Simulation has long been available for metalcasting optimization, and a new development has heightened its powers.

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For many metalcasters, the development process for a new casting often is limited by such factors as experience and trial-and-error. In the last two decades, however, casting process simulation has established itself as a tool that allows metalcasters to avoid numerous costly casting trials. With casting simulation, only one version of a casting needs to be poured in order to validate the final layout. This can be the deciding factor when casting buyers choose a supplier, as it simultaneously addresses all three of their major concerns:

1. **One-Dimensional Search**
   - Selection
   - Variation Generation
   - Simulation
   - Evaluation
   - End

2. **Design of Experiments**
   - Selection
   - Variation Generation
   - Simulation
   - Evaluation
   - Optimal Variation
   - More Variation as Needed
   - Simulation
   - Examination
   - Evaluation
   - Adjustment
   - Variation 2
   - End

3. **Autonomous Optimization**
   - Variation Generation
   - Simulation
   - Variation Generation
   - Examination
   - Evaluation
   - OK?
   - Yes
   - No
   - End

Fig. 1. The one-dimensional search (left) is the standard process to optimize a casting process layout. The expert performs the optimization, providing process layouts and evaluating and modifying them until satisfied. In a design of experiments (center), all parameter combinations are provided at the beginning of the process and are evaluated at the end of the calculations. In the autonomously running optimization (right), process parameter combinations are configured based on previously run simulations and undergo a loop to determine the optimal layout.
demands: cost (lowest possible price), quality (impeccable castings) and delivery (casting is right the first time with no delays).

Casting process simulation uses precisely defined fixed process parameters to provide results for each possible configuration. Still, the casting process needs to be considered within a relatively large process window, as many process parameters vary over a certain range. The knowledge of a metalcasting process expert is therefore irreplaceable even when simulation is used.

Usually, a simple optimization method is employed. Through sequential trials, “one-dimensional search,” reviews and improvements, an acceptable process configuration—a compromise—eventually is reached. Unfortunately, nobody knows if this final process configuration represents a true optimization or how big the process window is. If every possible parameter change of the casting process were evaluated, an unrealistically high number of experiments or simulation runs would need to be performed.

To address this concern, processes were developed to achieve valuable conclusions from a reduced number of experiments. These processes include methods for “design of experiments” (DOE), which were initially used for real world trials. By using them in conjunction with simulation runs, metalcasters were able to get a step closer to a truly optimized casting design. In other words, DOE simulations provide solutions that often are “good enough.”

The latest development in optimization technology takes this yet another step further. By using autonomous optimization, simulations today are not only closer to producing an optimized design, they produce the most optimized design possible. Autonomous optimization is available when “good enough” is not good enough.

Shifting Into Today

Computer processing speed has changed dramatically in the last 10 years, leading to a paradigm shift. In the past, metalcasting personnel were forced to wait for simulation results, as the simulations took longer than preparing and evaluating them. Today, computers wait for the operator’s inputs, as simulations crank out results faster than the operator can evaluate them and set up modified runs.

To gain the most advantage out of these computer advances, casting process modeling now has been combined with autonomous optimization tools, which produce simulations based on a range of parameters, rather than specific design points. For example, instead of setting up 10 simulations and evaluating 10 sets of results, only one simulation setup is required to yield the optimum results.

The one-dimensional search is characterized by a limited number of trials and can result in a dead end. Proposed solutions usually are not tested in regard to their limitations. The “one-dimensional search” faces another drawback, as well: the ability...
to transfer gained knowledge to new projects is limited with increasing casting complexity (Fig. 1, left).

DOE methods long have been used in the optimization of manufacturing processes, where they are configured and then evaluated using statistical methods. In a virtual DOE, real experiments are replaced by a number of simulation runs (Fig. 1, center). The goal is to evaluate the impact of each process parameter on the casting process in order to predict its behavior at any point of the process window. The DOE then is developed based on statistical patterns, after which the simulations are started. After all the simulations have finished, the operator can evaluate the results according to his or her objectives.

When autonomous optimization is utilized (Fig. 1, right), the operator defines not only the degrees of freedom for the process parameters, but also the objectives, before the simulations are performed. Following the calculation of each simulation generation, the program automatically evaluates the results according to the objectives defined by the operator. Then, dependent on the simulation results and the chosen objectives, a genetic algorithm creates new variations of the casting gating and riser layout. The procedure follows the rules of evolution: each layout variation is kept, eliminated, modified or combined with an already calculated or new design. This process is repeated until design modifications do not lead to additional improvements.

