MULTIOBJECTIVE OPTIMIZATION OF PROCESS PARAMETERS IN STEEL PRODUCTION

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Abstract: The paper presents a multiobjective optimization approach to process parameter optimization in continuous casting of steel, which is the most widely used steel production process. The optimization task is to find parameter values such that the target values of the empirical metallurgical optimization criteria are approached as closely as possible, since this in turn results in high quality of the cast steel. The problem is being solved with a multiobjective evolutionary algorithm coupled with a numerical simulator of the casting process. The resulting trade-off solutions are visualized to support decision-making about the preferred solutions.

Keywords: continuous casting of steel, process parameters, product quality, multiobjective optimization, Pareto dominance, DEMO algorithm

1 INTRODUCTION

Contemporary material production strongly depends on numerical methods and computer support. Numerical simulators are a prerequisite for performing computer experiments and enable insight into process evolution. Moreover, coupled with efficient optimization algorithms, they make it possible to automate process parameter optimization, improve material properties, increase productivity and reduce production costs.

An example of a material production process to which modern computational approaches are being intensively applied is continuous casting of steel. Here molten steel is cooled and shaped into various semifinished products. To produce high-quality steel, it is crucial to properly control the metal flow and heat extraction during the process execution. They depend on several process parameters, such as the casting speed and coolant flows. However, finding the optimal values of process parameters is hard because of several obstacles. Above all, the number of possible parameter settings grows exponentially with the number of considered parameters, the criteria are conflicting, and on-site parameter tuning is infeasible as it may be expensive and even dangerous. The simulator-optimizer coupling is a reasonable alternative to deal with the problem.

In the past, a common way of solving optimization problems with multiple objectives was to aggregate the objectives into a single cost function and solve the simplified problem with a suitable single-objective optimization method. Nowadays it is becoming an increasingly popular practice to address such problems in their original multiobjective form. For this purpose, population-based metaheuristics capable of finding sets of trade-off solutions in a single run, such as evolutionary algorithms and particle swarm optimizers, are typically used.

In this paper we report on multiobjective optimization of process parameters on a steel casting machine where the task is to find parameter settings that maximize the quality of the cast steel given the empirically defined quality indicators. An optimization environment consisting of a numerical process simulator and an evolutionary-algorithm-based optimizer, equipped with result visualization capability, was developed and installed at a steel plant where it was evaluated in continuous casting of a selected steel grade. The paper introduces the related work, presents the optimization problem, reports on the experimental setup and the obtained results, and, in the conclusion, summarizes the study and suggests future work.

2 RELATED WORK

Evolutionary multiobjective optimization algorithms (EMOAs) are widely used in industry to optimize various devices and processes. A comprehensive literature survey on the applications of EMOAs in materials science and engineering is presented in [1]. Here we focus on the optimization problems related to continuous steel casting process. The purpose of optimization is to find parameter settings (controls) that result in improved steel quality, reduced defects, minimized bulgings, or optimize specific parameters, such as the lubrication index and peak friction. If the constraints describing the technological requirements result in an empty set of feasible controls, the optimization problem is usually reformulated into finding a control that violates the constraints as little as possible.

To obtain high-quality cast steel, various algorithms and approaches are applied to different (sub)sets of process parameters. In [5], the authors used multiobjective ant-colony system to optimize the billet surface temperatures and the length of the liquid core. Both objectives were calculated as a difference between the actual and the target values. Additional examples of optimizing the casting process performance are presented in [9] and [10] where a genetic algorithm employing a knowledge base of operational parameters is used.

In [3], two variants of an evolutionary algorithm (generational and steady state) and the downhill-simplex method were applied to significantly improve the manual settings of coolant flows. The work continued in [4] where the core length and temperature deviations in the casting process were optimized with an EMOA called DEMO [8]. On a similar problem exhaustive search and DEMO were evaluated with various discretization steps for parameter settings [6]. The results, analyzed in view of effectiveness and efficiency, showed that the most suitable way to solve such optimization problems is to apply a stochastic optimization approach on the finest reasonable discretization.

3 OPTIMIZATION PROBLEM

Continuous casting of steel is a complex metallurgical process that starts with molten steel being transported from an electric furnace and poured into the ladle and further led through the tundish which serves as a buffer for the liquid steel. The material flow continues into the mold. Cooling water flowing through the channels in the walls of the mold extracts heat from steel and initiates its solidification. Liquid steel with a thin solid shell, called the strand, exits the base of the mold and enters the cooling chamber where it is supported by water-cooled rollers and sprayed with water from the wreath and spray cooling systems. Heat extraction and solidification continue, and at the exit from the casting machine solidified steel is cut into billets of the desired length.

