Optimal Solution

Quality

Yield

Best Designs

Simulation evolves to autonomous optimization

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Almost 30 years after its introduction into the metal casting industry, casting process simulation is a widely accepted tool in the engineering department of metal casters as well as in the design of tooling and castings. Simulations are typically performed by experienced technicians – the simulation results, therefore, reflect their metal casting experience, considerations and know-how. Each individual simulation is comparable to a virtual experiment. Based on the simulation results, these engineers evaluate e. g. whether a chosen rigging system or process parameter configuration leads to acceptable casting quality at acceptable costs and then propose changes to find improved solutions.

In the metal casting process, everything happens at the same time and is closely coupled. While this can be seen as a key advantage of metal casting over other manufacturing processes, it also makes decisions regarding the best, or at least an adequate, layout for a casting complex. Changing one process parameter, due to its interaction with other parameters, can have a multitude of impacts on the rest of the process and can influence the final casting quality in many different ways. This makes it challenging to manually optimize a casting process by evaluating the casting quality based on real-world trials and pursuing quality and economic objectives simultaneously.

Today's requirements on the development of a casting and the corresponding metal casting process demand methodologies and tools which allow a maximization of process robustness and profitability at the earliest possible point in time. Typically, the freedom to make improvements is in practice reduced to a small number of real trials during the development phase and is limited by the effort connected with changing process parameters in series production. A quantitative estimate of real casting quality based on casting trials and a reduction of the required number of experiments to optimize the casting process remain a challenge.

Opposed to real-world trials, autonomous optimization using simulation tools provides significantly more flexibility. Autonomous optimization enables engineers to modify several parameters, i.e. in the casting design and in the casting process layout, simultaneously and independently from each other, and quality criteria can be individually and quantitatively evaluated. Combined with established tools from statistical design of experiments, casting process simulation can be used to autonomously optimize casting processes and designs [1]. The software follows several targets simultaneously and finds the best compromise between them based on first principles. The automated assessment of all simulated quality criteria can be

used to quickly and easily find the optimal route to achieve the desired objectives. In addition, the number of real-world trials can be reduced and the impact various process parameters have on reaching a robust process window can be assessed in early phases of casting, tooling and process development [2].

The new methodology of autonomous optimization is not a replacement for process knowledge and expertise. Based on the technical and economical boundary conditions for his process, the foundry engineer needs to specify which parameters he has the flexibility to change and by how much, in combination with the requirements placed on the casting and the objectives to be achieved. These objectives are made measureable by relating them to corresponding quality criteria. The questions to be addressed to the software are simple: What characterizes a good gating system? How do I accomplish a robust process window? How do I select process conditions that provide the required casting quality? Quantitative descriptions of the important influencing factors, measureable quality and cost indicators, and the goals to be achieved are required to answer these questions. Just as when optimizing a casting process in the real-world, autonomous optimization uses the same three basic components (Figure 1):

- Variable **Process Parameters** (design variables)
- Selected **Quality Criteria** (output values), as calculated quantitative results
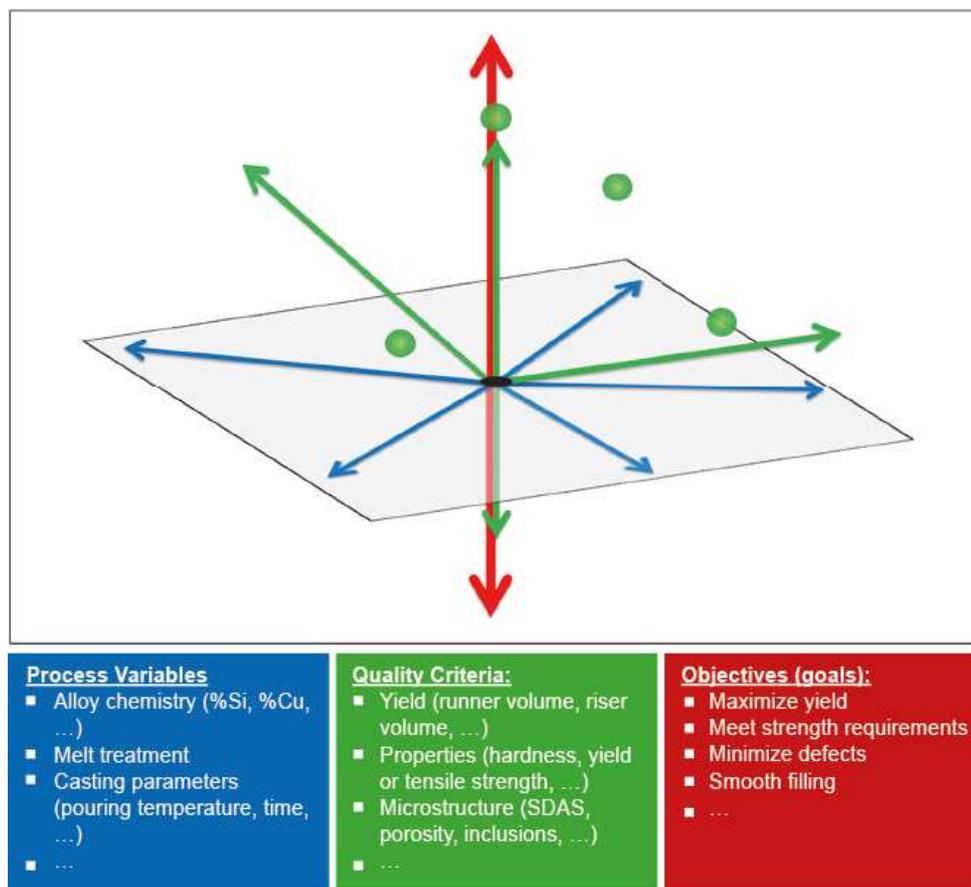- Differing **Goals** (objectives)

Fig. 1: Virtual design space for autonomous optimization composed of varying process parameters, calculated quality criteria, and optimization goals defined in the software.

