Optimizing Surface Profiles during Hot Rolling: A Genetic Algorithms Based Multi-objective Optimization

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Abstract: Several variants of Genetic Algorithms have been used to study the surface profiles of hot rolled slabs, quantified in terms of *crown,* a major parameter related to their geometric tolerances. Two different models are presented, and simulations in a multi-objective mode are carried out to generate the relevant Pareto fronts, which, in turn, are tested against the operational data of an integrated steel plant.

1. Introduction

The present paper is a part of our ongoing investigation on the surface profiles of the hot rolled strips produced by an integrated steel plant, and represents, in essence, a continuation and further extension of one of our recent work [1]. The strips produced by the hot rolling process, as schematically presented in Figure 1, need to satisfy a strict dimensional tolerance limit. To facilitate the subsequent cold rolling, the hot rolled strips are often deliberately provided with a differential surface thickness between their edge and the center, quantified through a parameter called *crown* (Figure 2) and to achieve this, the rolls themselves are provided with a curvature, and the so-called *continuously variable crown* (CVC) can work through a judicious shifting of the rolls [1].

The crown that is finally imparted to rolled strip at the exit is however heavily dependent upon a number of other factors. Primary among them are the thermal expansion of the rolls, their wear, as well as bending. Considering all these factors, two objective functions were formulated in our earlier work [1]. The first one ensured a smooth scheduling of the slabs that are being rolled during a particular

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campaign and the second one described the magnitude of crown. Both were simultaneously optimized following the concept of Pareto-optimality [2] and two variants of multi-objective genetic algorithms [3] were utilized to achieve that.

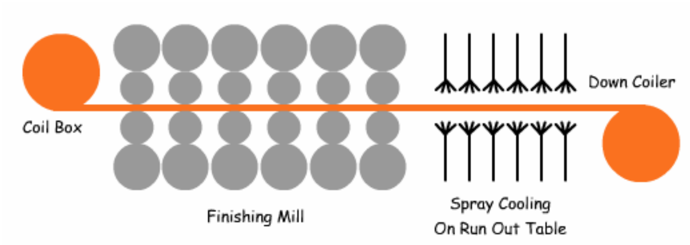
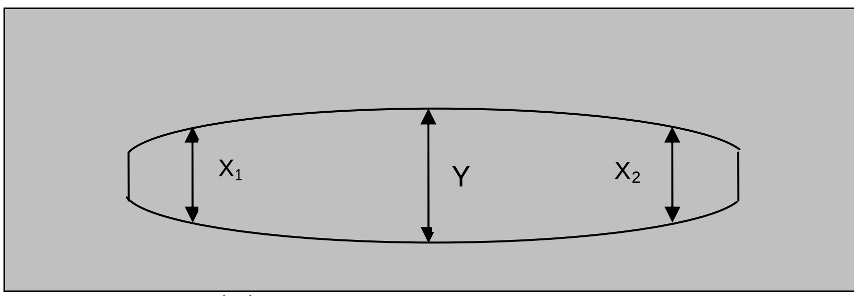


Figure 1: The finishing mill assembly in a typical hot rolling mill.



$$\subset = Y - \frac{(X_1 + X_2)}{2}$$

Figure 2: Crown $(\subset)$ and its measurement

In this work we extend this study further by utilizing an Ant Colony Optimization scheme [4-5] for the first objective function. A new objective function quantifying the power requirement is now introduced. Further details are provided below.

2. The Modeling Details

Only a limited amount of Genetic Algorithms related studies have been conducted for the rolling process and in this context one really has a very limited amount of prior work to fall back upon [6]. Here we have attempted to solve the problem in two different forms as discussed below.

