is not beneficial for the experimental room to extend far beyond the realm of objective target functions. Because this will automatically lead to more experiments and fuzziness due to more complex mathematics which is needed to describe cause and effect. (Fig. 18)

After the "test and analyzing phase" the gap between cause and effect could be closed with a mathematical prediction model. The purpose of the model is to reflect how factors and responses are related. On the basis of this, "model contour plots" (Fig. 29) can be generated and potential optima could be calculated and visualized.

Within in the oncoming Improve Phase, the optimum should be verified. After this verification, the robustness of this optimum setting could be rechecked with a reduced factor variation around this optimum to ensure the model-based calculations. In a last or parallel step to the robustness testing, the capability of the optimal setting, including the naturally given process variation, can be determined by using "Monte Carlo Simulations". The output will be, for instance: "Cpk"-value or "defects per million„ within an estimation of the work-point design space. These, "key process indicators" (which will be explained later) will then be a base for validating the process and making it comparable to other sub-processes. *(Cf.3)*

2. Familiarization

But again where to start? The following small collection of tools is a good start to get the first steps done, to reflect and research the process setup or process problem.

2.1 Ask why 5 times! (Michael L. George, 2005)

One of the easiest and most straightforward tools for getting familiar with a process setup or process problems is just to ask why, why and why again. Inquire if tree- or bubble diagrams can be used to document the root cause analysis. This and the following tools should be performed in a team only after it is certain that it follows the basic rules of good brainstorming / communication practice. This means: no direct "pointers" or school assignments should take place. Also there should be no criticism during the creative phase but rather only at the right time and then only constructively expressed.

Small Example of constructive, drill-down questioning:

Why is the injection part not of sufficient quality?
→ Because it contained some color strikes and dells.
Why does the part contain color strikes and dells?
→ Because the filling and cooling process are not as robust as they should be.
Why are the cooling and filling process not robust?
→ Because the density of the melted polymer is not homogenous.
Why is the melted polymer-density-distribution not as it should be?
→ Because the polymer granulate was not dry enough.
Why did the drier not work as it was supposed to?
→ Because the service hadn't been properly done.

2.2 Cause effect diagram

In addition to the "5xWhy", the cause effect diagram (Fig. 2), is very effective if there are people who already know a lot about the process. If they are used to it, they like thinking within cause and effect but still will be affected by suggestions from other team members to review their thought against the inputs from others and be motivated to think out of the box to find even more detailed reasons for product-rejects or process-failures. In combination with Brainstorming or the "5xWhy", it is even more focused and powerful.

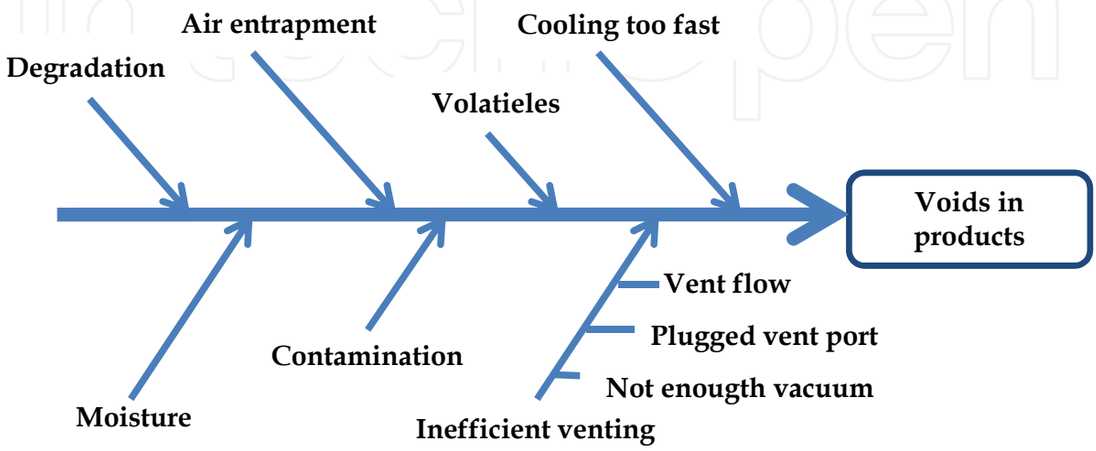


Fig. 2. Cause and effect diagram(Rauwendaal).

2.3 Ishikawa diagram

The Ishikawa diagram (Fig. 3) is the standard diagram to summarize cause and effect when concentrating on root cause and process-influence analysis. It is a good tool for discussing issues beyond the first impressions of why a process did and does not work or a product will not fulfill quality requirements. This is because this tool will guide the focus from different sources to a correlation of sources each time with a focus on a different reject-reason or process-failure. When meetings get stuck (because thoughts are spinning around) focus can be easily reset to another M-block[1]. In many cases, the output can be transferred to a FMEA "*Failure Mode and Effects Analysis*" or vice versa. The source of costs and process rejects are always defined by the product specification. Lowering these by adapting tolerances will instantly guide to lower costs, but may be critical for the next customer in a process line or the end customer who buys the product. The factor and its correlated target tolerances should be as wide as possible and as narrow as necessary.

2.4 AHP: Analytical Hieratical Process

Things are not always easy to interpret. Therefore, the AHP (combined with a grid analysis) is a very powerful tool to extract insights from a complex or fuzzy process. With process diagrams, Ishikawa diagrams or mind maps, the most influential factors are collected and can now be ranked according to Pareto's 20/80 law. This can be done by giving every team

[1] M-blocks are: Man, machine, management, measurement, method, material, milieu

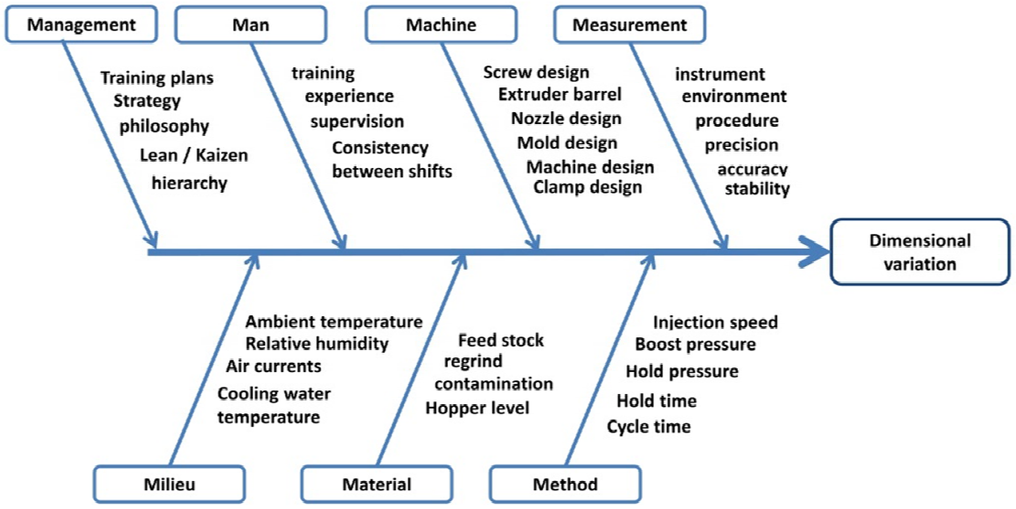


Fig. 3. Ishikawa diagram, (Rauwendaal).

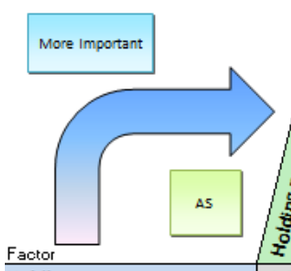
member the chance to write the numbers from one (very important) to ten (less important) behind the collected factors on a white board, or perform a simple hand-up voting (*each number only one time).*

After this is done, a maximum of ten factors of importance should be placed in the following matrix and weighted pairwise according to the importance of their influence. The direction of the questions is row versus column (Fig 4). Within the AHP, importance is leveled after the following scheme. (Vester, 2002) (Klein, 2007)

Weighting	Weights	Weighting counterpart	Weights
Extremely more important	9	Extremely less important	1/9
Significantly more important	7	Significantly less important	1/7
More important	5	Less important	1/5
Somewhat important	3	Somewhat less important	1/3
Equal important	1	Equally important	1

Table 1. Analytical hieratical process Weight basis.

In general, I recommend doing the weighting vice versa instead of filling the counterpart question automatically *(space below grey diagonal)*. Asking the questions "how much more is "Factor A" important than "Factor B"" and asking the opposite question staggered "how much more is 'Factor B' important than 'Factor A'"- again, will show the uncertainty of the knowledge and make it possible to reflect this fact within the grid diagram. In most cases, it is helpful to visualize the customers' demands prior to the factor ranking. A valuable input for defining customer values against product/process costs is for instance the "Kano model. If the prioritized quality criterion is not available, it needs to be developed because, in most cases, some target functions are more important to achieve then others, so compensating factor settings need to be developed after ranked target functions. On the grid-diagram (Fig. 5) the factors "holding pressure" and "nozzle temperature" are displaced a little bit laterally; this is because of the contradictorily ranked answers summarized in the matrix. Because of this inconsistency, influence of these factors should be discussed again. At some places, due



Factor	Holding pressure	injection speed	Holding pressure profile	Molding temperature	Cooling time	Nozzle temperature	Back Pressure	Barrel temperature	Holding time	Switching proint	Sum active (rank)	sum pasive (rank)
Holding pressure	1,00	5,00	7,00	7,00	5,00	5,00	0,20	0,20	0,20	0,11	3	3
injection speed	0,20	1,00	0,20	0,20	3,00	0,20	0,20	0,20	0,33	0,14	9	1
Holding pressure profile	0,20	3,00	1,00	0,20	5,00	0,20	3,00	0,20	0,20	0,14	7	5
Molding temperature	3,00	5,00	0,20	1,00	3,00	0,33	0,20	0,20	3,00	0,14	6	7
Cooling time	0,33	0,20	0,14	0,20	1,00	5,00	0,20	0,14	0,20	0,14	8	2
Nozzle temperature	0,20	0,20	0,33	0,14	1,00	1,00	0,20	0,20	0,20	0,20	10	4
Back Pressure	5,00	3,00	7,00	0,20	0,14	5,00	1,00	0,20	3,00	0,11	5	8
Barrel temperature	7,00	5,00	7,00	5,00	7,00	7,00	5,00	1,00	7,00	0,11	2	9
Holding time	7,00	7,00	0,33	0,20	5,00	3,00	1,00	0,33	1,00	0,14	4	6
Switching proint	9,00	7,00	5,00	5,00	5,00	5,00	7,00	7,00	7,00	1,00	1	10
Sum pasive (rank)	3	1	5	7	2	4	8	9	6	10		

Fig. 4. AHP Matrix[2].

