Numerical Optimization of Casting Processes –
Leveraging Coupled Process Simulation and Multi-Object Optimization to the Manufacturing Level

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Summary

Simulation technologies need the input of start and boundary conditions, usually given by engineers. Considering these conditions, models are applied to all kinds of mechanical, physical or chemical processes, and simulation tells the engineer what results he might expect when going through a process as defined by him.
It is a trial and error driven, iterative process, requiring an engineer's interpretation and decision after any of the simulation runs. It is an old dream of the engineers, to leave some of these required decisions to a computer, thus being unburdened and able to concentrate on decisions which can not be made by computers.

Casting simulation provides details about the mold filling, solidification, microstructure and residual stress formation phenomena, and with that a solid base of information about the non uniform distribution of mechanical properties and residual stress.
The practical working with casting simulation is an iterative, step by step, trial and error procedure, what is supposed to be state of the art for most FE analysis, lifetime calculations or manufacturing process simulations.

In this paper, the application of an optimization tool, made by the integration of the casting simulation program MAGMASOFT® with the optimization tool *mode*Frontier for the solution and optimization of casting process problems is shown. The three examples, all everyday problems of production engineers, are:

- Flow optimization in a high pressure die casting gating
- Riser optimization for a cast iron part
- Determination of heat transfer coefficients during quenching of a cylinder head

Keywords

Process optimization, casting simulation, genetic algorithm, MOGA

0. The Engineer's Dream: Automatic Computer-Aided Optimization

Engineer's everyday work is to lay out and to optimize designs and processes. Many CAE tools are in use today to assist the engineer by providing information what makes his decisions more solid grounded. Simulation technologies need the input of starting and boundary conditions, usually given by engineers. Considering these conditions, models are applied to all kinds of mechanical, physical or chemical processes, and simulation tells the engineer what results he might expect when going through a process as defined as start or boundary condition.
It is an iterative, step by step, trial and error procedure, what is supposed to be state of the art for most FE analysis, lifetime calculations or manufacturing process simulations. Let us assume that 20 simulation loops were necessary to find an acceptable solution. This means the simulation tool did provide 20 different, complex, often abstract results, to be left with the engineer for 20 decisions he has to make in order to push his design or process to acceptable performance. Even if it is for sure less frustrating to see a design or process fail in the simulation than to experience the costs and delays by these failures in reality, many engineers wish to leave most or all of the decisions to the computer. Particularly decisions that do not require unexceptional creativity or willingness to take risks (those being typical human attributes or strengths) could fairly be done by them to unburden the engineer.

1. Casting Process Simulation – Status Quo

The process of casting liquid metals into molds is a manufacturing process, where complex physical, chemical and thermodynamic processes take place, not really visible to viewers and not really measurable in a proof and broad manner. It is therefore a process, where simulation leads to unique, very valuable insights and information to designers and process engineers. Casting simulation provides details about the mold filling, solidification, microstructure and residual stress formation phenomena, and with that a solid base of information about the non-uniform distribution of mechanical properties and residual stress.

2. MOGA – Multi Object Genetic Algorithms

In casting simulation, as many as 20 simulation loops are often necessary to find an acceptable solution. This means the simulation tool did provide 20 different, complex, abstract results, to be left with the engineer for 20 decisions he has to make in order to push the casting design or casting process to acceptable performance. Even if it is for sure less frustrating to see a design or process fail in the simulation than to experience the costs and delays by these failures in reality, many engineers whish to leave many of the decisions to the computer. Particularly decisions that do not require unexceptional creativity or willingness to take risks (those being typical human attributes or strengths), could be taken over by computers to unburden the engineer.

An effective engine for this automatic optimization is MOGA, the multi object genetic algorithm. This algorithm has two features, being of particular importance in the context of casting simulation: It supports the tracking of several independent targets and can handle any type of process and design variables, even those variables occurring in casting simulation.
Applying genetic algorithms means at first to define a start generation consisting of several individuals. In this context "individual" is just another word for design resp. a variant of the involved project. The individuals can be selected resp. generated by using different DOE strategies like random, quasi-random (Sobol), full/reduced factorial, Taguchi or Monte Carlo methods.
The algorithm now starts for any of these individuals a casting process simulation and evaluates the results regarding constraints and optimization targets. After that the algorithm creates a new generation following the genetic rules of heredity, mutation and selection. Out of the total number of designs (a given number of generations multiplied by a given number of individuals), being defined and evaluated by the algorithm, we usually get several good designs.
In common it makes no sense to talk about "the optimum" or "the best solution" of a problem, because in almost any optimization task related to casting process simulation we get a set of good designs especially for multi-objective problems. The aim of the design optimization is to find a good compromise out of many possibilities; it is not to calculate an extreme of a function in the mathematical sense.

By the way, the genetic algorithm is based on statistical methods and has nothing to do with the classical convergence theory in mathematics. This fact results in advantages and disadvantages. The disadvantage is that for a statistical statement a certain amount of data has to be involved. In our case this means the calculation of several designs (usually at least 50) before we get useful answers to our problems.
The advantage is that it can handle any kind of problems and that it usually concentrates on global extremes.
The coupling of the casting simulation software MAGMASOFT® with the general optimization tool *mode*FRONTIER is done by integrating the second one in a new module called MAGMAfrontier (Fig. 1).