2.1. <u>The first model:</u> Analogous to our previous work [1] the first approach involved construction of the two objective functions as:

$$\sum_{j=1}^{3} W_j \sum_{i=2}^{M} \sqrt{\frac{\left(\Pi_{i,j} - \Pi_{i-1,j}\right)^2}{M}} \qquad (1)$$

where $\Pi_{i,j}$ denotes the j^{th} property, specifically, hardness, thickness or width, of the i^{th} strip to be rolled. The corresponding weight factor is denoted as W_j. A number of constraints, specific to the hot rolling practice at TATA Steel, were also considered. Minimization of this objective function had ensured a smooth transition of the hardness and dimension from one slab to the next, resulting in a lesser roll damage.

The second objective function was constructed with a purpose of minimizing crown from diverse sources. A total crown calculation was performed for the strips passing through all the six stands at the hot rolling facility of TATA steel such that:

$$\sum_{j=1}^{6}\sum_{i=1}^{N}\subset_{ij} \qquad (2)$$

where $\subset_{ij}$, the total crown imparted to the i^{th} strip after passing through the j^{th} stand, which can be expressed as:

$$\subset_{ij} = f(\subset_{O},\subset_{T},\subset_{W},P_j,F_j)\text{; and } \subset_{ij} \le K_{ij} \qquad (3)$$

where $\subset_O$ is the initial crown value, $\subset_T$ and $\subset_W$ denote crowns due to thermal and wear contributions, P_j denotes the roll force, while F_j is the bending force. K_{ij} denotes the acceptable level of crown tolerance for the i^{th} strip after it has passed through the j^{th} stand, assigned on the basis of the operational practices at TATA steel. The detailed formulation for crown calculation has been included in our earlier publication [1]. A brief summary is provided in Table 1.

Table 1: Equations used for Crown calculation

Type of crown	**Mathematical description**	**Remarks**
Thermal crown	Heat transfer equation: $\frac{\partial T}{\partial t} = \alpha\nabla^2 T + \dot{q}$	The boundary conditions and the details of the source term are provided in [1]
Crown due to wear	Wear equation: $C_m = \alpha\sum_{i=1}^{n}\left(\frac{P_i}{W_i l_i}\right)\left(\frac{L_i}{\pi D_i}\right)(ab)(r_i l_i)\delta_{i,z}$ where, $\delta_{i,z} = 1$ when $0 < z \le W_i/2$; $=0$ when $z > W_i/2$	The subscript i denotes the rolling pass number, while n is the total number of rolling passes, r is the reduction, l is the roll contact length, W is the strip width and L is exit strip length. The work roll diameter is denoted as D. The parameters a, b and α are three empirical coefficients depending upon the roll material, strip temperature, roll bite lubrication, roll coolant etc.

Crown due to bending	The equation for bending at a distance x towards the center of the roll: $EI_D \frac{d^2y}{dx^2} = \frac{Px}{2} - \frac{(x-a)^2}{2}\phi$ The equation for bending due to shear: $\frac{dy}{dx} = \frac{\alpha P}{GA}\left(\frac{x-a}{W} - \frac{1}{2}\right)$	The subscript D refers to the roll diameter, E is the Young's modulus and I_D is the moment of inertia. The parameter ϕ denotes the force (P) distribution over the barrel in the region of strip. G is the modulus of rigidity, and A is the cross-sectional area of the work-roll, and α equals to 4/3 for a circular section.

Once the crown values are known, the second objective function is evaluated as:

$$\delta = \frac{\subset_{in}}{h_{in}} - \frac{\subset_{out}}{h_{out}} \tag{4}$$

Here we sought to minimize δ, simultaneously with the first objective function, subject to a number of constraints, once again, based upon the operational practices at TATA steel.

2.2. The second model: During the next phase of our investigation we have looked into the performance of the individual slabs. So equation (1) became redundant in that case. Here we still kept equation (4) as one of the objective functions and minimized it along with an expression for power taken as:

$$\sum_{i=1}^{5} \sum_{\substack{j=2 \\ j \neq 1}}^{6} \left(\xi_i - \xi_j\right)^2 \tag{5}$$

where the ξ terms denote power in watts and the objective function is computed for the six stands that are used in the hot rolling mill of TATA steel. For a roll revolving at an rpm N the power term is computed as:

$$\xi = \frac{2\pi MN}{60} \tag{6}$$

where M denotes the roll torque.

