COMPUTER-ASSISTED ANALYSIS OF A METALLURGICAL PRODUCTION PROCESS IN VIEW OF MULTIPLE OBJECTIVES

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Abstract   Numerical experiments in optimizing secondary coolant flows on a steel casting machine with respect to multiple objectives were performed using the recently proposed Differential Evolution for Multiobjective Optimization (DEMO). Calculations were done for a selected steel grade under the assumption of steady-state caster operation. Their aim was to find suitable sets of coolant flow settings under conflicting requirements for minimum temperature deviations and predefined core length in the caster. In contrast to solutions produced in single-objective optimization, approximation sets of Pareto optimal fronts provide more information to a plant engineer and allow for better insight into the casting process behavior.

1.   Introduction

Like the majority of modern production processes, material production and processing nowadays strongly rely on numerical analysis and computer support. Numerical simulators enable insight into process development, allow for execution of numerical experiments and facilitate manual process optimization. Moreover, reliable process simulators and efficient optimization procedures make it possible to automate process parameter optimization and improve material properties. A way of achieving these goals is to couple the process

simulator with an optimization algorithm via a cost function which allows for automatic assessment of the simulation results.

Continuous casting of steel is an example of a process to which novel computational approaches have been applied intensively over the last years to enhance product characteristics and minimize production costs. In this complex metallurgical process molten steel is cooled and shaped into semi-manufactures. To cast high quality steel, it is important to properly control the metal flow and heat transfer during the process. They depend on numerous parameters, including the casting temperature, casting speed and coolant flows. Finding optimal values of process parameters is hard since various, often conflicting criteria need to be applied, the number of possible parameter settings is high, and parameter tuning through real-world experimentation is not feasible because of safety risk and high costs. Techniques applied to overcome these difficulties include knowledge-based heuristic search [2] and evolutionary algorithms [1, 6, 8, 9]. However, the predominant optimization approach taken in the applied studies so far was to aggregate multiple criteria into a single cost value and solve the optimization problem empirically using the simulator-optimizer coupling.

In this paper we report on preliminary numerical experiments in optimizing secondary coolant flows on a steel casting machine with respect to multiple objectives using a multiobjective optimization evolutionary algorithm. Calculations were done for a selected steel grade under the assumption of steady-state caster operation. Their purpose was to get better insight into process behavior and find optimized sets of coolant flow settings under conflicting objectives. The paper describes the optimization task and the multiobjective optimization approach, and reports on the performed numerical experiments and obtained results.

2.   The Optimization Task

In continuous casting, liquid steel is poured into a bottomless mold which is cooled with internal water flow. The cooling in the mold extracts heat from the molten steel and initiates the formation of a solid shell. The shell formation is crucial for the support of the slab behind the mold exit. The slab then enters into the secondary cooling area in which it is cooled by water sprays. The secondary cooling region is divided into cooling zones where the amount of the cooling water can be controlled separately.

In this study we consider a casting machine with the secondary cooling area divided into nine zones. In each zone, cooling water is dispersed to the slab at the center and corner positions. Target temperatures are specified for the slab center and corner in every zone. Water flows should be tuned in such a way that the resulting slab surface temperatures match the target temperatures as closely as possible. From metallurgical practice this is known to reduce cracks and

inhomogeneities in the structure of the cast steel. Formally, cost function c_1 is introduced to measure deviations of actual temperatures from the target ones:

$$c_1 = \sum_{i=1}^{N_Z} |T_i^{\text{center}} - T_i^{\text{center}*}| + \sum_{i=1}^{N_Z} |T_i^{\text{corner}} - T_i^{\text{corner}*}|, \tag{1}$$

where N_z denotes the number of zones, T_i^{center} and T_i^{corner} the slab center and corner temperatures in zone i, and $T_i^{\text{center}*}$ and $T_i^{\text{corner}*}$ the respective target temperatures in zone i.

There is also a requirement for core length, l^{core}, which is the distance between the mold exit and the point of complete solidification of the slab. The target value for the core length, $l^{\text{core}*}$, is prespecified, and the actual core length should be as close to it as possible. Shorter core length may result in unwanted deformations of the slab as it solidifies to early, while longer core length may threaten the process safety. We formally treat this requirement as cost function c_2:

$$c_2 = |l^{\text{core}} - l^{\text{core}*}|. \tag{2}$$

The optimization task is to minimize both c_1 and c_1 over possible cooling patterns (water flow settings). It is known that the two objectives are conflicting, hence it is reasonable to handle this optimization problem as a multiobjective one. Water flows cannot be set arbitrarily, but according to the technological constraints. For each zone, minimum and maximum values are prescribed for the center and corner water flows.