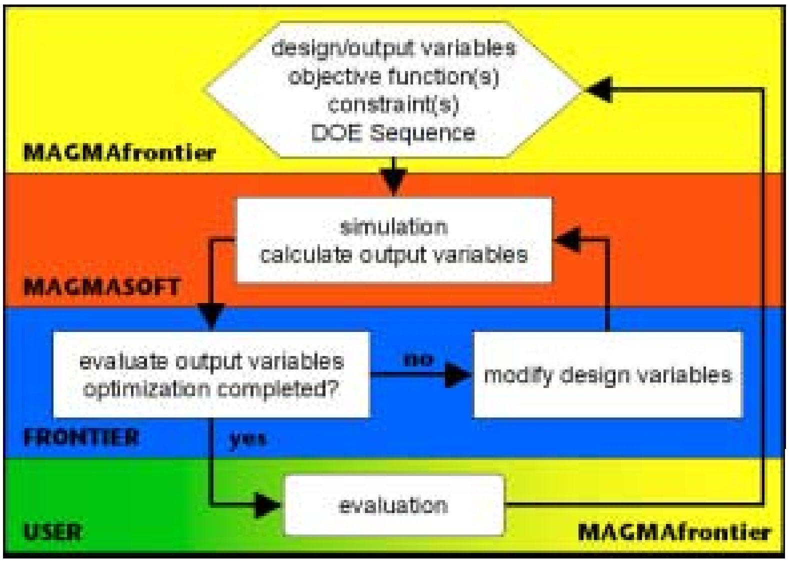

Figure 1: Flow chart of a computer-aided optimization with MAGMAfrontier®

In this module the user describes the problem by determining some parameters:

- design variables with their corresponding ranges of variation (these are the parameters of the simulation that will be varied)
- output variables (they contain the results of the simulation in concentrated form)
- constraints
- objectives (maximize or minimize certain combinations of output variables)

After all the information is available an optimization loop can be started.

3. The Coupling Between Casting Simulation and Optimization

The only significant way of modifying the quality of castings after having finished construction (Design Freeze) is the gating and feeding technique. Therefore much time is spent in practice for the optimal design of this technique. During optimization several optimization goals are pursued at the same time in most cases, which may be contradictory. This is why normally a large number of iterations must be performed until an acceptable solution is found. This exactly is the situation where the computed-aided optimization can be applied in an efficient way.

3.1 Gating Optimization

Designing the gating and running system has a significant impact on casting quality in all casting procedures. The following example is especially focussed on a topic that should be kept in mind while designing the gating and running system especially for HPDC in case you want to avoid air entrapments in castings. Detachments can lead to uncontrolled air entrapment formation in the runner, which are transported into the part together with the melt later (Fig. 2). Therefore these should be avoided.

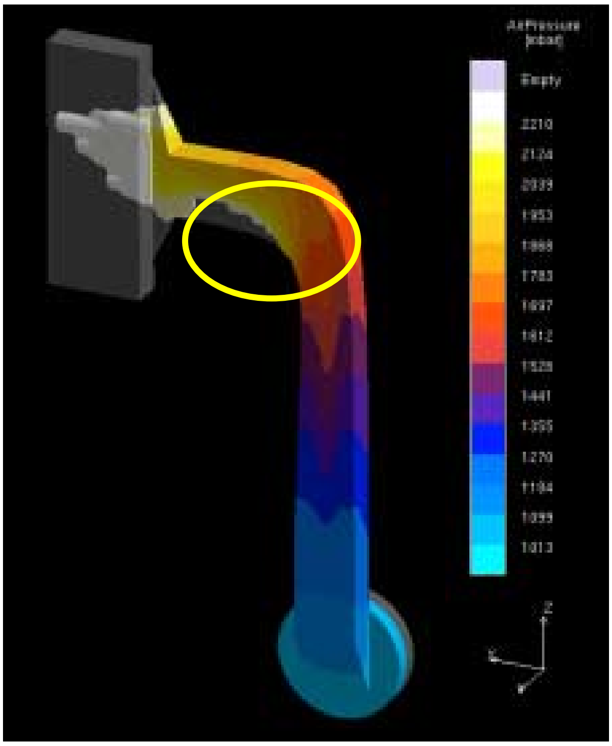

Figure 2: Typical separation within a runner caused by a strong bend of the melt stream. The detachment can be avoided by a suitable design of the runner, which must be found out.

In MAGMASOFT® there is a so-called AirPressure criterion that can be applied in order to minimize separations. Strong separations are represented by corresponding high values of the AirPressure criterion. Thus a minimizing of this display can be declared as the optimization goal for avoiding the separations. The image sequence (Fig. 3) illustrates the separations for differently designed runners by using the AirPressure criterion.

