Autonomous Engineering of Steel Casting – State-of-the Art, Applications and Ongoing R+D

40 years after its introduction, casting process simulation has become an accepted tool for the layout and process design of steel castings worldwide. Today, the results from simulation address many different quality issues in steel castings. The diversity of steel grades, the variety of factors that affect casting quality and complex interactions between physics, metallurgy, casting geometry and the process sequence all play a role in the quality of a steel casting. Empirical knowledge (even if supported by the insights of simulation) just confirms a single predefined operating point but does not provide information about the possible optimum nor about the robustness of the chosen process window. Autonomous Engineering overcomes these limitations by offering the foundry expert a virtual field for systematic experimentation. Autonomous Engineering is a methodology utilizing multiple Magmasoft simulations as a set of virtual experiments in order to achieve the best possible solution. This paper illustrates the benefits of Autonomous Engineering for steel castings using different industrial applications as examples. In addition, new capabilities and current R&D activities are discussed. Applying these developments, the steel foundry will be offered unique opportunities to achieve new and optimized applications as well as to define reliable manufacturing routes before the production of a high integrity casting has begun.

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1 Introduction

The beginnings of computer-aided predictions of casting processes date back to the 1960s and early 1970s. At first, it were mainly so-called expert systems that linked empirical knowledge with geometric information based on ideas proposed by Heuvers, Pellini and Chrorinov [1],[2] and applied them to steel castings.

This was followed by the first 2-dimensional simulation applications that for the first time took physical laws into account (e. g. Fourier's heat conduction equation). Finally - also thanks to increasing computing power - 3-dimensional simulation models were developed in the 1980's [3],[4].

Steel castings were the first materials to which "solidification simulation" was applied. This was due to the nature of solidification of steel castings, where the formation of shrinkage related defects is strongly linked to the formation of hotspots in the casting. In this way, even a limited heat flow simulation could aid steel casting experts in identifying critical areas in their design and methoding.

In metal casting processes, 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 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 the casting process by evaluating the final component's quality based on real-world trials and pursuing quality and economic objectives simultaneously.

This is especially true for steel castings, with their unbeaten diversity of grades, resulting microstructures and properties, and the multiple manufacturing steps to achieve the required quality from metallurgy through casting, heat treatment, upgrading to machining. To meet today's specifications in making high integrity steel castings requires a profound understanding of the material behavior and the process robustness for the en-

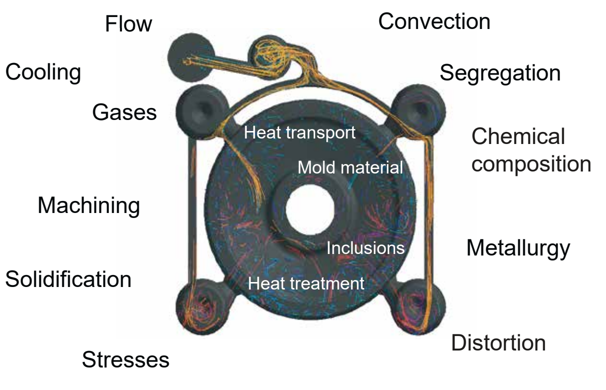

Figure 1: A challenging task: Simulating the entire casting process to predict component properties.

tire manufacturing route. The technology of simulating the casting process and predicting the resulting material properties has become an extremely instrumental methodology in two ways:

– Making the mold as a black box transparent for the foundry specialist, helping him to understand the root causes of possible problems prior to producing the first casting.

– Developing virtual simulation tools for the casting process requires a profound and quantitative understanding of the impacts of physics, metallurgy and chemistry as such.

This has changed the empirically driven process substantially into a first principle based and reliable manufacturing process (**figure 1**). Through these efforts, today foundrymen can assure the sustainability and growth of their businesses while maintaining a sizable technological edge over competition. Quantitative results provided by casting process simulation also help designers to understand the impact of the process on the performance of castings in use. For most steel foundries, casting process simulation is used daily as a standard tool to assess gating and risering and to predict feeding. It has become an instrument in quality systems and process optimization. State-of-the-art simulation tools consider the special material behavior of the diversity of steel grades with respect to their alloy composition, melting practice, and metallurgy [5],[6].

2 Casting Quality Prediction and Optimization

Until recently, casting process simulation tools have been used by foundry engineers to confirm the quality for a set of already decided process conditions and to evaluate a given casting layout. The results available today from process simulation address many different quality issues in steel castings [7],[8] (**figure 2**). The success of this sequential approach is strongly linked to the skills of the foundryman. Due to the variety of factors that affect casting quality and the complex interactions between physics, metallurgy and casting geometry, even the expert will not obtain information about a possible optimum nor about the robustness of the process window chosen. A new approach overcomes these limitations.

This new methodology, called Autonomous Engineering, utilizes multiple simulations with Magmasoft [9] as a set of virtual experiments in order to achieve the best possible solutions. Autonomous Engineering uses the simulation tool as a virtual experimentation or test field. By changing the casting technology of a steel casting, e. g. the gating and risering design or manufacturing parameters, the software aims to find an optimal operating point within the specified limits. Several parameters can be changed at the same time and can be evaluated independently from each other. In addition, the process robustness can be assessed already before the first casting has been made. This methodology is put into

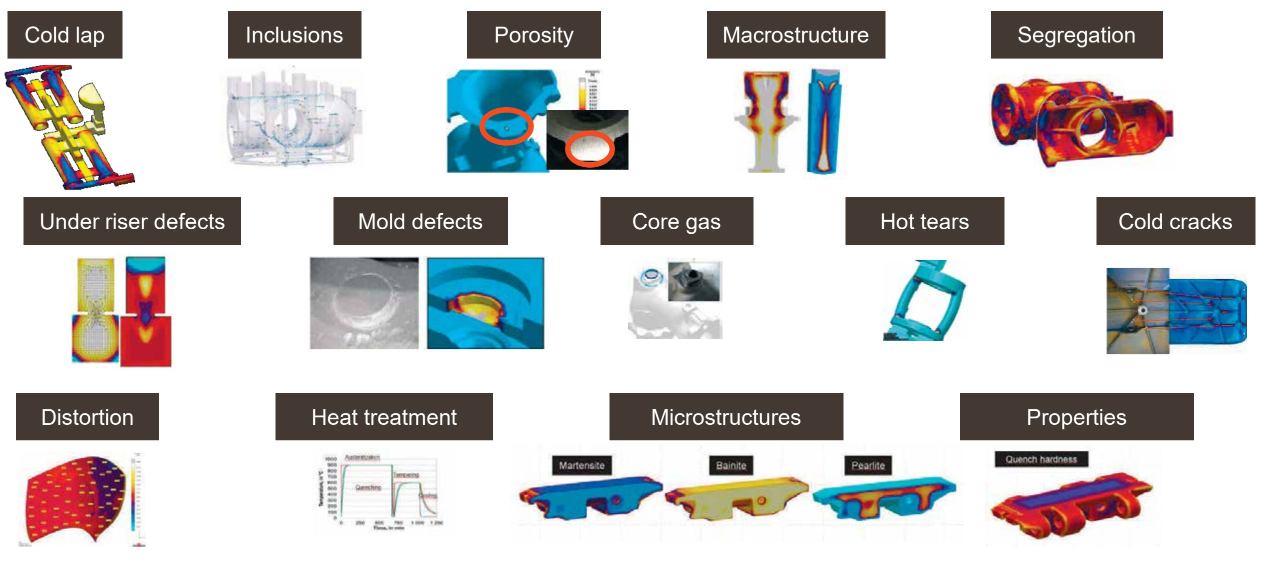

Figure 2: Simulation and prediction of different quality issues in steel castings.

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practice by foundries for defect avoidance, as well as for the optimization of the entire process route in making high integrity steel castings.

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 of various process parameters on reaching a robust process window can be assessed in early phases of casting, pattern and process development. Autonomous Engineering asks the foundryman to address the following questions before the first simulation is done (**figure 3**):

- select (different) objectives (quality and/or cost/yield),
- define what can be varied (geometry, process parameters),
- select relevant quality criteria (output values), as calculated quantitative results [10].

