Model-Based Tuning of Process Parameters for Steady-State Steel Casting

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We present an empirical study of process parameter tuning in industrial continuous casting of steel where the goal is to assure the highest possible quality of the cast steel through proper parameter setting. The process is assumed to be under steady-state conditions and the considered optimization task is to set 18 coolant flows in the caster secondary cooling zone to achieve the target surface temperatures along the slab. A numerical model of the casting process was employed to first investigate the properties of the parameter search space, and then iteratively improve parameter settings. For this purpose, two stochastic optimization algorithms were used: a steady-state evolutionary algorithm and next-descent local optimization. The results indicate the difficulty of the optimization task arises not from a complicated fitness landscape but rather from high dimensionality of the problem.

Povzetek: V članku predstavljamo uglaševanje procesnih parametrov za industrijsko kontinuirano ulivanje jekla na osnovi numeričnega modela procesa in z uporabo stohastičnih optimizacijskih metod.

1 Introduction

Manufacturing and processing of materials are nowadays largely based on numerical analysis and computer support. Material scientists and engineers rely on computational approximation both in process design and control. Numerical simulators enable insight into process evolution, allow for execution of numerical experiments and facilitate manual process optimization by trial and error. In addition, reliable process simulators and efficient optimization techniques allow for automated optimization of process parameters and improvement of material properties. These goals can be achieved by interconnecting a process simulator with an optimization algorithm through a cost function which allows for automatic assessment of the simulation results. This framework has recently been extensively studied and applied to a number of material processes under the project COST 526: *Automatic Process Optimization in Materials Technology* (APOMAT) [5].

Continuous casting is a predominant technology of steel production in modern steel plants. It is a complex metallurgical process in which liquid steel is cooled and shaped into semi-manufactures of desired dimensions. To achieve proper quality of cast steel, it is essential to control the metal flow and heat transfer during the casting process. They depend on numerous parameters, such as the casting temperature, casting speed and coolant flows. Finding optimal values of process parameters is difficult since different, often conflicting criteria may be applied, the number of possible parameter settings is high, and parameter tuning through real-world experimentation is not feasible because of costs and safety risk. Over the last years, however, several computational techniques have been used to enhance the process performance and product characteristics, including knowledge-based heuristic search [4], genetic algorithms [10, 2], and evolutionary multiobjective optimization [3].

In this paper we report on preliminary numerical experiments in optimizing secondary coolant flows on a casting machine of the Rautaruukki steel plant in Finland. Calculations were done for a selected steel grade under the assumption of steady-state caster operation. Their objective was to get better insight into the properties of this optimization task and tune the coolant flows with respect to the given temperature distribution requirements. The paper describes the optimization problem, the applied mathematical model of the casting process and the experimental setup, and reports on numerical experiments and results.

2 The Optimization Problem

Figure 1 shows a schematic view of a continuous casting machine. In the continuous casting process molten 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 the solid shell. The shell formation is essential for the support of the slab after mold exit. After the mold the slab 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.

The secondary cooling area of the considered casting device is 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. Formally, a cost function is introduced to measure the differences between the actual and target temperatures. It is defined as

$$\begin{aligned} c(T) &= \frac{1}{2}(\sum_{i=1}^{N_Z} l_i(T_i^{\text{center}} - T_i^{\text{center}*})^2 + \\ &\quad + \sum_{i=1}^{N_Z} l_i(T_i^{\text{corner}} - T_i^{\text{corner}*})^2), \end{aligned} \tag{1}$$

where N_z denotes the number of zones, l_i the length of the i-th zone, T_i^{center} and T_i^{corner} the slab center and corner temperatures, while $T_i^{\text{center}*}$ and $T_i^{\text{corner}*}$ the respective target temperatures in zone i. The optimization task is to minimize the cost function over possible cooling patterns (water flow settings). Water flows cannot be set arbitrarily, but according to the technological constraints. For each water flow, minimum and maximum values are prescribed.

Table 1 shows an example of the prescribed target temperatures and water flow intervals for continuous casting of the steel grade analyzed in this study. The slab cross-section in this case was 1.70 m $\times$ 0.21 m and the casting speed 1.4 m/min.