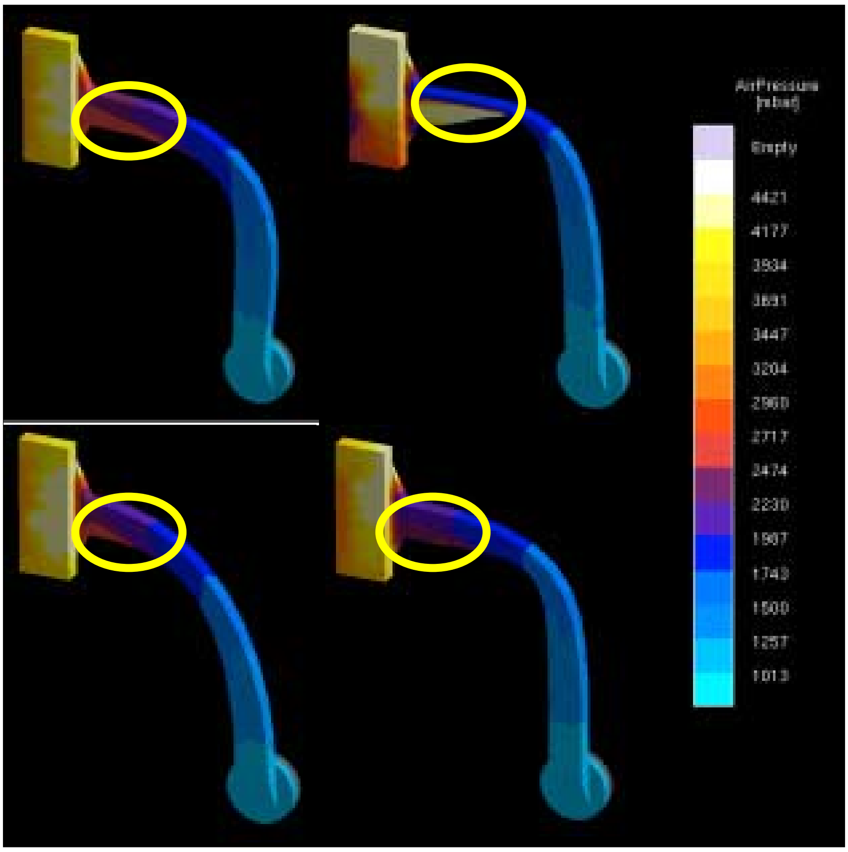

Figure 3: The images show the so-called AirPressure criterion for different runner designs. The separations appear within the encircled areas (light color indicates a large separations). The best result with the smallest separations – that is, with the smallest value for the AirPressure criterion – is shown in the lower picture to the right.

The best solution found is shown in Figure 4. Only the area within the red rectangle is being investigated regarding the optimization goal during the computer-aided optimization.

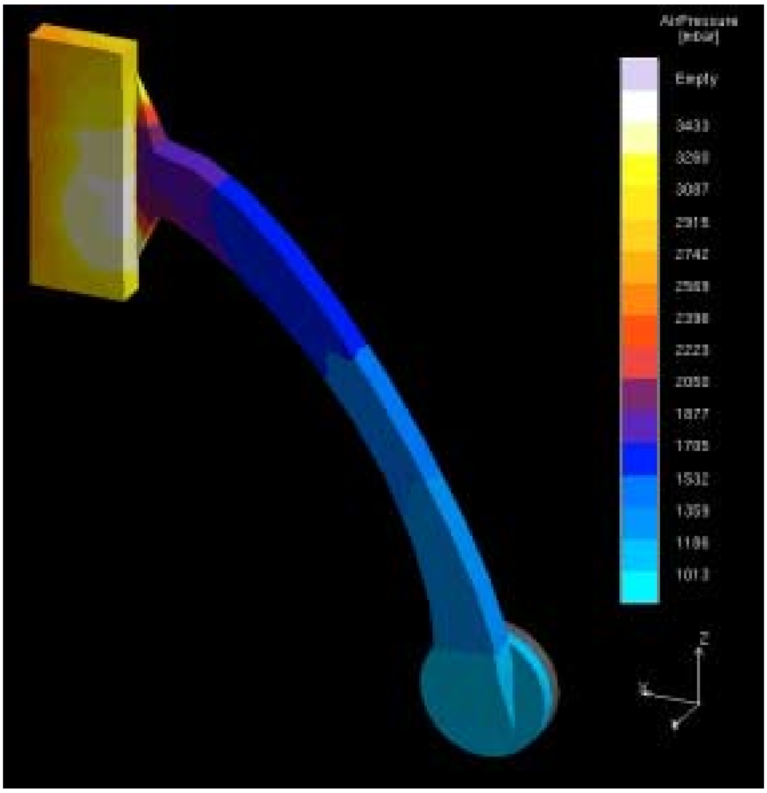

Figure 4: Runner design with no detachments, elicited by computer-aided optimization. Within the red area it will be investigated to what extent the optimization goal is reached.

The computer-aided optimization normally requires a quite large number of simulations, depending on the number of changeable parameters. The models should be reduced as much as possible in order to keep the computing times as short as possible. In the present case the goal is to minimize the detachment within the runner before the casting is filled. Therefore it is proper to ignore the casting for the optimization first, as no repercussions are expected. By this you can reach a significant reduction of the computing model. You are also quite free in choosing a fine or coarse mesh.

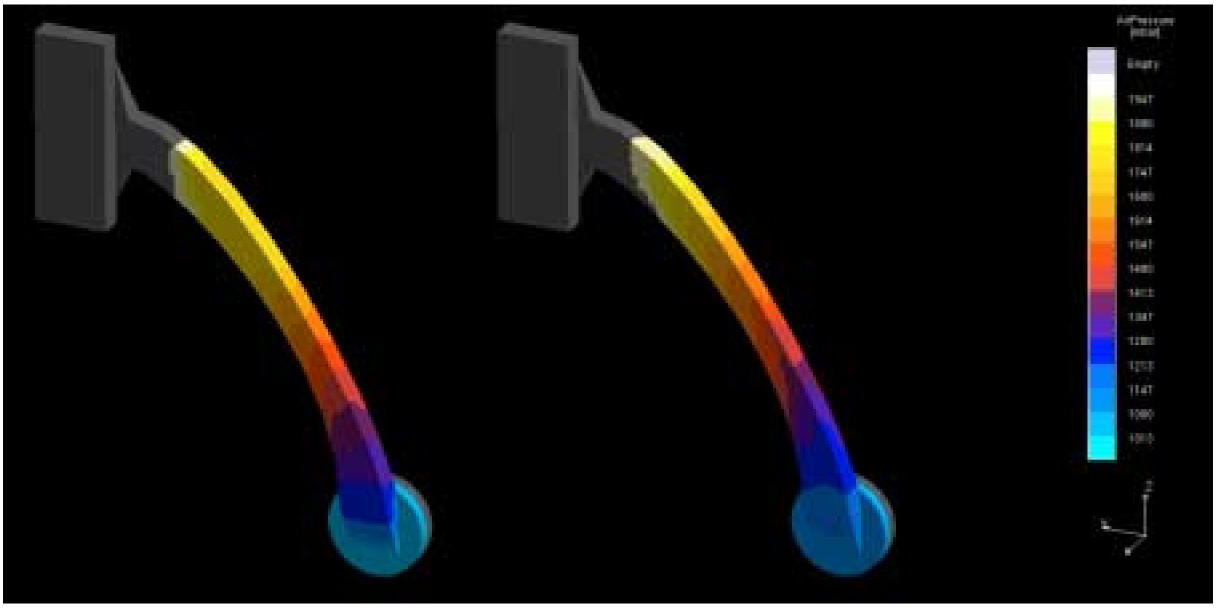

Figure 5: The filling results of the mesh used during optimization (left) and the mesh that is about 10 times finer match well. The applied simplifications did indeed work.