The effects of selected variables which span a process window are either evaluated using statistical tools such as a virtual DoE (Design of Experiments) or so-called Genetic Algorithms which search for an optimum autonomously. One possible outcome of this approach is to evaluate the impact of each process parameter on the casting process, in order to predict its impact on the investigated or measured objective at any point within the process window. A minimum number of experiments must be used to find critical parameters influencing the final objectives, i. e. casting quality or manufacturing costs. For an almost trivial example, **figure 4** shows the autonomously simulated results of changing the number of feeders on a ring shaped steel casting as a function of the maximum shrinkage indication. It demonstrates that Autonomous Engineering does not only find the best possible solution but also offers information on the robustness for a defect-free casting.

The methodology of Autonomous Engineering is not a replacement for process knowledge and expertise of the foundryman. 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. In combination with the requirements placed on the casting he has to decide on the objectives to be achieved. Quantitative descriptions of the important influencing factors, measurable quality and cost indicators and the goals to be achieved are required to answer these questions. Applying these developments as an integral part of Autonomous Engineering, the steel foundry is offered unique opportunities to achieve new and optimized applications as well as reliable manufacturing routes before the production of a high integrity casting has begun.

3 Assessment and Optimization of melt Cleanliness

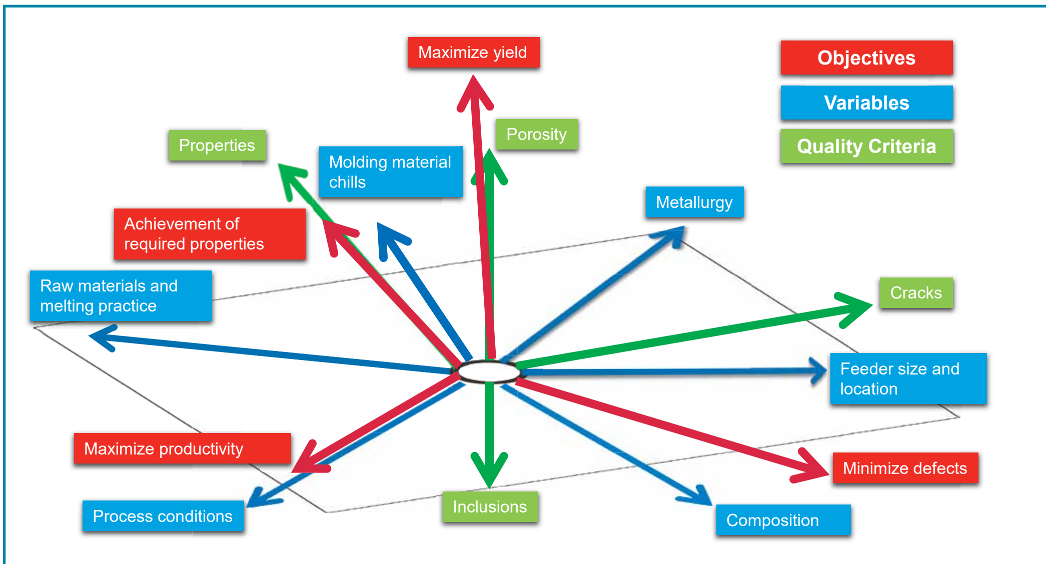

Figure 3: Virtual design space for Autonomous Engineering composed of varying process parameters, calculated quality criteria and optimization goals defined in the software [10].

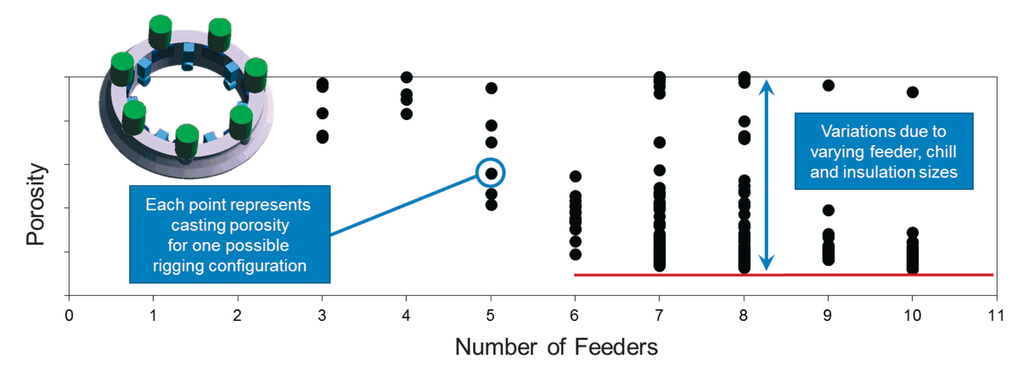

Figure 4: Porosity prediction in the casting versus number of feeders for the methodizing of a ring-shaped steel casting using Autonomous Engineering.

Cleanliness is a key criterion determining the quality of modern steel castings. The agglomeration of inclusions in critical sections can lead to an unacceptable reduction in mechanical properties, resulting in excessive cleaning or upgrading times. Most inclusions in steel castings are caused by reoxidation of the metal through contact with air during the mold filling process. In the following example (**figure 5**) [11] the impact of the gating design on the number and distribution of reoxidation inclusions on the surface of a steel casting was investigated. The software autonomously evaluated twelve different previously prepared gating designs. Without any interaction of the user, each simulation in the autonomous DoE was set up, calculated and its results were assessed based on the relevant quality criteria.

The results of the different designs (**figure 6**) were 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 6, each adjacent to its respective simulated surface cleanliness result.

4 Robust Casting Engineering

The manufacture of a sound and quality casting is highly dependent on its methoding. During engineering, the defined gating and risering as well as the chill concept will have a direct impact on the quality of the cast part. The majority of casting defects can be avoided with an optimized gating and risering system, mostly paying the price of reducing the yield or increasing the manufacturing costs. In the following case (**figure 7**) [12] multiple feeders, chills and also gating concepts have been investigated and demonstrate the benefits of a systematic use of Autonomous Engineering. The main objective is to find the best compromise between a minimized


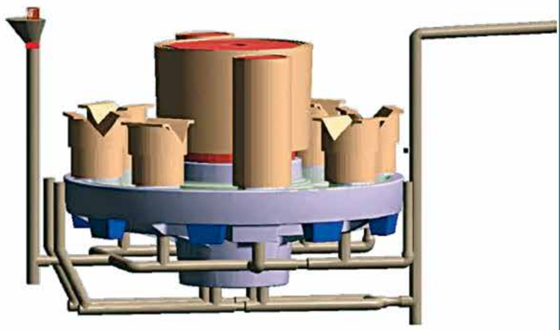

Figure 5: Finished part and typical gating design [11].

