Analyzing Production Process Performance through Evolutionary Multiobjective Optimization

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ABSTRACT: Nature-inspired computational techniques are nowadays being developed for and employed in various application domains. Evolutionary algorithms, known as general and robust optimizers, have recently been extended to deal with multiobjective optimization where search for the best among candidate solutions is performed not according to one, but multiple, usually conflicting objectives. In this paper we show how evolutionary multiobjective optimization can be used in parameter tuning and performance analysis of a metallurgical production process where several empirical criteria are applied to ensure the process safety and product quality. The paper introduces the concept of multiobjective optimization and the applied algorithm, describes the considered task of process parameter tuning and the performed numerical experiments, and discusses the obtained results. In contrast to single-objective optimization, the multiobjective approach enables a much better insight into the process performance.

KEYWORDS: steel production, continuous casting, numerical simulation, parameter tuning, product quality, evolutionary computation, differential evolution, multiobjective optimization

1 INTRODUCTION

Nature has long been considered among computer scientists as a source of inspiration in algorithm design. Nature-inspired computational techniques, such as neural networks, artificial immune systems and evolutionary algorithms, are nowadays capable of solving demanding problems, usually too complex to be handled by traditional methods. This particularly holds for search and optimization tasks with huge and ill-structured search spaces where exact algorithms are inapplicable, while nature-inspired algorithms can provide a means for obtaining acceptable solutions with feasible computational resources. A methodology of this type is evolutionary computing [3], which is concerned with design and application of stochastic search and optimization algorithms, taking inspiration from natural selection and genetics. Evolutionary algorithms are known as robust general-purpose optimizers suitable even for multimodal, time-dependent and multiobjective optimization problems that are known to be hard for other algorithms.

Many real-world optimization problems involve multiple, often conflicting objectives. Production under tough market competition, for example, requires continuous improvement of productivity and product quality, and reduction of production costs and environmental threats. Formal treatment of such problems calls for multiobjective optimization, which fundamentally differs from traditional single-objective optimization in that not only one, but numerous optimal solutions exist, each representing a particular trade-off among the objectives. Because of its complexity and unavailability of algorithms, true multiobjective optimization was rarely practised in the past. Instead, the problems were transformed into a single-objective form using the weighted sum of objectives, or selecting the most critical objective for optimization and dealing with others as constraints. In contrast to that, the multiobjective optimization techniques based on evolutionary algorithms [1] proposed in the last decade are capable of finding multiple trade-off solutions from which a user can choose the most appropriate one according to additional preferences.

In this paper we show how evolutionary multiobjective optimization can be used in parameter tuning and performance analysis of a metallurgical production process known as continuous casting of steel. This is nowadays the prevailing steel production procedure, consisting of cooling molten steel and shaping it into semi-manufactures, such as billets, blooms and slabs. The process safety, productivity and product quality depend on numerous process parameters that need to be properly tuned. This is a demanding task since the number of possible parameter settings is high and the involved criteria are conflicting. Assuming steady-state caster operation and having a reliable numerical simulator of the process available, it is however possible to perform off-line optimization of the process parameters with respect to multiple objectives. We use a multiobjective evolutionary algorithm integrated with a casting process simulator to tune coolant flows on a casting machine so that several empirical criteria of process performance are optimized.

The paper is structured as follows. Section 2 introduces the concept of multiobjective optimization and DEMO, the multiobjective optimization algorithm used in this work. Section 3 describes the multiobjective optimization task of process parameter tuning in continuous casting of steel. Section 4 presents the experimental setup, describes the numerical experiments performed for various problem formulations, and discusses the results. Section 5 concludes the paper.