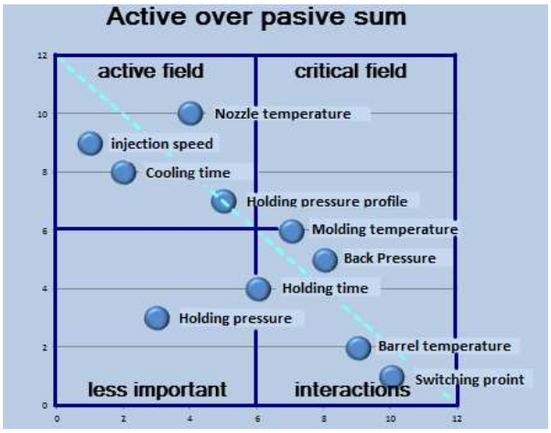


Fig. 5. AHP Grid.

to the complexity and a time reduction approach, it is sometimes recommended to do just a bilateral comparison-matrix with the part either below or on top of the grey diagonal. The other counterpart could also be filled out by asking or by being automatically computed. Often, therefore, the simplified schematic "2" = "more important"; "1" = "equal" and "0" = "less important" is used. This is also a good approach but will not be as differentiated as the previous AHP method.

In both cases, the factors can be weighted after importance by calculating the ranked row numbers at column "sum active ranked". This number and the calculated counterpart "sum passive rank" have to be plotted into the grid to visualize the factors' influence.

Now a new level of information has been extracted from the discussion. And the factors' importance can now be documented with the support of the whole team.

[2] Software Excel 2010, software operator S. Moser

Field	Meaning
Field "active":	factors with strong influence
Field "critical" :	factors with ambivalent influence
Field "less important" :	factors with less impact
Field " interactions" :	factors with possible interactions

Table 2. Interpreting of the grid (Fig. 5).

2.5 Contradictions and correlation

Besides the factor ranking, it is also important to get an understanding how these factors influence each other. For this reason, a similar matrix can be used in addition to a new question structure. Now the question should be: "Does factor 'A' reinforce the influence of factor 'B'?". In posing this question, one can get a better understanding of how the factors are correlated to each other or, in other words, how strong the interactions between these factors are. Thus the impact of potential contradictions can be exposed and documented. This is one of the most important project-management steps because of the necessary risk assumption. If the contradictions in the requirements are too stark to be compensated, the team needs to discuss whether the project should be stopped because of these "show stoppers" or "scope creepers". In any case, the risks should be displayed in a diagram which illustrates the probability of occurrence over the importance/impact of the risks. If there are any show-stoppers (i.e. risks with a large negative influence on the project and a high potential to occur) and they cannot be prevented, tools like TRIZ[3] may be helpful in resolving the contradictions. "TRIZ is problem-solving, analysis and forecasting tool derived from the study of patterns of invention in the global patent literature". In English the name is typically rendered as "the Theory of Inventive Problem Solving", and occasionally goes by the English acronym TIPS.

2.6 System modelling

A more recent approach to understanding process and complexity is to model the system interaction or dynamic. One interactive, easy-to-use software is the Consideo Modeler, which was used for Fig. 6, 7, 8, 9. At the beginning, this approach works similarly to mind mapping but can calculate feedback loops later on in order to visualize the system's dynamic. After the most influential factors have been collected and ranked due to importance, those factors can be connected with arrows to describe their impact. These arrows can be defined with the intensity of the factor-effect, the cause-direction *(enhancing, reducing),* and the time-dependence of their effect (Fig. 6). One other advantage of this software-approach is that also "attributive" and "qualitative" factors can be embedded into the net-diagram. These factors are treated mathematically equally to quantitative factors in a first step. This is possible because the impact of the feedback loops of each factor *(factor→arrows→factor loops)* will be calculated iteratively. From this, the influence of the factors to a response can be interpreted. This method is also useful for visualizing what has been worked out in a "team problem discussion" by displaying the result of the extracted process on a net diagram (Fig. 6). After this, plots such as a "weighting matrix "(Fig. 9), in addition to the AHP (see 2.4) "root cause" and "cause and

[3] TRIZ / TIPS for more information see http://en.wikipedia.org/wiki/TRIZ

effect" diagrams (Fig. 8) can be easily generated, as well as the "insight matrix" (Fig. 7), to show how the factors affect responses.

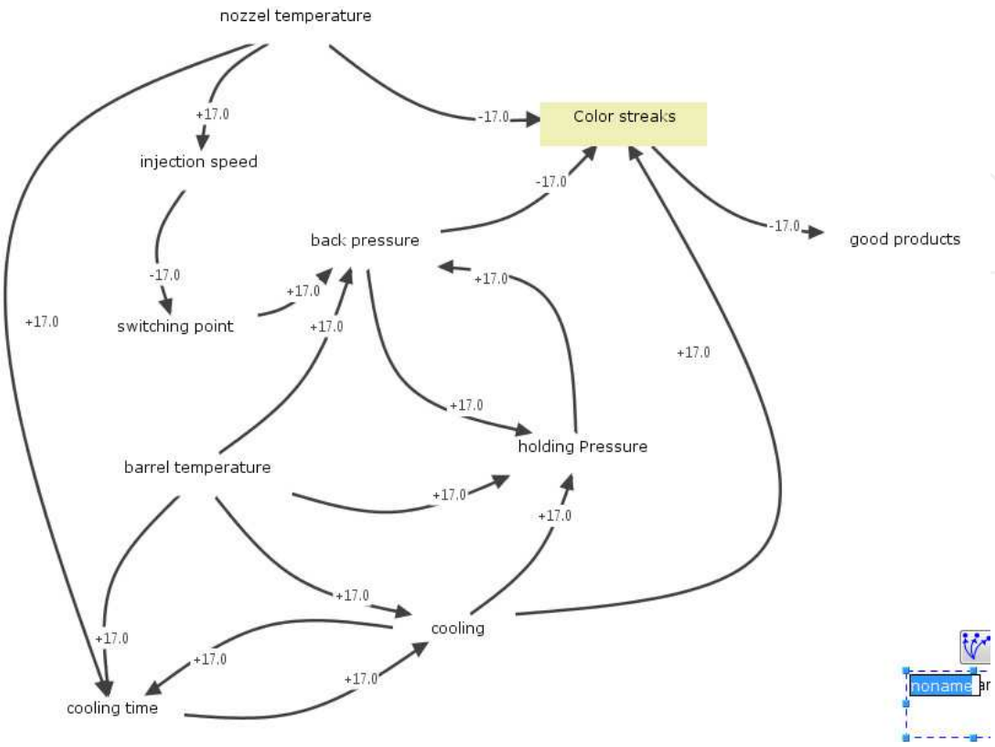


Fig. 6. Example "net diagram"[4].

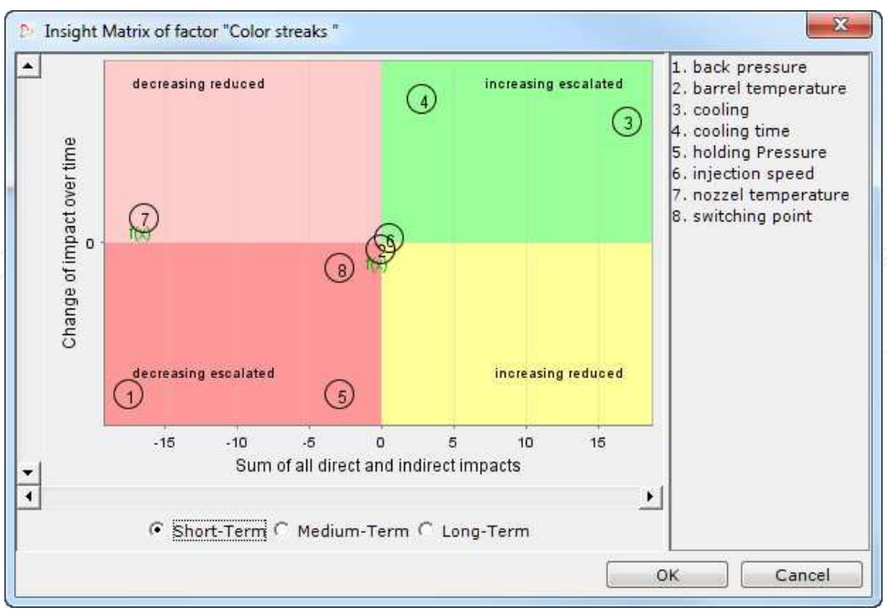


Fig. 7. Example Insight Matrix[4] of factor "color steaks".

