A Comparative Study of Coolant Flow Optimization on a Steel Casting Machine

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***Abstract*— In continuous casting of steel a number of parameters have to be set, such as the casting temperature, casting speed and coolant flows, that critically affect the safety, quality and productivity of steel production. We have implemented an optimization tool consisting of an optimization algorithm and a casting process simulator. The paper describes the process, the optimization task, and the proposed optimization approach, and shows illustrative results of its application on an industrial casting machine where spray coolant flows were optimized. In the comparative study two variants of an evolutionary algorithm and the downhill simplex method were used, and they were all able to significantly improve the manual setting of coolant flows.**

I. Introduction

Like most other production processes, manufacture and processing of materials are under strong market-driven pressure for shortening the process development time, reducing experimental costs, improving material properties, and increasing productivity. In achieving these goals, numerical analysis is playing an increasingly important role. Material scientists and engineers in fact consider empirical knowledge and computational approximation as the basis for material process design and control. Numerical simulators give insight into process evolution, allow for execution of virtual experiments and facilitate manual optimization by trial and error. The optimization procedure can be automated by connecting a simulator with an optimization algorithm and introducing a quality function which allows for automatic assessment of the simulation results.

The principle goal of material process optimization is to ensure the desired properties of the material being processed while taking into account technical and economical limitations. The underlying assumption is that the material properties depend on certain process parameters, hence we may redefine the optimization task as search for parameter values such that the resulting material properties would be as close to the desired as possible [1].

Automation of the optimization procedure requires three components: a process simulator, an optimization algorithm and a quality function. Given the values of process parameters, the simulator models the process evolution and delivers the quantities for evaluation of the objectives. The simulation procedure is usually implemented as a numerical approximation solver for conservation equations of quantities, such as temperature, stress and flow, which determine the material governing laws. These calculations may refer to complex three-dimensional geometries and are usually computationally expensive. However, simulators of this type are now a firmly established tool of material and component manufacture. They usually enable visualization of three-dimensional data reflecting the current status of the process, and investigation of the effects of various parameter settings on objective quantities.

The quality function, also called objective function or cost function, is used to evaluate the current parameter values based on the results delivered by the process simulator. The simulator data usually needs to be aggregated and required objective quantities extracted before the evaluation takes place. In general, the objective function incorporates material laws and process constraints and is most often constructed by the material engineer.

The optimization algorithm receives the evaluation result and suggests process parameter values to be evaluated in the next iteration. The automatic process optimization environment operates in this manner until the quality function reaches an extreme value. The procedure should be effective and efficient, and the critical question here is which optimization algorithm to use. Unfortunately, the answer to this question is problem-specific and requires the knowledge on the properties of the solution space as well as on the optimization algorithms.

While numerical simulators are widely applied in practical material process design and control, not many automatic optimization systems have been developed and employed so far. This situation is in part because of the complexity of the task and in part because interdisciplinary collaboration of material scientists and experts in numerical optimization is required, which we have not witnessed until recently. Over the last years, however, several advanced computer techniques have been used in attempts to enhance the process performance and product characteristics. Cheung and Garcia [6], for example, combine a numerical model of the process with an artificial intelligence heuristic search technique linked to a knowledge base to find parameters values that result in defect-free billet production. Chakraborti and coworkers [4] report that genetic algorithms have proved to be the most suitable for optimizing the settings of the continuous casting mold. They use a Pareto-converging genetic algorithm to solve a multi-objective problem of setting the casting velocity in the mold region. In a further study [5] relying on heat transfer modeling, genetic algorithms are used to determine the maximum casting speed and solidified shell thickness at the mold exit. Finally, Oduguwa and Roy [12] use a novel fuzzy fitness evaluation in evolutionary optimization and apply it in rod rolling optimization. They solve a multi-objective problem of optimal rod shape design.

Our work in material process optimization is focused on continuous casting of steel and dates to 1996 when an experimental version of the optimization system was implemented for the Slovenian steel plant Acroni [7]. Its purpose was to find process parameter values that would result in as high as possible quality of continuously cast steel. The system consisted of a numerical simulator of the casting process [13] and an evolutionary algorithm for numerical optimization. The automated optimization approach was able to deliver improved parameter settings that were later verified at the plant. However, using a simple implementation of an evolutionary algorithm, it spent thousands of parameter evaluations to find high-quality solutions. As the time aspect is critical, the purpose of further exploration presented in this paper is not only to find good solutions applicable in practice but also to find them with minimum number of evaluations.

The paper is further organized as follows. Section II describes the process of continuous casting of steel and explains the concept of assuring the product quality through metallurgical cooling criteria. Section III presents the simulation-based optimization system. In Section IV the performance of the optimization system is illustrated on coolant flow tuning for an industrial continuous casting machine. A comparative study is done using a generational and steady-state evolutionary algorithm and the traditional downhill simplex optimization method, and the results are compared with the manual setting used previously at the plant. The paper concludes with a summary of the work done and results achieved, and provides future research directions.

