SOMA APPLIED TO OPTIMUM WORK ROLL PROFILE SELECTION IN THE HOT ROLLING OF WIDE STEEL

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Abstract: The quality of steel strip produced in a wide strip rolling mill depends heavily on the careful selection of initial ground work roll profiles for each of the mill stands in the finishing train. In the past, these profiles were determined by human experts, based on their knowledge and experience. In this research, a Self-Organising Migration Algorithm (SOMA), a heuristic optimisation algorithm, has been used to find optimum profiles for a simulated rolling mill. The resulting strip quality produced using the profiles found by the optimisation algorithm and the quality produced using the original specifications are compared. The best set of profiles found by SOMA clearly outperformed the original set.

Keywords: hot strip, rolling, roll profiles, optimisation, SOMA

1 INTRODUCTION

There is a worldwide overcapacity for wide steel strip. In such a "buyers' market", producers need to offer a high quality product at a competitive price in order to retain existing customers and win new ones. Producers are under pressure to improve their productivity by automating as many tasks as possible and by optimising process parameters to maximise efficiency and quality. One of the most critical processes is the hot rolling of the steel strip [1].

2 HOT ROLLING OF WIDE STRIP

In a rolling mill a steel slab is reduced in thickness by rolling between two driven work rolls in a mill stand (Figure 1). To a first approximation, the mass flow and the width can be treated as constant. The velocity of the outgoing strip depends on the amount of reduction. A typical hot rolling mill finishing train might have as many as 7 or 8 close-coupled stands.

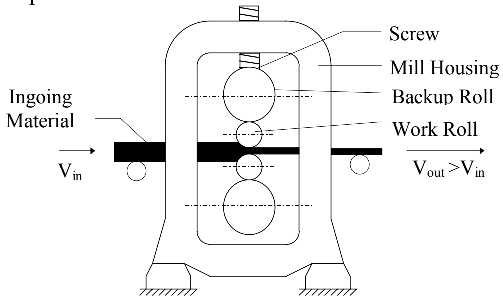

Figure 1 –*Layout of a 4-high rolling stand.*

2.1 Mill Train

A hot-rolling mill train transforms steel slabs into flat strip by reducing the thickness, from some 200 millimetres to some two millimetres. Figure 2 shows a typical hot strip mill train, consisting of a roughing mill (stands R1-R2) and finishing stands (F1-F7).

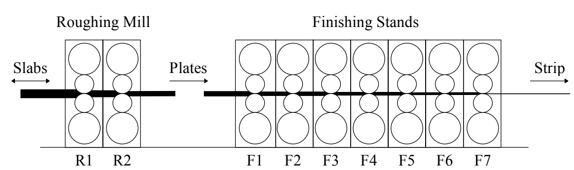

Figure 2 –*Typical hot strip mill train.*

The roughing mill usually comprises one or more stands which may operate in some plants as a reversing mill, i.e. the slabs are reduced in thickness in several passes by going through the stand(s) in both directions. When the slab or plate has reached the desired thickness of approximately 35 mm it is rolled by the "close-coupled" finishing stands in one pass. Strip dimensions, metallurgical composition, and the number of slabs to be rolled, together with other process dependent variables, are known as a *rolling program* or *rolling schedule*.

Within a rolling program, the width of the strip changes from wide at the beginning to narrow towards the end, because the edges of the strip damage the rolls. These damaged areas must not be

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in contact with the strip and therefore, only strip with a reduced width can be rolled at that point.

2.2 Strip Quality

The main discriminator for steel strip from different manufacturers is quality, which has two aspects: *strip profile* and *strip flatness*.

Strip profile is defined as variation in thickness across the width of the strip. It is usually quantified by a single value, the *crown*, defined as the difference in thickness between the centre line and a line at least 40 mm away from the edge of the strip (European Standard EN 10 051). Positive values represent convex strip profiles and negative values concave profiles. For satisfactory tracking during subsequent cold rolling a convex strip camber of about 0.5% - 2.5% of the final strip thickness is required [2]. Flatness - or the degree of planarity - is quantified in *I-Units*, smaller values of I-Units representing better flatness.