[4] Software Consideo Modeler, www.consideo.com , software operator S. Moser

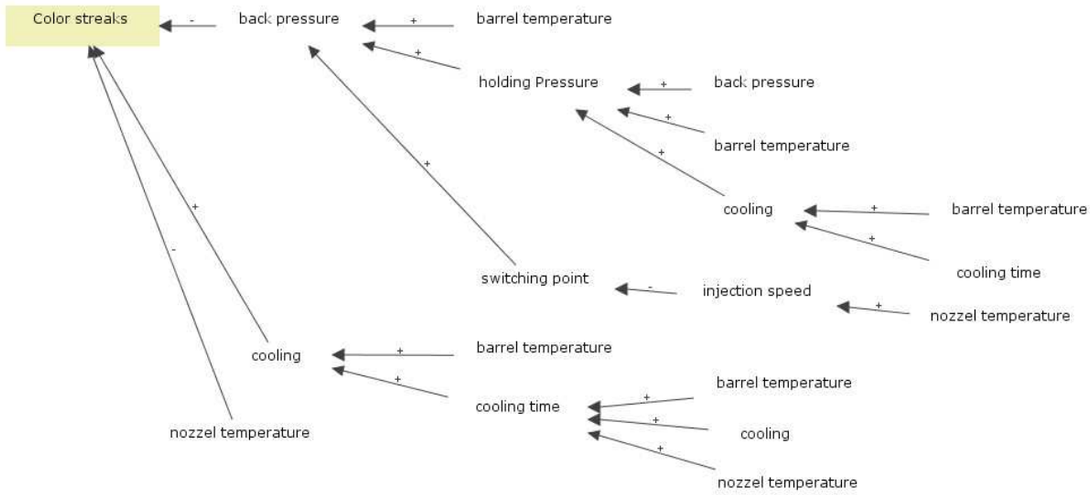


Fig. 8. Cause tree [4].

		1	2	3	4	5	6	7	8	9	10
1	injection speed						17				
2	good products										
3	cooling				17			17			17
4	holding Pressure									17	
5	barrel temperature			17	17			17		17	
6	switching point									17	
7	cooling time			17							
8	nozzel temperature	17						17			17
9	back pressure				17						17
10	Color streaks		17								
	Sum	17	17	34	51	0	17	51	0	51	51

Fig. 9. Weighting matrix [4].

2.7 Restrictions within familiarization steps

This approach *(and also the shortly described preceding methods)* will not deliver a whole picture of the process or an ideal setup, but it will help to concentrate on the really important factors. Furthermore, these tools will help to document the problem-solving process and to support the team in working results oriented and step by step -- in order to do the right things right.

So within difficult problems, tools are capable of raising the creative nouveau of generating innovative ideas or solutions. Instead of only endless problem-focused discussions, which only lead to "questions of power", "influence", "the problem history" and "particular blame" of team members, using supporting tools means the team can concentrate on solving problems by using the tools right! This helps to minimize distracting, time-consuming and conflicted meetings.

2.8 Reflecting the familiarization steps

After the "root cause analysis", factor prioritization and response target definition are done, it is necessary to review these values with a focus on "good project management practice".

Therefore, it has to be considered that doing a research on all desired functions will take time and will consume money and resources. In most projects, there is the sword of Damocles over the project team, which means that there is always not enough time, money and resources. In this context, one often hears a contradiction in terms such as, "We do not have the time for experiments ". This interaction is visualized in Fig. 10.

To briefly illustrate, it can be assumed that the functions to be examined need too much time. These circumstances can only be compensated by moving the timeline or tapping additional resources. Both options will impact the budget. Thus, it is always important to check at regular intervals if any (planned) actions are still result-related and necessary.

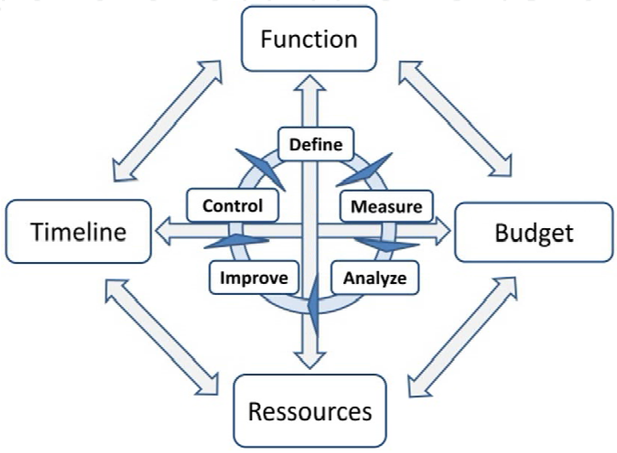


Fig. 10. Interaction between the main components of project management.

3. Screening

The challenge for machine operators is to get the run-in process done as quickly as possible. This means a minimum number of experiments with a maximum ability to describe cause and effect. The operators should be sensitized to the fact that small adjustments in the setup of the machine can have a great impact on the quality of the injection molding parts. Therefore, a well-structured approach and high quality data are needed. To reach these goals, the method of "Design of Experiments" will be introduced on the basis of the software "Modde"[5]. This is done because further steps "optimization" and the "Design Space Estimation" are incorporated tools within the software "Modde".

In general, the software is used when there is a lack of knowledge how cause and effect are related.

The use of "Design of Experiments" is an admission that the correlation of factors and effect could not be fully captured. This condition is depicted as a black-box (Fig. 11). By varying the factors within and according to a structured design, a regression model can be derived. From this model, the effect of the factors can be calculated. Since the experiments and thus the factors are varied to an estimated optimal range, some of the results are, of course, likely to deviate from the optimal targets. Nevertheless, all experiments and their results are very

[5] Modde is a software product of Umetrics, a company of MKS Instruments Inc.

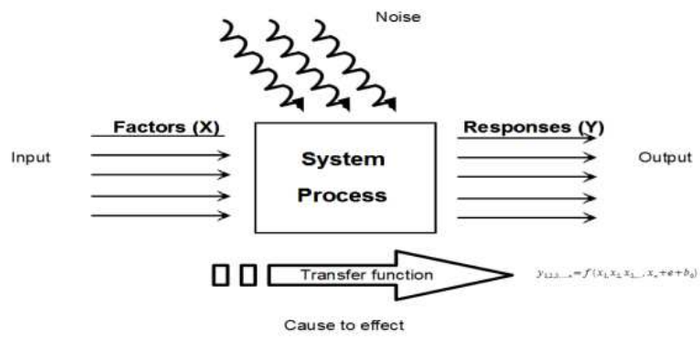


Fig. 11. Process Black-Box.

important because the basis of an entire image of it can be mapped on the work-space. The screening-process starts to extract the most influential factors from the familiarization process. These factors will be used to start with the Design of Experiments method. But not necessarily all factors must be examined in light of variability. So, some of these less important factors should be frozen at a certain level, which still ensures a good product quality. This is because the number of factors substantially affects the sum of the experiments; the number of evaluation criteria (responses) is of secondary importance. In the best case, the factors are quantitative, and so simple geometric designs can be generated. It is more difficult when they are qualitative, e. g. "machine 1" or "machine 2". Such qualitative or attributive parameters increase the number of experiments because they hamper the generation of the design. Once the factors have been identified, it is necessary to assess their effect. The effect is that which is exerted on the target variable when the factor is varied from its minimum to its maximum setting. Since all the factors are changed simultaneously in a factorial design, this effect is difficult to estimate.

It is therefore useful to debate and determine the factor variations within a group of experienced staff. Some factors are even trickier to formulate than the qualitative factors, such as temperature or pressure profiles. Just as in the machine, in the factorial experiment, the profiles can be programmed with some nodes such as (initial value + 9 nodes). The start and end values of the profile are known. Moreover, the process specifies a sloping curve (Fig 12, 13). If the profiles were programmed with real numbers, the sloping profile would necessitate the use of a great many programmed extra constraints. These factor restrictions limit the choice of experimental models and greatly increase the number of necessary experiments. For this reason, a mathematical formulation of the profiles is recommended which allows restrictions to be dispensed with entirely. Thus, the pressure profile is calculated, for instance, from the given initial value and the maximum decrease in pressure (in bar) per node:

$$\Delta p = \frac{\text{initial value max.} - \text{end value min.}}{\text{number of nodes} - 1} \qquad \text{The following variation thus arises for each node in (2):} \qquad (1)$$

$$\text{Node (i +1) = node (i) – (min. 0, max. } \Delta p) \qquad (2)$$

Another way to represent the profile is the use of a simple two point (FU 3).

$$\text{value of factor setting}_{(x)} = mx + b_0 + \varepsilon \qquad m = \textit{Cf.}\ (4)\ ;\ x = \text{node of factor profile;}\ b_0 = \text{bias}\ ;\ \varepsilon = noise \qquad (3)$$

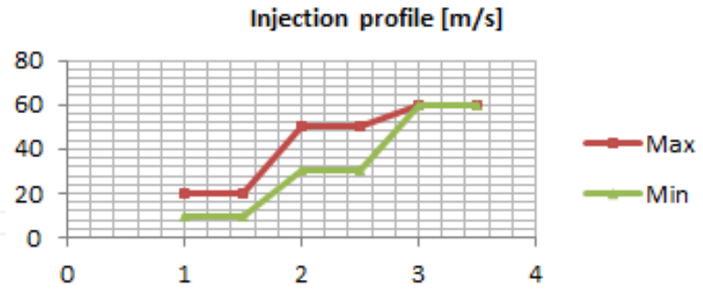


Fig. 12. Injection profile [2].

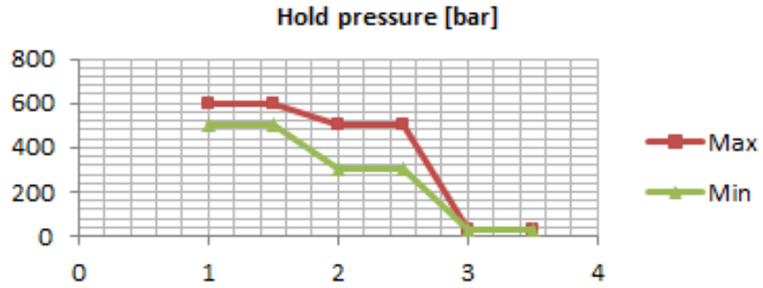


Fig. 13. Hold pressure [2].