A prerequisite for optimization of this process is an accurate numerical simulator, capable of calculating the temperature field in the slab as a function of process parameters and evaluating it with respect to cost functions Eqn. (1) and Egn. (2). For this purpose we used the mathematical model of the process with Finite Element Method (FEM) discretization of the temperature field and the corresponding nonlinear equations solved with relaxation iterative methods, already applied in previous single-objective optimization study of the casting process [7].

3.　　Multiobjective Optimization

3.1　　Pareto Optimality

Consider the multiobjective optimization problem (MOP) of finding the minimum of the cost function **c**:

$$\mathbf{c} \colon X \to Z$$
$$\mathbf{c} \colon (x_1, \ldots, x_n) \mapsto (c_1(x_1, \ldots, x_n), \ldots, c_m(x_1, \ldots, x_n)),$$

where X is an n-dimensional decision space, and $Z \subseteq \mathbb{R}^m$ is an m-dimensional objective space ($m \geq 2$). The objective vectors from Z can be partially ordered

using the concept of *Pareto dominance*: $\mathbf{z}^1$ *dominates* $\mathbf{z}^2$ ($\mathbf{z}^1 \prec \mathbf{z}^2$) iff $\mathbf{z}^1$ is not worse than $\mathbf{z}^2$ in all objectives and better in at least one objective. When the objectives are conflicting, there exists a set of optimal objective vectors called *Pareto optimal front*. Each vector from the Pareto optimal front represents a different trade-off between the objectives and without additional information no vector can be preferred to another.

With a multiobjective optimizer we search for an *approximation set* that approximates the Pareto optimal front as well as possible. When solving MOPs in practice it is often important to provide the user with a diverse choice of trade-offs. Therefore, beside including vectors close to the Pareto optimal front, the approximation set should also contain near-optimal vectors that are as distinct as possible.

3.2   DEMO

Finding a good approximation set in a single run requires a population-based method. Consequently, evolutionary algorithms have been frequently used as multiobjective optimizers [3]. Among them, the recently proposed Differential Evolution for Multiobjective Optimization (DEMO) [11] is applied in optimizing the described metallurgical process.

DEMO is based on Differential Evolution (DE) [10], an evolutionary algorithm for single-objective optimization that has proved to be very successful in solving numerical optimization problems. In DE, each solution is encoded as an n-dimensional vector. New solutions, also called candidates, are constructed using operations such as vector addition and scalar multiplication. After the creation of a candidate, the candidate is compared with its parent and the best of them remains in the population, while the other one is discarded.

Because the objective space in MOPs is multidimensional, DE needs to be modified to deal with multiple objectives. DEMO is a modification of DE with a particular mechanism for deciding which solution should remain in the population. For each parent in the population, DEMO constructs the candidate solution using DE. If the candidate dominates the parent, it replaces the parent in the current population. If the parent dominates the candidate, the candidate is discarded. Otherwise, if the candidate and its parent are incomparable, the candidate is added to the population. After constructing candidates for each parent individual in the population, the population has possibly increased. In this case, it is truncated to the original size using nondominated sorting and crowding distance metric (as in NSGA-II [4]). This steps are repeated until a stopping criterion is met.

DEMO is a simple but powerful algorithm, fully presented in [11] in three variants. Throughout this paper, the elementary variant, called DEMO/parent, is used.

4.   Experiments and Results

4.1   Experimental Setup

Numerical experiments in multiobjective optimization of the casting process were performed for a selected steel grade with the slab cross-section of $1.70\,\text{m}$ $\times$ $0.21\,\text{m}$. Candidate solutions were encoded as 18-dimensional real-valued vectors, representing water flow values at the center and corner positions in 9 zones of the secondary cooling area. Search intervals for cooling water flows at both center and corner positions in zones 1, 2 and 3 were between 0 and $50\,\text{m}^3/\text{h}$, while in the zones 4–9 between 0 and $10\,\text{m}^3/\text{h}$. Table 1 shows the prescribed target slab surface temperatures. The target value for the core length $l^{\text{core}*}$ was $27\,\text{m}$.

Table 1.   Target surface temperatures in $^\circ$C.