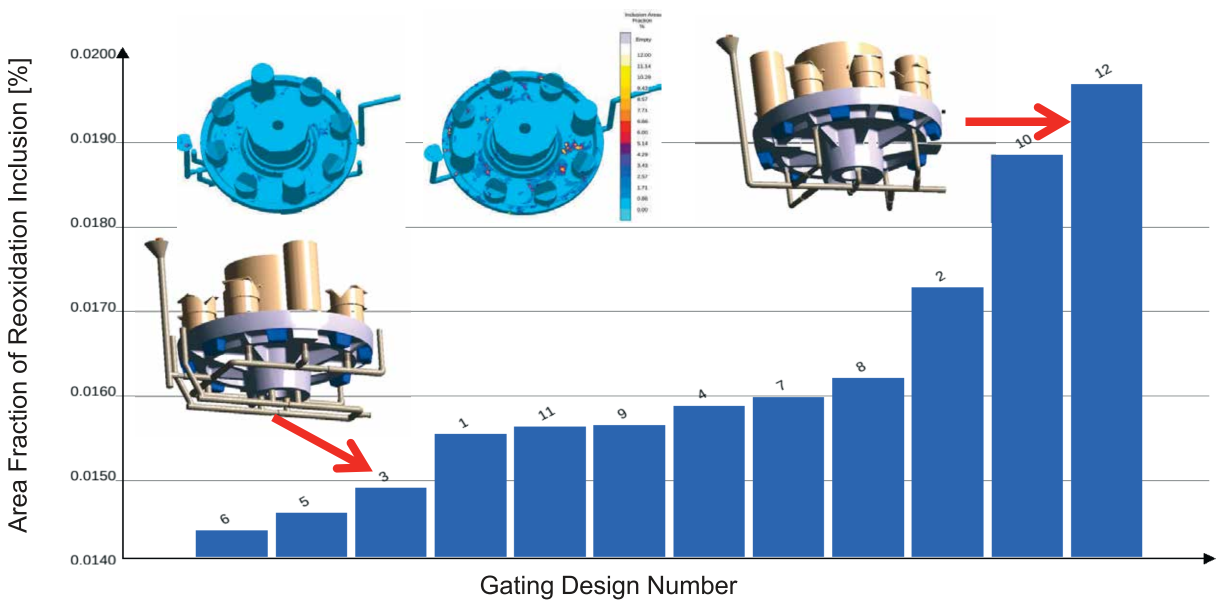

Figure 6: Automatic and quantitative assessment of several gating designs as they relate to surface quality - Ranking of different gating systems vs. area fractions of reoxidation inclusions.

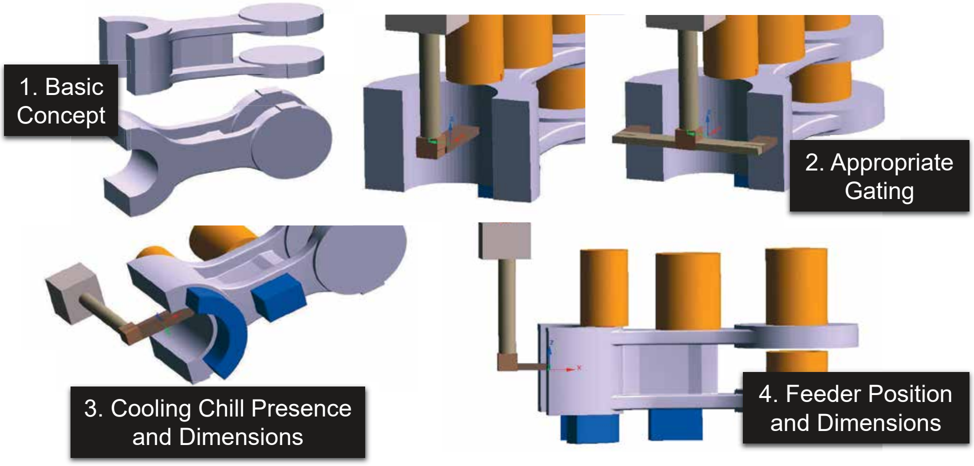

Figure 7: Casting geometry and necessary steps to layout the methodizing for a steel casting minimizing casting porosity and optimizing the yield [12].

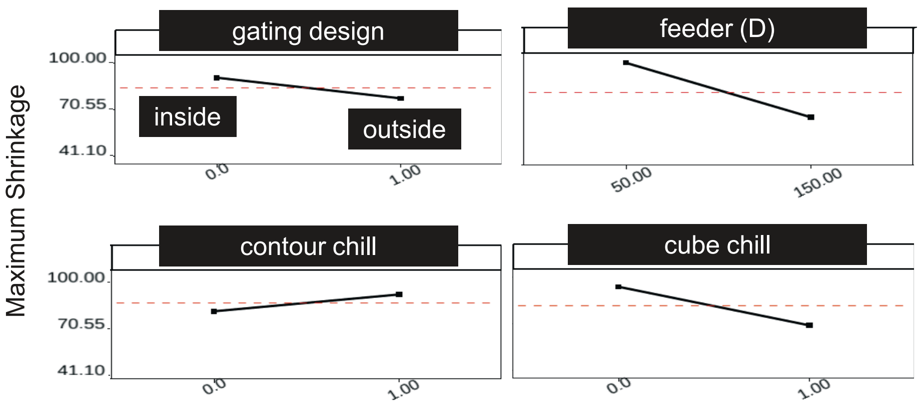

Figure 8: Main effect diagrams for shrinkage in the casting as a function of varied gating, feeder and chill designs.

amount of porosity in the part and a maximized casting yield. **Figure 8** shows the main effect diagrams of a virtual DoE evaluating the impact of different gating, feeder and chill designs on the shrinkage. The slopes of the corresponding lines show that especially the cube chill and the riser diameter are significant on the reduction of porosity in the casting. This information provides clear guidelines to optimize the gating, risering and chill layout for the given objectives.

5 Optimizing Feeder Dimensions to Maximize Weight Savings

The classical area of applying casting process simulation in steel casting methodizing is the layout of the feeding system. Major parameters of a feeding system include feeder shape and modulus, neck dimensions, feeder location and the utilization of different feeding aids. In the example (**figure 9**) the task was to find an optimal number, size and combination of feeders to maximize weight savings of a steel casting. The calculations were performed for the low alloy carbon steel (GS20Mn5) [13].

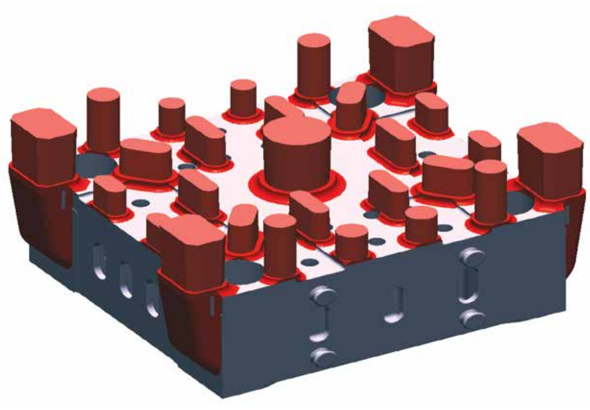

Figure 9: Complex feeding system for a steel casting: by parametric modeling of the feeding system it is possible to find an optimal set up and combination of feeders to maximize the casting yield [13].

Rank	Design	Increase Yield	Reduce Hot Sp	Reduce Microp	Reduce Porosi
Rank 1	Design 5	0.75	47147172.0	0.51	0.0
Rank 2	Design 6	0.74	19386774.0	0.52	0.0
Rank 3	Design 13	0.75	0.0	0.51	0.0
Rank 4	Design 14	0.74	0.0	0.52	0.0
Rank 5	Design 12	0.75	13762967.0	0.52	10.05
Rank 6	Design 7	0.74	0.0	0.5	0.0
Rank 7	Design 4	0.75	89863792.0	0.52	0.0
Rank 8	Design 15	0.74	0.0	0.5	0.0
Rank 9	Design 8	0.73	0.0	0.63	0.0
Rank 10	Design 16	0.73	0.0	0.63	0.0
Rank 11	Design 11	0.76	130405688.0	4.22	124.98
Rank 12	Design 3	0.76	170257072.0	3.71	165.34
Rank 13	Design 2	0.76	164709808.0	3.25	376.15
Rank 14	Design 10	0.76	335829216.0	4.22	209.39
Rank 15	Design 1	0.77	151549872.0	4.21	789.08
Rank 16	Design 9	0.77	379691904.0	3.9	659.48

Figure 10: Ranking and weighing of different quality criteria and yield for 16 different feeder designs. For illustration, selected respective 3D-views of the predicted porosity levels have been added to the table.