The quality of the cast steel depends on appropriate process control, specifically, on proper tuning of the process parameters. According to the empirical knowledge from steel production, the crucial process parameters include the casting speed, the change of the mold coolant temperature, and the coolant flows in the wreath and spray systems. On the other hand, the three key indicators of the process suitability and, consequently, the expected steel quality, are the length of the liquid core in the strand, known as the metallurgical length, the thickness of the solid shell at the mold exit, and the strand surface temperature at the unbending point.

Based on these observations, we formulated a multiobjective optimization problem, involving input variables (process parameters), output variables (quality indicators), and the desired output values. Both input and output variables are also provided with their boundary constraints. The task is to find the input variable settings resulting in the values of output variables as close as possible to the desired values.

Formally, given N input variables and M output variables, feasible solutions are the ones that satisfy the boundary constraints for each input variable x_i, $x_i^{\min} \leq x_i \leq x_i^{\max}$, $i = 1, \ldots, N$,

Table 1: Input variables, their boundary constraints and discretization steps.

Variable	Lower bound	Upper bound	Discretization
Casting speed [m/min]	1.0	1.2	0.01
Change of the mold coolant temperature [°C]	5	9	1
Wreath system coolant flow [l/min]	20	40	5
Spray system coolant flow [l/min]	40	70	5

Table 2: Output variables, their bounds and desired values.

Variable	Lower bound	Upper bound	Desired value
Metallurgical length [m]	10	12	10.5
Shell thickness [mm]	11	17	14
Surface temperature [°C]	1100	1140	1120

and each output variable y_j, $y_j^{\min} \leq y_j \leq y_j^{\max}$, $j = 1, \ldots, M$. Provided that an output variable is feasible, the corresponding optimization criterion (objective) $f_j \in [0, 1]$ is defined as

$$f_j = \frac{|y_j - y_j^*|}{y_j^{\max} - y_j^{\min}}, \tag{1}$$

where y_j^* is the desired vaue of y_j. The goal of otimization is to find the values of input variables that minimize the objectives.

4 EXPERIMENTAL SETUP

The above problem formulation was applied to the continuous casting process conducted at a specific steel plant where the considered steel grade was 70MnVS4. The optimization problem was approached using an integrated simulator-optimizer software environment named VizEMO-Steel [11]. As a simulator a numerical model of the steel casting process [12] was used, and the optimization procedure was the Differential Evolution for Multiobjective Optimization (DEMO) algorithm [8].

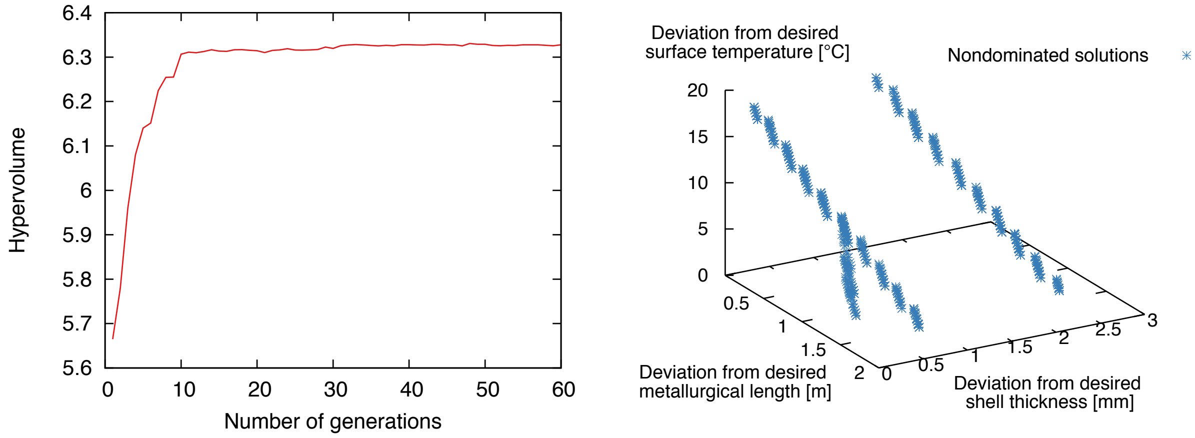
Given the values of input variables together with their boundary constraints and discretization steps (as listed in Table 1), the simulator numerically evaluates the casting process and returns the values of output variables. They are shown in Table 2 together with their lower and upper bounds and desired values as provided by engineers at the plant. Each output value is checked for satisfying the boundary constraints and, if feasible, mapped into a corresponding objective value according to Eq. 1.