In the present case the optimization was performed with a rather coarse mesh. The question is now if a rather coarse mesh can be applied for optimizing the runner desing at all. For this reason the mold filling optimization results have been compared to those of a mesh of the runner where no more detachments appear. The mesh of the latter results is about 10 times finer (Fig. 5). The results are nearly the same. Therefore the described method is permissible.

Due to the skilful reduction it was possible to perform the optimization of the runner on the basis of 159 simulations within 110 minutes.

3.2 Feeder Optimization

Being cast free of shrinkage is an important requirement for modern castings. This is not quite easy, because the casting materials are known to shrink during the cooling process, and cavities appear within the casting (Fig. 6) It is up to the foundryman's skill to ensure feeding as long as possible. In practice this is done by a suitable choice of the ingate position, the gating design and the skillful positioning of feeders.

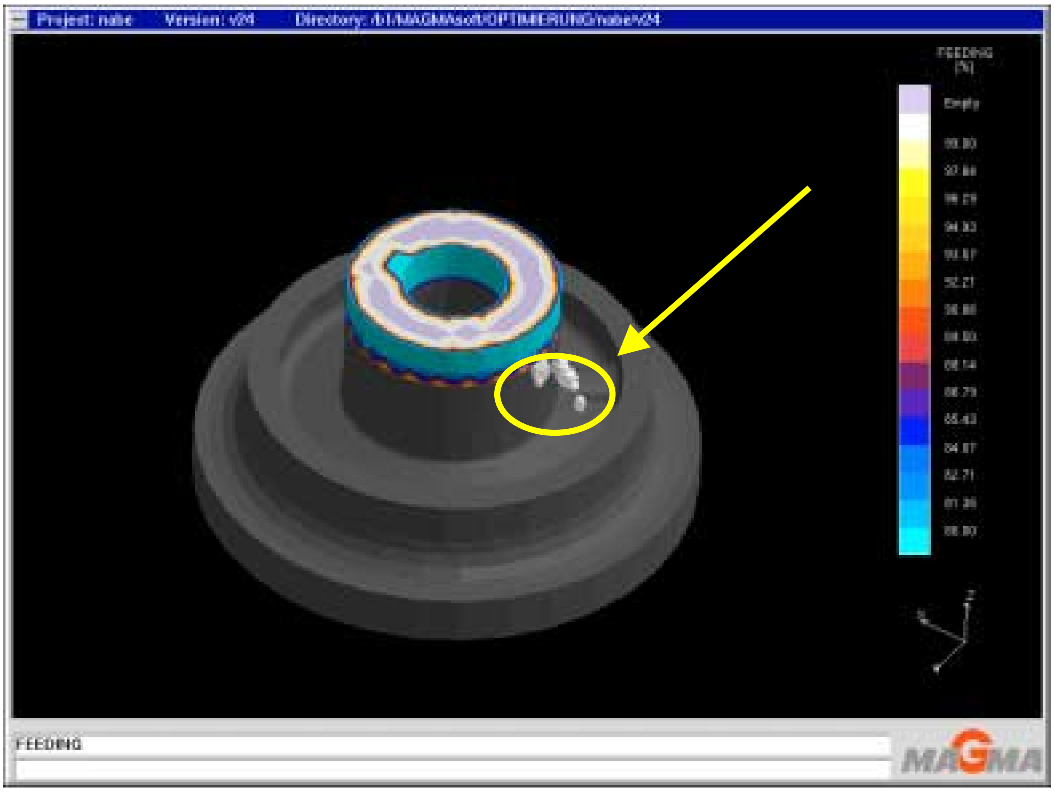

Figure 6: Casting without additional feeders at all. The display of local feeding shows shrinkage spots and feeding defects at the hub at the casting's upper part. The small shrink holes at the bottom right-hand corner in the thick spot area are critical, as they are relevant for quality.

This is exactly what the following example is about. On a model plate, the optimal arrangement of four hubs around a central feeder must be found (Fig. 7). The hubs are being cast with the GJS500 alloy in green sand. The arrangement within the computer model is built up fully parametrical, that is the feeder's and the ingates' dimensions can be modified as well as the hubs' positions on the plate (Fig. 8).