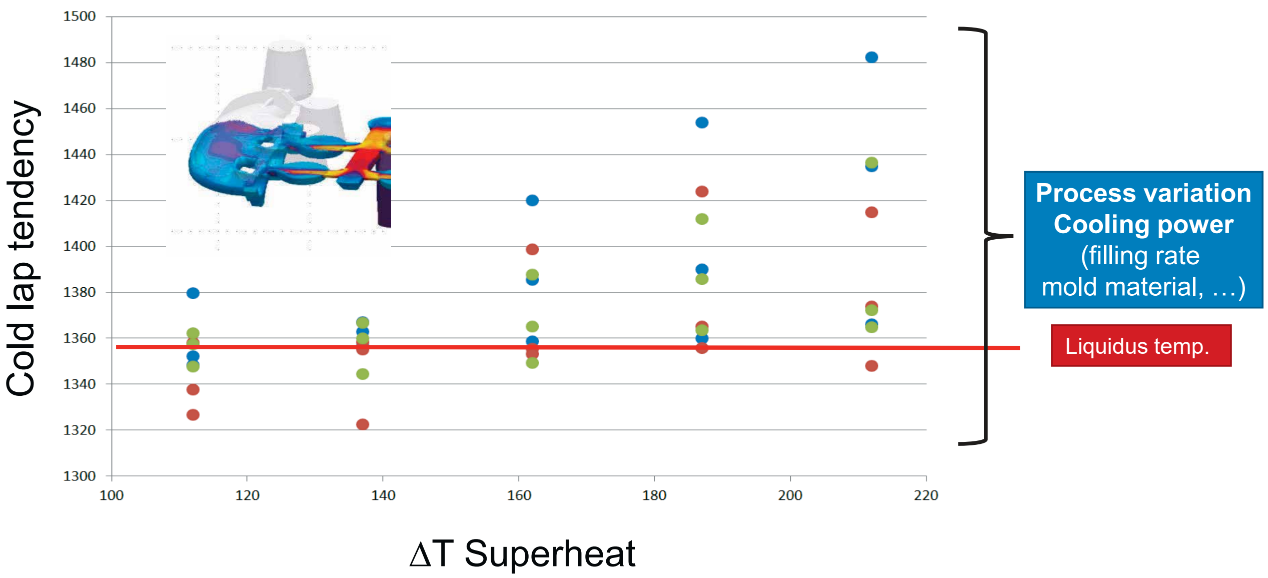

Figure 11: Quantitative prediction of cold lap tendency in thin-walled steel castings as a function of varied filling conditions, superheat of the melt and cooling power of the mold.

Figure 10 shows the ranking of different quality criteria and yield for 16 different feeder designs. The best design of the DoE (Rank 1) shows the best compromise between minimized porosity and maximized casting yield.

6 Robust Process Conditions to avoid Casting Defects

Especially in thin-walled steel castings, low temperatures on the metal front during filling or uneven local filling times may cause surface defects such as cold laps or misruns. Superheating of the molten metal will increase fluidity and retard freezing. On the other hand, excessive superheat can cause other problems such as gas pickup of the melt or increased metal-mold reactions causing defects such as burn-on or penetration. The case study in **figure 11** demonstrates how changing process parameters, like pouring rate and pouring time, cooling power of the mold material and pouring temperature, affect the cooling of the metal and consequently the cold lap tendency in thin-walled steel castings. Each point in the figure represents one virtual experiment. The chart shows the effect of superheat on the cold lap tendency, with temperatures below the liquidus temperature indicating an increased risk of incomplete filling. At the same time, the impact of the other varied process con-

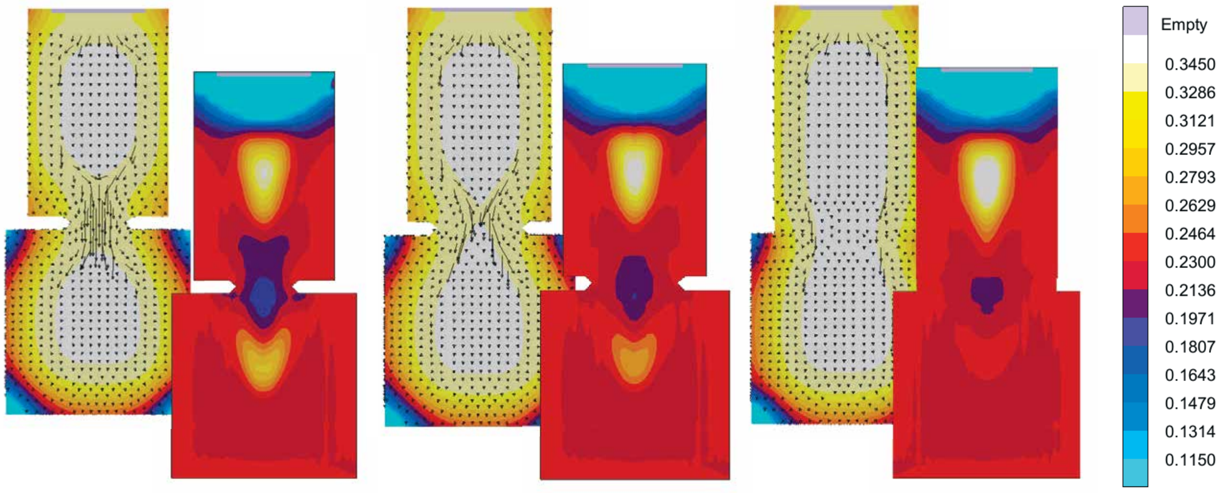

Figure 12: Predicting under-riser segregation considering feeding and convective flows.

ditions on the process robustness can be assessed. Here, a superheat of 160 or more degrees leads to high enough temperatures during filling to minimize cold laps, regardless of other process variations in cooling power or filling times.

7 Optimizing Casting Quality and Microstructure

The quality of the cast material is affected by many parameters such as metallurgical, casting process and solidification conditions. For heavy section castings, convective currents during solidification usually cause macrosegregation and change the feeding conditions in the casting. Segregation of alloying elements occurs in all steel casting processes. Natural convection during solidification is caused by density gradients in the liquid. Such density gradients arise from two driving forces: temperature gradients in the liquid and concentration differences. Magmasoft offers the ability to consider the impact of thermal convection on the development of macrosegregation within the casting. In addition, the software offers the coupled calculation of convective and feeding flows. This improves the quality of the segregation predictions and also the assessment of the feeding behavior, especially in risers that have a narrow feeder neck (**figure 12**). The under-riser segregation of especially carbon, which commonly occurs beneath risers, can cause significant problems like poor mechanical properties in a steel casting, because the steel chemistry in this region is different from the intended chemistry. Under-riser segregation can also lead to cracks in the casting when the riser is removed or when the surface is machined [14].

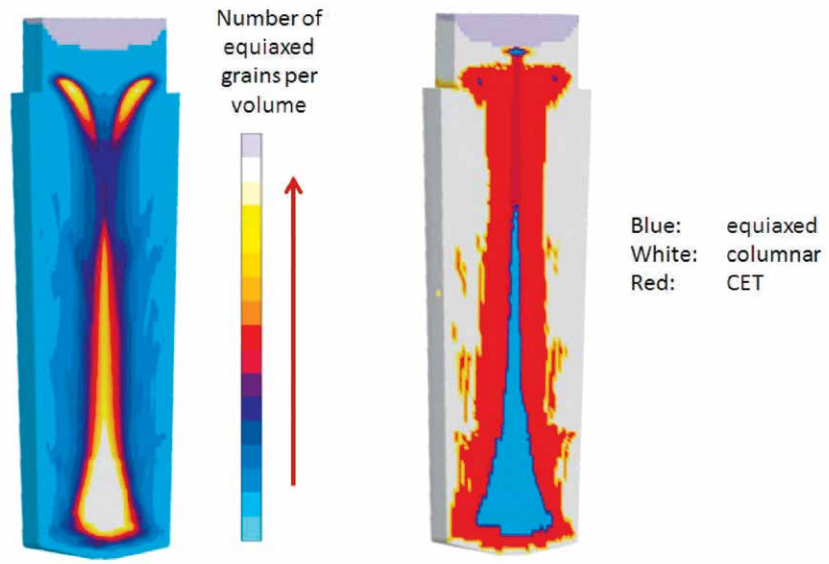

Figure 13: Predicting grain size and columnar to equiaxed transition in ingot castings.

