

## **Autonomous Optimization – The second generation of continuous steel casting simulation**

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Since its first application more than 20 years ago the simulation of casting processes has been strongly developed. Today, simulation is established to predict casting quality and supports the day-to-day business in many production places. The search for improved foundry processes has been shifted from the shop floor into the computer.

With increased computing power in recent years new possibilities have come up: It is possible to simulate quite a lot of variants of a casting process in comparatively short time. Autonomous computational optimization means that the software proposes the best combination of process parameters rather than only simulating a single operating point. The engineer enters the degrees of freedom for variation of the parameters and the appropriate goals to be achieved by the optimization instead of focussing on a particular process lay-out.

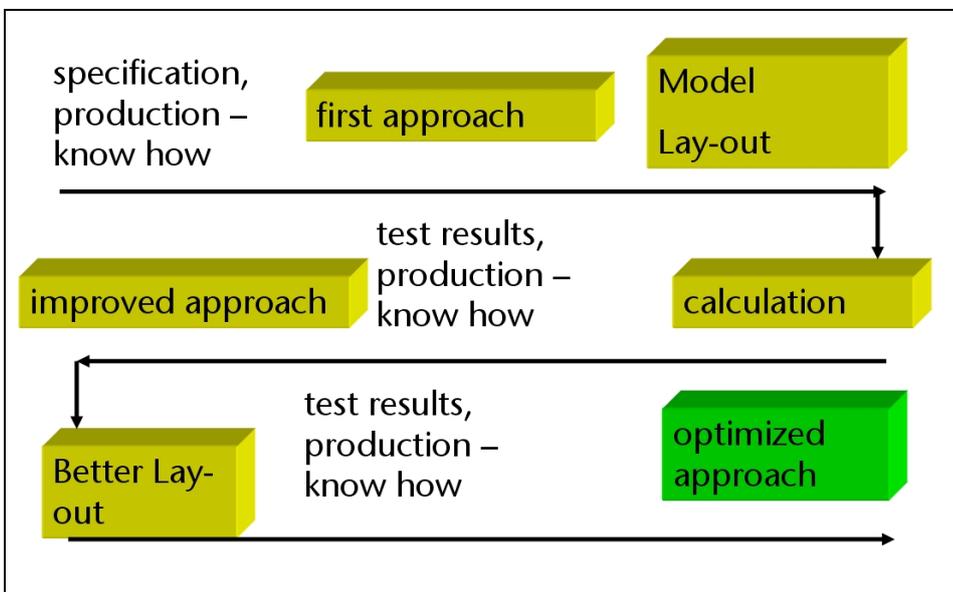
In this paper the application to continuous steel casting processes is demonstrated: First, a reverse engineering method is applied to gain knowledge about boundary conditions for simulation of the mould. Afterwards an example for optimization of the casting process is shown: The required spread of spray cooling intensity in the various cooling zones to achieve a desired liquid pool depth and keep it stable is predicted.

### **Process optimization by “one-dimensional search”**

Each production has to be optimized frequently because of economic factors and in order to ensure the best possible quality profile all the time. Usually, an easy approach to optimization is applied: During a one-dimensional search a number of tests and improvements (usually 3 to 4) are run through one after the other until finally acceptable results are achieved. Nobody knows whether really the optimum state has been reached or if further improvement would be possible. The lay-out of a strand cooling for example means to design a first candidate, check the strand quality and, if needed, further change the layout based on experience. This process is repeated until the quality of the cast steel strand is sufficient, see Fig. 1. The one-dimensional search is characterized by a low number of tests as well as by the danger to end in deadlocks. The specialist overcomes these difficulties with his experience:

Often, after a complete re-orientation of the search, solutions for problems are found that before seemed to be hopeless.

In recent years, the efficiency of this procedure has increased dramatically: Often, costly “real life” tests are prevented by running a simulation. It is still a “trial and error” driven, iterative process, that requires an engineer’s interpretation and decision after any of the simulation runs. At the same time, the demands towards productivity and robustness of production of high-quality products are increasing. The increased variety in grades and production range today makes it more difficult to transfer experiences to novel products. With more and more limited time until start of production there is an urgent need to eliminate the factor “trial and error” for the user.