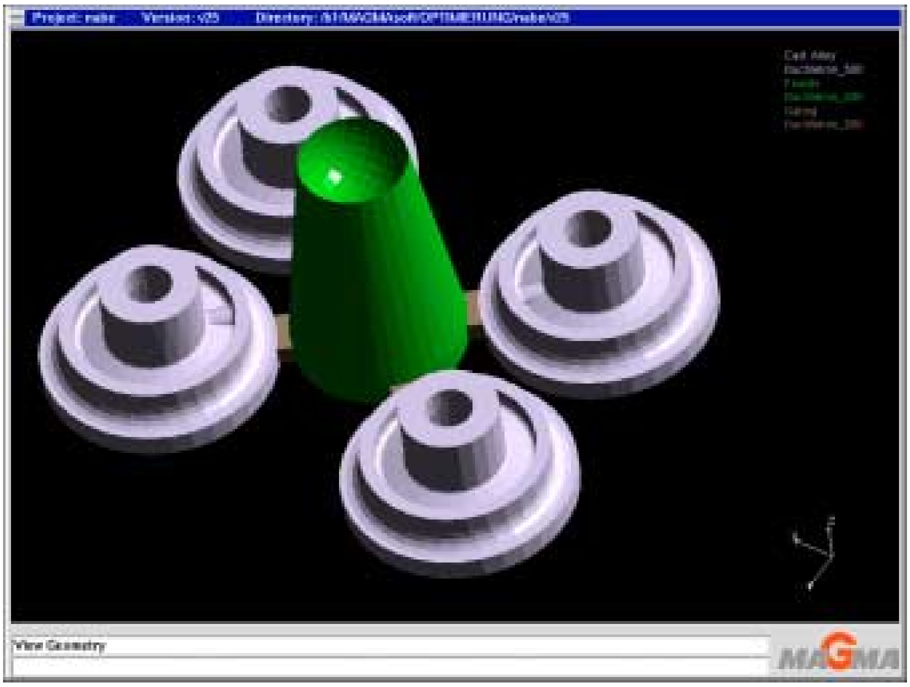

Figure 7: The castings' positions around the central feeder. The quality-relevant area with the thick spot is aligned towards the feeder.

During the design the foundryman primarily focusses on maximizing feeding, but he also wants to minimize the used amount of melt, that is the volume of the feeder in this case.

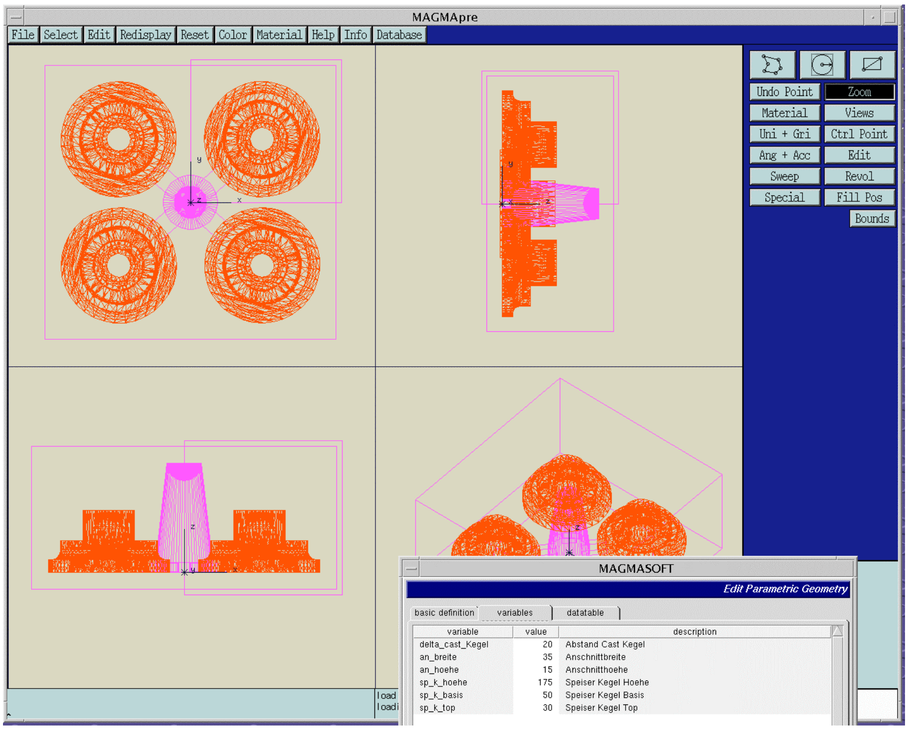

Figure 8: Geometry in the computer model. The computer model is built up fully parametrical. This means that the dimensions of the central feeder (magenta-colored), of the ingates' height and width as well as of the casting's position can be modified according to your wishes. As the system is symmetrical, you have to view only one quarter of the arrangement. Changeable parameters can be edited in the list at the bottom right-hand corner.

The usual procedure up to now was to create a design that was thought to be promising and then to simulate it. Several iteration loops were needed to approach an acceptable solution, which was to come as close as possible to the two goals of creating a casting free of shrinkage and of minimizing the feeders' volume.

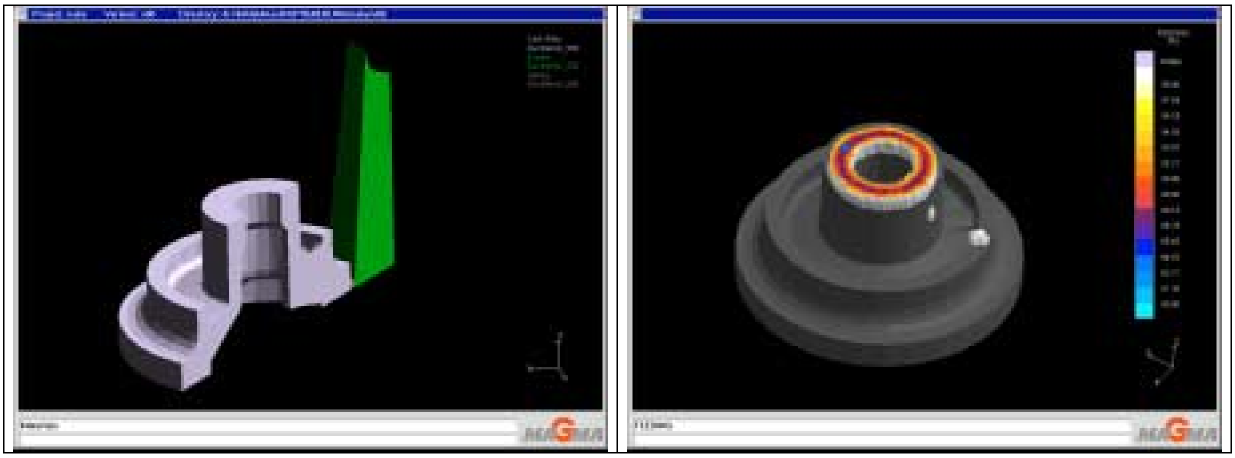

Figure 9: Promising starting position for an optimization. The user basically wants to reach an optimal result with the very first design. Practice shows, however, that, if there is a complex situation, normally a lot of optimization runs must be done in order to find the best compromise regarding the quality goals to be reached. In situations like this the computer-aided optimization is superior to a conventional "manual" optimization, because it purposefully scans the parameter range and evaluates the fulfilment of the strived for goals more reliably.