The basic computing scheme that we have adopted in this study is elaborated in the following section.

3. Computing Strategies

The concept of a unique global optimal solution, as utilized in the single objective case, often becomes redundant in a multi-objective scenario. The idea here is to seek a Pareto-optimal solution [2], based upon the weak dominance condition [3]. For a multi-objective minimization exercise this can be expressed as:

$$(\Omega_l \prec \Omega_m) \Leftrightarrow (\forall_i)(f_{il} \le f_{im}) \wedge (\exists_m)(f_{il} < f_{im}) \quad (7)$$

where the f terms denote the objective function and the Ω terms are the vectors formed by the objectives. If any Ω is dominated by a total of N other objective vectors, its rank is taken as $N+1$, the locus of the mutually non-dominant solutions of rank 1 constitutes the Pareto-front.

Although Genetic Algorithms were used in both the cases their exact nature varied from the first to the second approach. This is further elaborated below.

3.1 The Computing strategy used in the first model: In our earlier work [1], the search for the Pareto-optimality was conducted using a Strength Pareto Evolutionary Algorithm (SPEA) [7]. An extensive discussion of this method is provided elsewhere [1,8]. Here the first model required simultaneous minimization of the objective functions (1) and (4), and consequently it involved optimization of the sequence of slabs passing through the rolls. In our previous work this was achieved through a Genetic Algorithm that had involved a Position Based Crossover (PBX) [1,9]. Here we have adopted a strategy based upon an Ant Colony Optimization (ACO) technique [4-5]. This is essentially a crude mimicking of the behavior of the real ant species. Our algorithm for the present problem is essentially an adaptation of its more familiar version [4-5] used for the Traveling Salesman Problem (TSP) [10]. Instead of using the SPEA approach here we have utilized the concepts of *Crowding Distance Sorting* scheme proposed and utilized in NSGA-II algorithm [3], for obtaining the final Pareto-fronts. The salient features of this new approach are indicated below.

3.1.1 Ant Colony Optimization tuned for computing the rolling sequence: Once a real ant traces a certain route, secretion of pheromone, a complex chemical, takes place along its path. The ants are basically blind, however they can sense this chemical and navigate following a pheromone trail. If any ant discovers a shorter path it travels more through that route, accumulating more pheromone there in comparison to the longer paths. This in turn, draws more ants towards it, and the process continues till the entire colony traces out an optimum route.

Analogically we can take any particular sequence of slabs as a particular path traced by an ant. Fitness of the path traced by the k^{th} ant can be taken as $\Im_k$ which is effectively computed from equation (1). The sequence of any pair of slabs say i and j, however could be used by a number of ants tracing some different routes. At any point of time $t+\Delta t$ the amount of pheromone for that particular sequence,

$\Phi_{ij}^{t+\Delta t}$, can be computed as:

$$\Phi_{ij}^{t+\Delta t} = f\Phi_{ij}^{t} + \Delta\Phi_{ij}^{\Delta t} \tag{8}$$

Here we assume that $(1-f)$ is the fraction of the original pheromone present at time t which has naturally evaporated. In the context of the present problem this simply becomes an adjustable parameter. The second term in equation (8) denotes the pheromone increase for the sequence i and j. The ants which do not use this sequence do not contribute anything to it. However, if it occurs in the paths of M different ants, the increment in pheromone for this sequence is computed as:

$$\Delta\Phi_{ij}^{\Delta t} = \sum_{k=1}^{M} \wp \Im_k \tag{9}$$

where $\wp$ denotes an user defined parameter.

One of the factors that an ant would consider for selecting the sequence i to j is the *visibility* of i from j. In real life this could be taken as the reciprocal of the actual distance between i and j. In the present case $\Re_{ij}$ the reciprocal of an index of the property jumps between the slabs i and j can easily substitute the visibility.