2 MULTIOBJECTIVE OPTIMIZATION

In multiobjective optimization we wish to simultaneously optimize several objectives. Therefore, the cost function $\mathbf{c}$ to be optimized has the following form:

$$\begin{gathered}\mathbf{c}\colon X \to Z \\ \mathbf{c}\colon (x_1, \ldots, x_n) \mapsto (c_1(x_1, \ldots, x_n), \ldots, c_m(x_1, \ldots, x_n)),\end{gathered} \tag{1}$$

where X is an n-dimensional decision space, and $Z \subseteq \mathbb{R}^m$ is an m-dimensional objective space ($m \geq 2$). While two objective vectors cannot always be compared, there exists the concept of *Pareto dominance* which can be used to partially order the objective vectors from Z. We say that $\mathbf{z}^1$ *dominates* $\mathbf{z}^2$ ($\mathbf{z}^1 \prec \mathbf{z}^2$) if and only if $\mathbf{z}^1$ is not worse than $\mathbf{z}^2$ in all objectives and is better in at least one objective. When no objective vector from Z dominates the objective vector $\mathbf{z}$, we say that $\mathbf{z}$ is *nondominated*. All nondominated vectors from Z form the set of optimal objective vectors, called the *Pareto optimal front*. Each vector from the Pareto optimal front represents a different trade-off between the objectives and without additional information no optimal vector can be preferred to another. The output of a multiobjective optimizer typically consists of an *approximation set*, i. e. a set of nondominated vectors that approximate the Pareto optimal front.

Most of the proposed evolutionary algorithms for multiobjective optimization, including the well-known NSGA-II (Nondominated Sorting Genetic Algorithm) [2] use genetic algorithms to explore the decision space. However, a recent study has shown that Differential Evolution (DE) [7] outperforms genetic algorithms on multiobjective optimization problems [9]. For this reason we use the DE-based algorithm DEMO (Differential Evolution for Multiobjective Optimization) [8] to optimize the continuous casting process.

In DE, as well as DEMO, each solution is encoded as an n-dimensional vector. New solutions, also called candidates, are constructed from the existing ones using operations such as vector addition and scalar multiplication. After the creation of a candidate in DE, the candidate is compared with its parent and the best of them remains in the population, while the other one is discarded. In DEMO, on the other hand, the candidate and its parent are compared using the Pareto dominance relation. 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, when 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, DEMO truncates it to the original size using nondominated sorting and crowding distance metric known from NSGA-II [2]. A detailed description of DEMO can be found in [8].

3 MULTIOBJECTIVE OPTIMIZATION OF THE CONTINUOUS CASTING PROCESS

Continuous casting of steel starts with pouring liquid steel into a bottomless mold cooled with internal water flow. The cooling water extracts heat from the molten steel and initiates the formation of a solid shell. Exiting the mold, the solidifying steel slab enters the secondary cooling area of the casting system where it is cooled by water sprays. The secondary cooling area is divided into cooling zones where coolant flows can be tuned individually.

We deal with a particular casting machine with nine secondary cooling zones. In each zone, cooling water is dispersed to the slab at the center and the corner positions, hence in total 18 coolant flows need to be set. For the center and the corner positions in each zone the target slab surface temperatures are prespecified as shown in Table 1.

Table 1: Target surface temperatures in °C

Zone number	1	2	3	4	5	6	7	8	9
Center position	1050	1040	980	970	960	950	940	930	920
Corner position	880	870	810	800	790	780	770	760	750

Coolant flows should be tuned in such a way that the resulting slab surface temperatures approach the target temperatures as closely as possible. From metallurgical practice, satisfying this criterion is known to increase the quality of the cast steel. Accordingly, we define a minimization objective in the form of the sum of differences between the actual and target temperatures over the secondary cooling zones:

$$c_1 = \sum_{i=1}^{N_Z} |T_i^{\text{center}} - T_i^{\text{center}*}| + \sum_{i=1}^{N_Z} |T_i^{\text{corner}} - T_i^{\text{corner}*}|, \tag{2}$$

where N_Z is the number of zones, T_i^{center} and T_i^{corner} are the slab surface temperatures at the center and the corner positions in zone i, and $T_i^{\text{center}*}$ and $T_i^{\text{corner}*}$ the target temperatures in zone i.

