APPLICATIONS OF OPTIMISATION AND REVERSE ENGINEERING SOLUTION STRATEGIES IN THE MANUFACTURING OF ALUMINIUM ALLOY PRODUCTS

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Abstract: A number of input parameters such as material properties and boundary conditions are required to simulate filling and solidification of castings for process designs. The virtual casting design methodology uses reverse engineering modeling techniques to calibrate computer models. These models are then used in optimization that improves the operation of the foundry, thereby playing a major role in reducing costs and improving productivity and quality of cast products. This paper describes an application of virtual casting design methodology in a low-pressure permanent mold casting operation.

NOMENCLATURE

$f(\boldsymbol{x})$	objective function
$g(\boldsymbol{x})$	constraint function
h	heat transfer coefficient
M	number of time steps
n	number of constraint functions
N	number of thermocouples
p	number of points in $h(T)$ graph.
q	heat flux density
t	time
T	temperature
$\boldsymbol{x}$	vector of design variables.

1.0 INTRODUCTION

A major thrust of cast aluminium research is the development of computer-aided engineering methods to reduce cycle time and cost for producing high quality cast aluminium automotive components. The goal is to provide tools that simulate casting solidification and predict microstructure, mechanical properties and durability of a cast component. This paper describes applications of a methodology that uses numerical simulation and optimization to enhance a low-pressure permanent mould casting process for aluminium alloy wheels [1].

A common approach [2-4] for casting plant design is to build numerical models that represent all the relevant physical processes as accurately as possible. If appropriate boundary conditions and physical parameters that represent plant conditions can be found, these models produce accurate predictions of plant performance and can be used as design tools. The approach is to find the results (e.g. temperature distribution) from a known cause (e.g. boundary and initial conditions). Unfortunately, it is often impossible to provide input data commensurate with the capabilities of the model thereby reducing its effectiveness as a design tool. It is possible that the unknown quantities may be determined using extra conditions, which may come from physical measurements elsewhere in the problem domain. The process of recovering the boundary conditions is referred to here as ***reverse engineering***. Thus, an alternative modeling strategy is to use reverse engineering modeling with numerical optimization to adjust a computational model to match measured plant conditions and better understand and predict the stages of the casting process. Using this approach the model may not necessarily be as sophisticated as one used in a conventional analysis. Although the approach does, of course, rely on the availability of detailed plant measurements, its effectiveness for predicting directions for plant improvements can outweigh the expense and difficulty of the measurements.

The design methodology described in this paper uses a finite element model of a casting process that is embedded in an optimization procedure. Initial stages of optimization adjust boundary conditions of the model so that it more closely emulates measured temperature-time histories throughout the cast. A second optimization stage provides the design tool by adjusting die material properties to improve casting performance (i.e. productivity and quality). The modified material properties are then mapped onto suitable adjustments of the casting equipment to effect the improvements. Figure.1 illustrates the traditional and reverse engineering solution strategies, the latter of which has been employed by a number of researchers [5-8] to design casting mould geometry for optimum casting performance.

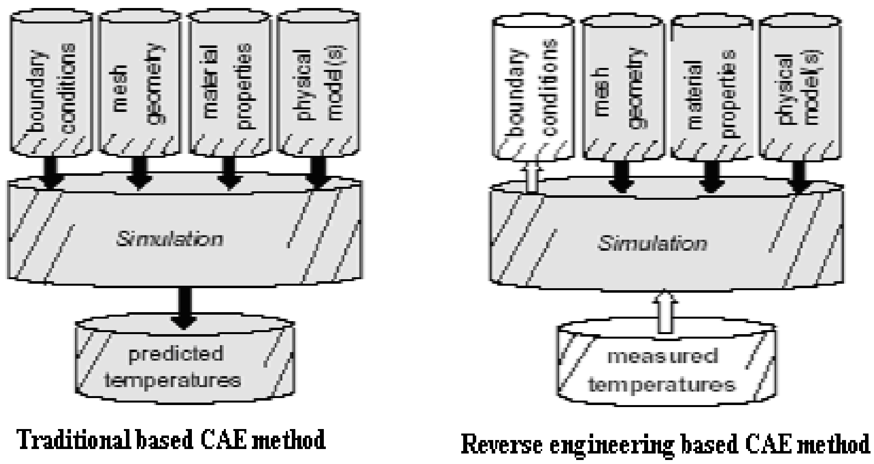


Figure. 1 Traditional and reverse engineering approach for a computational model

The approach is extended to adjust flow and thermal boundary conditions for a specified geometry and is demonstrated by application to a low-pressure die-casting manufacturing plant for aluminium alloy automobile wheels.