Just as in the biological world, the evolutionary process of autonomous optimization occurs over several calculation generations (Fig. 2). With this method, it is possible to work with multiple, potentially conflicting goals (e.g. improved casting quality, productivity and material usage). To achieve the desired objectives, process parameters such as pouring temperature, alloying elements and mold preheating, as well as geometries (gating design, ingates, riser dimensions), can be varied.

Demonstrating by Example

In the following example of the use of autonomous optimization, a three-step process was used to improve the yield of an existing high production, safety-critical automotive casting run on a vertically parted mold. This was a defect-free part currently in production, but the metalcasting facility wanted to achieve the optimum gating and riser design to increase profitability.

Step 1: Optimize the outside (cold) riser. As with many castings, the simulation of this automotive part naturally separated into several independent areas, including the outside riser (Fig. 3). As the gating layout assured similar filling and temperature conditions in each of the castings, the initial optimization could be conducted on just one casting. This procedure is commonly used at the beginning of complex optimizations to reduce the number of potential designs, as well as the size of each simulation run, primarily to save time. The optimization program requires inputs about objectives, such as “minimize shrinkage” and “minimize riser volume (improve yield),” as well as the range allowed for each dimension (e.g. the metalcaster cannot allow the riser to overlap the casting or other risers above or below it). In this case, a fixed shape for the riser neck was used, as the contact patch on the casting could not be changed.

The optimization tool creates multiple distinct designs and decides after each generation of designs which to try next. The

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Fig. 4. The next step in the optimization of the high-production automotive casting was to designate evaluation areas to focus on critical sections of the casting. The simulation results shown here indicated that the areas were defect free.
In addition to optimizing design layout, autonomous casting process simulation also can be used to perform inverse optimization, which can match thermocouple curves with simulated curves to calculate heat transfer coefficients or thermo-physical properties. Fig. A shows a conventional thermal analysis cup used in metalcasting facilities as a quality control tool.

Virtual thermocouples, placed in the same location as the actual ones throughout the cup, allow the detailed evaluation of the solidification process.

As the conditions found in a test cup differ from the conditions castings experience in the mold, specific boundary conditions different from the ones used in regular casting process simulations had to be derived. The autonomous optimization tool then could read the measured curves and compare them to simulated curves.

Two of the biggest factors affecting cooling behavior are the heat transfer between the melt and the test cup sand wall and between the melt surface and the outside air. As the outside can be simulated by considering it as a cooling medium and controlling the heat loss to that medium with a heat transfer coefficient, the tool must vary both heat transfer coefficients to match the measured curve with the calculated curve.

The simulation showed a good match between the measured and calculated curves using two independent temperature-dependent heat transfer coefficients between the casting and sand wall and the melt and air. Therefore, autonomous optimization was successfully used to fine-tune the boundary conditions in casting process simulation tools to match measured and simulated values.

**Inverse Optimization**

In this case, “design 309” showed the lowest riser volume and created a sound casting. Fig. 4 shows this optimum riser shape in its optimum location on the outside of each casting.

**Step 2:** Optimize the inside riser. As the inside riser has different temperature conditions than the outside riser, a separate optimization run was used. The optimization was begun using a design similar to that of the outside riser; however, as changes in the design of the inside riser could modify the filling profile of the entire casting, the outside riser was still allowed to change, although in a narrower window. Evaluation areas were used to assure that these critical areas of the casting were defect free (Fig. 4). The ability to handle these multi-objective optimizations is the key to autonomous optimization’s application in casting process simulation.

**Step 3:** Optimize yield of cup, down runner and ingates. This step had to be performed while ensuring that all castings filled in the same time. The final multi-objective optimization put the most emphasis on improving the yield of the gating system, but the castings had to be filled in the same time because they all had the same riser size and the critical areas had to stay defect free. The final ingate and riser design is shown in Fig. 5. The final design improved the yield of the entire mold by 11 lbs. (5 kg) with equal casting quality. The use of autonomous casting process optimization provided this optimal gating and riser design in far less time than conventional simulations or casting trials, as well as at a lower cost.

**About the Author**

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**For More Information**

“Rounding Up Casting Process Modeling,” Staff Report, MODERN CASTING, September 2007, p. 31-34.

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**Fig. 5.** The final ingate and riser design improved the yield of the high-production automotive casting mold by 11 lbs. The figures here show similar filling times and defect free castings.

**Fig. A.** Shown is the test cup and placement of the virtual thermocouples.