For this, the initial value and the maximum slope (FU 4) of "initial $value_{max}$" and "end $value_{min}$" is required. From this data the increasing/decreasing constant slope/node can be described with two factors instead of several nodes (Fig.14, 15). These factors are the "start-value" and the constant amount to increase/ decrease per node, both must have a min./max. variation. Therefore, a constraint (FU 4) needs to be defined that, if decreasing, or increasing with a bigger constant amount beginning from a varied start level cannot lead to exceeding the final max. or min. final-profile-levels.

$$m = \left(\frac{\text{initial value}_{max} - \text{end value}_{min}}{2}\right) \qquad \Delta p = \text{const. for each node, note (5)} \qquad (4)$$

$$\text{Node (i +1) = node (i) – } \Delta p \qquad \text{Value}_{min} < \bigcup_{i=1}^{i=9} \text{node}_i < \text{Value}_{max} \qquad (5)$$

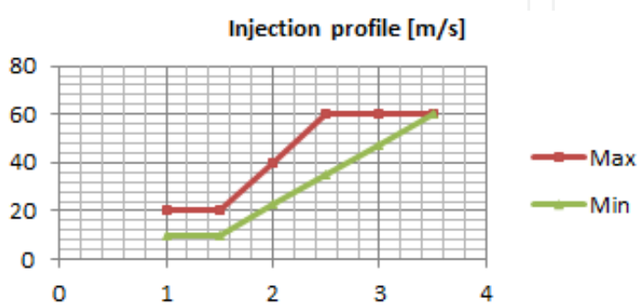


Fig. 14. Injection profile [2].

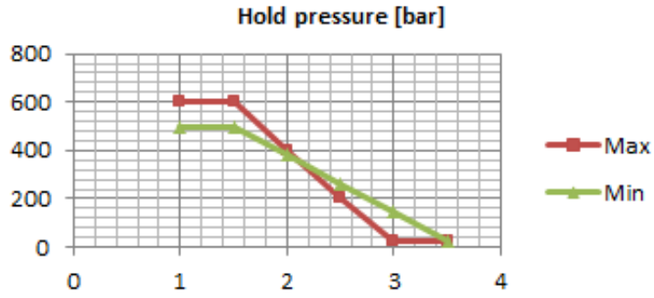


Fig. 15. Hold pressure [2].

Considering that the individual nodes from the first approach can be quantitatively described independently of each other, the experimental scope and so the following experiments are extremely reduced due to freezing of these node factors at a promising level or due to explaining them with the second formula approach (constant amount/node) and smaller variance space. The formulation with the second approach (slope) is also a good approach to describe the constraints with a very limited number of experiments, but not as independent and individual an approach as the first described approach. In the most circumstances, the more effective second approach is recommended. The profile of the injection values could be formulated in the same manner.

3.1 Responses and targets

The target variables could be geometrical variables, various criteria pertaining to surface quality, as well as some measured process parameters. Because the model which will be calculated later on could only be as good as the quantified quality of the test runs, it is very beneficial if the response or target values could be measured as quantitative numbers. If this is not the case, a qualitative ranking method should be discussed and implemented which contains at least 3 graduations or even better several more to support a better predictive model. If it is necessary to set up new qualifications-judgments, one should ensure that the ranking is symmetrical for instance "1" = too hard, "5" = optimum, "10" = too soft. Otherwise, if for instance "1" is optimal-filling and "5" could be more easily less-filled or over-filled, two sources of failure are mixed up, which is suboptimal to the predictability model. The mathematical reason is that the distribution model will be skewed (Fig. 16). Also

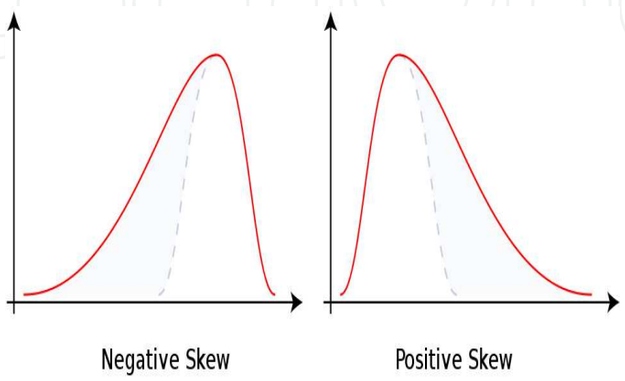


Fig. 16. Skew distribution (From Wikipedia).

the special responses (as results of product-life-tests) tend to deliver a Weibull distribution (Fig. 17) or skew distributed data; so, to handle this, additional knowledge of data, very sensitive factor-settings and possibly transformation of the response data are required in order to achieve good prediction models. For more detailed mathematical information see (From Wikipedia).

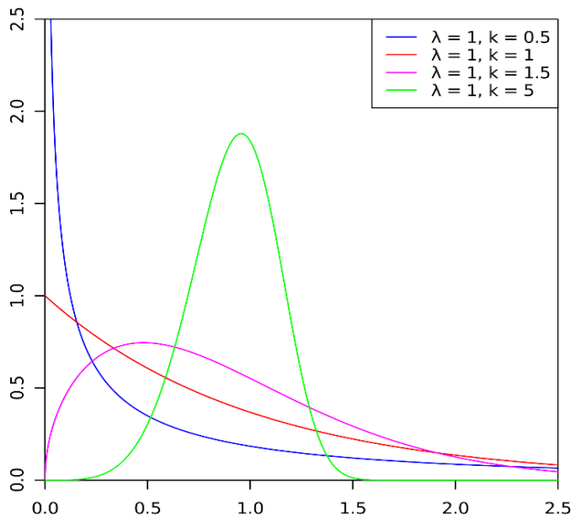


Fig. 17. Weibull probability distribution (From Wikipedia).

Also it should be verified that the quality judgments are reproducible, as well as have been measured with same accuracy over the whole experimental space (Fig. 18). Before any experiments are performed, the capabilities of test methods and test equipment need to be verified. The minimum of such tests should be a test of linearity and reproducibility, representative at the extreme factor settings within the experiment space. If the experimental procedure and the measurement tasks of more than one person are carried out, it should also be verified that the tasks are equally well conducted and reproducible. Optionally, the participants of the experimental design are documented as block variables *(uncontrollable factors)*. In an ideal case, the person-dependent influence can later be repudiated in a hypothesis test. The influence of the employee should then in such a case appear in a very small bar annonation in the diagram "coefficient plot" and therefore assessed as "not significant".

3.2 Safeguarding experiment design space/worksheet

The factorial design is the foundation upon which all further analyses are developed. Because the experimental scale is kept to a minimum, it is essential to measure the target variables of almost all experiments, as otherwise it is difficult to model reality from the results. The circumstances in which the experiments are preformed should as equal as possible *(same raw material, same machine, same operator and room condition);* otherwise, the occurring side effects will be represented by the model noise or modeled fuzzy into the terms of the model. Because some of all possible factors need to be assumed as constant in order to keep the number of varied factors small, the number of varied lasting factors and their variation will always describe a reduced reality. Factors which cannot be controlled,

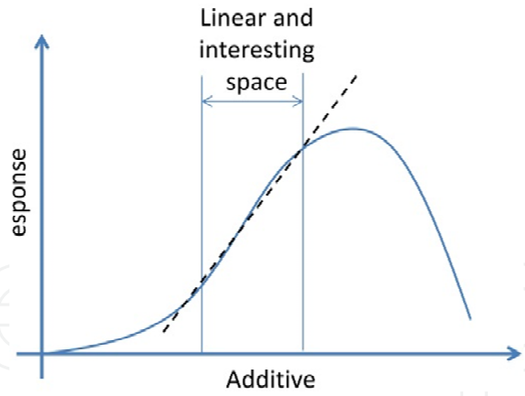


Fig. 18. Response-factor interaction.

like relative humidity or changes in raw-material, should be, if potentially influential, documented as uncontrolled factors. Later on, if the disturbance variation affects the responses, the correlation can be calculated and interpreted to a certain degree. The calculations want be as cause and effect but could be analyzed as a trend to work out a plan of verification or compensation if necessary. The reason why the factor influence could not be ideally assessed is because the uncontrolled factors vary randomly and not as geometrically organized within the design (Fig. 19).

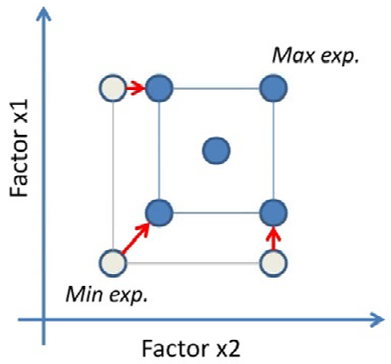


Fig. 19. Example of two factor design adjustment.

To specify the minimum and maximum of the target factor values, only a few preliminary tests integrated into the factorial design are needed -- usually, two successful experiments are commonly sufficient in which all factors are set to the lowest or the highest levels. This ensures that variation in the factors is still measurable in the outcome (responses). Otherwise, the variation in individual factors would have to be reduced as displayed in Fig. 19 or extended in a modified factorial design. Once the min., max. and one-center-point experiments have been performed, it should also be considered if the range of the factor variation is necessary because if these variations are too big, non- linear behavior of some factors will probably occur. In most cases only a small linear area is of interest (Fig. 18). At the start, because of the lack of knowledge about the factors' effects and especially because of the reinforcing interactions, the factor ranges are often sub-optimally set. If this is the case, the factors' impact could be non- linear. Usually, factorial experiments commence with a large number of factors which are initially studied only for their linear influence. This

approach has the advantage of requiring just a few experiments to find out which factors influence the targets, and to what extent. It is also possible to obtain an initial indication of the suitability of the evaluation criteria and the measuring technology. Since the focus of the investigation is on linear correlations, experiments are not conducted on the interaction between the factors. Were all factors and their interactions to be investigated, the experimental effort would be much greater. A complete linear description of the factors is given by the following rule of thumb. (FU 6)

$$\text{Number of experiments} = 2^{\text{number of factors}} \tag{6}$$

within full factorial designs. It is recommended that designs with more than four factors should be examined with advanced designs in order to keep the number of experiments small. A comparison of the linear design is in (Tab. 3).