Table 1: Target temperatures and water flow intervals for continuous casting of steel considered in the empirical study

Position	Zone number	Target [°C]	Flow number	Min. [m^3/h]	Max. [m^3/h]
Center	1	1050	1	7.1	26.1
	2	1040	2	22.8	57.5
	3	980	3	13.3	39.9
	4	970	4	1.5	7.9
	5	960	5	2.7	10.0
	6	950	6	0.8	6.5
	7	940	7	0.7	5.9
	8	930	8	1.0	5.8
	9	920	9	1.2	6.2
Corner	1	880	10	7.1	26.1
	2	870	11	22.8	57.5
	3	810	12	13.3	39.9
	4	800	13	1.2	3.5
	5	790	14	2.4	4.4
	6	780	15	2.4	2.9
	7	770	16	0.7	5.9
	8	760	17	1.0	5.8
	9	750	18	1.2	6.2

3 Mathematical Model of the Casting Process

The simulation model calculates the temperature field of the steel slab as a function of the casting parameters. We consider steady-state casting conditions, i.e. the parameters are constants in time. We denote the 3D geometry of the slab by $\mathcal{V} = \Omega \times [0, L_Z]$, where $\Omega = [0, L_X] \times [0, L_Y]$ is a 2D cross-section of the slab and L_Z is the length of the strand. Moreover, we denote by L_M the length of the mould. We divide the boundary $\Gamma = \partial\mathcal{V}$ into four parts:

$$\begin{aligned} &\Gamma_0 = \Omega \times \{0\}, \\ &\Gamma_N = \{(x,y) \in \partial\Omega : x = 0 \vee y = 0\} \times [L_M, L_Z], \\ &\Gamma_S = \{(x,y) \in \partial\Omega : x \neq 0 \wedge y \neq 0\} \times [0, L_Z) \cup \Omega \times \{L_Z\}, \\ &\Gamma_M = \{(x,y) \in \partial\Omega : x = 0 \vee y = 0\} \times [0, L_M]. \end{aligned} \tag{2}$$

The mathematical model for the temperature field $T = T(x,y,z,t)$ of the slab can be written as

$$\begin{cases} \frac{\partial H(T)}{\partial t} + v\frac{\partial H(T)}{\partial z} - \Delta K(T) = 0 & \text{in } \mathcal{V} \times (0, t_f], \\ T = T_0 & \text{on } \Gamma_0 \times (0, t_f], \\ \frac{\partial K(T)}{\partial n} + h(T - T_w) + \\ +\sigma\epsilon(T^4 - T_{ext}^4) = 0 & \text{on } \Gamma_N \times (0, t_f], \\ \frac{\partial K(T)}{\partial n} = 0 & \text{on } \Gamma_S \times (0, t_f], \\ \frac{\partial K(T)}{\partial n} = Q & \text{on } \Gamma_M \times (0, t_f], \\ T(x,y,z,0) = T^0 & \text{in } \mathcal{V}. \end{cases} \tag{3}$$

Here n is the unit vector of outward normal on $\partial\mathcal{V}$, h is the heat transfer coefficient, v is the casting speed, T_w and T_{ext} are known temperatures, σ is the Stefan-Boltzmann constant and ϵ is the emissivity. The cooling efficiency Q in the mould is a known constant and t_f is the simulation time. $H(T)$ and $K(T)$ are the temperature dependent enthalpy and Kirchoff functions (see [13] for details).

Equations 3 are discretized using the finite element method (FEM) and the corresponding nonlinear equations solved with relaxation iterative methods [7]. A more detailed description of discretization and construction of

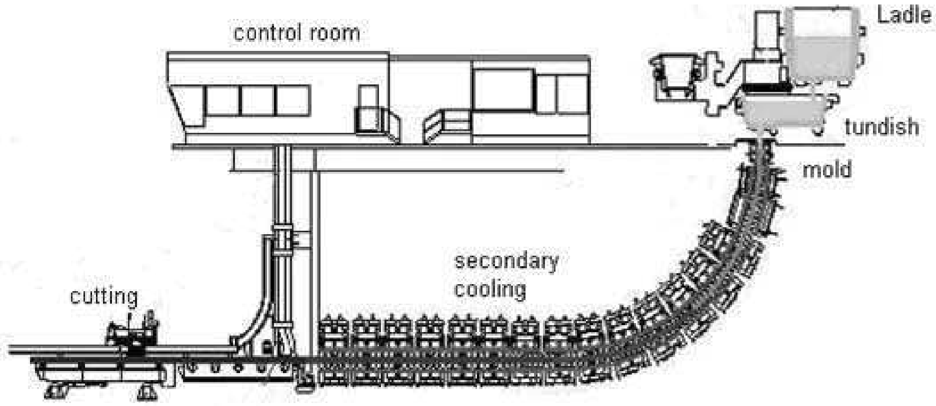

Figure 1: Continuous casting machine

FEM matrices is presented in [6]. We note that in our method it is sufficient to construct only 2D- and 1D-matrices. Therefore, it is obvious that the model is computationally much more efficient than in the case of using the ordinary 3D-brick elements.