2.0 NUMERICAL METHODS

The die filling process for the wheel illustrated in Figure 2(a) was represented by a 2D axisymmetric finite element model (Figure 2(b)) aligned along the plane of symmetry through a spoke. A commercial package (ProCAST) was used and, following a mesh convergence study, the model contained 4483 nodes and 3963 linear tetrahedral elements. The maximum allowable time step in the simulations was 0.1 seconds (time of fill was between 8 and 17 seconds) and each unsteady fill simulation took 33 CPU minutes using a SUN ULTRA-1 workstation. The speed of solution is important since the simulations must be completed many times in response to the adjustments made by the optimization algorithms.

The finite element model was linked through the user interface to optimization packages such as DOT [9]. This interface generates a design file that specifies all the relevant data for optimization, such as design variables, objective and constraint functions, etc. The design file is used as input to the solution process. The architecture of the optimization/simulation algorithm is illustrated in Figure 3. Recognizing that a wheel is not really axisymmetric, a 3D model of one fifth of the wheel was also constructed. This model contained 19,755 nodes and 90,683 elements and was used to confirm that the inverse modeling based on the 2D model produced parameters that were relevant to the fully 3D situation.

3.0 EXPERIMENTAL MEASUREMENTS

A critical aspect of obtaining data from a casting process under production conditions is to measure temperatures for multiple and consecutive casting shots without causing thermocouple breakage or freezing the thermocouples into the castings. If the thermocouples were to remain inside the solidified casting it would be extremely difficult to open the surrounding die at the end of a cycle and be equally difficult to keep the thermocouples intact. There would also be a high likelihood of damaging parts of the die and its mechanisms. After experimenting with several options, exposed thermocouples were coated with a lubricating graphite die coat during the usual diecoating procedure that allows easy extraction of the cast after solidification. Although the coating decreased the temporal responsiveness of the thermocouples slightly it proved to be the only practical way to record multiple and consecutive cycles during warm up and operating stages of production. A section of the die corresponding to a wheel spoke was instrumented with thermocouples distributed as shown in Figure 4.

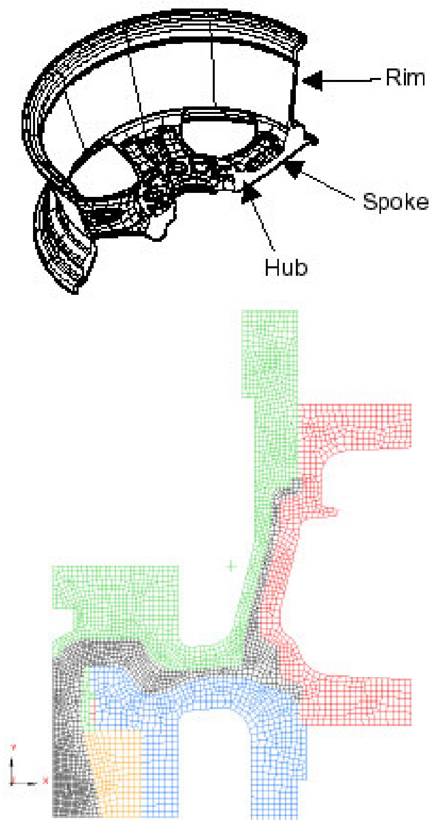


Figure 2 (a) Cross-sectioned solid model of an aluminium alloy wheel, (b) A two-dimensional model of a wheel and tool steel (H13) die, assuming axi-symmetry about the central plane of a spoke.