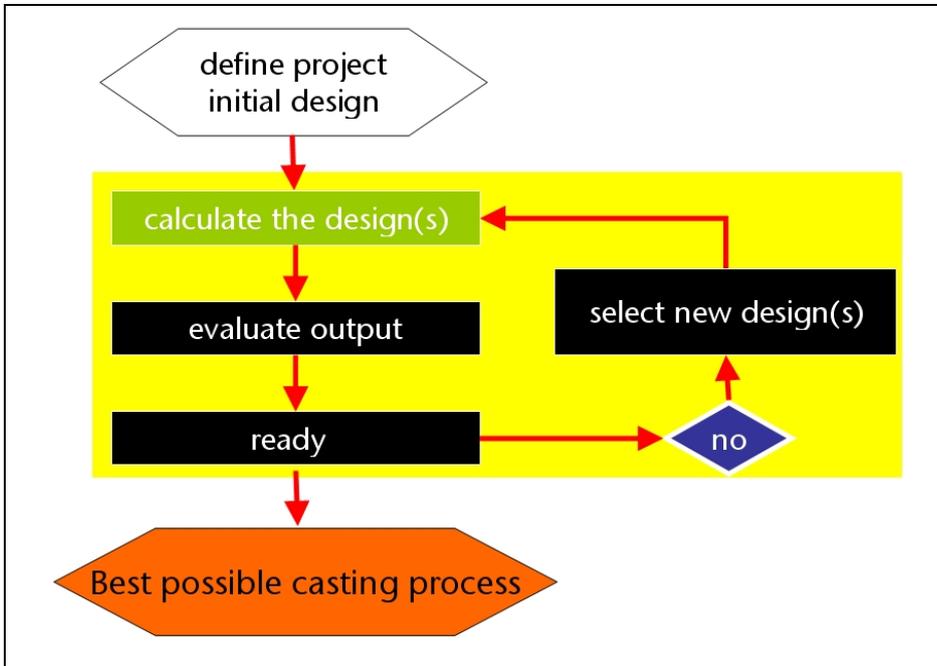
**Fig 1:** For conventional casting optimization a first process lay-out is made based on experience. The result of this is tested and will then be changed. This is repeated until a satisfying result is achieved.

### Autonomous computational optimization

With autonomous computational optimization a new method to design the best possible casting process is available. A multitude of variants are simulated and automatically evaluated for in how far they fulfil targeted criteria.

To achieve this, the MAGMASOFT® casting process simulation has been embedded into an optimization loop. After definition of optimization objectives (target criteria) and degrees of freedom this loop runs autonomously without interaction from the user. It is possible to focus on several maybe competing

objectives at the same time (e.g. depth of liquid pool, surface temperatures, segregations, cracks, yield, productivity). In order to take positive influence on these objectives, process parameters are varied (position and intensity of strand cooling, spraying nozzle layout, casting speed...), Fig. 2.



**Fig 2:** With MAGMAfrontier the casting process simulation with MAGMASOFT is embedded into an optimization loop. During the optimization process no interaction with the user is required.

The optimization program MAGMAfrontier is based on genetic algorithms. The first generation of variants is formed as a DOE (Design of Experience) out of the big number of possible variants. After that usually a number of generations is run through one after the other. Based on the laws of evolution positive characteristics of the proposed variants survive that process. Finally, the best possible compromise between the competing objectives is found.

During the optimization process quantitative information concerning the influence of particular process parameters is acquired. This can be used for sensitivity studies. Herewith the specialist learns about his process. “Trial and error” now have been shifted into the computer. The second generation of casting simulation proposes optimum parameter combinations or the best possible layout rather than only simulating a given state of the art [1,2,3].

## Project with continuous steel bloom casting process

In this project the production of a carbon steel bloom with a quadratic square section of 160 x 160 mm was looked at. Six cooling zones with different heat transfer coefficients in each zone were modelled.