Especially in ingot castings, a multitude of different microstructures are present. Due to thermal and concentration differences, two different types of grain morphologies are formed: columnar and equiaxed. A transition from columnar to equiaxed growth (CET) takes place when nucleation of equiaxed grains occurs in the liquid ahead of the columnar zone. CET and the final microstructure depend on numerous parameters such as cooling rate, speed of columnar growth, thermal gradient in the liquid, grain refinement and transport of growing grains in the melt. New developments in Magmasoft offer the ability to simulate the impact of these parameters on the columnar to equiaxed growth (CET), related typical segregation phenomena (A-type segregates) and final microstructure during the solidification of ingot castings [15] (**figure 13**).

Figure 14: Casting design for a carbon steel pump casing.

decisions. For example, pouring fast reduces inclusion costs by $34 on average and venting the core reduces costs by $109 on average. On the other hand, pouring hotter increases burn-in removal costs by $44, but also decreases inclusion defect rework by $32 and shrinkage porosity rework costs by $30. The range between the best and the worst case scenarios for the total rework cost amounts to $202. This reflects 9 % of the total casting costs. This example shows that using simulation systematically by varying design or process parameters quantifies the cost impact of engineering decisions.

8 Linking Technology Decision with Cost Optimization

Steel foundries are always aiming to optimize the production time and costs over the entire casting processes. Knowing the impact of technical decisions on resulting costs is a key to making reliable decisions. A systematic test plan using Autonomous Engineering can be utilized to assess different cost objectives of high quality castings. As an example, the variation of selected process parameters was investigated for a carbon steel pump casing with a part weight of 267 kg and a pouring weight of 706 kg (**figure 14**), in order to achieve the best possible compromise between casting quality and the repair costs of casting defects [16].

In this case, it is necessary to understand the influence of changing process parameters on the repair costs of different casting defects. The process parameters varied were pouring time (fast, slow), pouring temperature (low, high) and core venting (vented, not vented). This leads to a total of 8 different virtual experiments using automatic optimization. In order to show the influence of process variations on the manufacturing cost, the rework costs for possible inclusions, macroshrinkage and microporosity are considered. The resulting repair costs in **table 1** allow the quantitative assessment of engineering

9 Reduction of Hot Tearing Through Casting Design and Rigging

The majority of scrap in steel foundries results from shrinkage defects, inclusions and hot tearing. To select the best possible methoding and process conditions to reduce the rework cost of repair welding of hot tears, it is necessary to investigate the risks in a systematic manner. The following example illustrates this process for a crucial part of a pump assembly. The initial design and layout of the feeders produced significant scrap due to tearing at the inner corners of the longitudinal braces (**figure 15**). The foundry decided to carry out a virtual DoE to evaluate different combinations of the gating and feeding system layout. In order to understand the impact of the process variations on reducing hot tearing, the position of the casting, the casting geometry, the feeder configuration and the process parameters were varied. 12 different virtual experiments were considered in terms of feeding, porosity level and temperature history to evaluate the hot tear criterion during the stress analysis [17].

Figure 16 shows the results for all the design combinations and illustrates the opposing trends regarding porosity and hot tear formation. The objective is to find the best compromise between the two competing objectives. As expected, the stron-

Table 1: Cost effects of process variations based on 8 different virtual experiments

Design	Burn-in Removal	Gas Porosity Repair	Inclusion Repair	Shrinkage Porosity Repair	Total Rework Costs
1	$13.98	$201.90	$148.90	$230.00	$594.78
2	$14.32	$14.07	$124.50	$247.40	$400.29
3	$62.33	$206.90	$111.30	$208.80	$589.33
4	$65.53	$133.80	$120.70	$218.00	$538.03
5	$11.78	$207.80	$151.50	$231.50	$602.58
6	$11.98	$130.40	$77.11	$252.10	$471.59
7	$48.91	$160.00	$60.02	$200.00	$468.93
8	$50.92	$64.73	$80.14	$212.80	$408.60

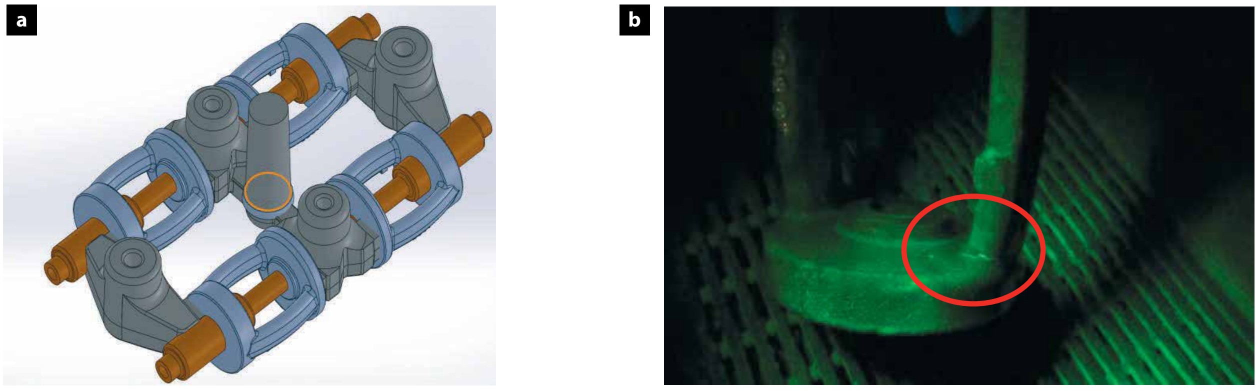

Figure 15: Original situation: a) CAD model of the casting and b) critical area with cracks identified by magnetic particle inspection.

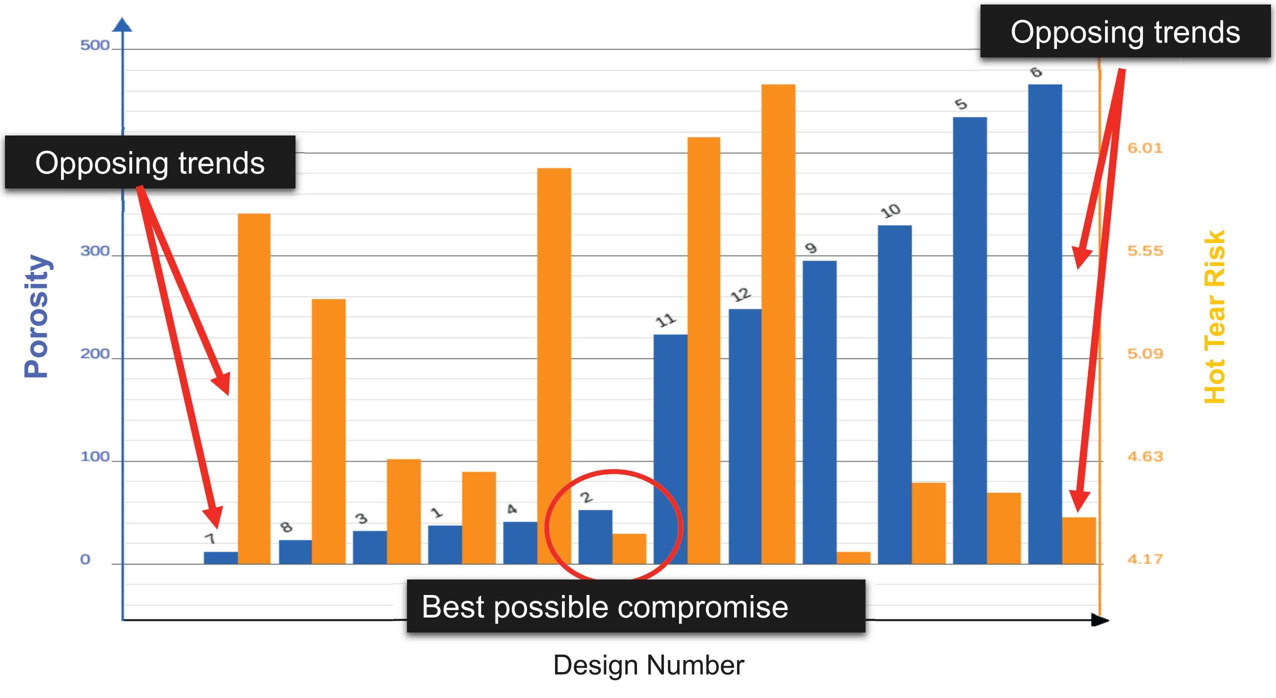

Figure 16: Porosity and related hot tear tendency for all virtual experiments in a bar chart; Design #2 provides the best compromise between the conflicting objectives.

gest tendency for hot tearing was revealed for optimum feeding with minimum porosity. This is due to longer solidification times and increased temperature differences between the casting and the feeders, promoting feeding but also resulting in higher strain rates and an increased tendency for hot tearing. Implementing the optimized solution, it was possible to reduce the hot tear risk in the critical solidification range by approximately 60 % compared to the original situation. As an additional benefit, it was subsequently possible to reduce both, the amount of magnetic particle inspections required as well as the amount of repair welding.