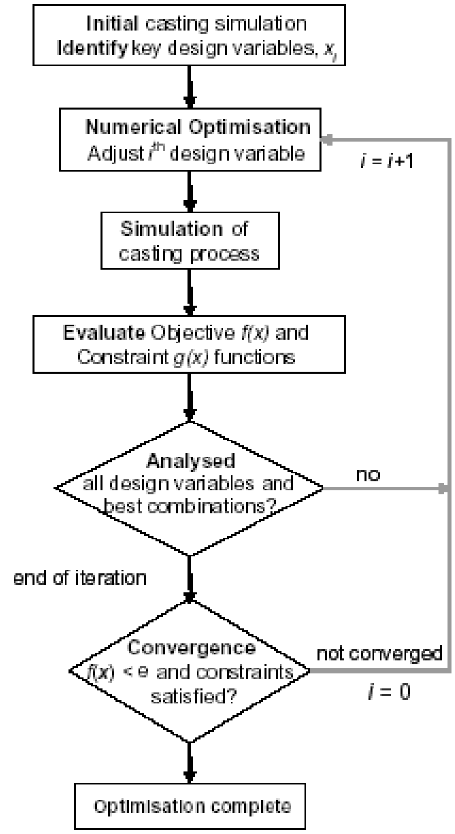


Figure 3 Architecture of the solution control module of the overall design methodology.

There were 15 thermocouples that protruded 5 mm into the cavity to measure temperatures in the molten and solidifying metal. A separate pilot study indicated that a coated thermocouple measured the cooling rate within 1% of that measured by an uncoated thermocouple. Temperature measurement errors from all sources were estimated to be less than 1.3% of the measured temperature. The thermocouples were sampled once a second which was sufficiently rapid to capture the cooling histories while allowing the data collection equipment to store the results from several consecutive cycles.

4.0 MODEL MODIFICATION USING OPTIMISED REVERSE ENGINEERING TECHNIQUES

Modeling of the die casting process is usually divided into a two-part problem. The first stage of the process involves simulating the fluid dynamics during filling of molten metal into the cavity. The second stage involves modeling the heat transfer during solidification. Generally, the filling sequence is determined by a prescribed velocity boundary condition at the cavity entrance and the solidification profile is controlled by heat transfer boundary conditions across the metal/mould interfaces. The latter is a more complex situation since the boundary conditions comprise a multitude of transient factors ranging from convection in the molten metal during filling, conduction from the solidifying casting to the mould and radiation across isolated air gaps between the casting and mould. The relative importance of these processes depends on experimental or manufacturing conditions and can possibly change as solidification proceeds. The cumulative effect of these heat transport phenomena is often represented by a single heat transfer coefficient, h, embedded in the heat flux condition prescribed at the casting/mould interface

$$q = h(T_{casting} - T_{surrounding}) \qquad (1)$$

where q is the heat flux through the interface. In the case of metallic moulds, h can control the solidification rate more than any other single parameter [10]. Hence an accurate calculation of h is essential for an accurate representation of the process. The matching of the model to plant conditions was done using two stages of inverse modeling. The first stage estimated the inlet velocity during filling. The second estimated the heat transfer boundary conditions during solidification.

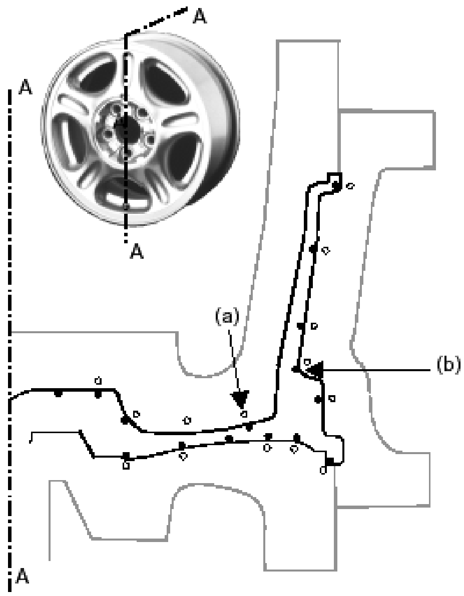


Figure 4 Thermocouple locations in the wheel and die (solid dots indicate thermocouples in the wheel). Cooling curves for the thermocouples marked (a) and (b) are presented in Figure 8.