Since Φ_{ij} and $\Re_{ij}$ are the two factors influencing the ants choice of the sequence i to j, we can assume that it does so with a probability P_{ij}, which can be defined as:

$$\mathrm{P}_{ij} = \frac{(\Phi_{ij})^{\alpha}(\Re_{ij})^{\beta}}{\sum_{n=1}^{N}(\Phi_{in})^{\alpha}(\Re_{in})^{\beta}} \tag{10}$$

where n denotes a typical slab that can be possibly placed after the slab, and N denotes the total number of such slabs. The parameters α and β are once again user defined.

We have initiated our algorithm with a random population of ants, each containing a random sequence of slabs. The next generations of ants are allowed to follow the accumulated pheromone trails, following the mechanism discussed above, and the process continued till the optimum sequence of the slabs to be rolled had emerged.

3.1.2. Obtaining the Pareto-fronts using ACO data: Once an ant returns a sequence the corresponding objective functions can be evaluated through equations (1) and (4). The family of solutions obtained through the ants in a certain generation is now mixed with the already existing solutions, if any, and the combined population is now ranked. A new set of solution is selected through a *crowded tournament selection* operator devised by Deb [3]. It requires calculation of a *crowding distance* which essentially measures the unoccupied region surrounding a particular solution in the objective function space. A larger crowding distance is favored as it helps to maintain the population diversity, and allows calculation of the maximum spread of the Pareto-front. On the basis of their rank and the crowding distance, the following hierarchy is maintained among the candidate solutions during a tournament selection:

(i) A solution of better rank wins the tournament.

(ii) Between two solutions of same rank, the one with larger crowding distance is favored.

Since the solutions here are generated through the ant colony movements, the crossover and mutation operations in more conventional genetic algorithms become redundant here.

3.2 <u>The Computing strategy used in the second model:</u> The recently proposed Generalized Differential Evolution (GDE) [11] was used for obtaining the Pareto-fronts from the second model. GDE is a multi-objective version of the original Differential Evolution (DE) algorithm [12]. It deals with a real coded population, instead of a binary or a Gray representation [13], and devises its own crossover and mutation in the real space. Differential Evolution uses the concept of *fitness* in the same sense as in Simple Genetic Algorithms (SGA) [14]. However, there are some major philosophical differences between SGA and DE. Although DE uses a population based computing strategy, unlike SGA, it does not require any binary representation. Here a real coded representation is used and an individual is formed by a vector array of all the variables in the problem. DE uses both crossover and mutation. However, both the operations need to be redefined in the present context. DE attempts to create $\aleph_{\spadesuit}$, a mutated form of any individual $\aleph$, using the vector difference of two randomly picked individuals $\aleph_{\diamondsuit}$ and $\aleph_{\heartsuit}$, such that

$$\aleph_{\spadesuit} = \aleph + \vartheta\,(\aleph_{\diamondsuit} - \aleph_{\heartsuit}) \tag{9}$$

where ϑ is a user-supplied scaling factor, often kept between 0 and 1.2. In DE this operation is known as *mutating with vector differentials.* Next, the crossover is applied between any individual member of the population $\aleph_{\clubsuit}$ and the mutated vector $\aleph_{\spadesuit}$, which is done essentially by swapping the vector elements in the corresponding locations. Like in SGA, this is also done probabilistically and the decision of doing (or not doing) crossover is monitored by a crossover constant ς, $(0 \leq \varsigma \leq 1)$. The new vector, $\aleph_{\oplus}$ produced this way, is known as the *trial vector* in DE parlance.

It is made sure that the trial vector inherits at least one variable from the mutated vector $\aleph_{\spadesuit}$, so that it does not become an exact replica of the original parent vector. In DE the trial vector is allowed to pass on to the next generation if and only if, its fitness is higher than that of its parent vector $\aleph_{\clubsuit}$. Otherwise, the parent vector proceeds to the next generation.