A typical casting speed is 3 m/min which was kept fixed during this investigation. Results of the influence of casting speeds to the depth of the liquid pool were already shown in earlier publications [4]. For the first part of the project the focus was on the heat withdrawal in the mould. With the help of measured temperatures in the mould a heat transfer coefficient should be determined by autonomous computational optimization.

### **Reverse engineering of heat transfer coefficient**

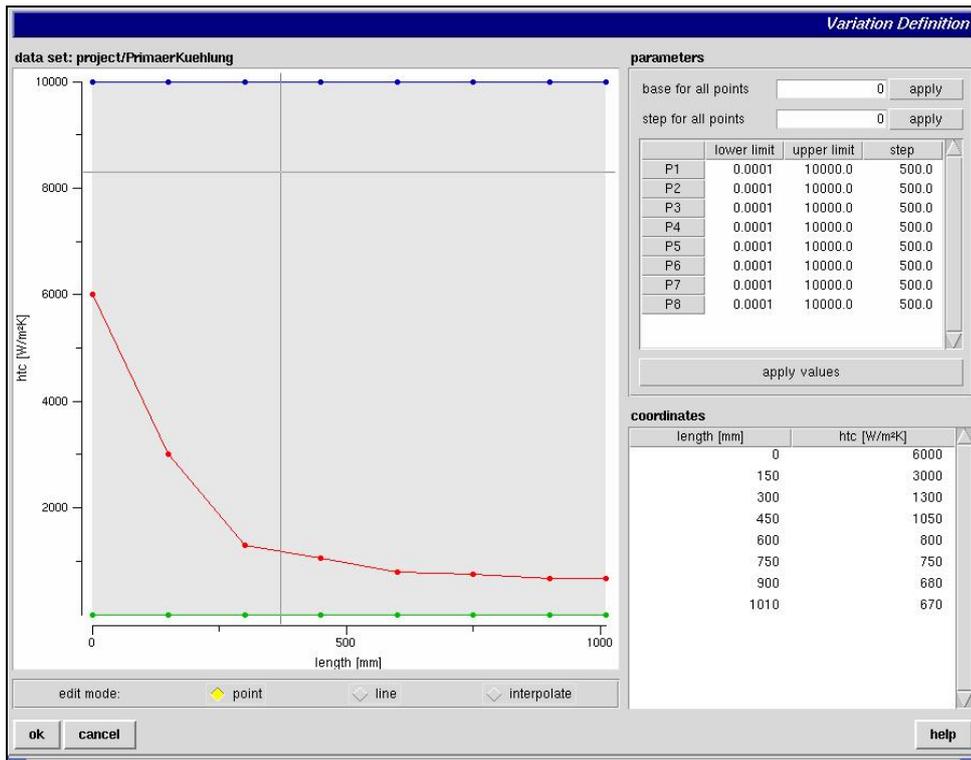
In order to carry out a simulation, knowledge about some boundary conditions is needed. Heat transfers, however, that are characteristic for the contact between the water cooled copper mould and the strand can not be measured directly.

The best possible way to calculate heat transfer coefficients is to retrieve them from a comparison between measured and simulated temperature plots. Using autonomous computational optimization the heat transfers are modified until the difference between measurement and calculation is minimized. This procedure is called inverse optimization.

In this project thermocouples have been placed at different positions in the model, one control point in the strand near to the surface and four control points in uniform distances within the mould. After that the optimization objective function were defined. In the described example the difference between measured and simulated temperatures should be minimized by variations of heat transfer coefficients within the mould. Therefore the measured curves have to be selected.