II. Continuous Casting of Steel

A. Process Description

Continuous casting is a steelmaking technology that is nowadays used to produce the vast majority of steel semifinished products worldwide. It is a complex metallurgical process where molten steel is cooled and shaped into semimanufactures of desired dimensions.

The main components of the casting system are the ladle, tundish, mold, and the cooling subsystems. The ladle is a transfer vessel used for moving batches of liquid steel from a steelmaking furnace into the tundish. The tundish holds steel while casting is carried out. It is preheated to enable easier control of the steel temperature. Its most important function is to ensure the continuity of steel flow into the mold. The mold is the heart of the casting system. It extracts heat from the liquid steel and initiates the formation of a solid shell on the slab coming out of the mold. When operating, the mold oscillates to prevent the steel from sticking to the copper-alloy plates of the mold. Heat extraction is performed by coolant flowing through the channels built in the mold. This represents the primary cooling subsystem of the caster. The heat extraction and solidification continue as the slab, led by support rolls, passes through the caster. Along the slab water sprays are located, which form the secondary cooling subsystem. Cooling in this region results in complete solidification, and the solidified slab is finally cut into pieces of the ordered lengths. The process is schematically shown in Fig. 1.

B. Product Quality and Metallurgical Cooling Criteria

The continuous casting process is subject to various safety, quality, productivity and environmental requirements, but product quality is among the primary concerns of competing steel producers. The quality of continuously cast steel is determined with respect to the desired composition and cleanliness of the melt, the required shape and surface smoothness of the products, and the degree of cracking and segregation [3].

Control of fluid flow and heat transfer are crucial to the achievement of product quality and associated productivity in continuous casting of steel [9]. The experience gained in the process control over the last decades has evolved into empirical metallurgical cooling criteria. They restrict variations in the slab temperature field to assure desired product characteristics. Examples of the criteria include:

- maximum depth of the liquid pool,
- maximum cooling rate of the slab surface in the spray cooling zone,
- maximum reheating rate of the slab surface in the spray cooling zone,
- minimum slab surface temperature in unbending point,
- maximum negative deviation of the slab surface temperature in the spray cooling zone, and
- maximum positive deviation of the slab surface temperature in the spray cooling zone.

They were originally proposed by Laitinen [10] and are being gradually accepted into metallurgical practice. The empirical cooling criteria can be fulfilled by properly setting the parameters of the continuous casting process, such as the casting temperature, casting speed, coolant temperatures and flows, etc. However, tuning the process parameters is a demanding task, since the number parameters is high (usually between 20 and 30), and the criteria pose conflicting requirements for their values. In addition, parameter tuning based on real-world experimentation is infeasible because of the costs and safety risks. Alternatively, the process can be assessed and checked for possible improvements through a numerical optimization procedure.

III. Simulation-Based Optimization of the Casting Process

To search for process parameter settings that would result in higher product quality, we have designed an integrated optimization environment originally consisting of a numerical simulator of the casting process and an evolutionary algorithm for numerical optimization [7], [8], [14]. The integrated system