Up to today, casting process simulation tools have been used by metal casting engineers to confirm a set of selected process parameters and evaluate a given casting layout. They then make manual changes to process parameters or geometries, like runners, gates or tooling, to get closer to achieving the objectives they have in mind, and repeat this process until they find a solution with which they are satisfied. This step-by-step approach can be described as 1-dimensional, manual optimization (Figure 2).
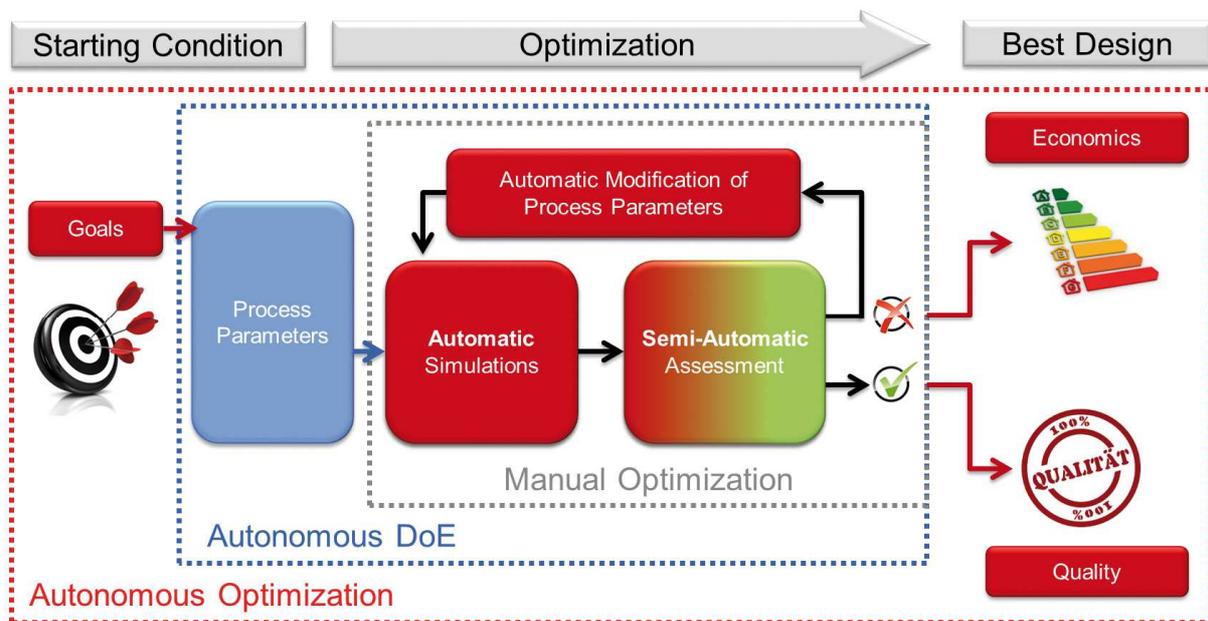

Fig. 2: Various optimization methodologies for finding the best solution

In MAGMASOFT®, this internal loop (gray) is now fully automated. It can be expanded by setting up an autonomous design of experiments (autonomous DOE) where variable geometry and process parameters are predefined (blue). This creates a set of designs, which can be run automatically to e.g. change the number, location and size of risers or change process related parameters or vary metal chemistry. For each virtual casting trial or design, the program automatically evaluates the defined quality criteria. These criteria can be based on any of the results available in MAGMA[5], i.e. process information like solidification time, quality information like porosity or entrapped air, or characterization of local microstructures and properties such as dendrite arm spacing, nodule count or tensile strength.

Integrating objectives leads to a complete autonomous optimization (red), where simulated designs are automatically assessed with regard to how they contribute to the, sometimes conflicting, objectives. Just like the metal caster in his daily work, this means that the program needs to find compromises between different demands on the casting and process (e.g. avoiding critical porosity while maintaining an acceptable yield). Using genetic algorithms and statistical tools, the program can follow these conflicting goals simultaneously and learn from the results of the virtual casting trials which are carried out.

The following are selected examples of how this new approach supports foundry engineers to systematically develop their process understanding to develop robust layouts and casting processes before the first metal is poured.

Assessment and optimization of cleanliness of a steel casting

Cleanliness is a key criterion determining the quality of modern steel castings. The agglomeration of inclusions in critical sections often means excessive cleaning times and can lead to an unacceptable reduction in mechanical properties. Castings are frequently scrapped due to inclusion related surface defects discovered during machining.

Most inclusions in steel castings are caused by re-oxidation of the metal through contact with air during the mold filling process. It is a well-known fact that foundry engineers counteract this mechanism with cleverly designed gating systems. They know that calm flow patterns and avoiding the creation of air pockets in the metal flow lead to significantly better cleanliness.

The cleanliness of a real-world casting can only be evaluated by surface machining, counting inclusions, and a statistical evaluation of two-dimensional samples. To avoid destroying the casting, this investigation may be carried out on separately cast samples, meaning that only the metallurgical quality is evaluated. The important effects of local flow patterns inside the steel casting are completely ignored. The experimental assessment of the distribution of non-metallic inclusions is always time and cost consuming and not practical to implement in production for each casting.

Autonomous DOEs and optimization, however, can be quickly run with minimal effort. They allow for the systematic variation and the quantitative evaluation of different gating layouts (Figure 3). In this example, the impact of gating design on the number and distribution of re-oxidation inclusions on the surface of a steel casting was investigated. The software ran twelve different previously prepared gating designs. Without any interaction of the software user each simulation in the autonomous DOE was set up, calculated, and its results were assessed based on relevant quality criteria. The different designs are shown in the bar chart in Figure 3 and ordered according to their surface cleanliness. This allows for a fast selection of good and bad designs as they relate to this quality criterion. A good (#3) and a less effective (#10) gating system are displayed in Figure 3, each adjacent to its respective simulated surface cleanliness result.

Figure 4 assesses the surface quality of four selected designs. As an additional quality criterion, the degree of turbulence during the filling process is shown. This can be easily evaluated using the amount of surface area on the metal front which was available for oxidation during filling. The design with the most surface inclusions also shows the most turbulent filling pattern. This chart reconfirms the commonly accepted correlation between a quiet filling pattern and better cleanliness. Autonomous optimization provides the opportunity to quickly and safely assess quantitative quality criteria. The comparative evaluation of autonomous optimization