Zone number	1	2	3	4	5	6	7	8	9
Center position	1,050	1,040	980	970	960	950	940	930	920
Corner position	880	870	810	800	790	780	770	760	750

DEMO was integrated with the numerical simulator of the casting process into an automated optimization environment. DEMO evolved sets of candidate solutions in search for a good approximation set, and the simulator served as a solution evaluator. Steady-state operation of the casting machine was assumed and optimization performed in the off-line manner.

The most limiting factor for experimental analysis is the computational complexity of the casting process simulation. A single simulator run takes about 40 seconds on a 1.8-GHz Pentium IV computer. In initial experimentation we found DEMO runs with 5,000 solution evaluations (and therefore taking about 55 hours) well compromising between the execution time and solution quality. Further algorithm settings were also adopted according to the initial parameter tuning experiments [5] and were as follows: population size 50, number of generations 100, scaling factor 0.5 and crossover probability 0.05.

4.2   Results and Discussion

The primary result of this study were approximation sets of Pareto optimal fronts. Figure 1 shows the approximation sets found by DEMO for five casting speeds, ranging from $1.0\,\text{m/min}$ to $1.8\,\text{m/min}$. Each set of nondominated solutions is the final result of a single DEMO run at a constant casting speed.

We can observe that the two objectives are really conflicting in the sense that finding a minimum for one of them the optimization procedure fails to do so for the other and vice versa. It is also obvious that the casting speed has a
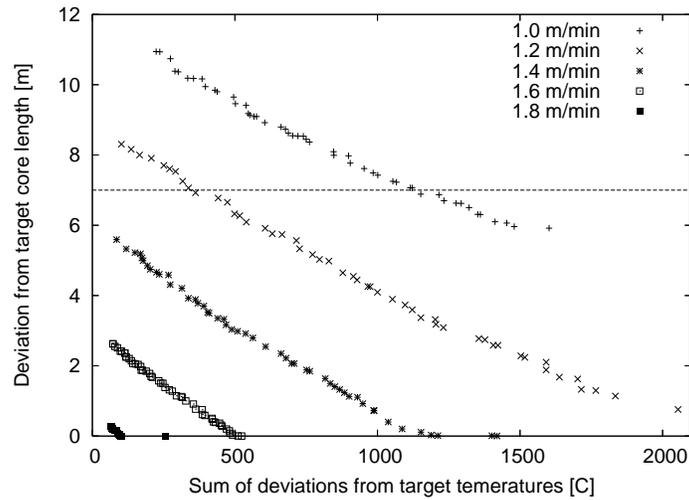
Figure 1.   Nondominated solutions found with DEMO for different casting speeds. The dashed horizontal line denotes the maximum allowed deviation of the core length from the target value (7 m).

decisive impact on the result. Moreover, the higher the casting speed, the more the two objectives can be met simultaneously. This corresponds with practical experience on the considered casting machine, where the process is easier to control at the usual casting speed (1.6–1.8 m/min). Lower casting speed is clearly shown as disadvantageous and in practice it is only set exceptionally, for example, when a new batch of steel is awaited.

A detailed analysis of the solution properties also reveals that, in view of the objective c_1, the majority of actual surface temperatures are higher than the target temperatures, while regarding c_2, the actual core length is almost always shorter than the target value. Unexpectedly, the deviation is sometimes even greater than 7 m, meaning that the actual core length is less than 20 m, which is unacceptable. This threshold value is shown in Figure 1 and should be considered as an additional constraint in future studies.

Looking into decision space, one can also observe certain rules. In case of applying trade-off solutions from the middle of the approximation sets, the amount of coolant spent increases with the casting speed (see the left-hand side diagrams in Figures 2–6). This is an expected result as higher casting speed implies more intense cooling. On the other hand, the distributions of temperature differences across the secondary cooling zones (right-hand side diagrams in Figures 2–6) exhibit two characteristics. First, the target temperatures are much more difficult to achieve at the center than in the corner slab positions. Second, the differences at the center are rather non-uniform. While some are

close to zero, others reach up to $200\,^{\circ}$C at lower casting speeds. Such a situation is not wanted in practice calls for reformulation of objective c_1.
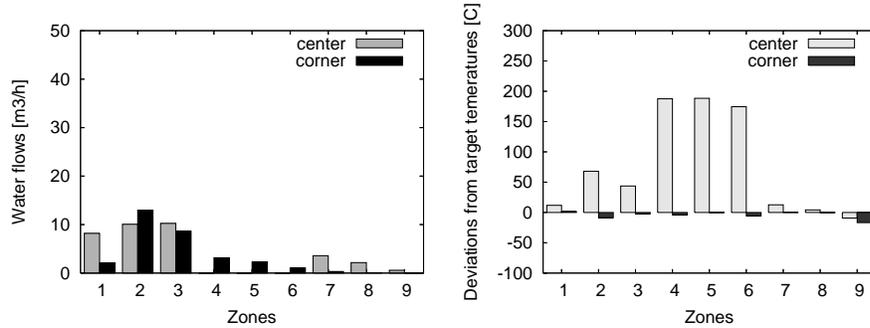