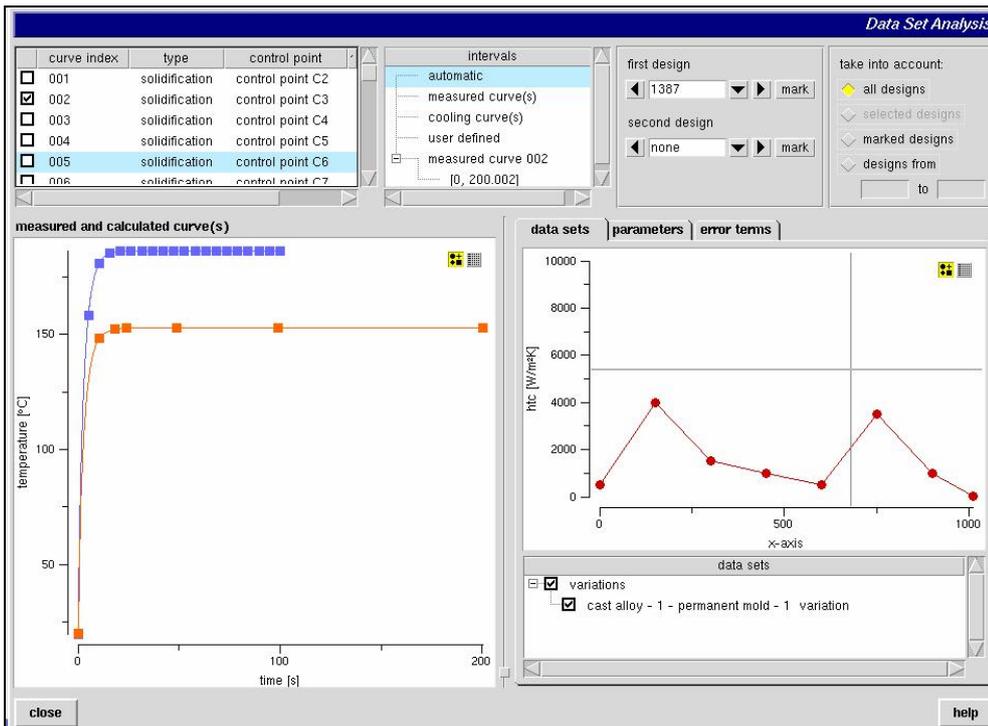
The heat transfer coefficients between mould and strand and its characteristics can be described by just a few parameters. These parameters are varied by the optimization algorithm until a minimum deviation between measured and calculated temperature/time plots is reached. The best possible fit between simulation and measurements is then attained.

In Fig. 3 the curvature of heat transfer coefficient over the length of the mold is shown. During the particular castings the melt level in the mould was at around 150 mm. Therefore, the shown starting point at 6000 W/m<sup>2</sup>K is only an approximation, but in general the curve has a shape like this. The heat transfer should decrease from the top to the bottom of the mould.