results allows the determination of correlations between process parameters and quality criteria.
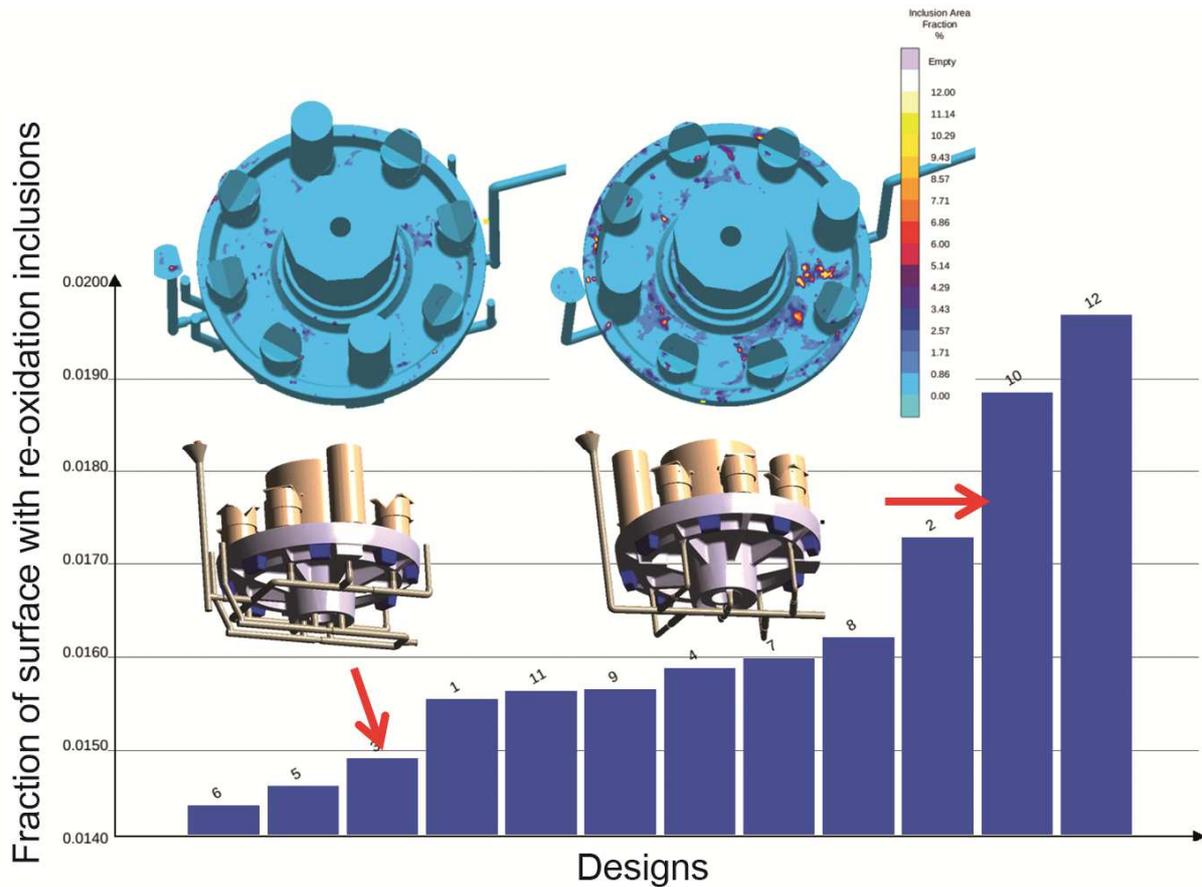

Fig. 3: Automatic and quantitative assessment of several gating designs as they relate to surface quality
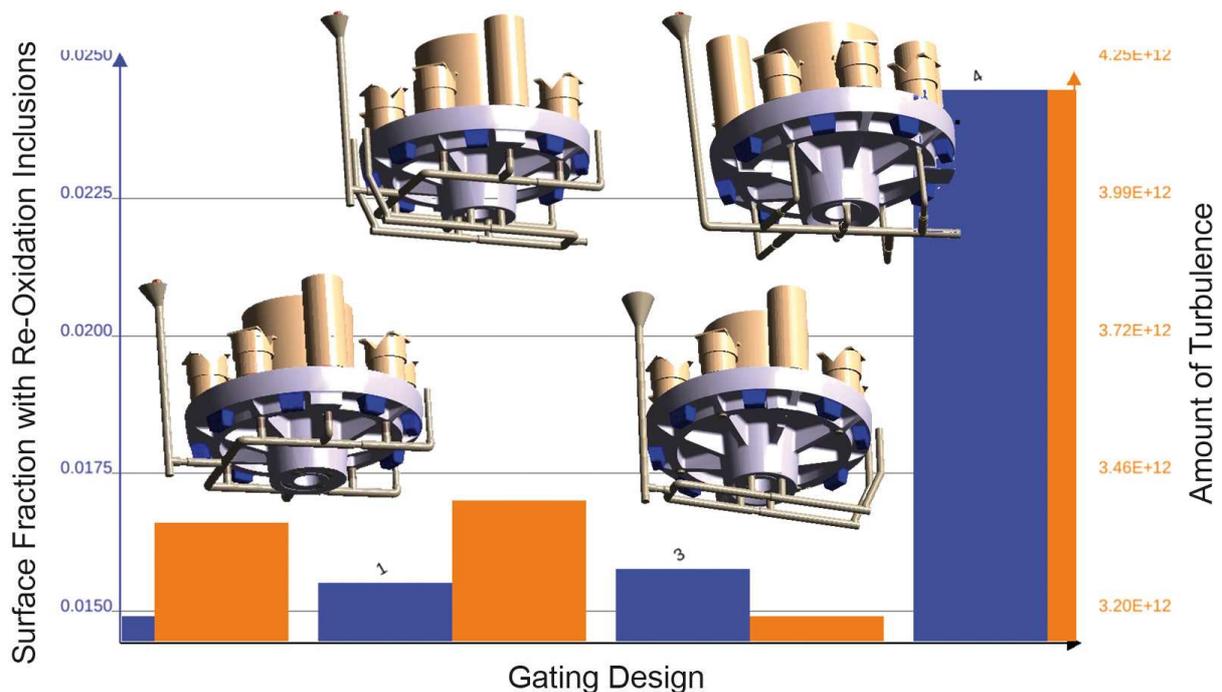

Fig. 4: Assessment of surface quality and turbulence during filling for 4 gating designs

Riser optimization for a planetary gear carrier

Autonomous optimization allows foundry engineers to locally assess casting quality based on any quantitative quality criteria. Combining this with the flexibility to vary almost any casting process and design related parameters opens nearly unlimited options to evaluate what the most relevant factors influencing casting quality are and to determine the optimal configuration for production.

The risering configuration of a ductile iron planetary gear carrier is optimized in this example (Figure 5). The feeding of the critical flange area (dashed red line) is provided by a combination of top risers and several chills outside and below this area. An additional variable is the option to increase the wall thickness of the area below the risers (padding), leading to several different layouts.
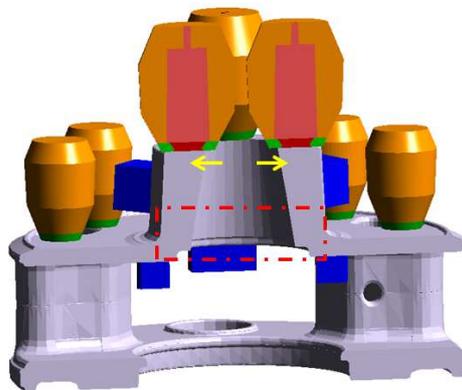

Fig. 5: Cut view of a ductile iron planetary gear carrier and its riser and chill configuration; the red dashed line depicts the critical area; the yellow arrows show where the wall thickness of the casting can be increased

Several parameters were varied to assess which of them has a significant impact on the shrinkage porosity in the critical area. Specifically, the influence of the size of the risers, the size of the padding, and the chill configuration outside and below the critical area were investigated. This led to an autonomous design of experiments (DOE) with 32 designs run autonomously by the software.

The results of this DOE (Figure 6) show the impact each parameter variation has on the evaluated quality criteria, the amount of shrinkage porosity in the flange. Each marker in the scatter diagram represents one design and is the result of an individual simulation.

The results indicate that for all of the varied parameters, a low level of porosity can be achieved. It can be clearly seen that the chill configuration has a significant impact on the shrinkage porosity. The layout with the maximum number of chills on the right of Figure 6, always leads to the least amount of shrinkage defects, regardless which other variations are made. In this respect, this solution is robust to variations in other production conditions. As to expected, increasing the size of the padding also narrows the scatter in the range of defects, but its impact is smaller than that of changing the chills.