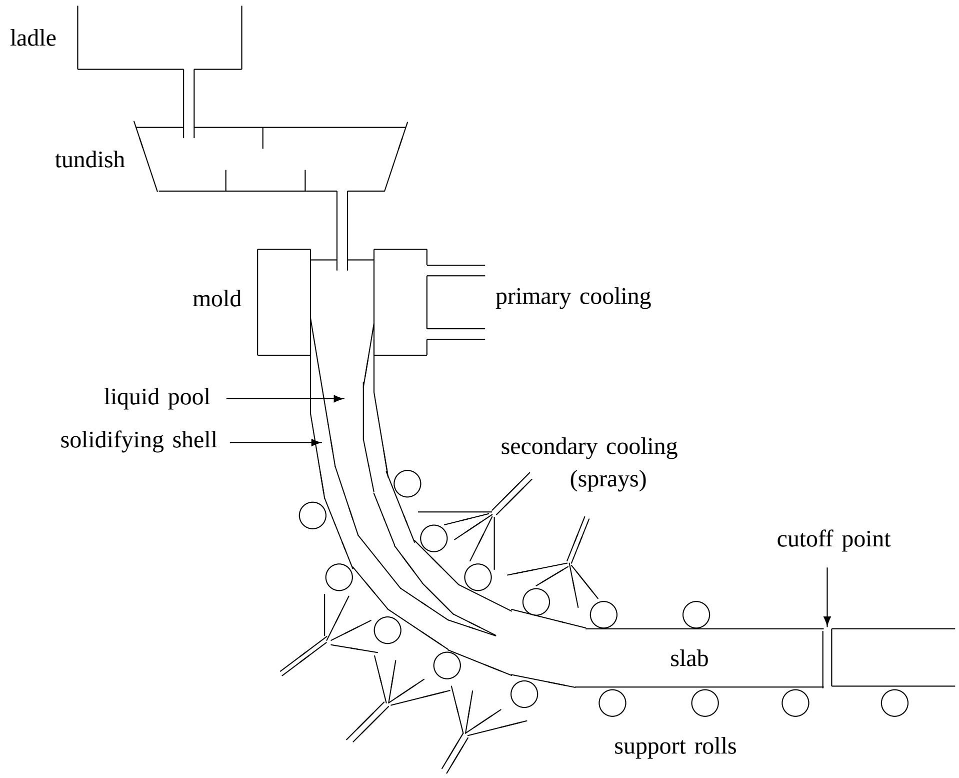

Fig. 1. Continuous casting of steel

operates autonomously: the evolutionary algorithm navigates the search through the parameter space and invokes the simulator to evaluate the parameter settings, while, given the parameter values, the simulator computes the temperature field in the slab and assesses the metallurgical cooling criteria.

The simulator employs detailed models of heat transfer mechanisms, contains a material properties database for various types of steel, and uses an iterative numerical method to compute the temperature field. The built-in heat transfer mechanisms include heat transfer to the mould, to the spray coolant in the secondary cooling zone, to the support rolls, and to the rolls stagnant and running water.

The simulator employs a finite volume method with Crank-Nicolson time discretization and Voller-Swaminathan iteration strategy to compute the temperature distribution in the slab. Using this iterative approach, a temperature field of approximately 10 million points is typically generated. From this data, values of the empirical metallurgical criteria are derived based on the analytical formulation of the criteria [13]. Finally, an overall measure of the caster performance is obtained as a weighted sum of the normalized values of the the metallurgical criteria c_i, $i = 1, \ldots, N_c$:

$$f = \sum_{i=1}^{N_c} w_i \, \frac{c_i - c_i^{\min}}{c_i^{\max} - c_i^{\min}} \tag{1}$$

that needs to be minimized. Here N_c is the number of the involved criteria, w_i are empirically determined weights denoting the importance of the criteria, and $c_i^{\min}$ and $c_i^{\min}$ the lower and upper bounds for the i-th criterion that are obtained in an initial series of simulator runs. Once the optimization procedure converges, the resulting parameter values are passed to the caster control system that generates appropriate control signals for the casting device.

IV. Empirical Evaluation in Coolant Flow Optimization

A. Experimental Setup

The evolutionary approach to process parameter setting was experimentally applied at the Acroni steel plant in continuous casting of construction steel AC-0113. The computation was performed for a slab with the cross-section of 1.03 m x 0.20 m. Out of more than 20 influential process parameters, 12 spray coolant flows were subject to optimization. The six metallurgical cooling criteria listed in Subsection II-B were considered and the task was to check whether the manual coolant flow setting used at the plant can be improved. Table I shows the predefined parameter search space used in the numerical optimization procedure. The total number of possible parameter settings for this optimization task equals to $5^{12} = 244\,140\,625$.

The iterative optimization procedure used real vector representation of candidate solutions and was run for 400 steps (process evaluations). Two versions of the evolutionary algorithm [2] were used, generational and steady-state. They both operated with the population size of 20 individuals. The

TABLE I

DISCRETIZED SEARCH SPACE FOR OPTIMIZATION OF SPRAY COOLANT FLOWS IN CONTINUOUS CASTING OF STEEL AC-0113

Coolant flow number	Min. value [l/min]	Max. value [l/min]	Step size [l/min]
1	120	160	10
2	65	85	5
3	200	280	20
4	190	270	20
5	160	240	20
6	150	230	20
7	120	160	10
8	140	180	10
9	120	160	10
10	120	160	10
11	130	170	10
12	120	160	10

operators involved to select and variate candidate solutions were tournament selection with the tournament size 4, multi-point crossover with probability 0.8, and uniform mutation with probability 0.05.

For the purpose of comparison, the downhill simplex method [11], also named the Nelder-Mead method after its authors, was incorporated into the optimization environment and applied to the same problem. Finally, random search of the process parameter space was performed to obtain a lower bound for the results of empirical optimization. With all tested methods, the parameter space was searched in a discrete manner, i.e. in the points prescribed by Table I. The calculations were run on a 1.8 GHz Pentium computer and the execution time to evaluate a single solution through numerical simulation was 2.5 minutes.