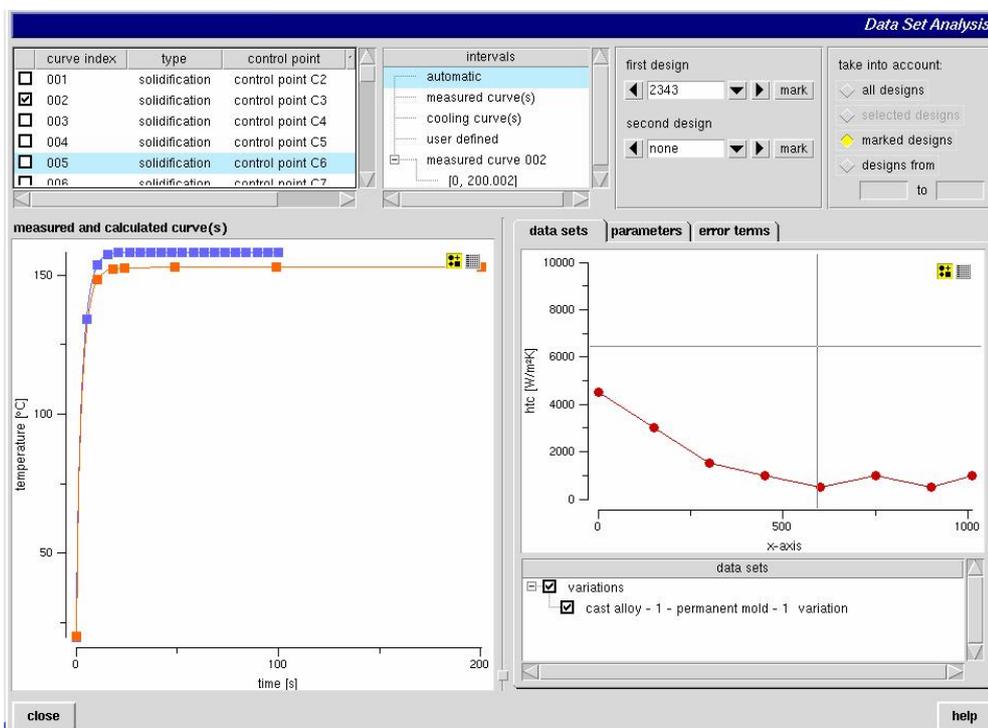


**Fig. 3:** Typical plot of heat transfers between a water cooled copper mould and a strand. This characteristic curve plot can be described by a small number of parameters.

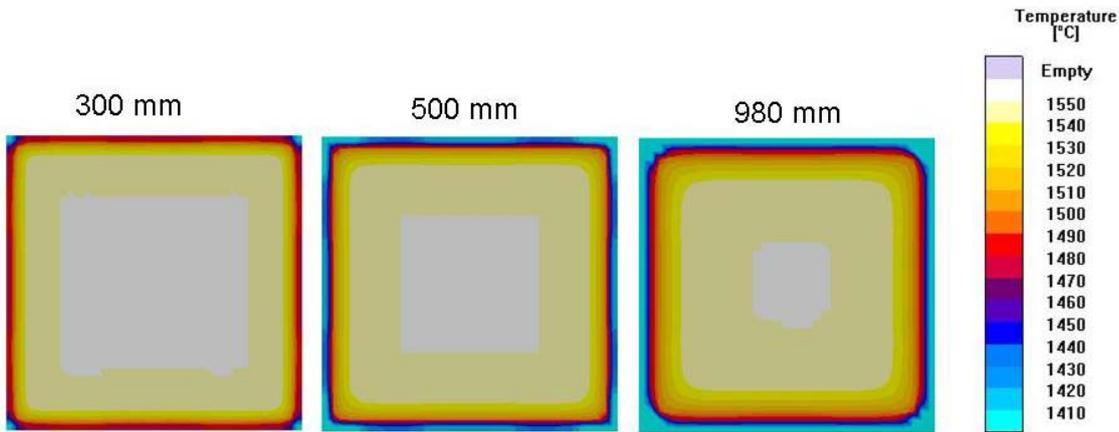
As expected before, the deviation between measurement and simulation was quite big for the first simulated variants of the heat transfer coefficients, Fig. 4. After the optimization the measured and the calculated temperature plots show a good matching, Fig. 5: Here, the heat transfer coefficients have been identified well. For