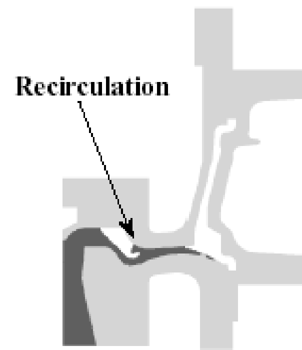


Figure 5 Snapshot of the filling sequence a wheel as predicted by a calibrated 2D finite element model (ProCAST)

5.0 INLET BOUNDARY CONDITION FOR A LOW PRESSURE FILLING SEQUENCE

The objective function, $f(\boldsymbol{x})$, for optimization was expressed as:

$$f(\boldsymbol{x}) = {}^{N}\sum_{i=1}(t_i^{model} - t_i^{experimental}) \qquad (2)$$

where t_i^{model} and $t_i^{experimental}$ are the times when the i^{th} thermocouple and its respective node in the model first respond to molten metal contact. The summation is over the total number of cooling curves measured by the 15 thermocouples that protruded into the cast volume. The only design variable in the optimisation was the vertical component of velocity of the metal entering from the riser tube. Unconstrained optimization using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm was used. Previous filling models for wheels have relied on estimates ranging from 50 to 120 mm/s for the inlet velocity boundary condition [3]. Convergence of the objective function (Equation 2) was achieved in 16 iterations and produced a tuned inlet velocity of 185 mm/s. As shown by the visualisation snap shots in Figure 6, the solution that corresponded to the optimum match had an unsatisfactory flow pattern. Recirculation occurred, causing colder metal to swirl over and mix with hotter incoming metal, increasing the likelihood of trapped air/gas in the cavity.

Although previous filling models, based on the lower estimates of inlet velocity, had not predicted the recirculation, that region of the cast had been known to have porosity problems. The prediction of air/gas entrainment indicated by the solution in Figure 5 has since been validated using a full-scale water analogue model. Figure 6 shows bubbles being generated at the predicted location and propagating throughout the cavity under the influence of the fluid momentum. The optimized calibration has shifted the model to a more representative condition and ultimately led to the identification and understanding of a problematic aspect of this industrial casting process.

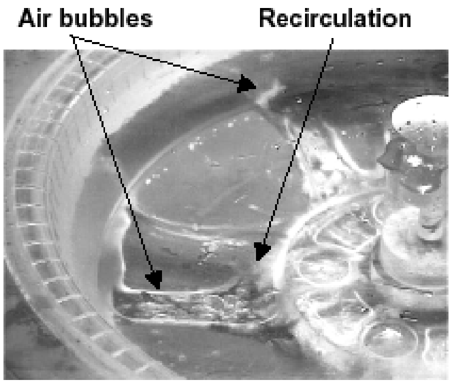


Figure 6 Plan view of filling sequence in a full scale water analogue model.

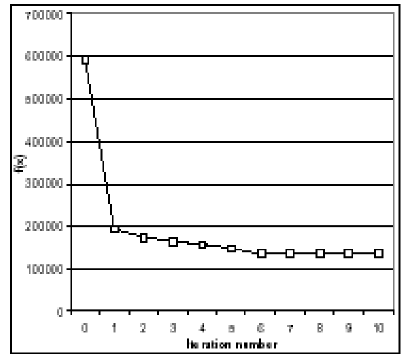
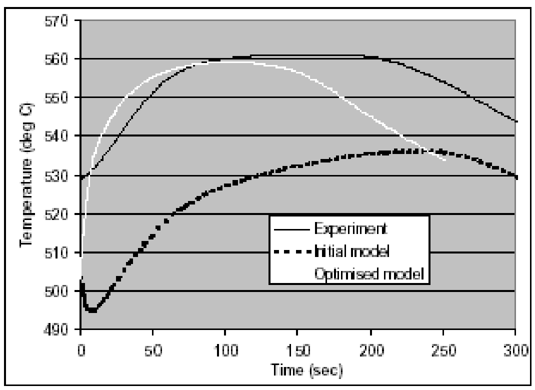
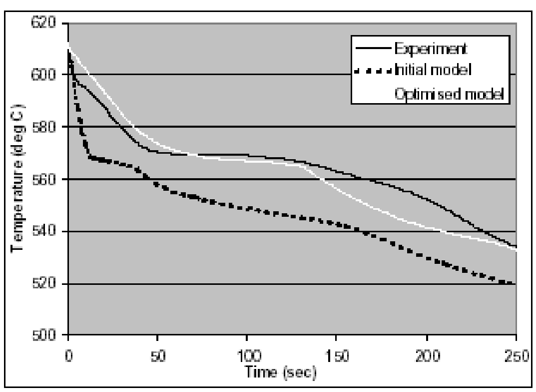


Figure 7 History of the objective function (Equation 3) used to estimate heat transfer coefficients.



a)



b)

Figure 8 (a) T-t profiles of the point in the wheel marked "a" in Figure 4, (b) T-t profiles of the point in the casting, marked "b" in Figure 4.