Another empirical metallurgical criterion refers to the core length, l^{core}, i.e. the distance from the mold exit to 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, while longer core length has to be avoided for safety reasons. Formally, this gives another objective to be minimized:

$$c_2 = |l^{\text{core}} - l^{\text{core}*}|. \tag{3}$$

Moreover, coolant flows cannot be set arbitrarily, but according to the technological constraints. For each zone, minimum and maximum values are prescribed for the center and the corner coolant flows. To avoid unacceptable core length, an additional constraint is considered: $c_2 \leq \Delta l_{\text{max}}^{\text{core}}$.

In summary, we deal with a constrained 18-variable two-objective optimization problem. As a prerequisite for computer optimization we employ a numerical simulator of the casting process that, given the coolant flow values, calculates the temperature field in the slab and returns the values of objectives c_1 and c_2. For this purpose we use a 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. The model has previously been used in a single-objective optimization study of the casting process [4] and is accurate enough to serve for online process control [6].

4 NUMERICAL ANALYSIS

A multiobjective analysis of the casting process performance was carried out to find coolant flow settings that result in trade-offs between the two conflicting objectives. Steady-state operation of the casting machine was assumed and the calculations executed for different casting speeds: the usually practised speed of 1.8 m/min, and two lower speeds of 1.6 m/min and 1.4 m/min that are used when the process needs to be slowed down to ensure the continuity of casting, for example, when a new batch of molten steel is delayed. Numerical experiments were performed for a selected steel grade and slab cross-section of 1.70 m $\times$ 0.21 m. Candidate solutions were encoded as 18-dimensional real-valued vectors, representing coolant flow values at the center and the corner positions in the nine zones of the secondary cooling area. Search intervals for coolant flows at the center and the corner positions in zones 1–3 were between 0 and 50 m^3/h, and in the zones 4–9 between 0 and 10 m^3/h. The target core length, $l^{\text{core}*}$, was 27 m and the maximum allowed deviation from the target, $\Delta l_{\text{max}}^{\text{core}}$, was 7 m.

The numerical simulator of the casting process was coupled with DEMO to form an automated optimization environment. Searching for good approximation sets, DEMO evolved populations of candidate solutions, while the simulator served as a solution evaluator. Reasonable algorithm settings found in preliminary experiments were 50 for the population size and 100 for the number of generations. An execution of the optimization algorithm under these setting involved 5000 solution evaluations (roughly 50 hours of CPU time) and ensured high repeatability of results.

Figure 1 shows the resulting nondominated solutions (approximation sets for Pareto optimal fronts) found by DEMO for different casting speeds. It can be seen that the two objectives can simultaneously be fulfilled to the highest degree at the regular casting speed of 1.8 m/min. On the other hand, the lower the speed, the more evident the conflicting nature of the two objectives: improving the coolant flow settings with respect to one objective makes them worse with respect to the other. In addition, a systematic analysis of the solutions confirms that the actual slab surface temperatures are in most cases higher than the target temperatures, while the core length is shorter than or equal to the target core length. Figure 2 shows the temperature differences for trade-off solutions from the middle of the approximation sets where the criteria are assumed to be of equal importance. From the distributions of temperature differences it can be observed that the target temperature requirements are much easier to accomplish at the corner positions than at the center positions of the slab. Not only is the sum of temperature differences high at lower casting speeds, it also consists of very nonuniformly distributed contributions from various positions. While the differences at certain center positions are close to zero, at others they amount up to 200°C.