No of Factors	Full Factorial	Frac. Factoriall
2	4	4
3	8	4
4	16	8
5	32	16
6	64	16
7	128	16
8	256	16
9-16	>512	32

Table 3. Summary of fractional factorials designs, excluding replicates (AB, 2009).

Now one could say "With this many experiments, I can do it without a plan/ design." This is probably right and therefore, there are more efficient designs in Tab. 4. But the difference will be that, in case there is no statistic software available, results cannot be visualized adequately; hence, most of standard spreadsheet programs are limited to 2 parameter diagrams. Besides, the whole statistic has to be calculated by hand, which makes this approach highly susceptible to calculation errors[6]. In the case of evolutionary-by-hand-experiments, some time is always necessary between the experiments to discuss and decide what has to be done next. In contrast to this approach, the structured Design of Experiments method enables more experimentation within shorter intervals. From the perspective of identical-process-conditions, the time-consuming, by hand process is also more susceptible to errors and must be more critically conducted. Fig. 20 represents the "by-hand" versus the "statistically-structured" process. The Fig. 20 also highlights another benefit of the structured approach: after each set of experiments, the number of factors to be discussed could be reduced on the basis of the regression models. This will further decrease the number of factors and so the experimental design experiments by freezing the unimportant factors to promising levels.

[6] One option could also be to not calculate anything but just perform experiments. Not performing any statistics at all, will never enable experimenters to judge the quality of their process-setup. And even more important is the fact that if the process is running less sufficiently, the room for improvement cannot be described and project sense and definition cannot be estimated.

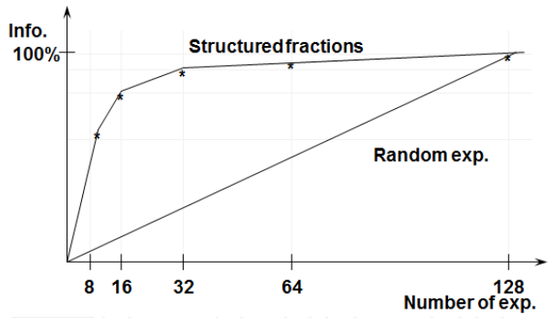


Fig. 20. Structured versus random experiments (AB, 2009).

The solid line in Fig. 21 visualizes, that within the structured Design of Experiments approach, the largest proportion of experiments is done at the project beginning. This ensures a better and faster process-knowledge growth and a more robust production launch. While in the other case (dotted line) a lot of resources are needed for improvements after the production launch, which block resources needed for instance for developing the next product- or process generation.

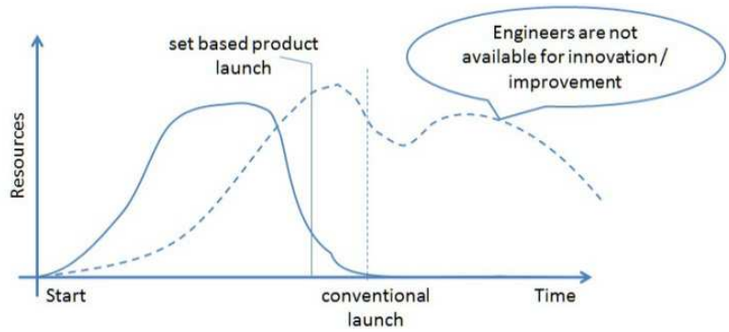


Fig. 21. DoE vers. COST (Kennedy, 2003).

Table 4 shows number of runs (excluding replicates) and alternative supported models. With six or more factors for instance, "Rechtschaffner" designs (L. Eriksson) may constitute a viable alternative to the fractional factorial designs (for the interaction models).

Number of Factors	Factorial / fractional factorial Design	Plackett Burmann design	Rechtschaffner design	L-design
2	4	8_l	n/a	9_l(q)
3	8	8_l	7_i	9_l(q)
4	16	8_l	11_i	9_l(q)
5	16	8_l	16_i	18_l(q)
6	16_l or 32_i	8_l	22_i	18_l(q)
7	16_l or 32_i	8_l	29_i	18_l(q)
8	16_l or 32_i	12_l	37_i	18_l(q)
9	32_l or 64_i	12_l	46_i	27_l(q)
10	32_l or 64_i	12_l	56_i	27_l(q)

Table 4. Summary of screening design families l= linear; i= interaction; q= quadratic (AB, 2009).

3.3 Reproducibility

So- called center-points experiments serve to evaluate the reproducibility of the measuring method and the process relative to the variation within the factorial experiment. In order for the influence of the respective factors to be determined, these are varied about a mean value upward and downward in equal measure. The software "Modde" visualizes these relationships with the replicate plot (Fig. 22) and the 4th bar within the summary plot (Fig. 27, 28). If the center points are not close together within the replicate plot, the reason must be analyzed.

Deviating center points could, for instance, be potentially caused by missing factors, incapable measurement equipment or measurement methods, different machine operators, different machines, different batches of raw material and much more. Also it must be assumed that other experiments' results fluctuate the same as the center- point experiments, otherwise the quality of the prediction model would be weak.

3.4 Design

A common geometric factorial design is chosen to create the following exemplary but actually performed experiment (Moser & Madl, 08/2009). This fractional factorial design entails far fewer experiments than full factorial design. For comparison: Were a full dual level factorial design to be applied to this factorial experiment, 227 experiments would be needed. Although other designs, such as "Plackett Burmann" designs (L. Eriksson), would entail fewer experiments (28+), they would rule out the possibility of studying interactions or quadratic terms at a later date.

This screening design consists of two profiles, each of which has ten nodes and seven quantitative factors. This yields 27 factors from which, with the aid of fractional factorial design, an experimental scale of 64 + 3 center-point experiments are generated. This number is derived from the experimental design in which all the factors are studied independently and without interaction at two levels (min./max.). A feasibility study was conducted in which the part is injected in a 1-cavity mold. To ensure constant melt and mold temperatures in the process, 30 moldings were initially produced. Two molded parts were then produced and characterized. After the experiments, the moldings were measured in a coordinate measuring table.

The values were transferred to the software. Before a model can be generated out of the data, it is very important to look at the raw data. Therefore, common statistical software supplies the replicate, histogram and correlation plots. The first plot to look at is the replicate plot (Fig. 22), which plots all the experiments in a row in order to see if experiments with equal factor settings (center- points and replicates) cause equal results. The second plot is the histogram (Fig. 23), which is important for reviewing the data and ensuring a symmetrical Gaussian distribution (Fig. 34, bell distribution). Because of the limited number of experiments it is very important to have close to normally distributed data in order to get a good regression model, fitted with the method of least squares.

After this, the "black box" (Fig. 11) between factor setting (cause) and targets (effect) can be graphically modeled. The model itself is a tailor polynomial, the mathematical formulation of the relationships being derived from the results of the factorial experiment. Since

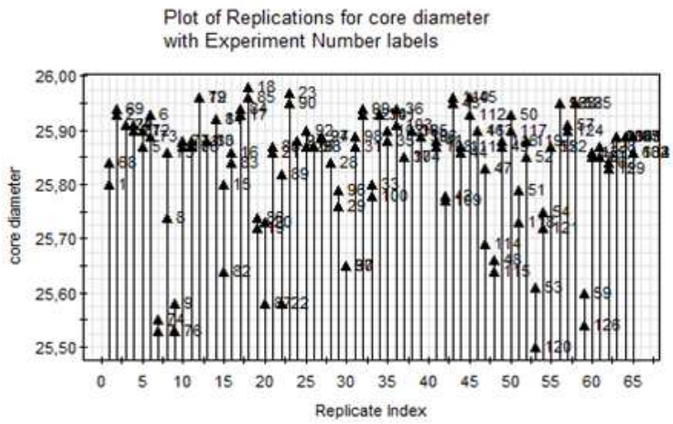


Fig. 22. Replicate plot [5].

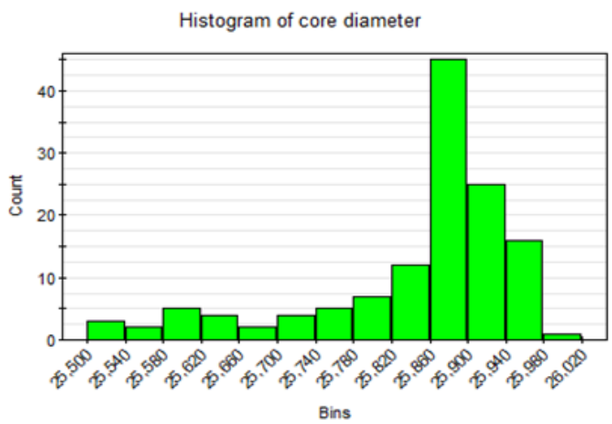


Fig. 23. Histogram [5].

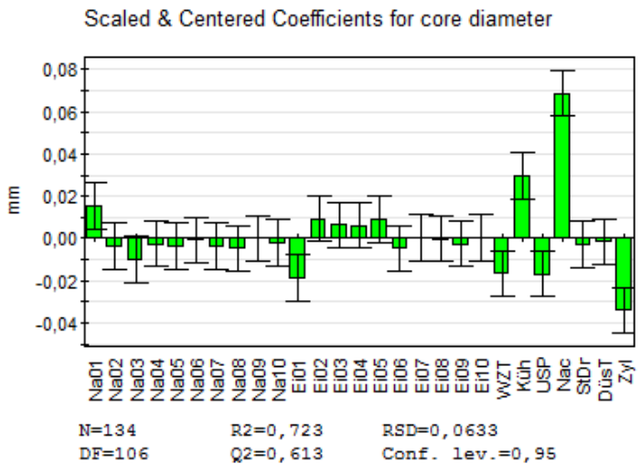


Fig. 24. Coefficient plot [5].

screening examines only the linear correlations, only the linear effects of all factors are plotted in a coefficient bar graph (Fig. 24).The next set up to study is the "N- residual probability plot" (Fig. 25).