Modern steelmaking techniques and the subsequent working and heat treatment of the rolled strip usually afford close control of the mechanical properties and geometrical dimensions. In selecting a supplier, customers rank profile and flatness as major quality discriminators. Tolerances on dimensions and profile of continuous hot-rolled uncoated steel plate, sheet and strip are also defined in European Standard EN 10 051.

Both the flatness and profile of outgoing strip depend crucially on the geometry of the loaded gap between top and bottom work rolls. As a consequence of the high forces employed, the work rolls bend during the rolling process, despite being supported by larger diameter back-up rolls [3]. Figure 3 shows a pair of cylindrical work rolls. In Figure 4 the effects of the loading can be seen. Due to contact with the strip at temperatures between 800°C and 1200°C the rolls expand, despite being continuously cooled during the rolling operation. Figure 5 shows the effect of thermal expansion of the unloaded work rolls on the roll gap.

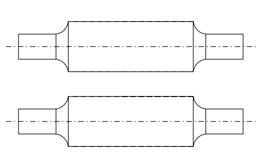


Figure 3 –*Unloaded rolls.*

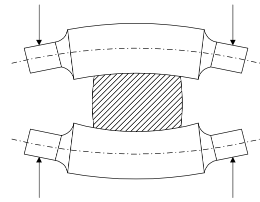


Figure 4 –*Loaded cold rolls.*

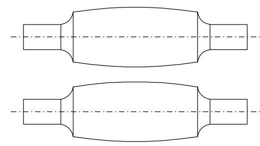


Figure 5 –*Unloaded hot rolls.*

If the geometry of the roll gap does not match that of the in-going strip, the extra material has to flow towards the sides (Figure 6). If the thickness becomes less then about 8mm, this flow across the width cannot take place any longer and will result in partial extra strip length, and therewith in a wavy surface (Figure 7).

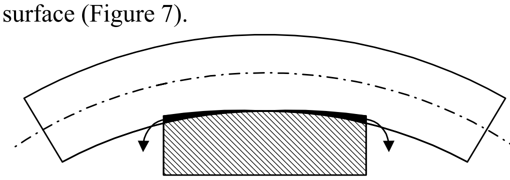


Figure 6 –*Mismatch between roll gap and strip geometry.*

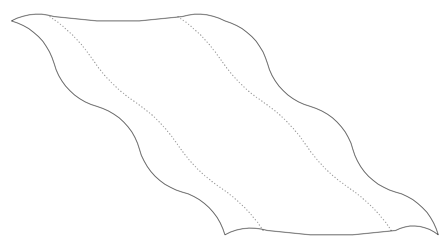


Figure 7 –*Wavy strip surface.*

The effects of bending and thermal expansion on the roll gaps, and the strip tension between adjacent mill stands, results in a non-uniform distribution of the internal stress over the width of the strip. This can produce either latent or manifest bad shape, depending on the magnitude of the applied tension and the strip thickness [4]. Bad shape, latent or manifest, is unacceptable to customers, because it can cause problems in further manufacturing processes.

2.3 Initially Ground Work Roll Profiles

To compensate for the predicted bending and thermal expansion, work rolls are ground to a convex or concave camber, which is usually sinusoidal in shape (Figure 8).

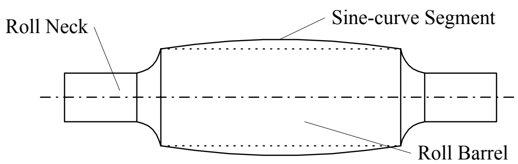
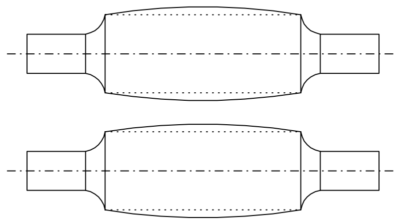
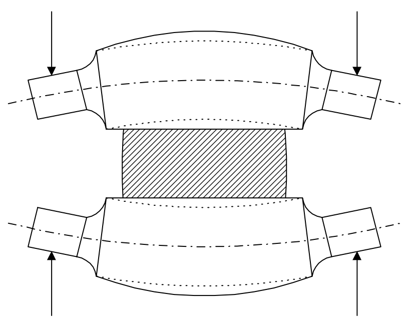


Figure 8 – *Cambered work roll.*

Figure 9 shows how the initially ground camber can compensate for the combined effects of bending and expansion.