In Generalized Differential Evolution these basic features of crossover and mutation are retained. In order to make it suitable for the multi-objective case it adds few newer rules [11] which are elaborated below for a two-objective optimization case:

(i) Select the trial vector if it produces better values of both the objective functions, and neither the trial vector nor the parent violates any constraints.
(ii) Select the trial vector if it does not violate any constraints, while the parent vector does.
(iii) Select the trial vector if both the trial and the parent vectors violate some constraints, but the trial vector does not violate more number of constraints than the parent vector.
(iv) Select the parent vector in any other situation.

As evident from the abovementioned set of rules, keeping the solutions in the feasible range is one of the top priorities in GDE, and therefore it is geared to restrict any constraint violations. During this study we have written our own GDE code tailor-made for the present problem, which executed well with the characteristic fast converging nature of Differential Evolution.

4. Results and Discussion

The calculations using our first model were performed for a typical hot rolling *campaign* at TATA steel, using their automated roll shifting profile, discussed in detail in our earlier work [1]. The computed Pareto-front is shown in Figure 3. It seems that the ant-colony based algorithm performed well, and the computed data are well in accord with the results obtained through the SPEA route. The ant-colony results however, show a much better spread of the Pareto-front and, on that count, resolves the problem in a more efficient manner.

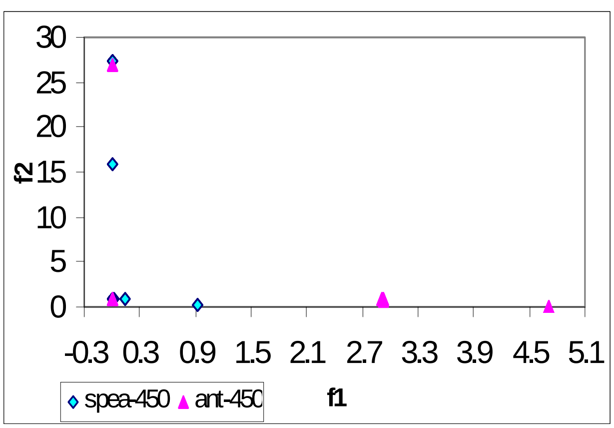


Figure 3: Comparison of Pareto-fronts generated through the ant-algorithm and SPEA after 450 cycles. f1 and f2 are calculated using objective functions (1) and (4) respectively.

The second model was applied to a number of slabs actually rolled in TATA steel. The operating conditions varied in those slabs and hence the nature of the Pareto-fronts also got changed, as shown in Figure 4 for four typical cases. In most cases the Pareto-fronts are concave, and any lowering of delta function defined by