DEMO is a population-based algorithm designed for numerical multiobjective optimization. It assumes candidate solutions are encoded as real-valued vectors and creates new solutions from the existing ones using vector addition and scalar multiplication. After creation of a candidate, 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 size possibly exceeds the predefined value. In this case, the population is truncated to the original size using the nondominated sorting procedure and the crowding distance metric known from NSGA-II [2].

The algorithm parameter values in this study were as follows: population size 50, number of solution evaluations 3000, scaling factor 0.5, and crossover probability 0.3.

5 RESULTS

This section presents and discusses the results of the performed optimization experiment. Figure 1(a) shows the value of the hypervolume indicator over 60 generations of the algorithm execution. We can see that the algorithm is able to converge rather quickly to a hypervolume value that is close to the best value achieved. After generation 30 only minor improvements in the hypervolume indicator can be observed. This implies that in order to save some time without significantly deteriorating the results, we could have stopped the algorithm earlier. Note that the entire run (3000 sequential solution evaluations) took approximately 6.5 days on a 1.9-GHz Intel Xeon server with 32 GB RAM.



(a) algorithm performance (b) nondominated solutions

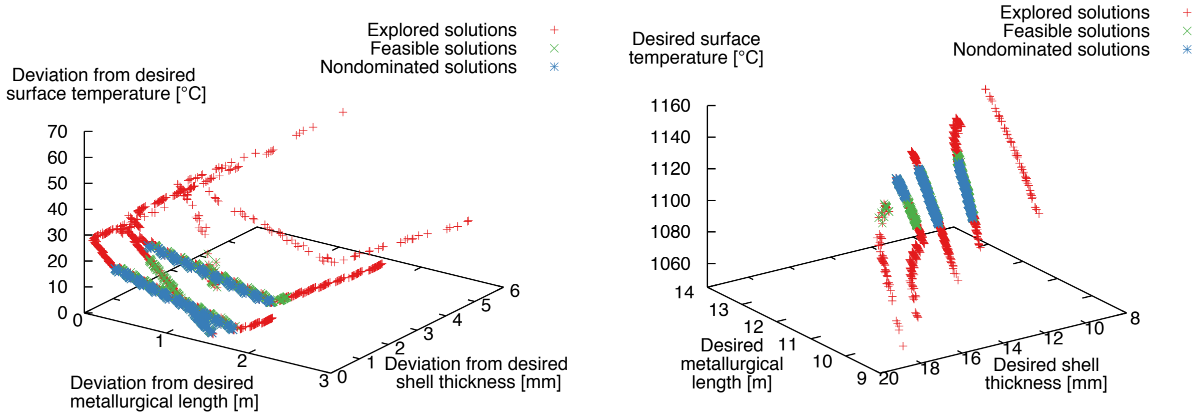
Figure 1: Final results: (a) algorithm performance in terms of the hypervolume indicator and (b) resulting nondominated solutions in the objective space.

Of the 3000 explored solutions, 2090 were feasible and 282 mutually nondominated. The latter are presented in Figure 1(b). The nondominated solutions form three distinct 'strips' in the objective space, which is caused by the discretization of input variables. Figure 2(a) reveals that the shorter strip is actually longer, but only its small part consists of nondominated solutions. Intrigued by the fact that these strips of solutions cross each other in the objective space, we visualized all solutions also in the output variable space. The resulting plot can be seen in Figure 2(b). The solutions are again positioned in strips, but they appear more parallel, which better fits the physics behind the steel casting process. Clearly, the shape of the nondominated front depends on the calculation of objectives from the output variables.

Finally, Figure 3 presents all nondominated solutions in the parallel coordinates plot, which connects the values of the input and output variables for each solution. By interacting with this plot, it is easy to see that the three strips containing nondominated solutions correspond to three different values of the input variable 'Change of the water temperature in the mold'. The parallel coordinates plot is of great help to the decision maker when (s)he needs to select the preferred solutions out of all nondominated ones.