Tasks like this can be handled in a much more purposeful way by computer-aided optimization. For this purpose the computer needs input of the parameters that are allowed to be changed and their admitted variation ranges. The two goals must be formulated.

The computer performs the simulations with different parameters, evaluates the results regarding the goals' realization and generates new parameter sets. An intermediate stage like this, where complete feeding is not yet reached, is shown in Fig. 10. After a given number of generations, the best compromises are given out in case there are several optimization goals. In this case: a shrinkage-free casting that is fed with a minimized feeder volume (Fig. 11). Of course the best solution would be to use no additional feeders at all. But this solution cannot be reached, due to the physical facts.

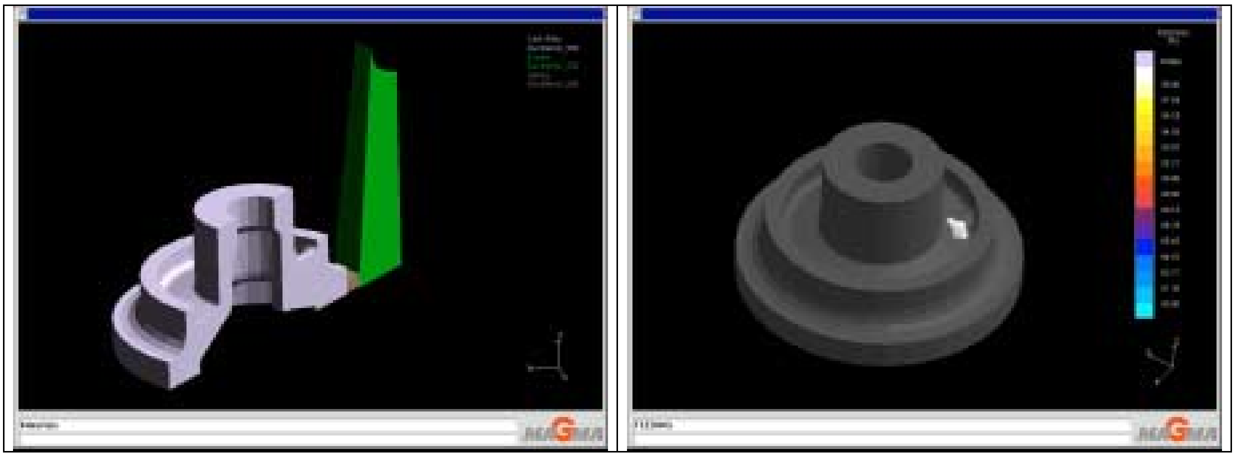

Figure 10: One solution on the way towards a good compromise between optimal feeding and minimized feeder volume.

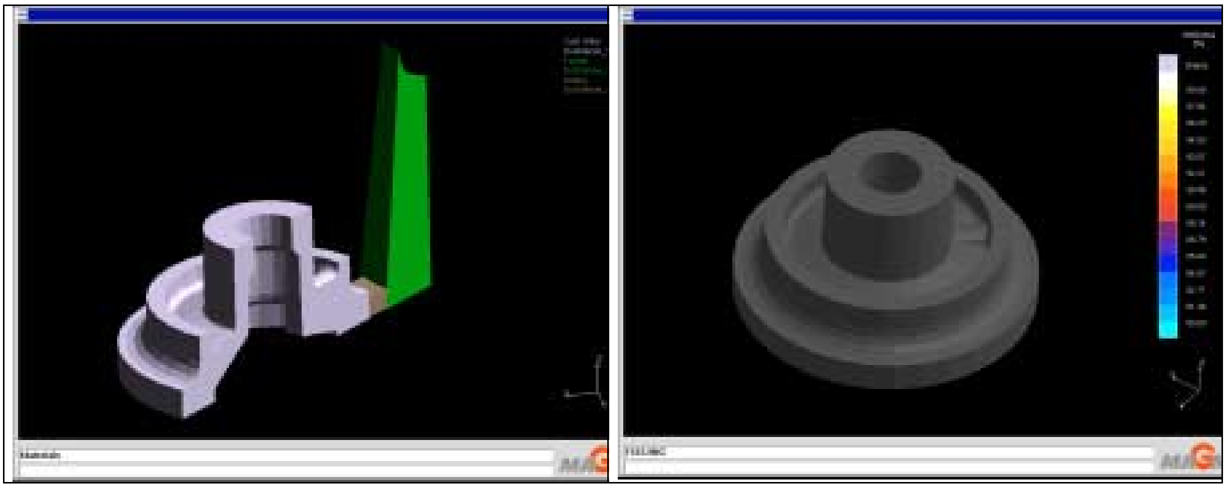

Figure 11: Shrinkage-free casting with minimized feeder volume, found after 546 simulations. For the optimization a computing time of 50 h was needed.

3.3 Inverse Problem

Thermophysical data are needed for the computer-aided simulation. Heat transfers, however, that arise while quenching a cylinder head in water cannot be measured directly.

A workaround for identifying the heat transfers is to compare measured temperature plots at the same places to calculated temperature plots. The heat transfers are modified using computer-aided optimization. The goal is to minimize the difference between measured and calculated temperature plots. Such a problem is called an inverse problem. In this case not the casting is optimized, but a dataset of the simulation.