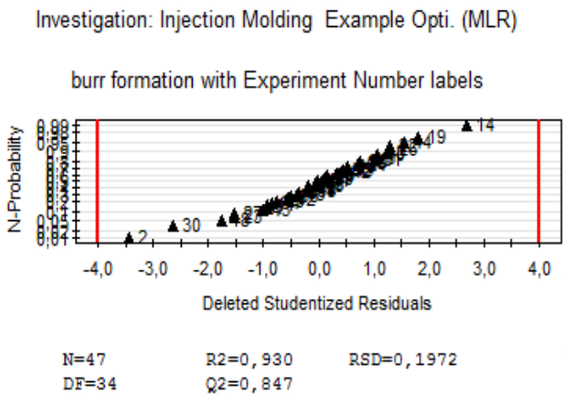


Fig. 25. N-Residual Plot [5].

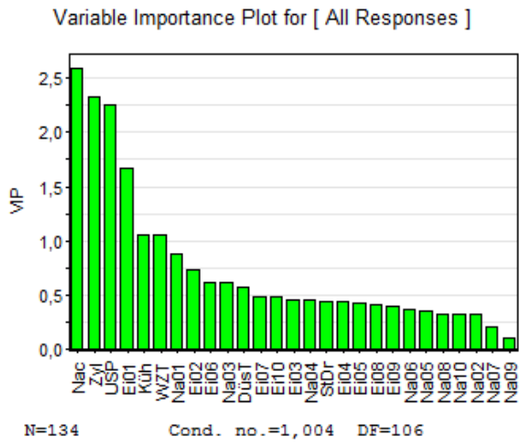


Fig. 26. Variable importance plot [5].

The residuals are plotted on a cumulative normal probability scale. This plot makes it easy to detect normality of the residuals. If the residuals are normally distributed, the points on the "N- residual probability plot" follow close to a straight line and will also support detection of outliers.

Points deviating from the normal probability line with large absolute values of studentized[7] residuals, i.e. a larger than 4 standard deviations indicated by red lines on the plot.

According to the Pareto Principle, about 20 % of the factors account for 80 % of the effect. In line with this hypothesis, any factor without influence (significance) can be graphically removed from the coefficient plot, while the software works in the background to calculate the updated model from the remaining terms[8]. In the next step, the experimenter can focus on the significant factors. To see what factors are important for all considered responses, the "variable importance plot" (Fig. 26) could be analyzed. This is crucial because the number of factors decisively determines the extent of further experiments. The quality of the test series and its calculated model are also illustrated as several four bar plots (Fig. 27, 28). These

[7] For more details see Student's t-distribution at (From Wikipedia)
[8] For this reason, the order in which non-significant terms are removed is important.

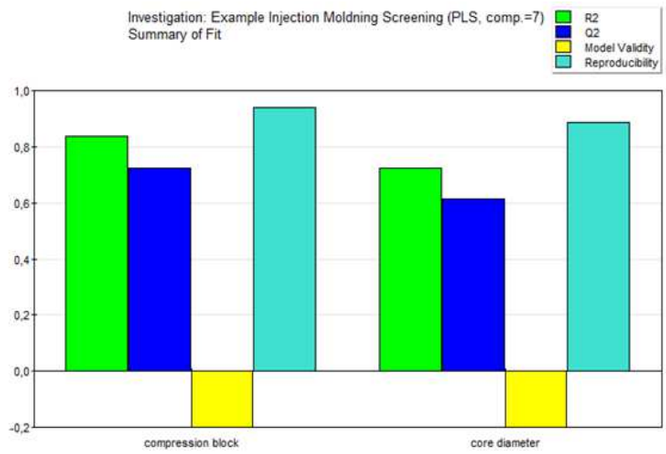


Fig. 27. Summary plot after screening [5].

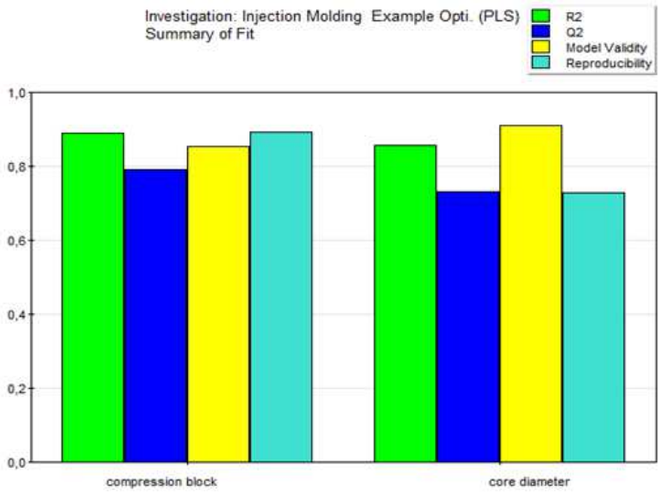


Fig. 28. Summary plot after optimization [5].

stand for the quality of the results (1th bar), the prognosis for targets in new experiments (2th bar), validity (3th bar) and the reproducibility of the model (4th bar). The bars are shown normalized (0 to 1), i. e. the closer the values are to 1, the better. The model calculated after the screening phase (Fig. 27) was of surprisingly good quality. Fig. 28 is the summary of the enhanced "optimization model". In detail the "summary plot" is calculated as follows: (L. Eriksson) (AB, 2009)

R^2 (Fig.27, 28; 1St bar): Quality of results or the Goodness of fit is calculated from the fraction of the variation of the response explained by the model (FU 7): The R2 value is always between 0 and 1. Values close to 1 for both R2 and Q2 indicate a very good model with excellent predictive power.

$$R^2 = \frac{SS_{REG}}{SS} \qquad (7)$$

SSREG = the sum of squares of the Response (Y) corrected for the mean, explained by the model.
SS = the total sum of squares of Y corrected for the mean.

The second column in the summary plot is **Q2** (Fig.27, 28) and is the fraction of the variation of the response predicted by the model according to cross validation and expressed in the same units as R2. Q2 underestimates the Goodness of fit (FU 8). The Q2 is usually between 0 and 1. Q2 can be negative for very poor models. With PLS negative Q2 are truncated to zero for computational purposes. Values close to 1 for both R2 and Q2 indicate a very good model with excellent predictive power.

$$Q^2 = 1 - \frac{\text{PRESS}}{\text{SS}} \qquad \begin{array}{l}\text{PRESS= the prediction residual sum of squares}\\ \text{SS = the total sum of squares of Y corrected for the mean.}\end{array} \tag{8}$$

The third column in the summary plot is the "model validity" (Fig.27, 28) and a measure it. (FU 9). When the model validity column is larger than 0.25, there is no lack of fit of the model. This means that the model error is in the same range as the pure error. When the model validity is less than 0.25 there is a significant lack of fit and the model error is significantly larger than the pure error (reproducibility). A model validity value of 1 represents a perfect model.

$$\text{Validity} = 1 + 0.57647 * \log(\text{plof}) \qquad \text{where plof = p for lack of fit.} \tag{9}$$

The forth column in the summary plot is the Reproducibility (Fig.27, 28) which is the variation of the response under the same conditions (pure error) (FU 10), often at the center points, compared to the total variation of the response. A reproducibility value of 1 represents perfect reproducibility.

$$\text{Reproducibility} = 1 - \frac{\text{MS(Pure error)}}{\text{MS(total SS corrected)}} \qquad \text{MS = Mean squares, or Variance} \tag{10}$$

4. Optimization (of process parameters)

The screening experiments for this project revealed the region in which the profiles for holding pressure and injection speed must lie. This enables the nodes to be dispensed with in favor of a description of the profiles with a varying initial value that decreases constantly Formula (FU 3). Every experimental approach also got less significant factors, such as in this case: The back pressure and the temperature of the hot runner nozzles. These factors were frozen at a calculated optimal value. This reduced the number of factors to be varied from twenty-seven to six. These six factors holding pressure, injection speed, mold temperature, cooling time, switching point and barrel temperature have been studied further in a multilevel geometrical experimental design ("Central Composite Face") with 44 experiments and three center-points. After executing the additional experiments the raw data analysis has to be performed again, such as checking the data for normal distribution and possibly transformation of responses, checking the reproducibility and pruning the model terms at the "coefficient plot" in order to get the best possible prediction model. The summary plot is visualized within (Fig. 28):

Now with regard to the predictive quality of the model, contour plots (Fig. 29) can be generated. These plots are like a map of a process; the ordinate and abscise represent factors, and the contour lines visualize response values.

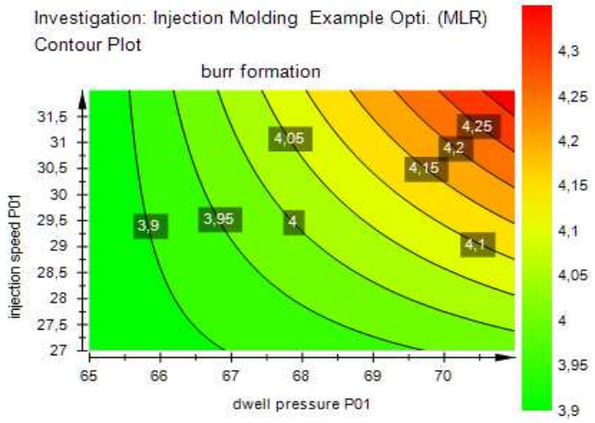


Fig. 29. Contour plot [5].