4 Experimental Setup

Evaluation of cooling patterns and their assessment with respect to cost function (1) was done using the described mathematical model implemented in the form of a computer simulator. Its principal task is to dynamically track the temperature field in the slab as a function of process parameters. In this study it was applied under the assumption of steady-state caster operation, and the search for optimal cooling patterns performed in the off-line manner. A single simulator run takes about 40 seconds on a 1.8 GHz Pentium IV computer.

Before the integration of the simulator with the optimization algorithms, a number of simulator runs were performed to get an initial insight into the properties of the fitness landscape associated with the optimization problem. Specifically, the cost was analyzed as a function of individual parameters and pairs of parameters, while keeping the remaining parameters fixed at the values from the middle of their intervals.

The resulting plots show simple dependencies between the parameters and cost function in the form of monotonic or at most U-shaped curves and surfaces (see examples in Figures 2 and 3). They are much simpler than usual artificial test functions for numerical optimization, which is understandable because of the underlying physical process. Similar properties were found in the analysis of the fitness landscapes in parameter tuning for a continuous casting machine at the Acroni steel plant in Jesenice, Slovenia [11]. However, one should bear in mind that such analyses offer a very limited view of the problem characteristics. Nevertheless, the real difficulty comes with high dimensionality of the problem, as there are 18 independent process parameters subject to optimization.

Before the application of optimization procedures one has to decide whether to search for optimal solutions in continuous or discretized parameter space. In analogy to previous studies performed on similar task from the Acroni steel plant [9, 14, 8], the discrete version was considered. The rationale behind it is in the engineering approach to coolant flow tuning where it is meaningless to consider changes below certain amount as they do not reflect in changing the cost value. For the purpose of numerical experiments three discretizations were defined, a very rough one for initial tests of the optimization algorithms, another one with medium step sizes to refine the results, and the one with the uniform step size of 0.1 m^3/h which is the minimum change considered in practice for all coolant flows (see Table 2).

Given these dicretizations, one can to calculate the number of possible parameter settings. For a parameter from the interval $[p_i^{\min}, p_i^{\max}]$ with step size p_i^{step}, there are $v_i = \lfloor (p_i^{\max} - p_i^{\min})/p_i^{\text{step}} \rfloor + 1$ values possible, and the total number of settings is $v = \prod_{i=1}^{N_p} v_i$, where N_p is the number of parameters. This results in $4.6 \cdot 10^{12}$ possible setting for discretization 1, $4.9 \cdot 10^{23}$ for discretization 2, and $4.7 \cdot 10^{33}$ for discretization 3.

5 Numerical Experiments and Results

Two stochastic optimization techniques were applied to the coolant flow optimization problem, the steady-state evolutionary algorithm [1] and the next-descent local optimization algorithm. They were selected as they performed well in solving similar optimization problems for the Acroni steel plant [9, 14]. Both methods iteratively improved candidate solutions represented as real vectors of coolant flow values. The evolutionary algorithm was run with the

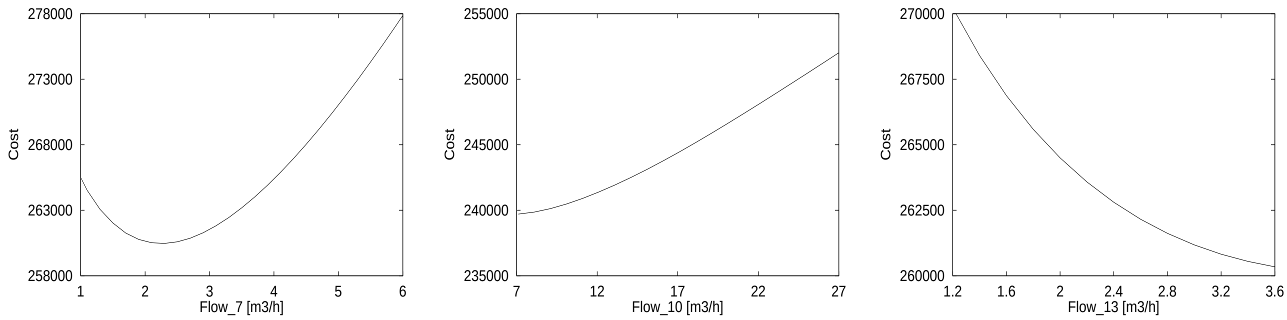

Figure 2: Examples of cost function dependencies on individual process parameters