6.0 BOUNDARY HEAT TRANSFER COEFFICIENTS

In this section, inverse engineering is applied to the solidification phase of the same casting process, the objective being to find a distribution of temperature dependent heat transfer coefficients so that the computed and experimental cooling curves closely match. Although the heat transfer during solidification between the casting and die is a function of several variables, temperature was assumed to be the dominant variable. The objective function can be expressed as:

$$f(x) = {}^{M}\sum_{i=1} {}^{N}\sum_{j=1} (T_{i,j}^{model} - T_{i,j}^{experimental})^2 \qquad (3)$$

t_{ij}^{model} and $t_{ij}^{experimental}$ are the model and experimental temperatures at the j^{th} time step for the i^{th} thermocouple and M is the total number of time steps over which the optimization was applied. The second summation is over all the thermocouples, those protruding into the melt and those located in the die. A constraint in this optimization problem was to maintain decreasing heat transfer coefficients with decreasing temperature to represent the formation of air gaps between the casting and mould, due to casting contraction and mould distortion during solidification. There were three sets of constraint functions, representing the number of die components and interfaces with the casting. These were represented as:

$$g(\boldsymbol{x})_t^{top} = h(T)_t - h(T)_{t+1} \quad , \quad t = (1,p) \qquad (4)$$
$$g(\boldsymbol{x})_b^{bottom} = h(T)_b - h(T)_{b+1} \quad , \quad b = (1,p) \qquad (5)$$
$$g(\boldsymbol{x})_s^{side} = h(T)_s - h(T)_{s+1} \quad , \quad s = (1,p) \qquad (6)$$

where t, *b,* and *s* refer to discrete points on each $h(T)$ curve. The Sequential Quadratic Programming (SQP) algorithm was used in the optimization. Starting with heat transfer coefficients that were based on previous models and engineering experience, the optimization produced a 76% improvement in the objective function relative to this initial estimate (Figure 7).

An independent analysis has also been conducted to determine the sensitivity of the optimum solution to the initial values of variables in the design space. The results have produced similar optimized solutions for all initial guesses. Sample cooling curves are summarized in Figure 9. Although an exact match was not produced, an improvement in the thermal predictions for the casting and die was achieved. A reason for the unmatched cooling curves in the die is that some of the blind thermocouples may not have been in complete contact with the internal mould surface, leaving a small air gap between the thermocouple tip and the die.

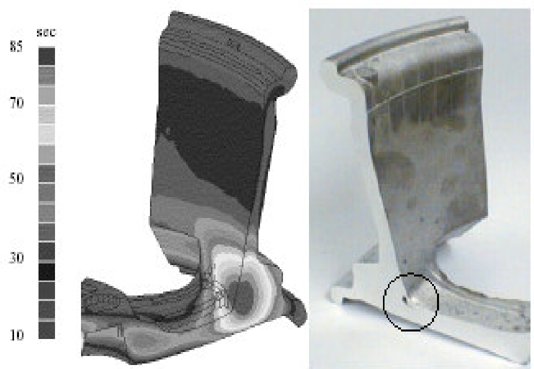


Figure 9 (Left) A calibrated model showing solidification times that indicate a hot spot at the spoke-rim junction. (Right) Photograph of a spoke shrinkage defect at the same location.

As well, during the experiment there were effects and occurrences in the actual process that are reflected in the experimental data, but not modeled (e.g. Variations in die open and close times, breaks in the cooling cycle, metal refills in the furnace and misruns). The effect of any combination of these events can contribute significantly to a source of difference between the plant conditions and the predictions of the model. However, despite these issues, Figure 8 shows that the optimum cooling curves (white lines) show more realistic solidification characteristics than the initial model (dotted lines). The calibrated heat transfer coefficients were used in the 3D wedge model and a resulting isochron plot (reflecting times taken to cool to specified temperatures) was compared with an actual cast piece. The distribution of times taken for the cast to cool to 570°C is shown in Figure 9(a) and indicates a hot spot in the rim / spoke junction. The cast in Figure 9(b) exhibits a corresponding shrinkage defect.