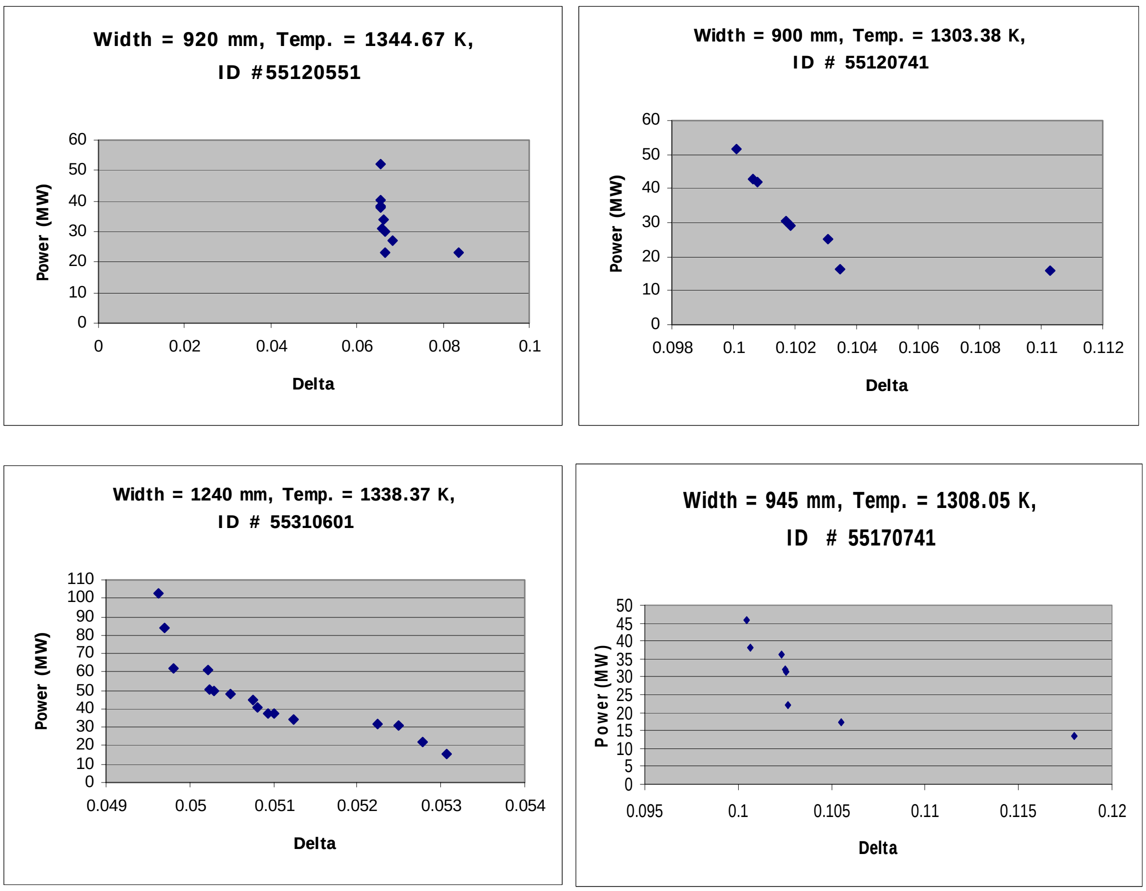


Figure 4: Computed Pareto-fronts for typical slabs rolled at TATA steel. The input temperatures and the width varied, as indicated on the figures.

equation (4) is accompanied by a gradual change in the power function space. This trend however, can not be generalized at this stage of the work since the operating conditions fluctuated a lot and an acceptable statistical analysis is yet to emerge for this process. We plan to take up this issue further during the next phase of our work. At this stage we have however, the capability of analyzing each slab individually, and are able to recommend the optimum power requirement corresponding to a desired crown limit.

In the next stage of the analysis we tried to compare the reduction imparted to slabs at various levels of power input. Three typical points were selected in the Pareto-front for this purpose, one was chosen close to the maximum value of power, the second one was taken close to the maximum computed delta and an average point was chosen in between. The reductions at each stand were computed for all the three cases and compared with the on line data obtained from the hot strip mill of TATA steel. This is demonstrated in figure 5. A careful analysis of the data shown in this figure would reveal that in order to operate at a large power or in other words, at a small crown range, one would require to provide a very large reduction in the first couple of stands. A more gradual reduction profile can be provided if one decides to operate at a lower power regime. For all the slabs analyzed in Figure 5, the reductions provided at the first stand of the finishing mill of TATA steel seems to be larger than the corresponding computed values with maximum power. A corrective measurement on this aspect is likely to enhance the performance of rolling, and we plan to try it out in a near future.