10 Quality Prediction and Process Optimization of Heat treatment

The heat treatment of a steel casting has a major influence on its final material properties. Cast steels are characterized by a large variety of microstructures and related mechanical properties after the heat treatment process. For the determination of microstructure and mechanical properties in a heat treated casting, it is important to have a precise local temperature history in the casting for the various stages of heat treatment (e. g. austenitization, quenching and tempering). Process simu-

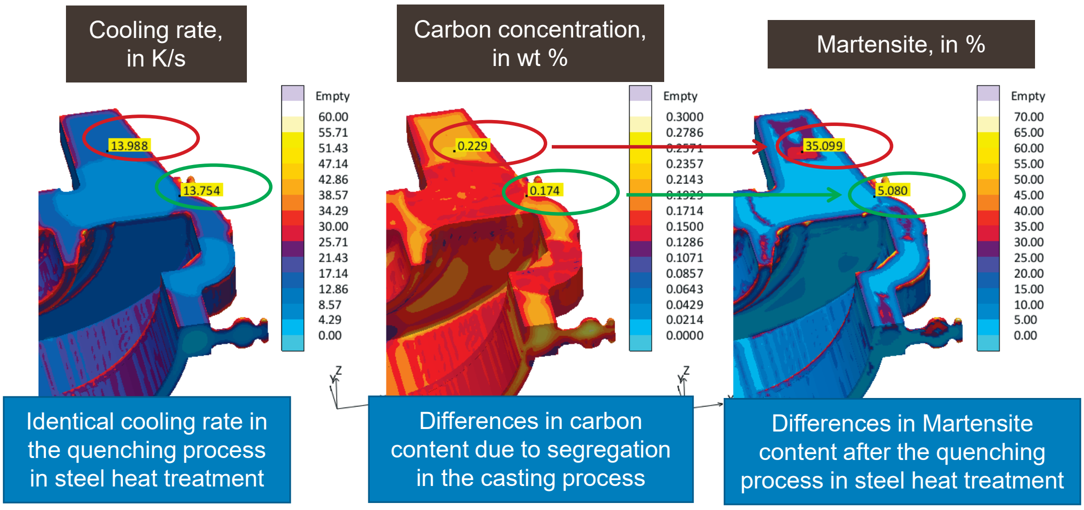

Figure 17: Effect of carbon segregation on martensite formation during quenching.

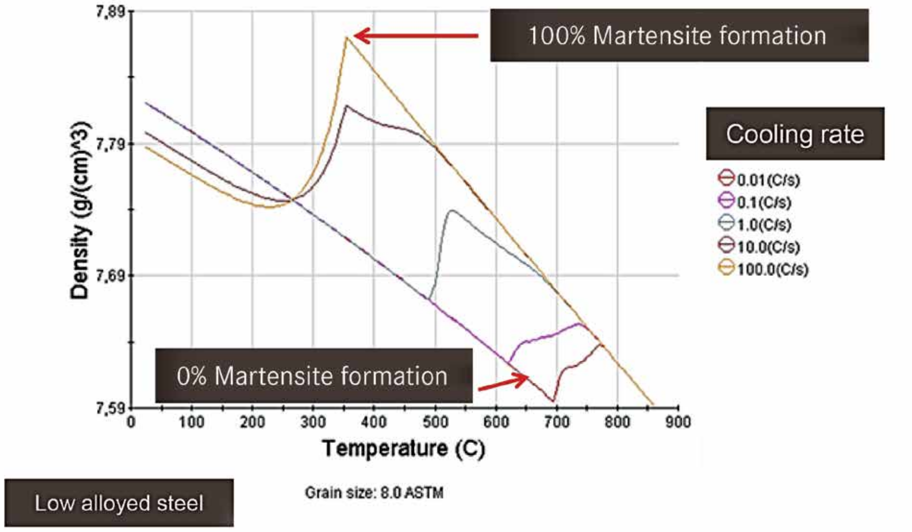

Figure 18: Density as a function of temperature. The density curve changes locally depending on the microstructure formation.

lation using Magmasoft is able to predict microstructures and also resulting mechanical properties as a function of the heat treatment process conditions. All significant process variations such as cooling rates and conditions, austenitization time and temperature and also chemical composition during the heat treatment process are taken into account to establish a robust industrial process design for high quality cast steel products [18]. This is possible for carbon, low and high alloy steel grades. New developments also allow the prediction of local microstructures and material properties considering segregation profiles from the casting process. A cross-section of a steel turbine housing is shown in **figure 17**. It shows the impact of carbon segregation on the local martensite formation after quenching for two regions with similar cooling rates during the quenching process.

A further aspect that can be modeled during heat treatment are residual stresses during the heat treatment process. During austenitization, the stress level and stress relief in the casting is governed by creep effects. During quenching, stresses are built up strongly, driven by high temperature gradients and also volume and density changes in the cast part (**figure 18**), which increase crack risks during quenching. In order to minimize part distortion and crack risks, it is necessary to establish a good compromise between material characteristics and tolerable stress levels. **Figure 19** shows the predictions of various microstructures as well as mechanical properties for a chain link (low alloy carbon steel). As expected, the higher the cooling rate during quenching, the higher is the martensite content and tensile strength near the surface of the casting.

To establish robust production conditions, also here performing a Design of Experiments virtually before the real process allows assessment of the impact of heat treatment process variables on material properties quantitatively. In order to realize the best compromise between the microstructure (martensite content after quenching) and material properties (hardness and elongation) different parameters were investigated. Process parameters varied were carbon content, austenitization

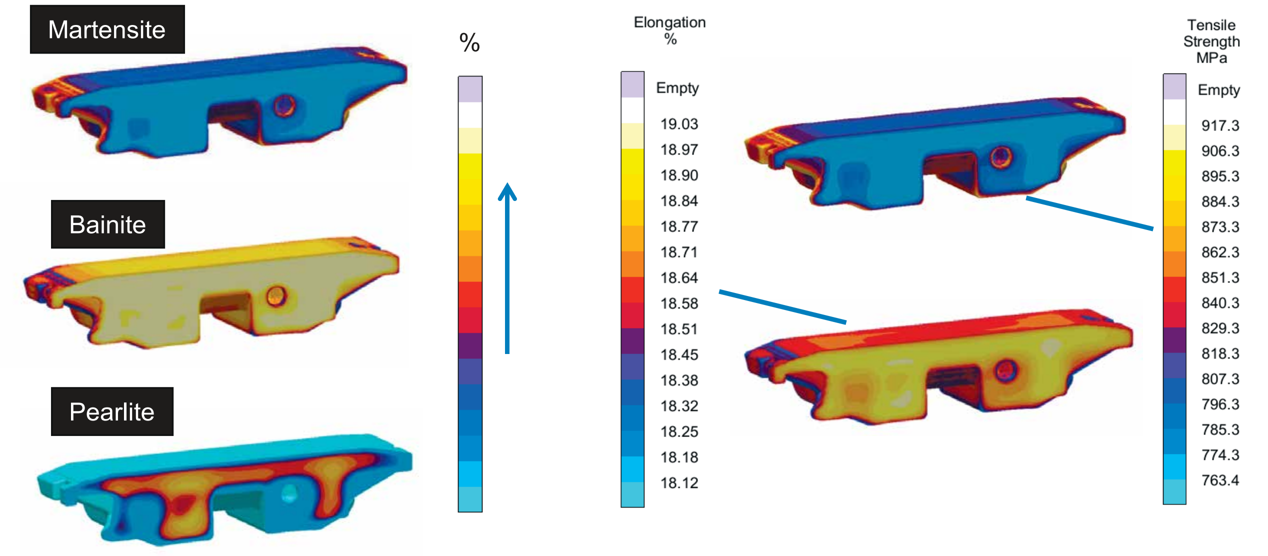

Figure 19: Typical results of the heat treatment simulation of a low alloy steel chain link: predicted microstructures in the cross section after quenching and related mechanical properties.