Using an autonomous DOE, it becomes clear which parameters have a significant effect on the casting quality and where the foundry engineer should focus in on (in this case the chill configuration) to find the final and optimal configuration.
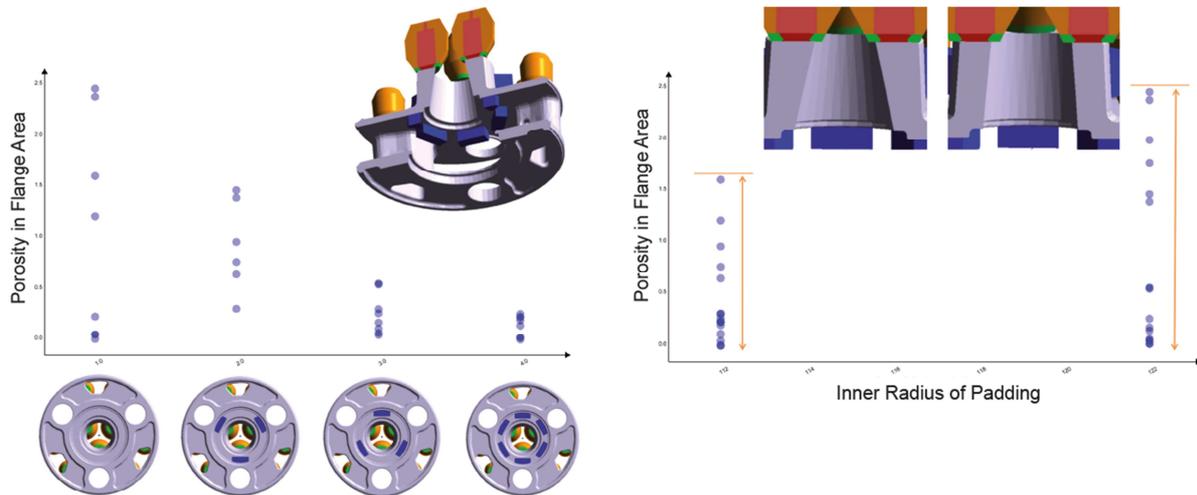

Fig. 6: Impact of chill configuration (left) and padding (right) on shrinkage porosity in the critical area

Robust process layout of an aluminum gravity sand casting
In the high volume production of castings, it is essential to consistently meet the quality requirements. Process parameters can vary or drift over time. Due to the complex interactions between these parameters, casting processes always operate in a process window. External factors, e.g. melt chemistry or sand variations, impact the casting process and may move it away from the secured operating point.

Autonomous DOEs and optimization provide quantitative insight into the relationships between process parameters and casting quality. Additionally, they provide valuable information on how quality criteria are impacted when process parameters or other factors fluctuate. This means that the utilization of autonomous optimization can not only help determine the best casting process configuration but also provide information about how robust that process set-up is.

The following example optimizes the riser configuration of an aluminum sand casting [3] (Figure 7). The casting is produced with six parts on the pattern plate.
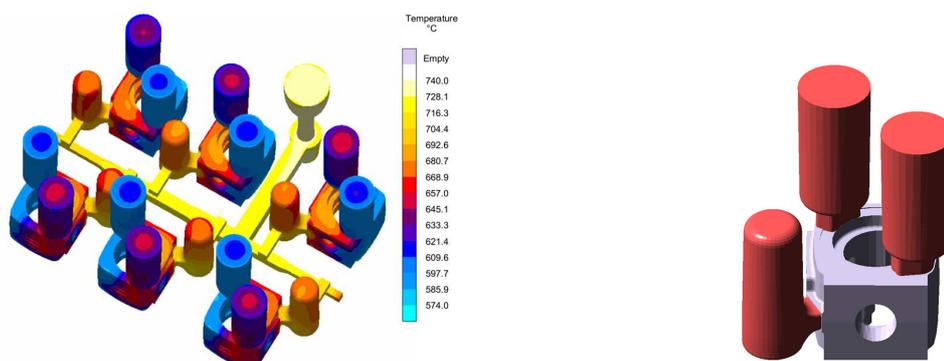

Fig. 7: Gating system with 6 castings – temperature distribution at the end of filling (left) and original riser configuration for one part (right)

In a first step, the shape and size of the hot riser was optimized. After filling the mold cavity, the temperature distribution in each of the different castings is quite different. Each casting is filled through a "hot" riser. Additionally, two "cold" risers are located on top of each casting. An autonomous optimization with the objectives "minimize shrinkage porosity inside the casting" and "minimize riser volume" was performed. A total of 45 designs (simulation of filling and solidification for each) were carried out autonomously in less than 8 hours. The scatter chart in Figure 8 displays the shrinkage porosity versus riser volume for each of the simulated designs. The configuration which best satisfies both objectives, a casting free of porosity and having the smallest possible riser volume, is colored in green. The chart also shows that there are numerous other options to produce a defect free casting (horizontal group of markers near the x-axis) but they all would lead to a reduction in yield through a larger hot riser.
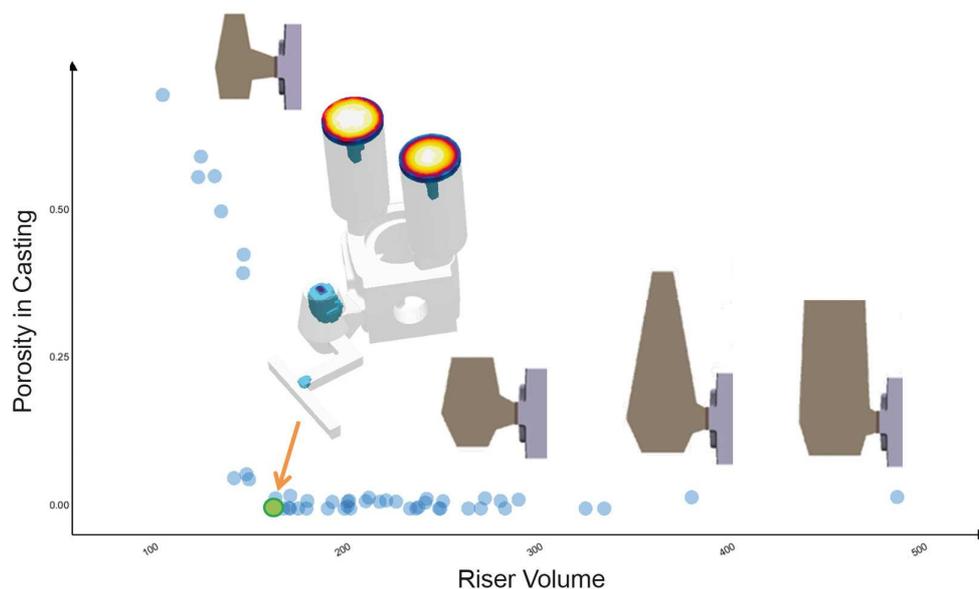

Fig. 8: Influence of the shape and size of the hot riser on porosity in the casting and riser volume, shown in a scatter diagram (green point is the best design).