It is known from practice that within the inner cavities cooling is worse than at the outer surfaces (Fig. 12). In order to consider this, two different heat transfers are searched simultaneously for the cavities and the surfaces. For determining these heat transfers, two of four measured temperature plots are applied. The heat transfers can be called the design variables of the project.

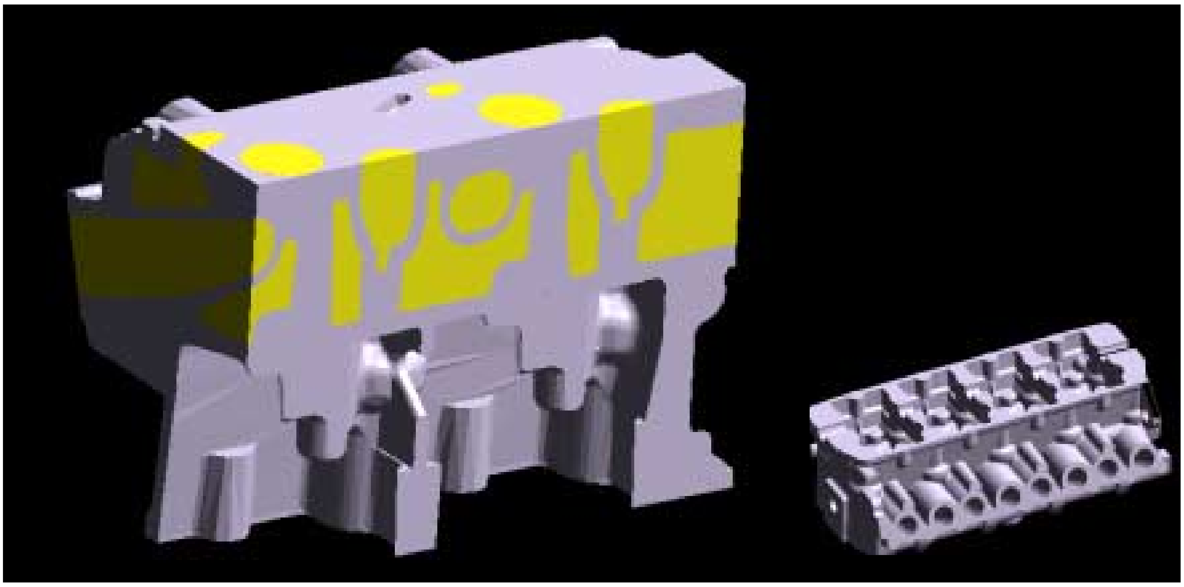

Figure 12: Cut through a cylinder head that is quenched in water. The inner cavities (yellow) have a worse heat transfer than the outer surfaces. Both heat transfers are to be identified at the same time. At the bottom right-hand corner: Overall view of the cylinder head.

The best way of approximizing the plot of heat transfers is to know it basically (this is the case here) and to describe it by curve parts that can be described by just a few parameters (Fig. 13).

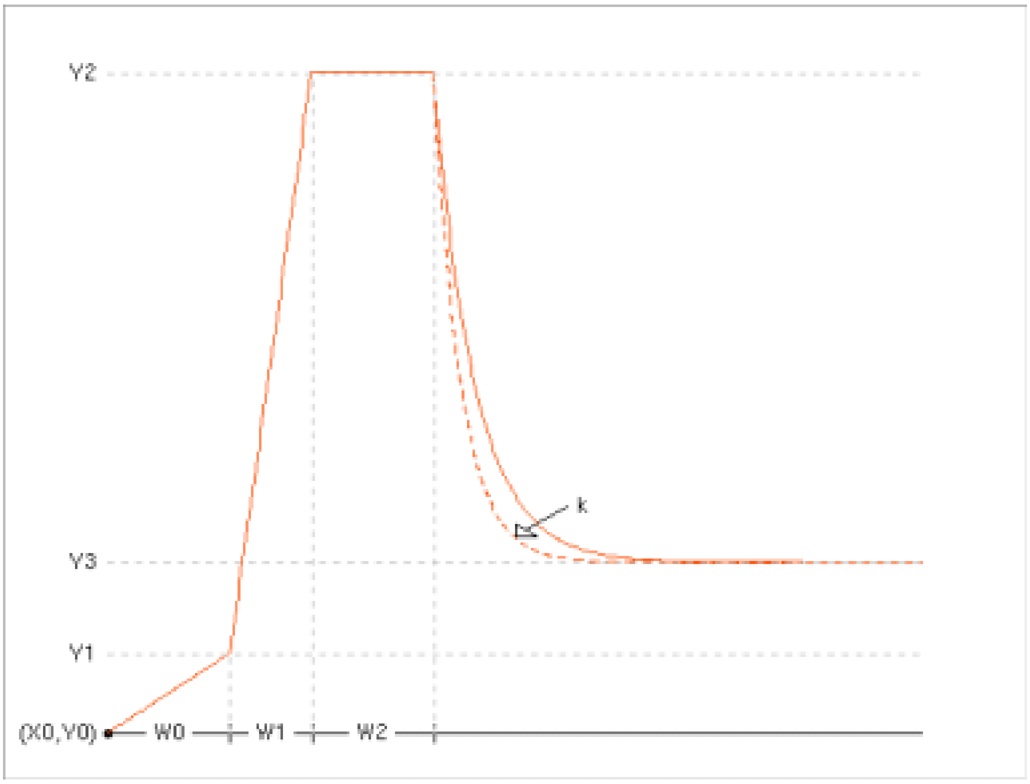

Figure 13: Typical plot of heat transfers during the quenching of castings. This basic curve plot can be described by a small number of parameters and is advantageous for determining the heat transfers.