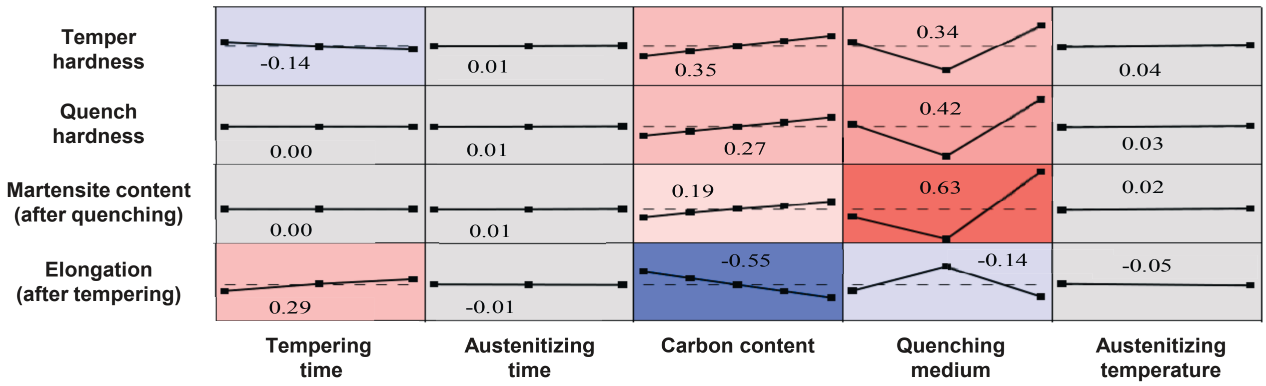

Figure 20: Correlation matrix between process parameters and objectives.

Blue colour: negative impact
Red colour: positive impact

temperature, quench media and austenitization and tempering times. **Figure 20** shows the correlation matrix between the objectives and process parameters. Red colors correspond to a positive correlation of the process parameter with the respective objective; a blue color indicates a negative one. As indicated in figure 20, the variation of carbon content and quench medium have the strongest effect on the martensite content and consequently on the quench and the temper hardness. This is confirmed by the chart in **figure 21**, which shows the variation in the martensite fraction as a function of the carbon content for three different quench media.

11 Optimization of Stresses and Distortion for the Entire Casting and Heat Treatment Process

During casting and heat treatment, the cast part experiences inhomogeneous temperature fields. Due to the thermal contraction of the metal these temperature gradients cause residual stresses and distortions. Today, simulation allows the consideration of casting distortion throughout the entire process chain. It is possible to simulate the entire sequence of process steps and evaluate the final stress levels and distortion after both, casting and heat treatment. Calculation of stresses and distortion during heat treatment are performed considering the stress state at the end of casting process [19]. The heat treatment process can be analyzed to evaluate the level of stress relaxation at high temperatures and the building up of stresses during cooling and quenching. Furthermore, the change in shape can be evaluated at the end of heat treatment by comparing the final level of distortion with the part shape after casting. The model used considers the time and temperature dependency of the cast material during the heat treatment process, which governs the stress relaxation at high temperatures in the furnace.

These capabilities provide the possibility to optimize the casting design and make sure that support frames provide

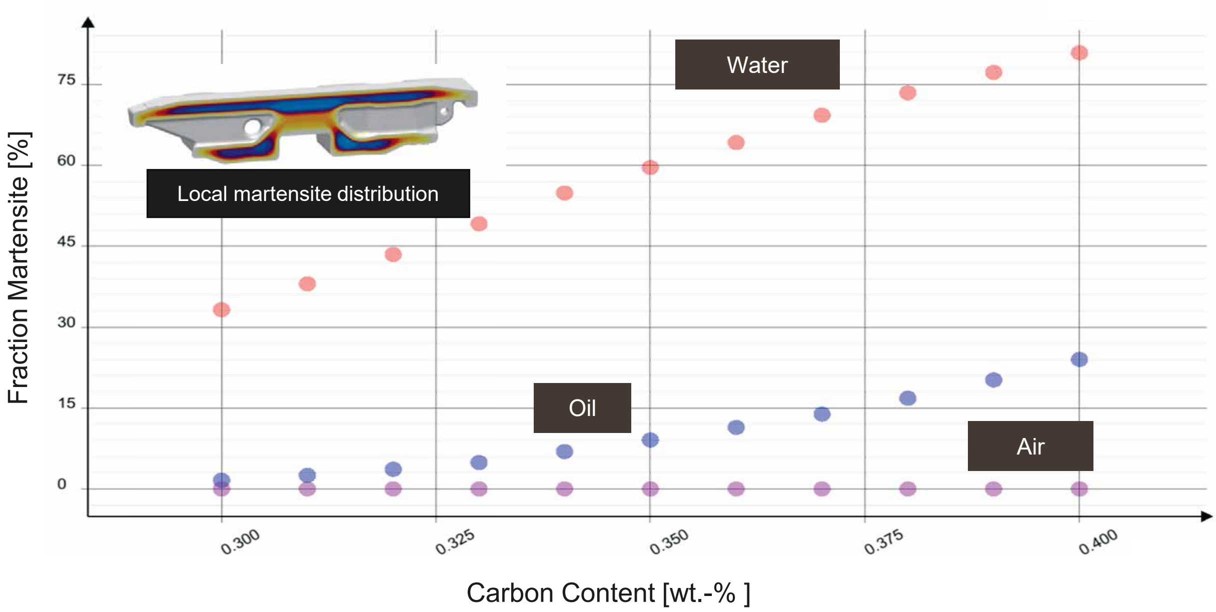

Figure 21: Influence of the carbon content and quench medium on the fraction of martensite in the casting.