The indicated optimal design provides the best combination of getting defect free castings from each of the cavities at the lowest cost, assuming the other casting process parameters are kept at the corresponding operating point. By evaluating all of the designs showing castings free of porosity, it is possible to investigate how robust this selected riser configuration will be in production. Since the software allows the retroactive specification of addition quality criterion with which the previously simulated process lay-outs can be evaluated, conclusions regarding the robustness of the process can also be reached. The quality criterion "critically fed regions" shows areas of the casting which have the longest need for feeding. If the indications from this criterion extend into the casting from the feeder, there is the danger that even smaller fluctuations in the process parameters will lead to porosity in the casting.

Figure 9 shows the predicted porosity distribution (left) together with the "critically fed regions" result (middle) as an evaluation of the feeding performance for the layout

characterized as being the best. As expected, the casting is free of porosity, with indications only being seen in the risers. On the other hand, the "critically fed regions" criterion extends into the casting from the hot riser for this configuration. The user now has the flexibility to select another riser design for which both criteria are fulfilled. In this case, the hot riser only had to be increased slightly in size in comparison with the "best" design in order to ensure that the "critically fed regions" criterion did not enter the casting (Figure 9, right) and therefore provide a more robust setup [3].

Fig. 9: Predicted porosity and "critically fed regions" results for the optimized layout (left) and a more robust situation with a slightly larger riser.

Simultaneous autonomous optimization of runner design and shot curve for a die casting

Since the conceptual design of the runner and gating system and the determination of the casting process parameters for a die casting are closely coupled, the runner geometry and the progress of cavity filling for a given casting always have to match. As an example, here the simultaneous variation of the runner design and the shot curve on resulting casting quality for a four-cavity die is investigated.

The section size of runner systems for high pressure die castings is usually smaller, the farther it is from the biscuit. The runner design for this example (Figure 10) is autonomously optimized by varying the location of the runner cross-sectional contraction between the bottom and top cavities (see solid and dashed red lines in Figure 10). The position of the cross-section reduction has a significant influence on the filling behavior of the castings, in particular whether the four cavities are filled uniformly. This is an important pre-condition for the reproducible production of high quality castings.

Figure 11 shows the local filling times for two different variations of the runner cross-section area change. Utilizing the symmetry, only the right side is shown. The layout on left shows significantly different filling times in the top and bottom cavities. The

layout on the right is obviously better in this respect, as the cavities show a nearly identical filling behavior.

In order to simultaneously investigate the influence on the resulting filling of variations in runner geometry and the acceleration of the piston during the shot, both the positon of the runner contraction and the time for acceleration of the shot from slow to fast speeds were varied.
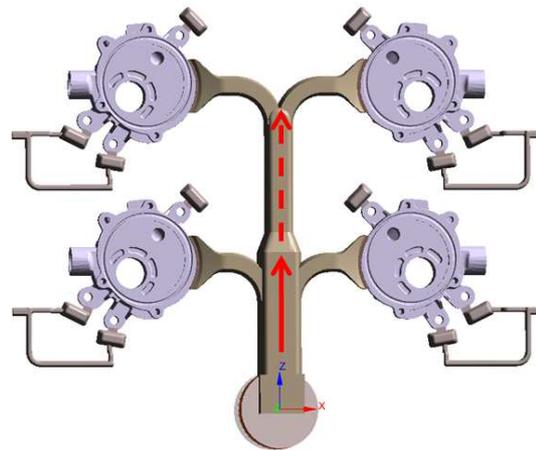

Fig. 10: Variation of the position of the cross-section change in a high pressure die casting runner

An autonomous DOE with 98 distinct designs was performed, where all geometry and shot curve variations were autonomously generated, simulated, and then assessed.
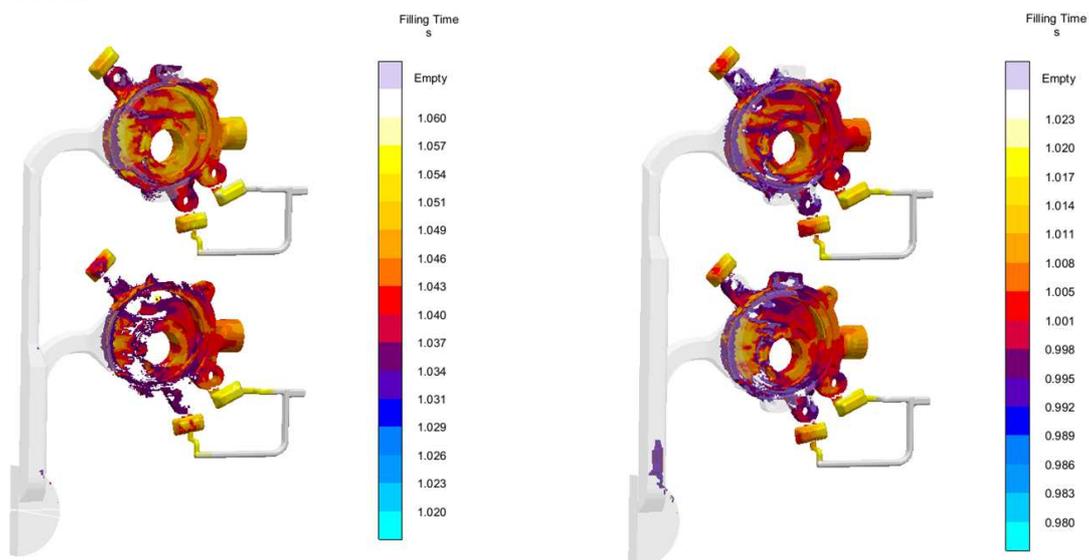

Fig. 11: Local filling times for two different positions of runner contraction. (Due to symmetry only one-half of the casting is shown.)

The piston velocity profile versus piston travel is shown in the upper section of Figure 12. The time of the start of the acceleration phase for the investigated designs was always between the vertical green and blue lines. The lower section of Figure 12 shows main effect diagrams, depicting the impact of changing the start of the acceleration phase (upper diagram) and the impact of moving the runner contraction

location (lower diagram) on the differences between the filling times of the casting cavities. The smaller this difference, the more uniformly the cavities are filled. Each marker in a main effect diagram represents one average value of all simulations of the autonomous DOE for a specific acceleration point or runner contraction location. The incline of the lines represents the significance of the respective process parameter on the selected quality measure. The steeper the incline, the greater the impact is.

These results show that starting the acceleration at a later point in time leads to increasing difference in the filling of the cavities. In comparison, the effect of the runner contraction location is relatively weak. The higher the contraction is the more uniform the filling of the cavity.