6 CONCLUSION

Quality standards in the steel industry are becoming increasingly stringent, and in continuous casting of steel optimization of process parameters is crucial for achieving high product quality. At contemporary steel plants this optimization is carried out through virtual experimentation involving numerical simulators of the production process and advanced optimization techniques. In this study, the traditional single-objective treatment of the problem that involves multiple



(a) objective space (b) output variable space

Figure 2: All explored, feasible and nondominated solutions in the (a) objective and (b) output variable space.

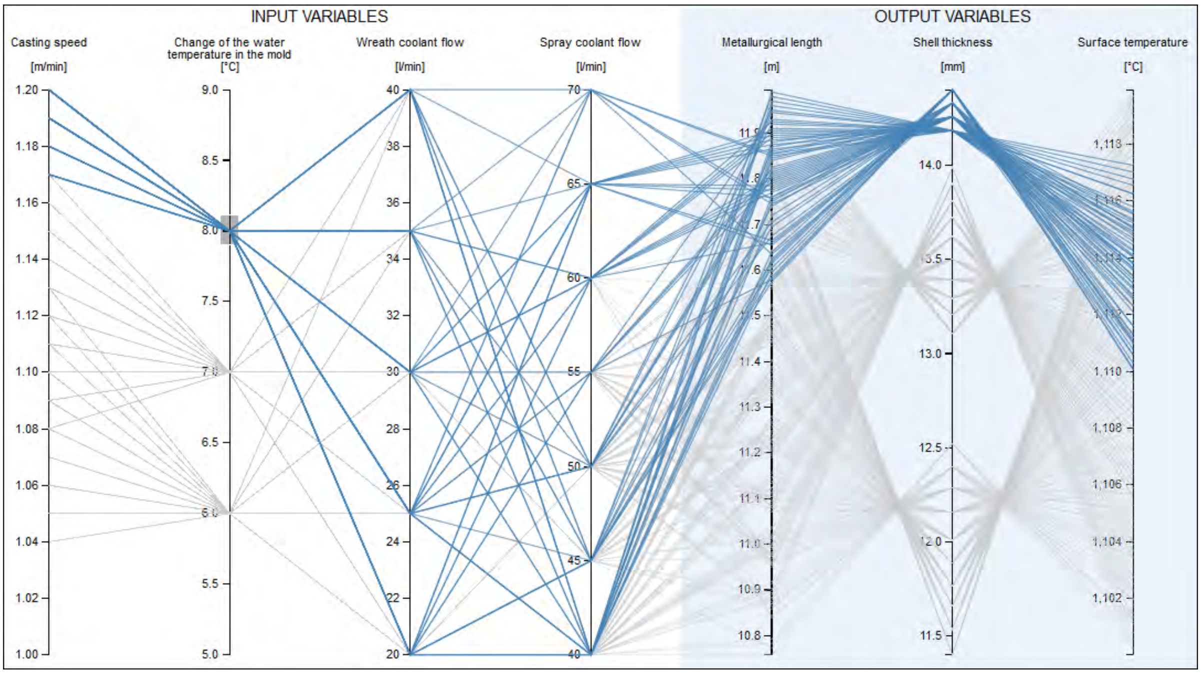


Figure 3: Screenshot of the parallel coordinates plot from VizEMO-Steel showing the connection between input and output variables for the nondominated solutions. Emphasized (blue) solutions correspond to value 8.0 of the input variable 'Change of the water temperature in the mold'.

criteria was replaced with multiobjective optimization as performed by an iterative population-based technique. Specifically, the DEMO algorithm coupled with a numerical process simulator was deployed in tuning critical process parameters with respect to three indicators of the product quality. The study assumes steady-state process conditions, where the optimization results are mainly intended to analyze the process and evaluate the casting machine performance, and not control the process itself.

The simulator-optimizer environment was equipped with a visualization tool and experimentally installed at a steel plant. As illustrated in this paper for a specific steel grade, the resulting approximation sets of Pareto optimal fronts offer an informative insight into process properties and, when appropriately visualized, support decision making about the final parameter setting to be applied. The decision depends on the user preferences that may change from one order to another.

As a key direction for future work, the presented optimization environment will be extended by involving a surrogate model to reliably approximate the process at a significantly lower computational cost than the currently used numerical simulator. This will increase the efficiency of the optimization procedure, which is an imperative for its regular deployment in practice.

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