Figure 2. A trade-off solution from the middle of the approximation set for the casting speed speed of 1.0 m/min: $c_1 = 740\,^{\circ}$C, $c_2 = 8.5$ m.
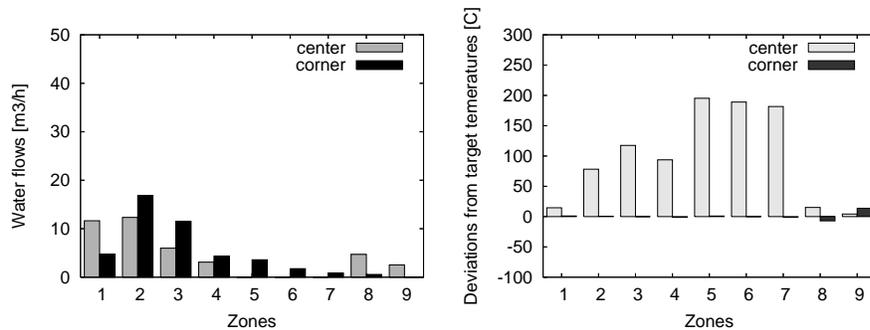

Figure 3. A trade-off solution from the middle of the approximation set for the casting speed speed of 1.2 m/min: $c_1 = 915\,^{\circ}$C, $c_2 = 4.5$ m.

Finally, it is worth checking the extreme solutions from an approximation set at a given casting speed. Figures 7 and 8 clearly show how one objective is met at the expense of the other. None of these would normally be used in practice. Instead, a plant engineer would rather select a trade-off setting balancing between the two objectives.

5.   Conclusion

Optimization of process parameter settings in continuous casting of steel is a key to higher product quality. Nowadays it is often performed through virtual experimentation involving numerical process simulators and advanced optimization techniques. In this preliminary study of optimizing 18 cooling
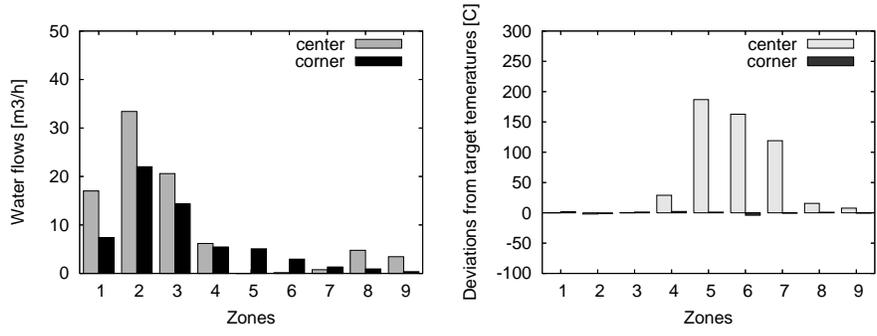
Figure 4.   A trade-off solution from the middle of the approximation set for the casting speed speed of 1.4 m/min: $c_1 = 537\,^\circ$C, $c_2 = 2.9$ m.
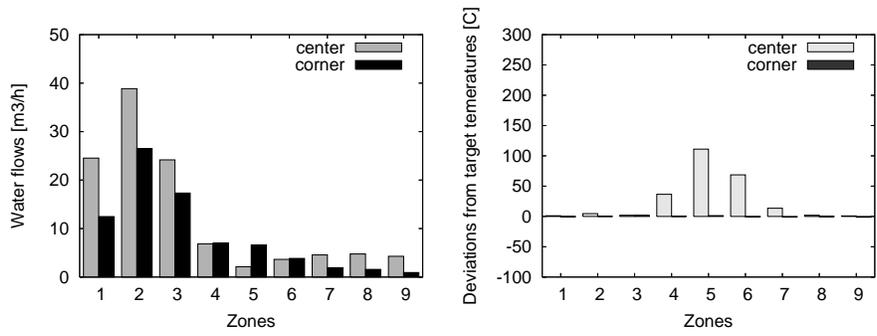