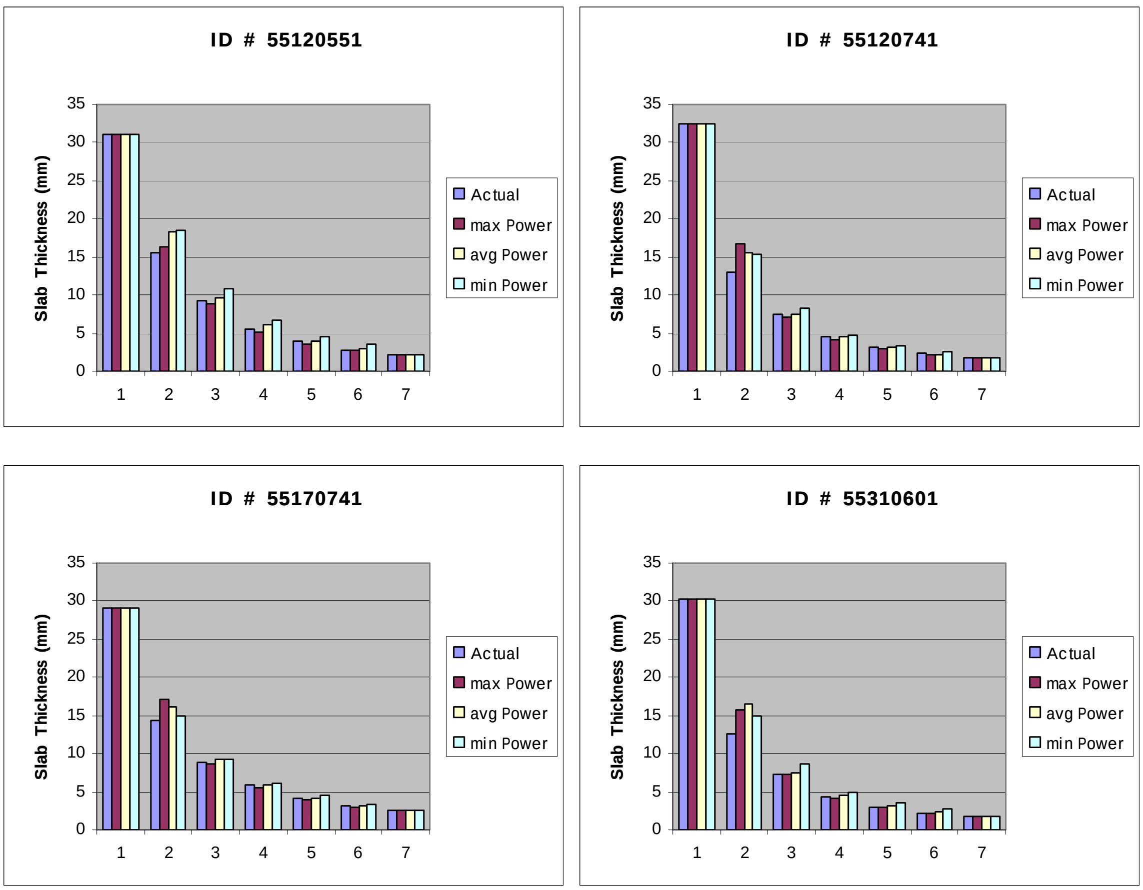


Figure 5: Comparison of the reduction profiles obtained for the various regimes of the Pareto-fronts. Actual data obtained from TATA steel are also shown. The initial slab thicknesses are shown against band 1. The rest indicate the corresponding reductions at the exit of each of the six stands, denoted by numbers 2 to 7.

Since the roll velocity is one of the crucial operational parameter that we could optimize during this study, as in case of reduction, we have compared the optimized data at the maximum, minimum and the average power regions of the Pareto front with the operational data from TATA steel. This is demonstrated in Figure 6. It seems that for all the slabs the actual rolling speed used was significantly above the optimized requirements. A corrective measure can possibly be taken in this regard, by lowering the roll speed, at the same time keeping the performance level intact. For an integrated steel plant this would possibly mean a considerable amount of cost savings in the long run. Since a very sophisticated level of automation currently runs at the hot-strip plant of TATA steel, only a handful of them are actually under the explicit control of the operators. However, even there, a judicious choice can indeed make a difference, as demonstrated through the results obtained in this study.