B. Results

The optimization procedures were tested both for the solution quality and repeatability of results. Fig. 2 shows the performance traces of the tested methods averaged over five runs and compares their results with the cost of the manual parameter setting (denoted by the horizontal line). Table II provides the numerical results and their statistics. It can be seen that the resulting solutions, including the ones obtained with random search, consistently outperformed the manual setting of the spray coolant flows previously used in practice. Furthermore, despite their stochastic nature, the applied optimization procedures were able to find solutions with small deviations of both the cost values obtained according to Eq. 1 (see the standard deviation column in Table II) and the coolant flow settings themselves.

Regarding the relative order of the methods we see that the steady-state evolutionary algorithm outperformed the generational one which has often been confirmed on numerical optimization problems. Roughly 300 evaluations were sufficient for the steady-state evolutionary algorithm to converge to the fittest solutions found in the numerical experiments. The downhill simplex delivered the second best result which may indicate that simple gradient techniques might be efficient in searching the coolant flow parameter space, too.

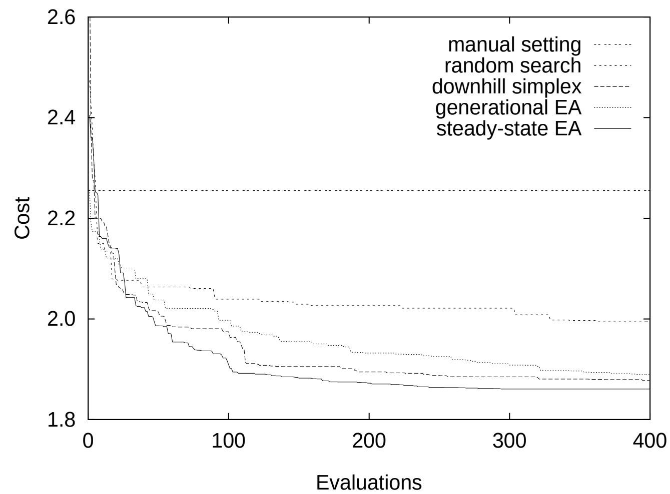

Fig. 2. Average performance of selected optimization algorithms

TABLE II

RESULT STATISTICS FOR THE TESTED OPTIMIZATION METHODS

Optimization method	Best	Average	Worst	St.dev.
Manual setting		2.2550		
Random search	1.9765	1.9916	2.0226	0.0182
Downhill simplex	1.8598	1.8775	1.8879	0.0137
Generational EA	1.8638	1.8892	1.9137	0.0192
Steady-state EA	1.8587	1.8606	1.8640	0.0021

Of primary interest to process engineers at the plant were, of course, the resulting coolant flows. It turns out that they are generally higher than manual settings for the first half of the sprays in the secondary cooling zone, and lower in the ending section of the secondary cooling zone. Fig. 3 compares the best settings found with the steady-state evolutionary algorithm and the manual settings. The optimized settings are now under evaluation for practical use at the plant.

V. CONCLUSION

Modern material manufacture and processing strongly relies on numerical analysis of the related processes made possible by powerful modeling and simulation software packages. To use them efficiently, an upgrade is needed towards process automatic optimization. The methodology studied in this paper consists of a numerical process simulator and empirical optimization algorithms linked with a quality function. We have illustrated the capabilities of this scenario with optimizing the process parameters for continuous casting of steel. Coolant flow settings in the spray cooling zone were tuned for possible improvement. Settings better than manual ones were found and a comparative study of performance of various optimization techniques was done.

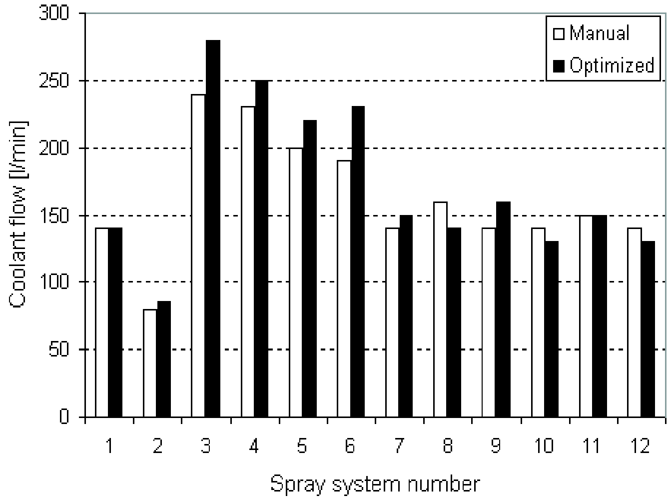

Fig. 3. Manual and optimized settings of spray coolant flows for continuous casting of steel AC-0113

The presented results should be viewed as preliminary. Systematic tuning of algorithm parameters would probably further improve the results and a number of additional methods could be tried. Moreover, problem the specificities, such as the discretization step size, also play important role in the performance of individual methods.

Challenging questions with important practical implications we hope to answer in the future work are how to define quality functions for the increasing number of conflicting criteria, and how to further reduce the number of process simulations required in the optimization procedure.

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