the variant with the heat transfer coefficient from Fig. 5 the strand temperature in the mould is distributed as shown in Fig. 6. The corresponding surface temperatures of the mould are visualised in Fig. 7. The surface temperature of the mould decreases as expected with formation of the solidified shell.



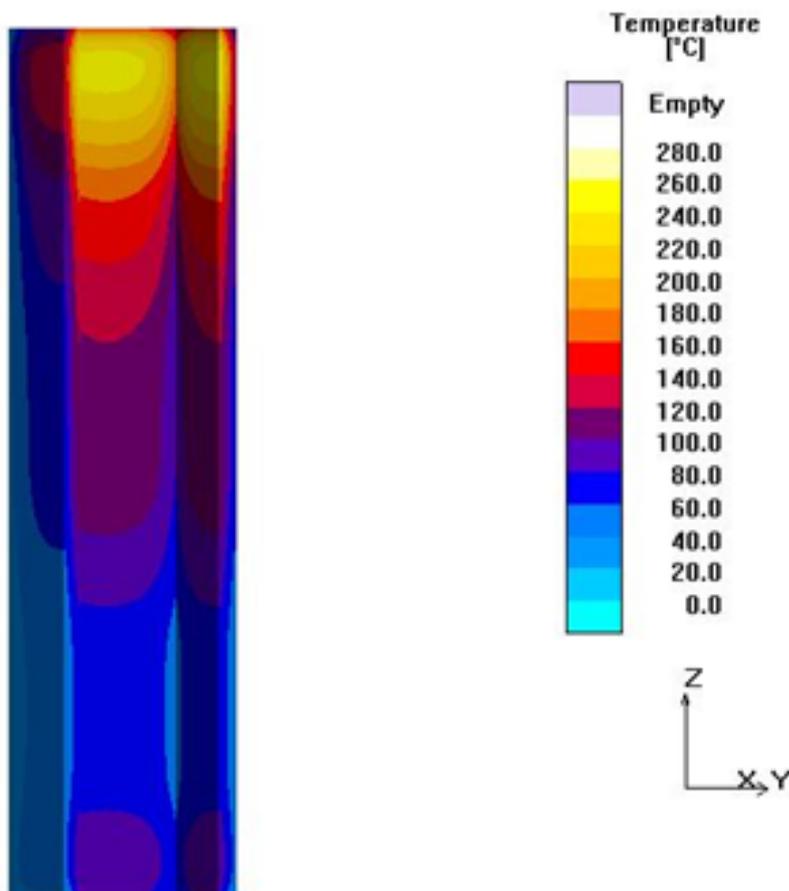
**Fig. 4:** Comparison of measured (orange) and calculated (blue) temperature plots at the beginning of the optimization. On the right the corresponding heat transfer coefficient is visualized as it varies over the length of the mould.