Figure 5.   A trade-off solution from the middle of the approximation set for the casting speed speed of 1.6 m/min: $c_1 = 247\,^\circ$C, $c_2 = 1.5$ m.
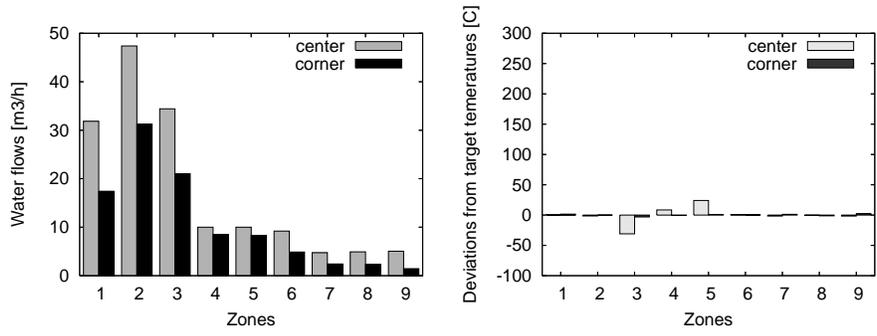

Figure 6.   A trade-off solution from the middle of the approximation set for the casting speed speed of 1.8 m/min: $c_1 = 80\,^\circ$C, $c_2 = 0.2$ m.

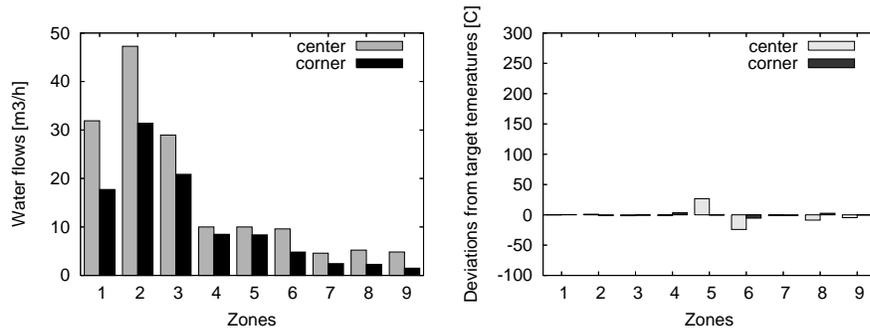water flows for an industrial casting machine the multiobjective optimization was brought into play.

Figure 7. The leftmost solution from the approximation set for the casting speed speed of 1.4 m/min: $c_1 = 85\,^\circ$C, $c_2 = 5.6$ m.
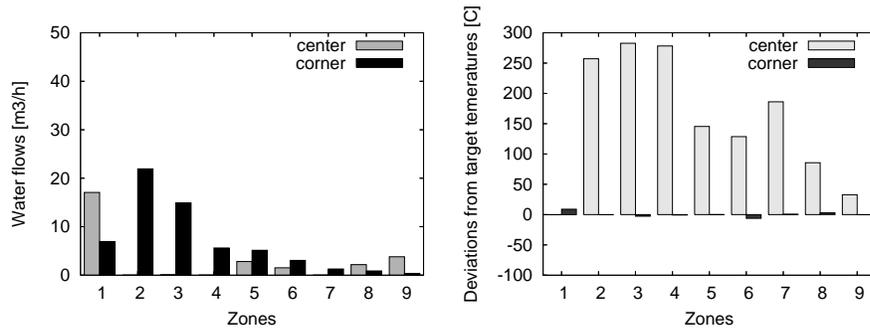

Figure 8. The rightmost solution from the approximation set for the casting speed speed of 1.4 m/min: $c_1 = 1{,}419\,^\circ$C, $c_2 = 0.0$ m.

The analysis assumes steady-state process conditions, hence the results are not primarily intended for control purposes but rather for better understanding of the process and evaluation of the casting machine performance. The resulting approximation sets of Pareto optimal fronts indeed offer a more general view of the process properties. The results support some facts already known in practice and, at the same time, show critical points, such as the need to reformulate the temperature deviation criterion to ensure uniform distribution of temperature differences over the zones, and extend the optimization problem definition with an additional constraint. From the practical point of view, further studies will also explore how much the optimization results are affected by the factors that were kept constant so far, such as steel grade, slab geometry and casting machine characteristics.

Acknowledgment

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