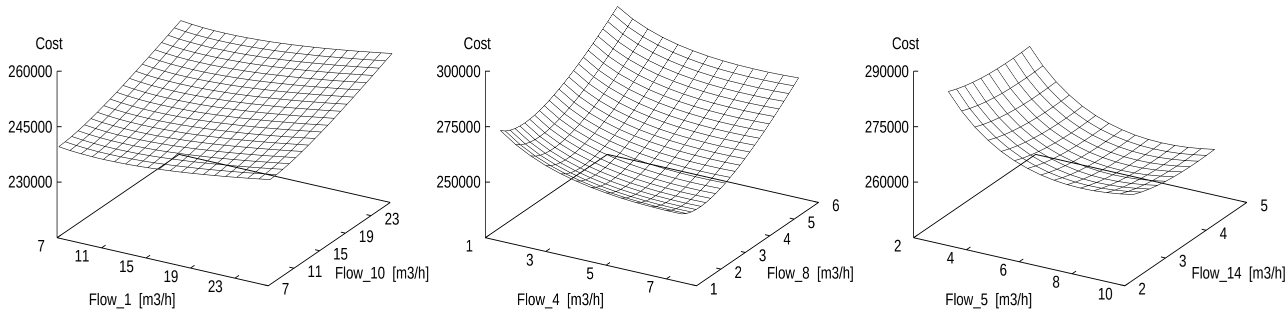

Figure 3: Examples of cost function dependencies on pairs of process parameters

Table 2: Parameter discretizations used in the optimization process; #val denotes the number of values possible for each parameter

Flow no.	Discretization 1 Step [m^3/h]	#val	Discretization 2 Step [m^3/h]	#val	Discretization 3 Step [m^3/h]	#val
1	4.7	5	1.0	20	0.1	191
2	8.6	5	1.0	35	0.1	348
3	6.6	5	1.0	27	0.1	267
4	1.6	5	0.5	13	0.1	65
5	1.8	5	0.5	15	0.1	74
6	1.4	5	0.2	29	0.1	58
7	1.3	5	0.2	27	0.1	53
8	1.2	5	0.2	25	0.1	49
9	1.2	5	0.2	26	0.1	51
10	4.7	5	1.0	20	0.1	191
11	8.6	5	1.0	35	0.1	348
12	6.6	5	1.0	27	0.1	267
13	0.5	5	0.2	12	0.1	24
14	0.5	5	0.2	11	0.1	21
15	0.1	6	0.1	6	0.1	6
16	1.3	5	0.2	27	0.1	53
17	1.2	5	0.2	25	0.1	49
18	1.2	5	0.2	26	0.1	51

population of 20 solutions, applying arithmetic crossover and Gaussian mutation adjusted to perform vector variation with prescribed discretization. The local optimization algorithm relied on the neigborhod relationship among candidate solutions. Two solutions were considered neighbors if differing in the i-th vector component for $\pm p_i^{\mathrm{step}}$. In this way each solution, with the exception of those on the edge of the search space, had $2N_p = 36$ neighbors. The algorithm started from a randomly selected point and was restarted after reaching a local minimum.

For each of the three search space discretizations the algorithms were run five times and their results evaluated statistically. The number of solutions checked (parameter settings evaluated) in each algorithm run was 200 for discretization 1, 500 for discretization 2, and 2000 for discretization 3. No other parameter adjusting was involved as this empirical study was a preliminary one.

The performance of the algorithms under different search space discretizations is illustrated in Figure 4 and the results in terms of cost summarized in Table 3. For discretization 1, the performance of random search is also shown to provide an empirical upper bound for the results. In this case, the local optimization algorithm clearly outperforms the evolutionary algorithm, but the cost values produced are still high which indicates the discretization is too rough to allow for detection of the near-optimal solution. With the refinement of discretization better results are found by both methods and their performance compares differently. The finer the discretization, the closer the final results, while in the initial stage of the search the evolutionary algorithm outperforms the local optimization algorithm. The solutions found with local optimization are however not dispersed as with the evolutionary algorithm. It turns out that the more complex the search space the more obvious the efficiency of the evolutionary algorithm in identifying the promising regions which suggests an appropriate hybrid of the two algorithms would reduce the number process simulations needed in the optimization procedure.