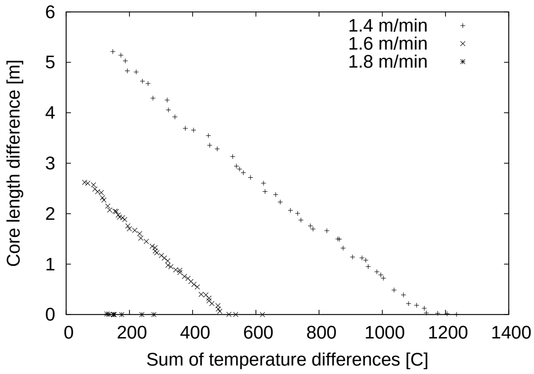

Figure 1: Nondominated solutions to the two-objective steel casting optimization problem for different casting speeds

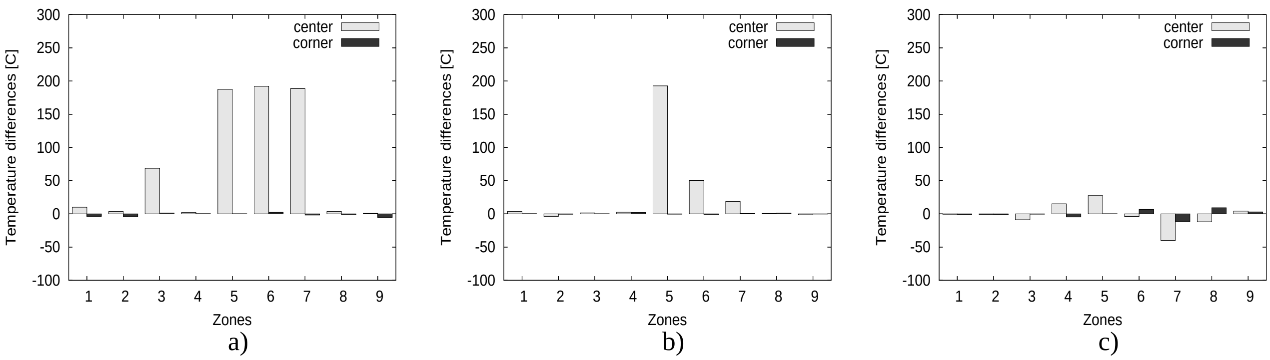

Figure 2: Temperature differences for trade-off solutions at different casting speeds: a) 1.4 m/min (sum of temperature differences 677°C, core length difference 2.2 m), b) 1.6 m/min (281°C, 1.3 m), c) 1.8 m/min (151°C, 0.0 m)

As noted in a preliminary analysis of these results [5], high variations of surface temperatures over the cooling zones are not desired. We therefore refined the optimization problem definition to address not only the minimization of temperature differences and core length difference, but also reduce the variation of temperature differences. A straightforward idea in this direction might be to consider each temperature difference as an individual minimization objective. However, it is important to note that dealing with a 19-objective problem (18 temperature differences and the core length difference) is beyond the capabilities of any known multiobjective optimization algorithm. To get a computationally feasible problem, a three-objective version was then formulated where the two original minimization objectives were supplemented with an additional one, the standard deviation of temperature differences. Run on this problem with the population size 50 for 200 generations, DEMO found nondominated solutions in the three-objective space as shown in Figure 3. Furthermore, Table 2 gives the values of objectives for the three extreme solutions and a trade-off solution from the middle of the approximation set, and Figure 4 illustrates the corresponding temperature differences.

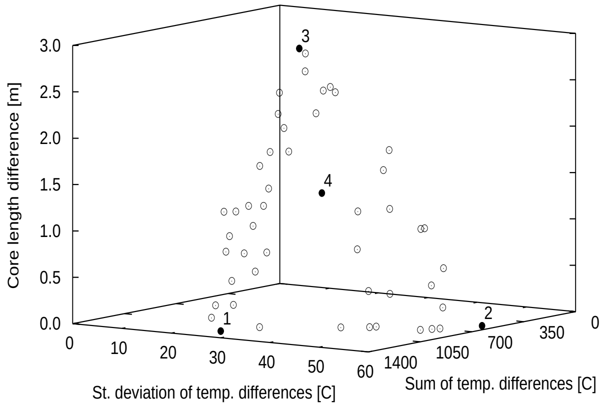

Figure 3: Nondominated solutions for the three-objective steel casting optimization problem (casting speed 1.6 m/min)

Table 2: Values of objectives for selected nondominated solutions from Figure 3

Solution number	Sum of temperature differences [°C]	St. dev. of temp. differences [°C]	Core length difference [m]
1	1282	25.5	0.0
2	584	58.5	0.0
3	107	7.2	2.6
4	588	26.2	1.3

The obtained results provide a clear insight into the continuous casting process performance in view of multiple objectives. They show to what degree fulfilling a selected objective comes at the expense of the remaining ones. It is now up to a plant engineer to decide how to balance among the objectives in various practical situations.