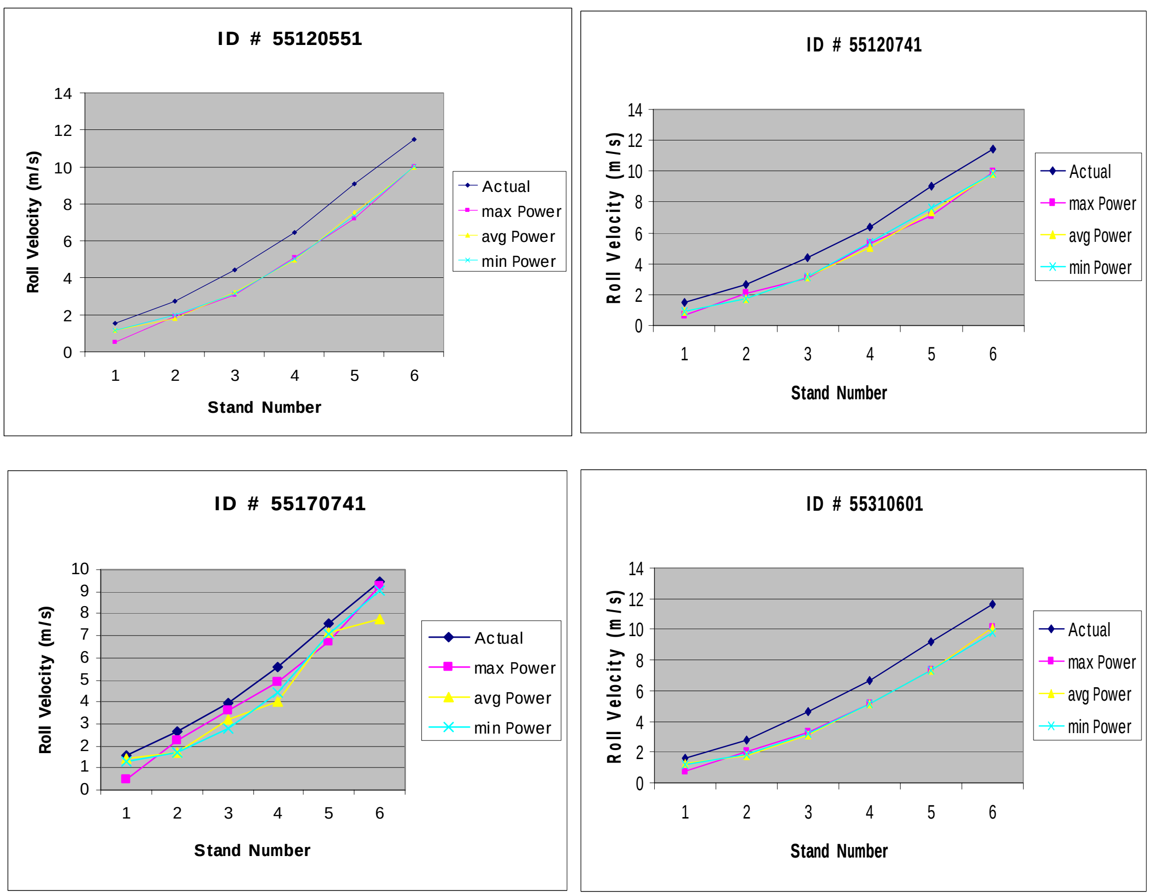


Figure 6: Comparison of the computed roll velocities at the three different regimes of the Pareto-fronts with the actual data provided by TATA steel.

Concluding Remarks

Analyzing the rolling process through evolutionary algorithms is an emerging trend in this field. Although its ubiquitous presence in the rolling literature is still a matter of some more time, however, the general robustness of the genetic algorithms and its several variants, plus the success stories reported in this work and some of its predecessors [1, 15-17] provide a strong candidature for this class of algorithms in the context of material deformation area in general, and the rolling processes in particular.

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