**Fig. 5:** The two temperature curves are now in a good agreement. The corresponding heat transfer coefficient is shown on the right.



**Fig. 6:** Temperature distribution of the strand in the mould (top view) at three different locations relating to the top edge of the mould with a total length of 1000 mm. The shown temperature distribution is the result of a simulation with the optimized heat transfer coefficient.

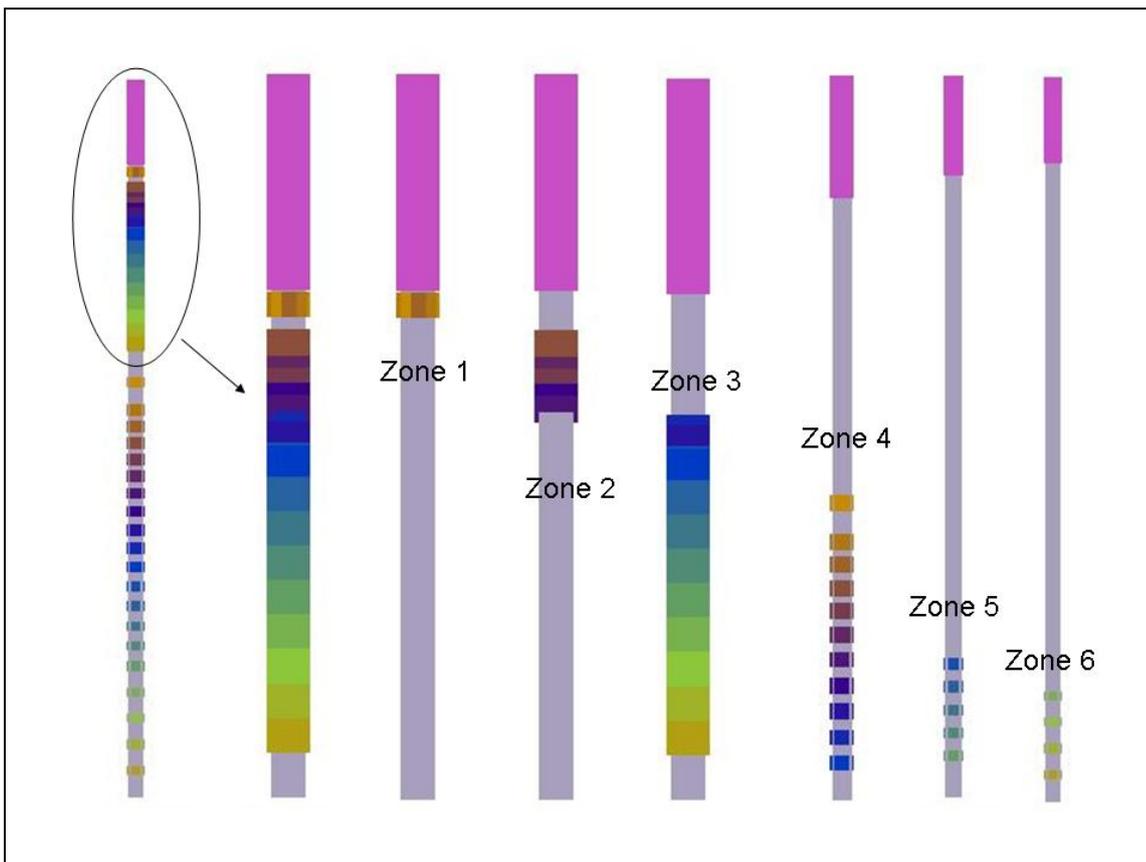


**Fig. 7:** Temperature distribution at the mould surface with the optimized heat transfer coefficient. In order to evaluate calculated mould temperatures the cast strand can be hidden, so that the temperatures of the mould itself are shown. Here, only half of the mould is sketched so that it is possible to look into it and see the temperatures of the inner walls.

## Process optimization

The heat transfer coefficients calculated in the inverse optimization now are used for process optimization. In the second part of the project best possible secondary strand cooling conditions should be worked out to ensure that the liquid pool depth is at the desired value and remains stable. The optimization should help to set the depth of the liquid pool as close to 16.5 meters as possible. The position of the pool tip was set by variation of the characteristics of the secondary cooling zones, Fig. 8.

The intensity of spray cooling was varied for the different zones. In the simulation model this was performed by variation of the different heat transfer coefficients. With help of the autonomous optimization the spread of cooling intensity that is required to set liquid pool depth to the desired value was worked out.