Certainly, the key result for material engineers at the plant are the optimized coolant flows. Their values will

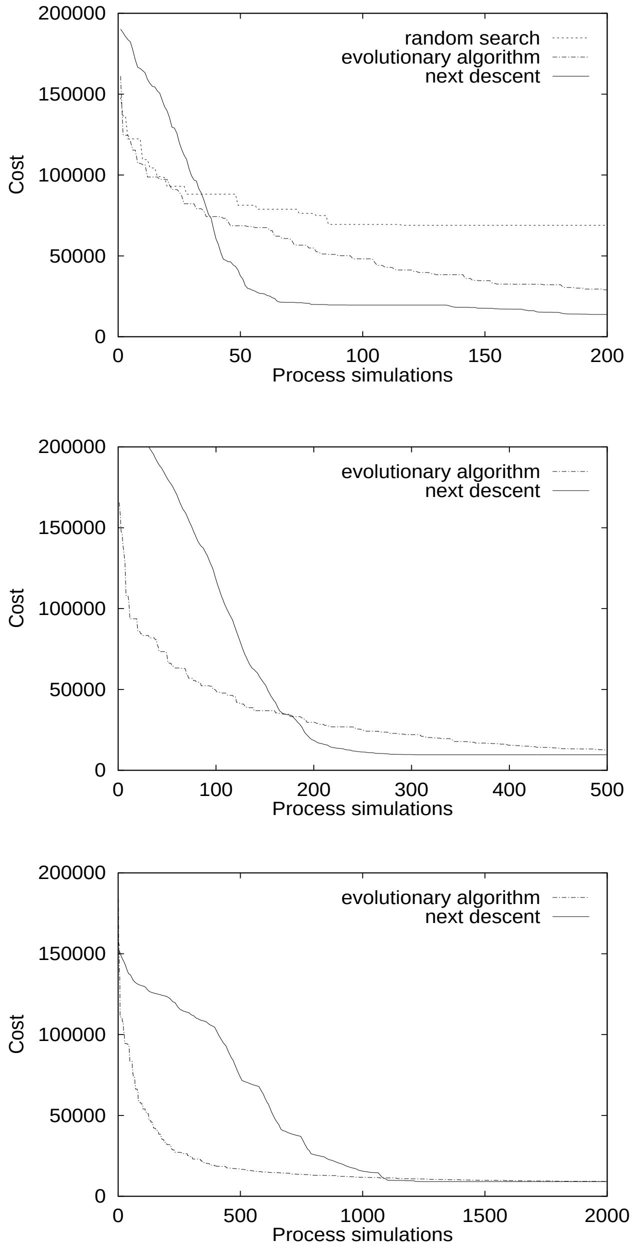

Figure 4: Performance of the optimization algorithms averaged over five runs of each algorithm for parameter discretizations 1 (top), 2 (center), and 3 (bottom)

Table 3: Summary of the optimized cost values found for three parameter discretizations; EA denotes the steady-state evolutionary algorithm, and ND next descent local optimization

Discr.	Method	Best	Average	Worst	St. dev.
1	EA	24988.8	28965.9	32842.5	2800.8
	ND	13417.9	13794.9	15062.7	716.3
2	EA	10371.3	12466.6	14092.0	1790.4
	ND	9592.9	9592.9	9592.9	0.0
3	EA	9078.5	9194.0	9247.2	73.7
	ND	9070.4	9070.4	9070.4	0.0

be compared with the empirical settings used in practice, and checked for possible contribution to the improvement of steel quality.

6 Conclusion

Optimization of coolant flow settings in continuous casting of steel is a key to higher product quality. It is nowadays to a high degree performed through virtual experimentation involving numerical process simulators and advanced optimization techniques. In this preliminary study of optimizing 18 cooling water flows for a Rautaruukki casting machine under steady-state conditions, an empirical investigation of the problem properties was done, two stochastic algorithm applied and their performance compared.

The results indicate the importance of the applied search space discretization and suggest the construction of a hybrid algorithm to find near-optimal solutions in smaller number of solution evaluations. With the same objective in mind, the algorithms will be systematically tuned and enhanced with the mechanisms of gradual refinement of the search focus, such as dynamic parameter encoding [15] or the multilevel technique [12]. On the practical side, the optimized coolant flows will be evaluated with respect to the settings used on the caster machine and checked for potential further improvements of the casting process.

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