This example shows that changing one process parameter always has an impact on other process conditions or on decisions regarding casting and tooling design.
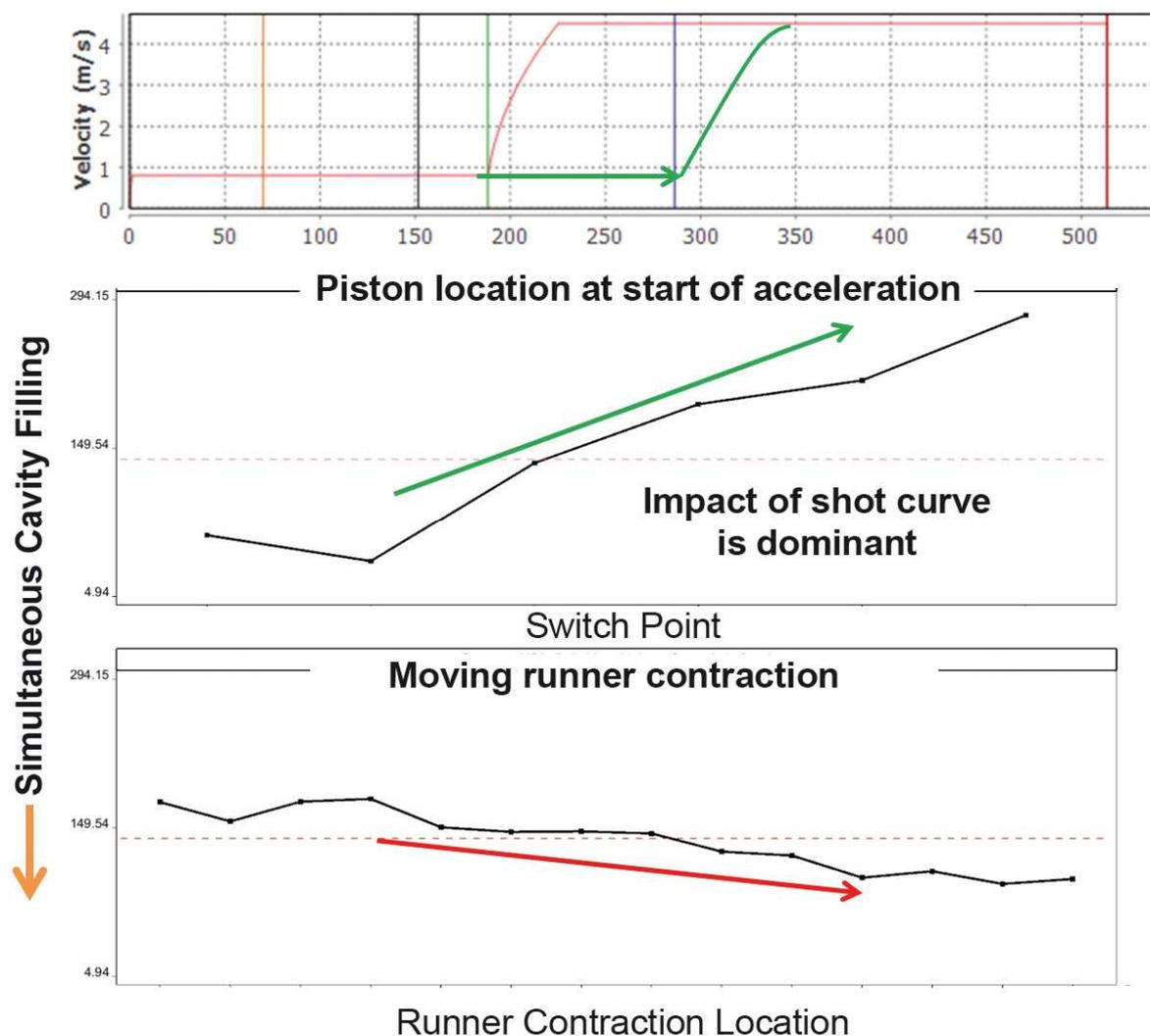

Fig. 12: Variation of the shot curve (top) and main effect diagrams for the influence of switch-over time in the shot curve (middle) and height of the runner contraction (bottom) on the uniform filling of all the cavities

Autonomous optimization of a support frame for the heat treatment of a structural casting [4]

Casting process simulation tools can predict residual stresses and the resulting distortion of castings over their entire manufacturing process, also including the heat treatment process. This example illustrates how an autonomous DOE and optimization can be used to minimize the distortion of even complex die-cast structural part.

Solution treatment is the first step in a T6/T7 heat treatment for aluminum castings. Due to the low strength of the material close to the solidus temperature, and through the influence of gravity acting on the casting, there is always the danger of creating a permanent plastic deformation in a thin-walled structural casting during this process step. Figure 13 quantifies the relationship between different solution treatment temperatures and times with the calculated distortion of a structural automotive casting. The clear tendency towards higher deformations for longer treatment times at the same temperature level becomes obvious. Hence, virtual experimentation not only provides a means quantitative assessment to realize the component's specifications. It also offers the potential to establish both robust process conditions and energy savings already during product development.
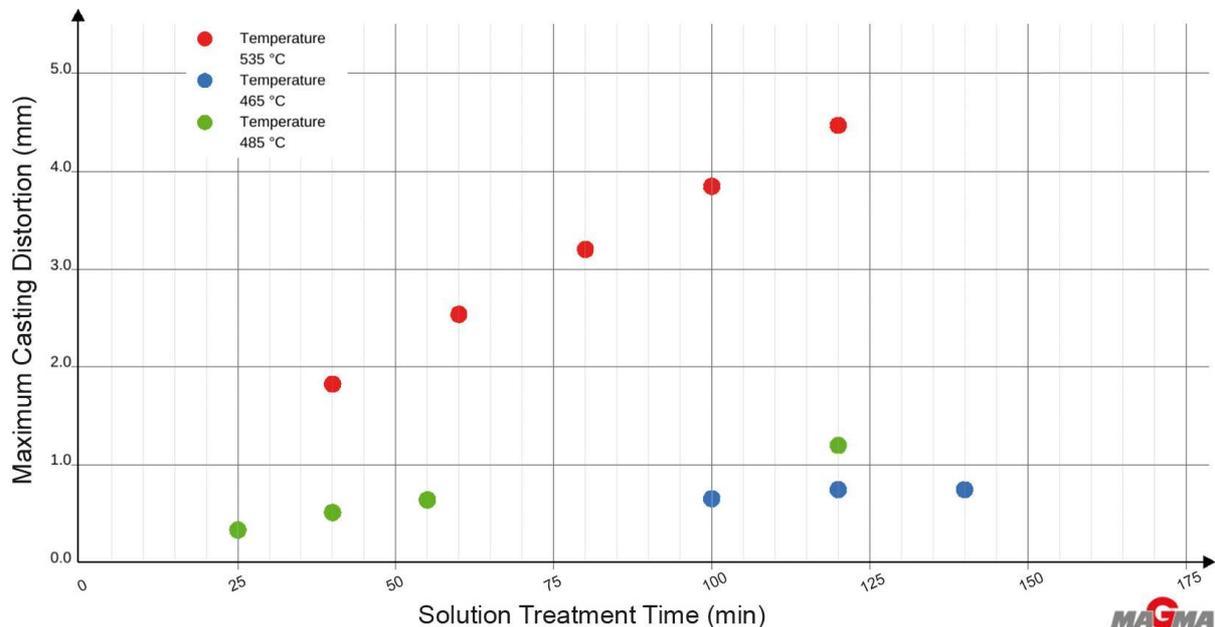

Fig. 13: Virtual Design of Experiments investigating the maximum deformation of a die cast structural part during heat treatment for different solution treatment temperatures and times.