4.1 Finding an optimal process-setup

While the color shading is value-neutral, it is predefined by default with blue as low and red as high response values.

Since humans are incapable of thinking in more than three dimensions, it is difficult to display more than two factors, plus a target. However, it is possible for software to calculate the degree of fulfillment of any number of evaluation criteria as a function of several factors. This can be shown in a sweet-spot plot (Fig. 30).

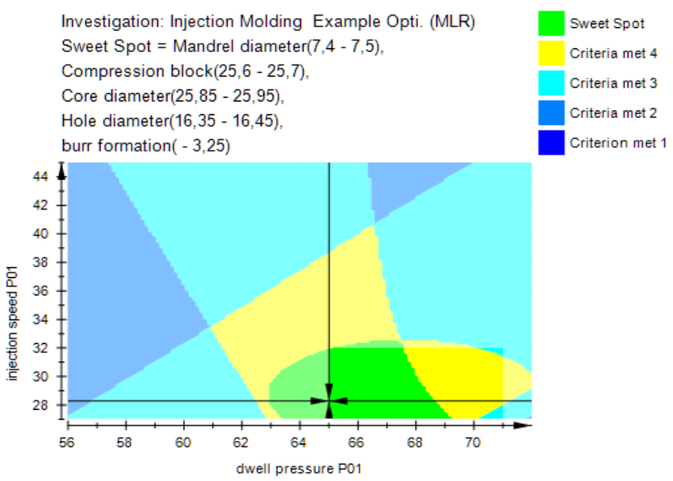


Fig. 30. Sweet spot plot [5].

As in set theory, the target functions obtained are displayed on top of each other in different colors. The region in which all targets are met is called the sweet spot (green).

The injection prototype tool was created to ascertain the process capability of the tool. The determination of the process optimum from the model proved to be so good and reproducible that the project team eschewed a study of the robustness of the optimum. On production tools, and especially when it comes to large piece numbers of very high requirements to produce, further verification steps are inevitable.

5. Robustness testing

In most cases, some of the target definitions could be fully met, others only to a certain degree. Sometimes a compromise has to be defined to outline actionable new demands of targets and specifications to be derived from this updated knowledge.

After this important step of reflecting the possible and defining new process specifications in the light of costs over benefits, a potential optimum can be calculated with the optimizer and visualized with the sweet spot plot. The Modde-Optimizer is a software tool which cannot optimize anything but is a very helpful tool for searching in a multidimensional space for a setting in which all targets are met max. To do this, the target limits and the factor settings have to be taken or updated.

At this point, it is also possible to narrow the factor limits or to expand them. This inter- or extrapolation is combined with the possibility of estimating the accuracy of the factors setting; this means how accurately this factor can be adjusted to a certain limit. From this data, a reduced linear design will be used to place small, mathematical isosceles triangles into the multidimensional working space. From there, these triangles will be mirrored on their flanks in order to check if the new additional peaks of the mirrored triangles (Fig. 31) are better positioned to fulfill the predefined targets' requirements.

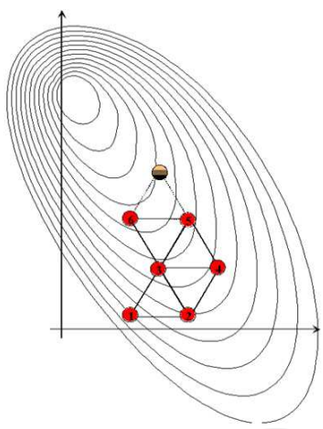


Fig. 31. Sketch: simplex algorithm, (L. Eriksson).

This process will be repeated iteratively till no better solution can be found. Because one of the small triangles could be easily trapped at local maxima or minima, a small proportional number of triangles are used to form a different position of the factor space. This can be seen with the ending lines in Fig. 32. This so-called "simplex algorithm" is a very simple but is powerful tool to check to which degree targets' values can be simultaneously fulfilled. The previously discussed target priorities can be weighted within the response target settings. The process model serves as a basis for finding a setting in which the molded part can be produced within the required quality. For the purpose of evaluating robustness in the region of the calculated optimum, it often takes only a few experiments, so that the effect of the factor variations may be adequately described. To do this in fine-tuning or a robustness check, a new small set of linear experiments with a factor variation similar to realistic process conditions should be performed. After executing the experiments and doing the repetitive data analysis, the results can be summed up in one of these four cases:

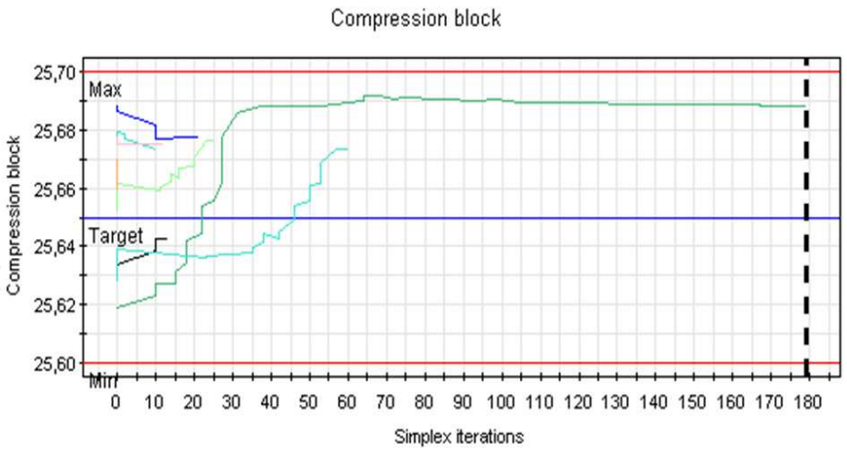


Fig. 32. Response simplex evaluation [5].

1. **Case one:** All target values are fulfilled; a good predictive model can be developed. This means the process is robust, but the variation of the factors is still influential on the target functions. It should be discussed if some of the process conditions should be improved.
2. **Case two:** All target values are fulfilled; no model can be achieved. This is the best outcome because factor variations seem to be too small to affect the results. This case should also be discussed if the process setup can be simplified in order to make the process more cost efficient
3. **Case three:** No target values are fulfilled; a model can be developed. This means that the model prediction was not as accurate as expected. The quality of the "predictive basis model" should be rechecked; maybe the Q2 and the validity are not as good as supposed, or there are outliers in the experiments. By implementing these test experiments in the Modde-File, the model-quality can be checked as to whether it can be enhanced or whether these results deviate and if so, for which the reasons.
4. **Case four:** No target values are fulfilled; no model can be developed. Typical reasons for this outcome are that process conditions have been changed among the experimental blocks, likewise different raw materials, machines, operators, tools etc. Another common reason is that due to the models' quality, the requirement has been underestimated.

6. Validation/process capability

Finally after a process setup has been found and verified to produce parts with a sufficient quality, the process capability should be checked. This is a very important step for summarizing the quality and robustness of the process. Within this step, a variation caused by realistic production conditions can be attached to the calculated optimum of the regression model. This is done by performing a Monte Carlo Simulation. This means that 100,000 simulations are computed while the uncertainty of factor settings is randomly applied. One way is to define a narrow factor range, such as in a robustness model or a certain factor setting spot within an optimization design. To explain the concept, a more practical Fig. 33 is shown, where the process target borders are displayed by the road shoulders and the process itself as a car on this road.

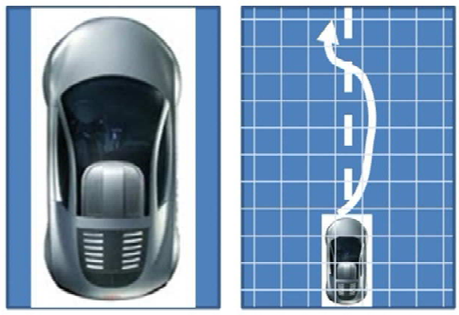


Fig. 33. Car example.

The smaller the car, in comparison to the road width, the more easily the process can be controlled. If a grid is applied on the street and the horizontal car positions during driving is added up, the positions within the grid intervals can be plotted as bars in a histogram (Fig. 23) or distribution plot (Fig. 34). Again, it is easy to interpret how close the car is driving right-handed relative to the middle lane marking and thus how safe the driving is. If the standard deviation to the "ideal driving line" is checked as a critical indicator between the expected value *(ideal driving line)* and each process border *(road shoulder),* then the process can be described in terms of quality and robustness. Consequently, it can be assumed that process quality can be described as a function of tolerance and process variation. This number is called Cpk (FU 9), the process capability or capability index and has its origin in "SixSigma" statistics. Within in Fig. 35 normal distributions with differed sigma levels are plotted. At higher CpK levels the underlying data is centered closer to the expected value (μ).

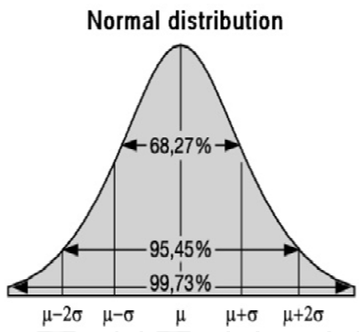


Fig. 34. Normal distribution.

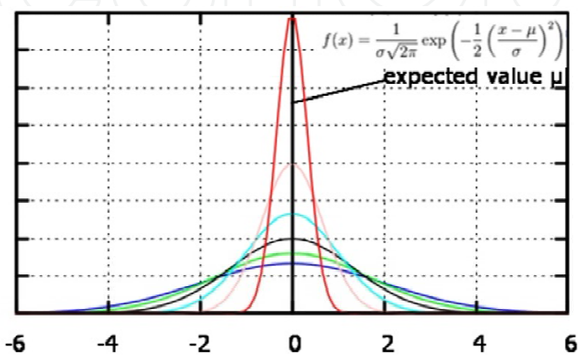


Fig. 35. Sigma distributions 1-6 sigma.

$$\text{Cpk} = \min\left[\frac{\text{USL} - \mu}{3 * \sigma}, \frac{\mu - \text{LSL}}{3 * \sigma}\right] \quad \text{USL = Upper specification limit, LSL = Lower specification limit and } \mu \text{ = estimated standard deviation for predictions.} \tag{9}$$

$$DPMO = Ho * \frac{1\,000\,000}{NS} \quad \text{Ho = Hits outside specifications, Ns = Number of simulations based on an infinite number of predictions.} \tag{10}$$

Another way to describe the process quality is to calculate the DPMO which is short for "Defects per Million opportunities outside specifications" and is used as stop criteria in the design space estimation (FU 10).