5 CONCLUSION

Nature-inspired optimization algorithms represent a powerful means of solving difficult problems, including those of high dimensionality and with multiple objectives. Among them, evolutionary multiobjective optimization algorithms have reached the stage of applicability to real-world problems. Using this approach, we analyzed the performance of industrial continuous casting of steel for a specific casting machine, steel grade and slab geometry. The task was to tune 18 coolant flows in the secondary cooling zone of the casting machine with respect to multiple objectives. The objectives were defined empirically to ensure the highest possible process safety and product quality. An integrated optimization environment consisting of a DE-based optimization algorithm and a reliable process simulator was used to perform calculations for various casting speeds and optimization problem formulations.

The resulting approximation sets of Pareto optimal fronts confirm the conflicting nature of the imposed objectives. They are beneficial in that they allow for better understanding of the process behavior and provide a clear picture of trade-offs in deciding among various process parameter settings. Future work in this domain will focus on the effect of other process characteristics, such as steel grade and slab geometry, on the optimization outcome, as well as on reducing the number of time-consuming process simulations needed to obtain good approximation sets.

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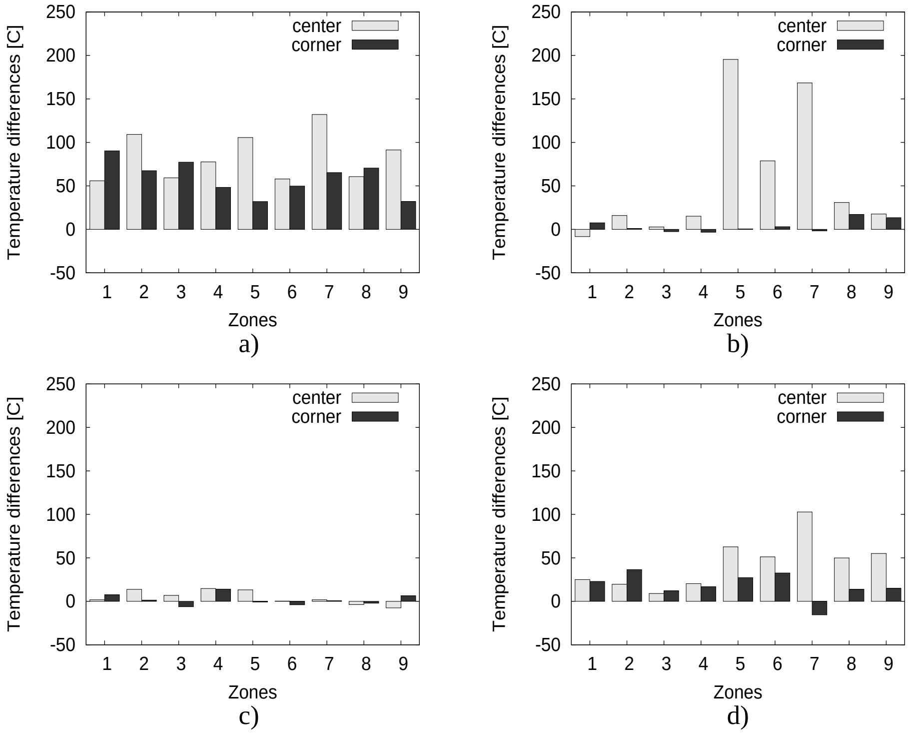

Figure 4: Temperature differences for selected nondominated solutions from Figure 3: a–c) extreme solutions 1–3, and d) trade-off solution 4

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