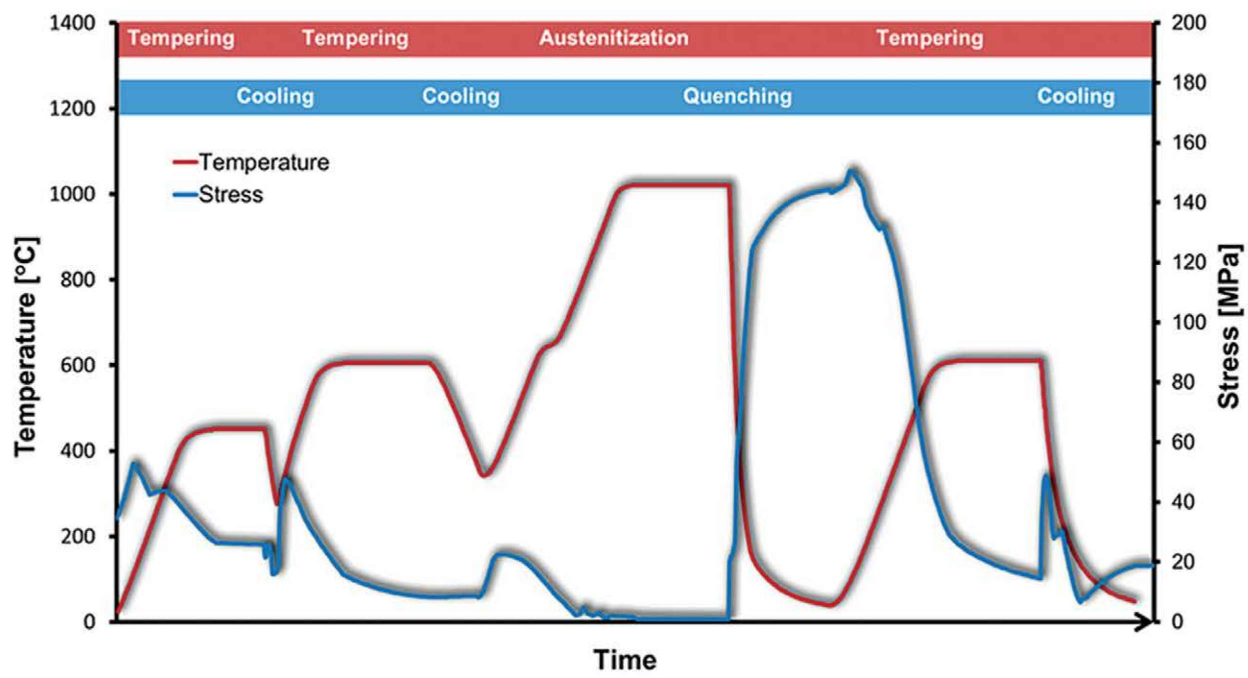

Figure 22: The geometry and positioning of the blade during heat treatment [13].

sufficient stability at high temperatures during heat treatment. In the example shown here, a large steel turbine blade was investigated. The blade is part of a Francis turbine, with a weight of 13.4 tons, where the weight of the feeders and gating system is 8 tons. The dimensions are 4.3x3.5 m and the alloy is the martensitic stainless steel CA-6NM. After casting, the part is heat treated by quenching from 1,020 °C and tempered at 600 °C. The geometry of the blade and how the blades were positioned for the heat treatment process are shown in **figure 22**. The two curves shown in **figure 23** visualize the temperature and stress levels at a point in the thick section of the blade as a function of time during the different heat treatment steps. The temperature and stress profiles from the heat treatment process clearly indicate the expected stress relaxation at elevated temperatures, followed by an increase in stress levels during cooling. The stress level sensitivity to cooling rate and thermal gradients is visible in the big increase in

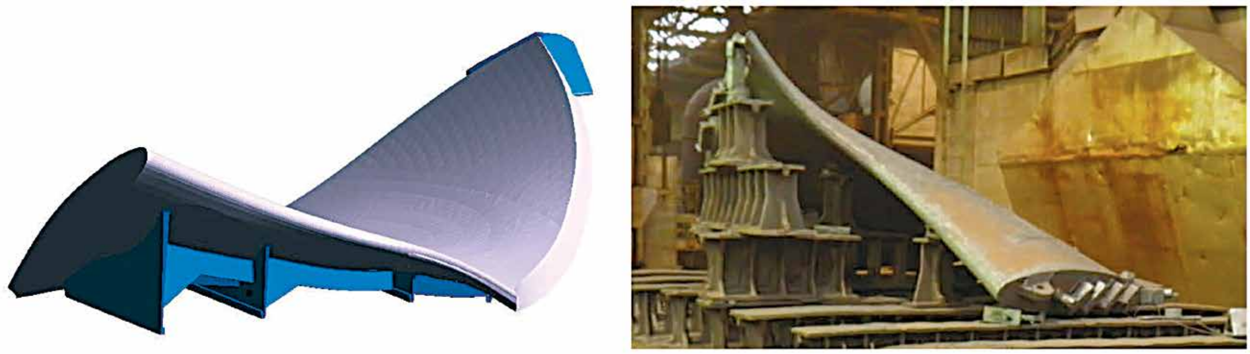

Figure 23: Temperature profile during heat treatment and the corresponding stress development in the interior of the thick section of a blade for a Francis turbine.

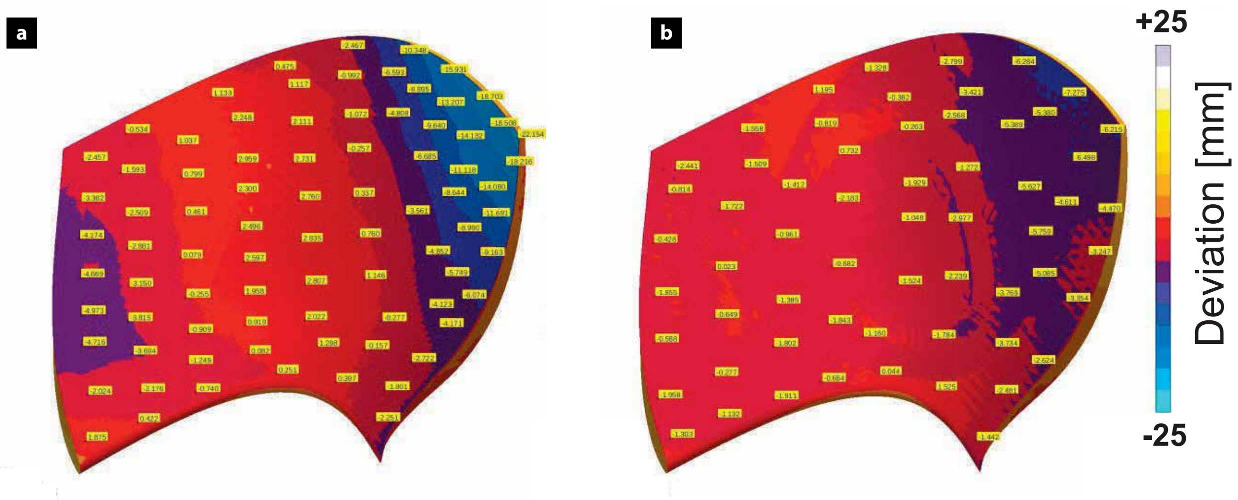

Figure 24: Deviation between the simulated distortion and the target geometry: a) initial calculation and b) after pre-shaping the pattern.

the stress level during quenching, compared to the lower increase in stress level during the slower cooling steps.

For this particular case, a step-wise integrated analysis of the casting and heat treatment processes was performed. Results from the casting stress analysis were used to pre-shape the pattern to compensate for the thermal contraction and distortion built up during the casting process. Pre-shaping was done to the CAD geometry by applying the negative of the distortion between the results from the first simulation and the target geometry. Based on the updated CAD design, a second simulation was performed and compared to the target geometry. This first iteration of pre-shaping the design showed a significant reduction in the distortion compared to the target geometry. In **figure 24**a the deviation from the target geometry is shown for the simulation with the original pattern dimensions and figure 24b shows the deviation after simulating the pre-shaped pattern design. The maximum deviation on both sides of the blade is reduced from around 22 mm to 6 mm.

The quality of the comparison between the simulation results and the measurements depends on a careful positioning of the curved surfaces. Measurements of the six parts showed some spread in the deformation between the real parts. The overall agreement was found to be within only a few millimeters of difference especially in the thicker sections, with maximum deviations in local areas in the range of 6-9 mm. A source of larger difference seems to be local fluctuations in the measurements and as well as local deviations in the curvature. Nevertheless, the foundry found the agreement acceptable. With the help of pre-shaping the CAD design, they were able to manufacture the parts within the tolerances of the machining allowance and minimize repair welding.

12 Conclusions

During the last 30 years, casting process simulation has become an essential tool in the steel foundry for various aspects in design and process optimization. Current capabilities allow the prediction of many different quality aspects and address the entire manufacturing route of high integrity steel castings. This supports the foundry expert to gain quantitative information regarding the best possible conditions for the required casting quality, while maximizing casting yield and reducing manufacturing costs.

Together with ongoing developments in modeling the material behavior of steel grades, the new methodology of Autonomous Engineering offers unique opportunities to realize new or optimized applications as well as to define reliable manufacturing routes before the production of a steel casting.

Due to the diversity of steel grades and the flexibility of the processing route, this new approach provides quantitative information for a better and faster decision-making process. This will strengthen steel casting as a robust and competitive manufacturing process for high integrity components used for advanced applications in industry worldwide.

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