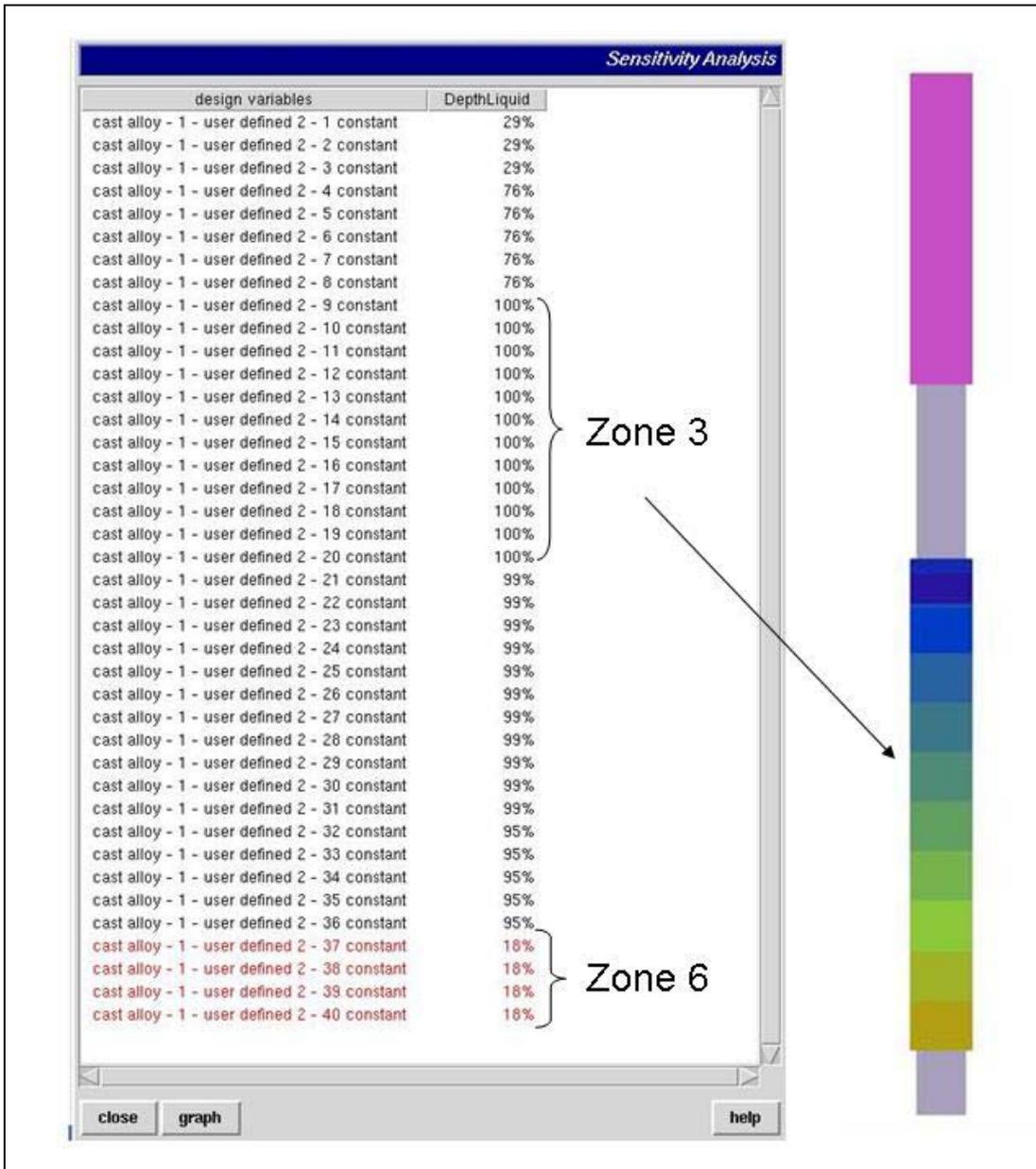


**Fig. 8:** The secondary cooling is partitioned into 6 different zones; the left picture shows the cooling zones in total.

With the variety of simulation results that belong to the different combinations of heat transfer coefficients it is possible to investigate the influence of each

particular cooling zone on the depth of the liquid pool. The sensitivity analysis gives a measure of the influence of each zone by a percentage value – 100% for a particular zone means that it has a significant influence, low values in contrary mean that the influence is rather low.

As can be seen in Fig. 9, zone 3 has the biggest influence on liquid pool depth and zone 6 (red colour) is nearly without influence. It could therefore be neglected.



**Fig. 9:** Sensitivity analysis of the influence of changing the heat transfer in the different zones on the objective to reach a desired liquid pool depth. The percentage value gives information about how much influence each particular parameter has on the result. Most sensitive is Zone 3. Zone 6 does not show any correlation with liquid pool depth.

## Conclusions

An example for the application of autonomous computational optimization to the continuous steel casting process has been shown.

At first, heat transfer coefficients between the water cooled copper mould and the strand were predicted by fitting calculated to measured temperature curves. The results of this inverse optimization were then used to optimize the casting process with the aim to attain the best possible liquid pool depth. Based on information about the position of the different cooling zones the particular zones that have significant influence on the position of the pool tip were identified. The required spread of cooling intensity over the strand length to set the pool depth to the desired value was then worked out.

By switching off the factor “trial and error” the engineer gets the chance to develop his processes with maximum possible quality and efficiency at the same time. He attains knowledge about the influence and interaction of the process parameters. The possibilities that arise from this are just at the beginning – it is the second generation of process simulation.

## References

- [1] G. HARTMANN, V. KOKOT, R. SEEFELDT, Numerical Optimization of Casting Processes, 21<sup>st</sup> CAD-FEM Users´Meeting 2003, International Conference on FEM Technology, Potsdam, Germany, 2003
- [2] I. HAHN, G. HARTMANN “Selbständige Rechnerische Optimierung von Druckgussteilen und –Prozessen”, Konstruktion, Springer / VDI Verlag, March 2008.
- [3] W. SCHÄFER, G. HARTMANN, E. HEPP, D. SENK, S. STRATEMEIER „Autonomous mathematical optimization of continuous casting processes”, 6<sup>th</sup> Europ. Conf. on Continuous Casting, Riccione/Italy, 3-6 June, 2008
- [4] E. HEPP, P. BERNBECK, W. SCHÄFER, D. SENK, S. STRATEMEIER “New Developments for Process Modelling of the Continuous Casting of Steel”, SteelSim 2007, Graz/Seggau, Austria, p. 203