The casting is positioned on a support frame during heat treatment. Finding appropriate contact points between the frame and casting is extremely important for achieving dimensional stability. Starting from the selected best solution treatment temperature and time, the objective was to further reduce the amount of distortion by

optimizing the positons of the casting/frame contact points. An autonomous DOE was set up to evaluate different options for the positions of the contact points (Figure 14). Figure 15 shows the distortion results for some selected frame designs. The distortion of the part due to gravity can be seen clearly. The first support frame (upper left) shows a distortion of 3.2 mm in the left front area of the part. Adding an additional support in the front left corner (upper right in Figure 15) already shows a significant improvement. The next design (lower left) shows that the removal of one of the supports in the front has almost no effect. Of the shown positioning options, moving the left front support backwards and even more to the left leads to the smallest distortion of around 0.5 mm (lower right).
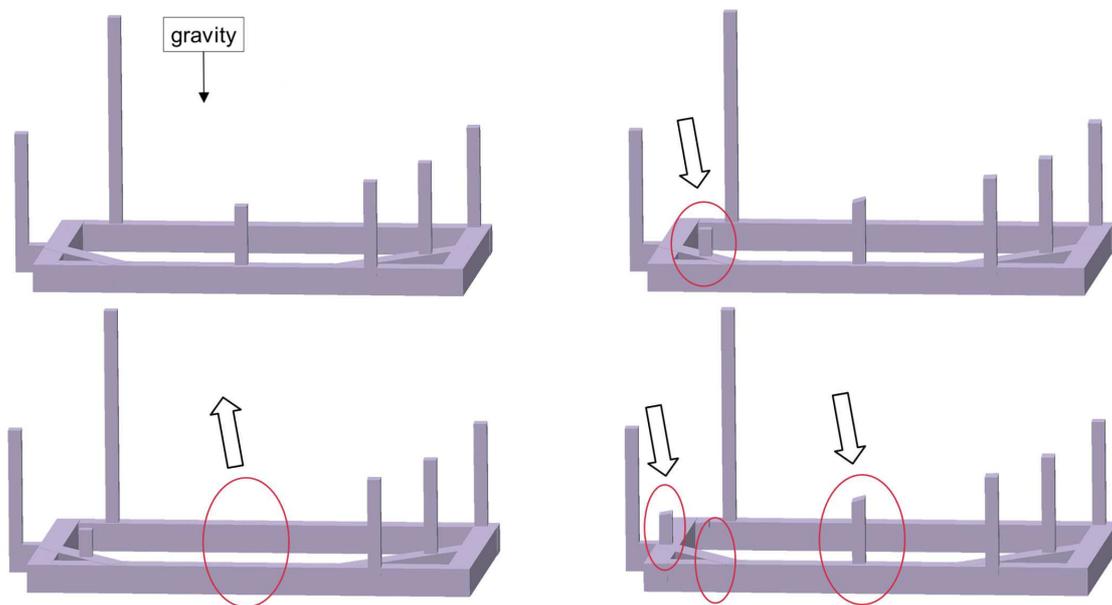

Fig. 14: Four different support frame designs for minimizing heat treatment distortion
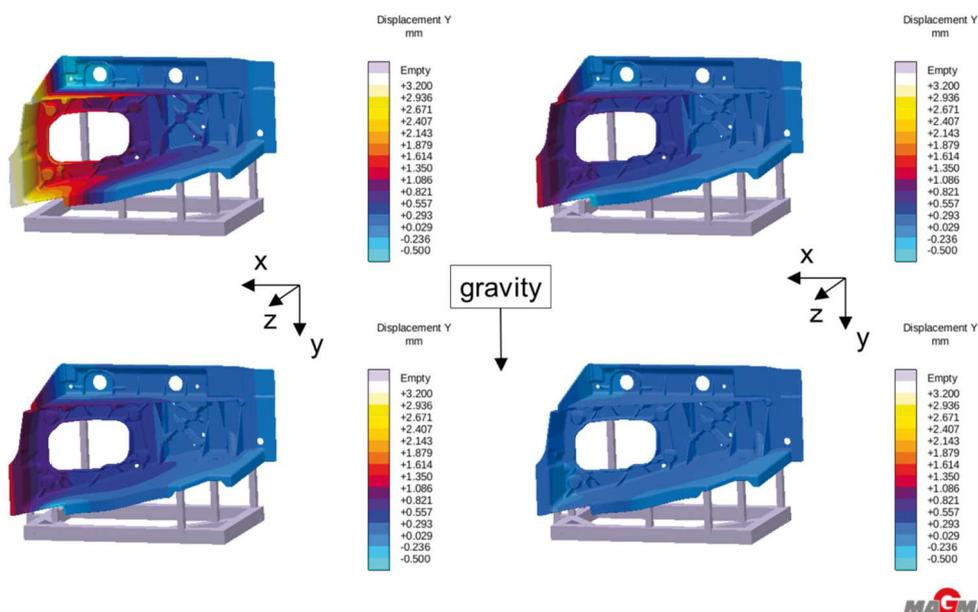

Fig. 15: Distortion of a structural die casting during solution heat treatment when placed on the four different support frames shown in Figure 14

Targeted autonomous optimization of heating element temperatures in a core box

The lifetime of core boxes is strongly related to the thermal balance of the tooling and cyclical stresses created by temperature changes over the core making process. It is, therefore, desirable to minimize the temperature changes the core box experiences during core making as well as to keep temperatures as uniform as possible over the entire core box volume. The complete core making process, covering core shooting, curing of the binder, and thermal cycling of the core box, can be analyzed using simulation and autonomous optimization.