At first two heat transfers are assumed as the starting point of the simulation in this case. Two error terms are formulated as the optimization goal, which serve as the measuring unit for the deviation between the corresponding measured and calculated temperature plots. As you could expect, the differences between these two plots are still quite big after the first simulation (Fig. 14).

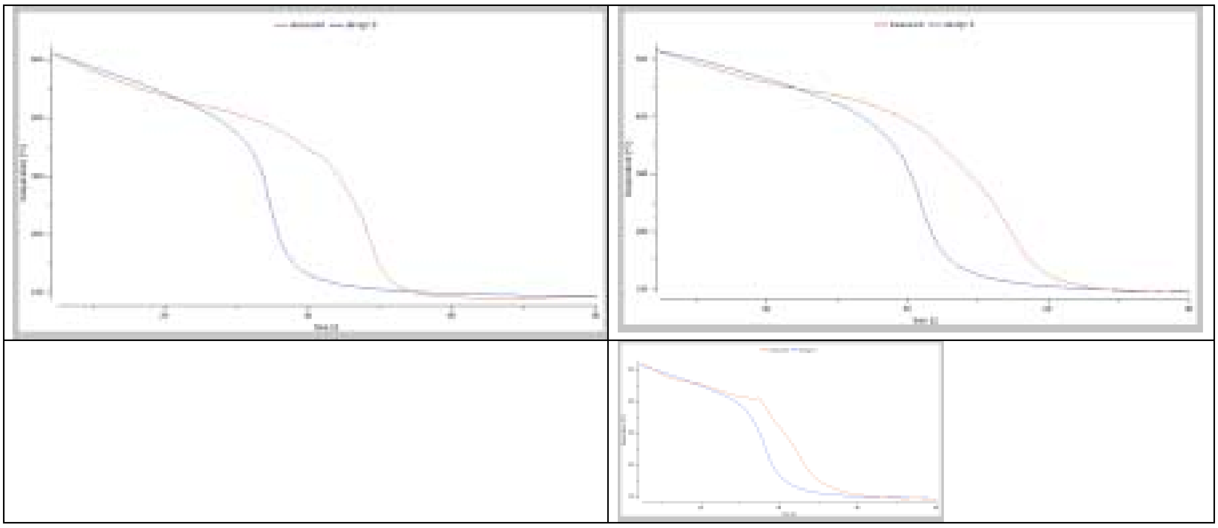

Figure 14: Comparing measured (red) and calculated (blue) temperature plots for three measuring points at the beginning of the computer-aided optimization. The two upper large diagrams show the temperature plots applied for computer-aided optimization, the small chart shows another measuring point that was viewed for controlling the results.

After optimization – minimizing the error terms between measured and calculated temperature plots – you can view a good matching. This is also true for the curve plots that are viewed for control (Fig. 15). Thus the heat transfers have been identified well.

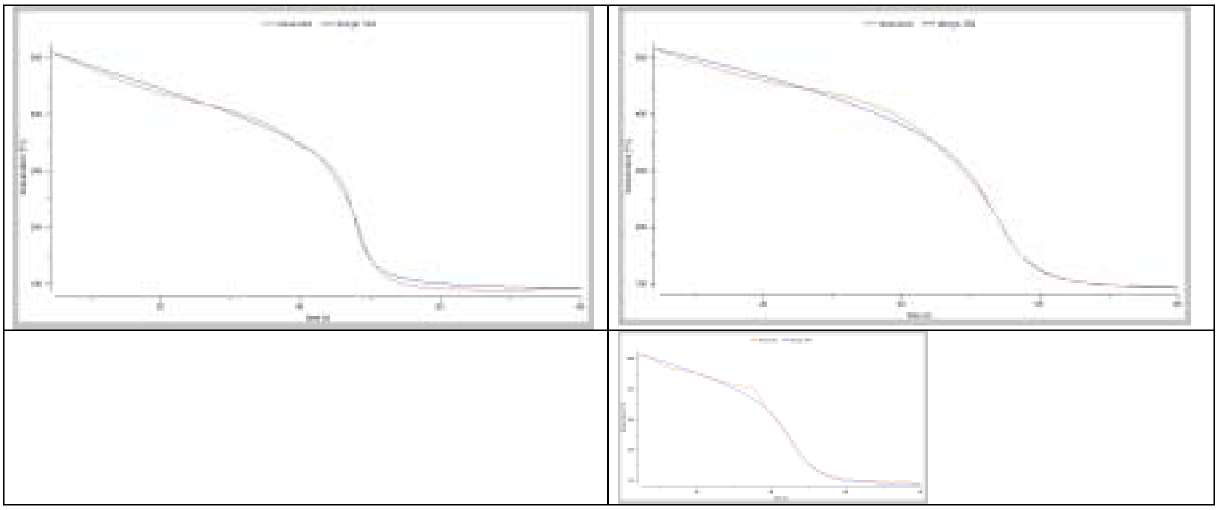

Figure 15: Comparison of measured (red) and calculated (blue) temperature plots for three measuring points after the computer-aided optimization. The two upper large diagrams show the temperature plots applied for computer-aided optimization, the small chart shows another measuring point that was viewed for controlling the results

For identifying the heat transfers, an overall of 1231 simulation calculations were performed on a PC with Pentium III Processor, 1Ghz, which altogether took about 50h.

4. Conclusions

Automatic optimization of processes, as complex as metal casting, is an ambitious intention. The work being described in this contribution shows the methodology of applying a proofed genetic optimization algorithm to a proofed casting process simulator. Today, the automatic optimization still requires a lot of optimization knowledge from the user, and is hardly more efficient or faster than a good process engineer. But it is already clear that the coming improvements of process specific optimization templates and hardware power will help to leverage genetic optimization algorithms to the manufacturing level.