Within the Table 5 higher the Cpk is, the better the process capability and robustness are. This can be seen also within the numbers of "DPMO" or the "%Outside" specification. To calculate these numbers from the Design of Experiments experiment data, the "Monte Carlo simulation" (MCS) can be computed round the previously calculated optimal. The factor variance is adjusted to the approximated variance of the process settings within normal working conditions (Assumption 5%). The response variance calculated by the MCS is caused then by the factor setting -- and the model uncertainty. At Fig. 36 The black T-bars represent the space in which one factor can be varied while freezing the other factors and still keeping the calculated response fulfillment (Fig. 37). This is a very important information to set the process tolerances as closely as necessary and as wide as possible.

Cpk	DPMO	% Outside
0,4	115070	11,51
0,6	35930	3,59
0,8	8198	0,82
1,0	1350	0,13
1,2	159	0,02
1,5	3,4	7,93328E-05
1,8	0,03	3.33204E-06
2,0	0,0010	9.86588E-08

Table 5. Six Sigma, source: (From Wikipedia).

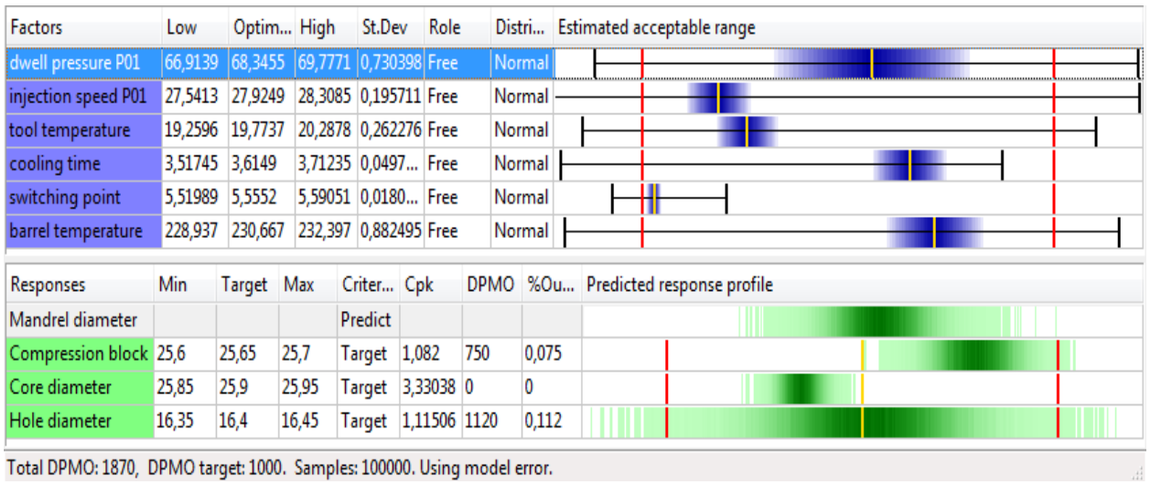


Fig. 36. Design space estimation [5].

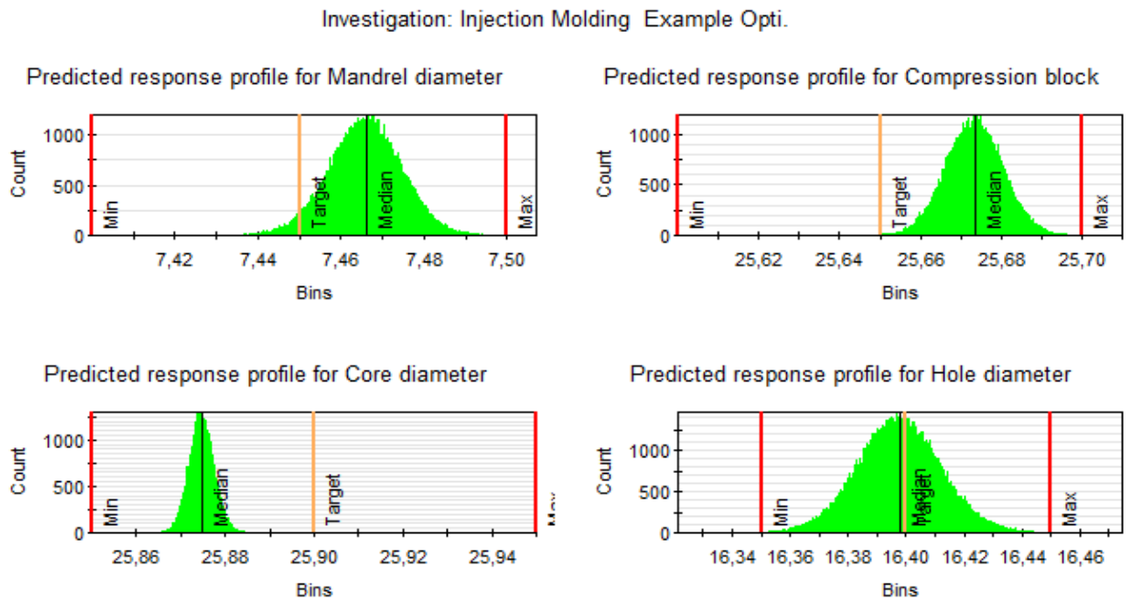


Fig. 37. Predictive design space histogram [5].

Chart legend of Modde-predicted response profile

- The yellow line represents target value for the responses as specified in the Optimizer.
- The red lines are the specification limits for each response as specified in Optimizer.
- The faded green region represents the probability of a prediction for a random distribution of factor settings in the given ranges (low-optimum-high), the design space.
- The black T-bars represent the space in which one factor can be varied while freezing the other factors and still keeping the calculated response fulfillment.

The histograms of Fig. 37 represent the response targets based on the regression model at an optimal factor setting including the factor uncertainty variation calculated by the MCS.

7. Success with restrictions

Assuming the predictive model is of good quality, the responses and its degree of achievement can be evaluated against priorities of the projects' definitions. Within the most experimental setups, responses targets are optimistically defined and with a high degree of safety. Sometimes not all of these targets can be fully achieved. Therefore, and as described in the optimization, responses can be weighted again according to their priorities and their targets, in order to find a sufficient compromise. This compromise could mend not only the factors and responses that need to be adjusted but could also mean that conditions that act as disturbances need to be compensated. Potential disturbance factors are, for instance: Relative air humidity, temperature, water content in raw materials, using different machines or bad machine calibration.

Also predictive models are only as good as their data. Even if factors are sufficiently enough arranged to describe the target functions, there are still a lot of things which could impair the prediction model such as bad pruning of the model terms, bad distributions or deviating experiments, missing factors, bad measurement *(calibrated)* equipment.

In addition to this, the approach is always to minimize the work, time and budget with efficient designs *(fewer experiments)* and fewer factors, so that not all important factors are implanted or the effect of factors are underestimated, and are, for instance, of a higher order than assumed. So, if a process is not linear and linear designs are used, the predictive capability of this model is very limited. If necessary due to interaction-, squared- or cubic factor-terms, the design could be complemented step-wise. The design of higher-order processes, complex designs are not recommended at the beginning, since these drastically increase the number of experiments. Complexity can always be reduced by focusing only on a small process space (Fig. 18).

8. Conclusion/summary

After reading the chapter, the readers should now have a good understanding how far the combined methods could help them to achieve the predefined requirements. In addition, they should also be sensitized to the fact that non-structured approaches are weak and time-consuming. It is also important to understand that while the design of experiments "DoE" does not necessarily lead to good results or capable processes, they can help to describe and document the potential of a process. Even if the targets could not be achieved, it is still possible to derive useful, cost-effective and robust knowledge with this structured approach in order to identify and assess possible disturbance factors or possible process constraints. This can provide beneficial clues for fine-tuning the factors and conditions in order to ensure and optimize process capability and success.

By following this good "DoE" practice recommendation, the iterative difficulties in finding the fulcrum or lever at the beginning of an optimization process first hand can now be reduced--- if not eliminated. And by following this consistently structured approach, the right things can be done in the right way with the right tools. Thus, Pareto's law can be intelligently leveraged, and finally, the optimization team can operate in the most efficient and effective fashion.

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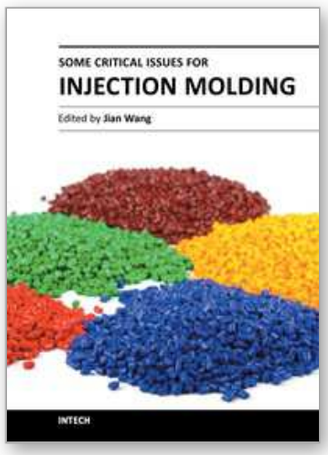

Some Critical Issues for Injection Molding

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This book is composed of different chapters which are related to the subject of injection molding and written by leading international academic experts in the field. It contains introduction on polymer PVT measurements and two main application areas of polymer PVT data in injection molding, optimization for injection molding process, Powder Injection Molding which comprises Ceramic Injection Molding and Metal Injection Molding, ans some special techniques or applications in injection molding. It provides some clear presentation of injection molding process and equipment to direct people in plastics manufacturing to solve problems and avoid costly errors. With useful, fundamental information for knowing and optimizing the injection molding operation, the readers could gain some working knowledge of the injection molding.

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