Figure 16 shows a snapshot of the temperature distribution of both core box segments during a core making cycle. The areas corresponding to the thickest wall sections of the core remain at very low temperature levels. This leads to high cyclical stress, reducing the lifetime of the core box.
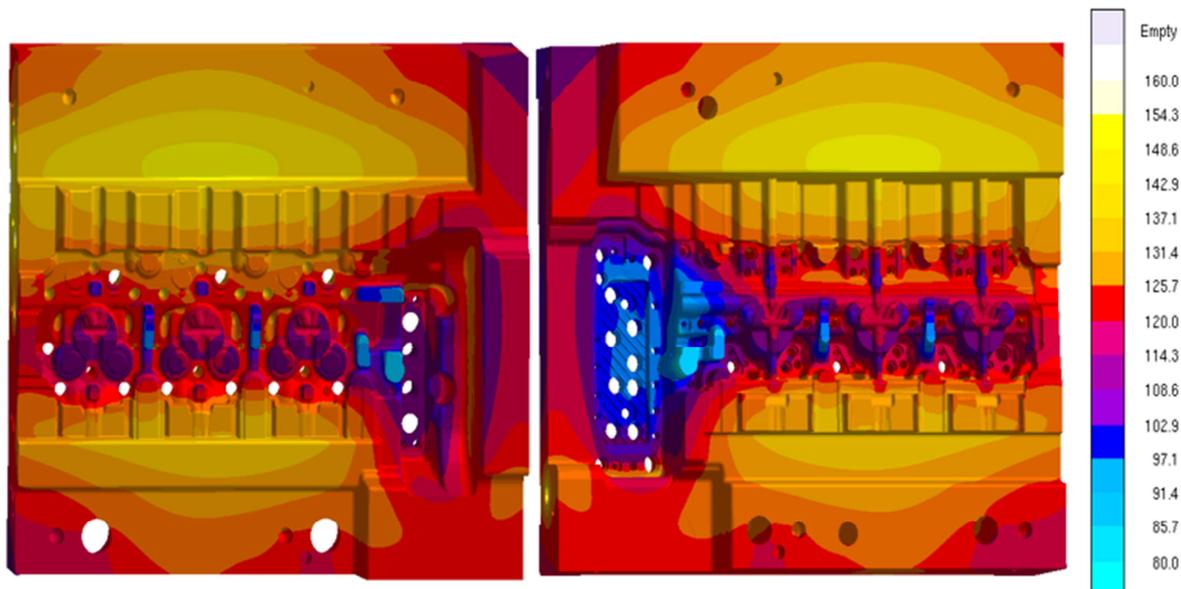

Fig. 16: Temperature distribution in both core box segments during cyclical core production

A more homogenous temperature distribution can be achieved by a targeted adjustment of the heating elements in the core box. Each heating element has its own individual influence on the temperature distribution in the tooling during cyclical production. In the real world, determining the effects of each individual heating element on the temperatures in the core box would require an extensive series of measurements. Autonomous optimization is therefore the ideal tool to evaluate a multitude of heating element configurations and their individual impact on the temperature distribution during core production. For this example, the effect of each heater on the temperature in the critical area can be seen in a main effect diagram (Figure 17). Heater #6 has the biggest impact on the temperature of the area of the core box that was deemed to be too cold, as indicated by the steep incline of the corresponding line. In contrast, the nearly horizontal line for Heater #3 shows that this element has nearly no effect on the temperature in the cold region.
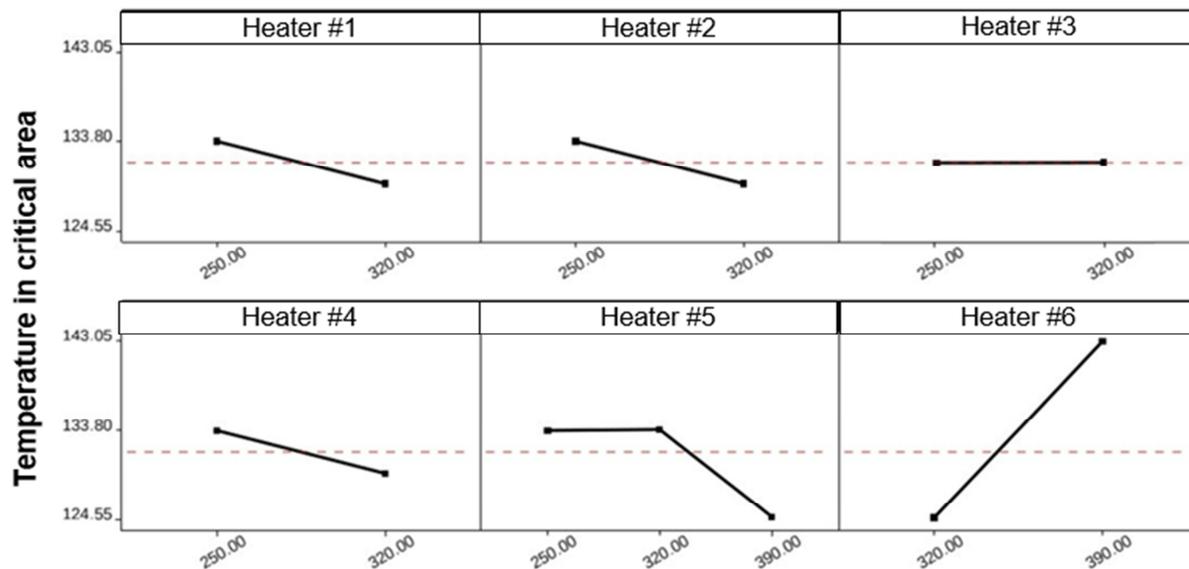
Fig. 17: Impact of individual heating elements on average temperature of the core box at a thermocouple located in the critical location.

Summary

Several examples have been used to show how the complete integration of autonomous optimization in the casting process simulation tool MAGMA[5] can be used to ensure optimized and robust casting layouts and process windows before the first metal is poured. The software searches for the best possible process parameters, optimal runner and gate positions and dimensions, as well as locations and sizes of risers and chills. Foundry engineers can use autonomous optimization as a virtual field for experimentation, to simultaneously achieve different quality and cost targets.

The goal of retaining the user-friendliness of the simulation tool while integrating this new methodology was achieved through the implementation of capabilities for parametric geometry creation and automatic parameter variation, together with tools for statistical analysis of autonomous designs of experiments and genetic algorithms for autonomous optimization. The simultaneous assessment of the derived results enables the foundry engineer to easily compare and evaluate outcomes from numerous simulations. Dependencies between design and process variables, quality criteria and objectives are clearly visualized.

Thirty years after the introduction of casting process simulation, foundry engineers now can combine single simulations, autonomous DOEs and autonomous optimizations to gain better process understanding and to establish robust casting processes making quality castings at the lowest possible cost.

Literature

[1] Hahn, I., Sturm, J.C.: Versuchspläne in der gießtechnischen Simulation, GIESSE-REI 96 (2009), Nr. 7

[2] Bramann, H., Pavlak, L.: Innovatives Produktdesign und robuste Prozessausle-gung durch virtuelles Experimentieren mit der Gießprozess-Simulation. GIESSEREI 102 (2015), Nr. 2

[3] Dieckhues, G., Gummersbach, T., Schmidt, D.: Feeder Design for an Aluminium Sand Casting, presentation at the International MAGMA User Meeting, Potsdam, Germany, October 2014

[4] Gaspers, H.J., Thorborg, J.: Design Optimization of Heat Treatment Support Frames for Aluminium Alloy Structural Cast Parts using Virtual Experimentation, European Conference on Heat Treatment (2015), Venice, Italy, May 2015.