7.0 CASTING PERFORMANCE OPTIMISATION

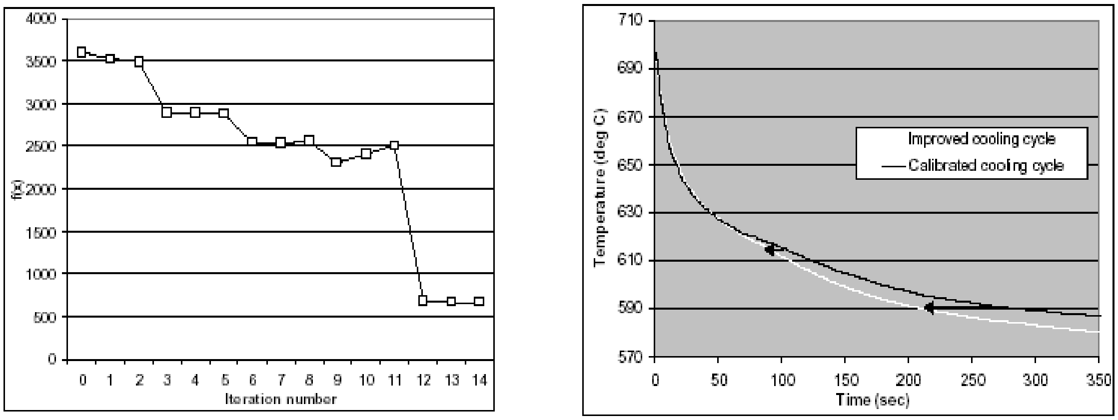
The calibrated model was used to optimize the performance of the casting process by modifying thermo physical properties in the die. The objective was to reduce casting defects and achieve a shorter casting cycle time. Constraint functions, $g(\boldsymbol{x})i$, in the optimization analysis which were designed to achieve a uni-directional solidification profile are represented by

$$g(\boldsymbol{x})_i = T_j - T_k \leq 0 \qquad i = 1,n \qquad (7)$$

where the subscripts for temperature denote selected nodes in the model and *n* denotes the total number of constraint functions. The objective function for this analysis can be expressed by

$$f(\boldsymbol{x}) = (t_{1\text{-}model} - t_{1\text{-}target})^2 + (t_{2\text{-}model} - t_{2\text{-}target})^2 \quad (8)$$

where $t_{n\text{-}model}$ and $t_{n\text{-}target}$ denote model and target time, respectively, of the cooling cycle. For the results reported here, the two points in the arbitrarily chosen target cooling curve for a node located in the sprue were 615°C at *t1-target* = 75 seconds and 590°C at *t2-target* = 160 seconds. A node in the sprue was chosen since it is the last part of the casting to solidify, and is hence a good indicator for the end of a cycle. Figure 10(a) indicates that a 78% improvement from the initial value of the objective function was achieved and Figure 10(b) illustrates the corresponding reduction in cycle time.



a) b)

Figure 10 (a) Optimisation history (Equation 8). (b) Initial and desired cooling curves for a selected node.

In a separate analysis the activation periods of four cooling circuits were also optimized using the same objective and constraint functions, producing further refinement in virtual casting performance. Regions of optimum thermal properties in the die have suggested ideal placements for cooling and insulation and the results have been implemented into an existing low-pressure die cast process that manufactures aluminium alloy wheels. The direct outcome for the industrial plant has been an 80% increase in production capacity (10 to 18 wheels per hour) and a 15% reduction in the design lead time.

8.0 CONCLUSIONS

The results presented here have shown how optimization and inverse modeling can be used initially to tune a computational model so that its predictions match more closely data measured in the industrial casting equipment. The tuned model can then be used in a subsequent optimization to predict changes that could be made to the casting plant to increase productivity. In the case of molten metal filling, the tuning produced a model that identified problematic areas in the casting due to recirculation that had not been predicted by previous models. The solidification phase of the casting process was then calibrated and the resulting cooling profiles accurately reflected typical defects in the casting. Both observations were indications that the optimization had produced better estimates of boundary conditions than had previously been used. The use of numerical optimization and modeling has been demonstrated to predict casting phenomenon at macroscopic scales, with very successful predictions for directions of improvement. The inverse methodology encapsulated as a design tool has since been directly incorporated into several vehicle component programs in the industry.

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