9a. Unloaded rolls



9b. Loaded, hot rolls

Figure 9 –*Compensating combined effects.*

Due to the abrasive nature of the oxide scale on the strip, the rolls also wear significantly. Due to this roll wear, the rolls need to be periodically reground after a specified duty cycle (normally about four hours), to re-establish the specified profile.

2.4 Roll Profile Specification

The challenge is to find suitable work roll profiles - for each rolling program - capable of producing strip flatness and profile to specified tolerances. In a new mill, these profiles are initially specified individually for every single roll program. These are often later changed, e.g. by the rolling mill technical personnel in an effort to establish optimum profiles! This fine-tuning of the roll profiles is nearly always carried out empirically.

Due to the lack of accurate model equations and auxiliary information, like derivatives of the transfer function of the mill train, traditional calculus-based optimisation methods cannot be applied. If a new rolling program is to be introduced, it is a far from straightforward task to select the optimum work roll profiles for each of the stands involved.

3 OPTIMISATION OF PROFILES

The seemingly obvious solution of experimenting with different profiles in an empirical way is not acceptable because of financial reasons - the earning capacity of a modern hot strip mill is thousands of pounds per minute, and the mills are usually operated 24 hours a day. Any unscheduled interruption of strip production leads to considerable financial loss. The use of unsuitable roll profiles can seriously damage the mill train. The approach chosen in this research is to simulate the mill and then apply experimental optimisation algorithms. Figure 10 shows the closed optimisation loop, containing the mill model and an optimisation algorithm.

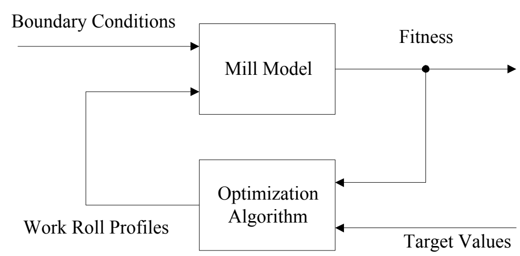


Figure 10 –*Optimisation loop.*

A finite constant volume elements model was used, which was developed in previous research. The accuracy of the model was increased by using real world data to train an Artificial Neural Network to compensate for the model error [5][6].

3.1 The Fitness Function

In the past, a number of optimisation algorithms were used to find optimum profiles for a single steel slab [5]. However, in the real world, a sequence of different slabs is rolled with the same set of profiles (see 2.1). Therefore, the profiles need to be suitable for each of the different slabs in the same rolling program. This has been taken into consideration in this research by adjusting the fitness function used to measure the fitness of a set of profiles.

The fitness (objective function) has been calculated by a combination of crown and flatness values of the centre-line, the edge, and the quarter-line (Equation 1). To avoid a division by zero, one been added to the denominator. The theoretical maximum value of this objective function is 1.0.

$$f(x,\alpha) = \frac{1}{n}\sum_{s=1}^{n}\frac{1}{1+\frac{1}{\alpha}\sum_{i=1}^{3} I_i(x) + |c_{aim} - c(x)|} \quad (1)$$

where:

- n: number of different slabs in rolling program
- $f(x)$: fitness of solution x,
- $I_i(x)$: I-Units at line i for solution x,
- c_{aim}: target crown,
- $c(x)$: achieved crown for solution x,
- α: constant to select the relative contribution of flatness and camber, chosen to be 5000 for the experiments.

As it can be seen from Equation 1, the fitness for the rolling program is the average fitness for each of the different slabs rolled during the program.

3.2 Optimization Algorithm Used

In recent years, a broad class of optimisation algorithms has been developed for stochastic optimisation, i.e. for optimising systems where the functional relationship between the independent input variables *x* and output (objective function) *y* of a system *S* is not known. Using stochastic optimisation algorithms such as Genetic Algorithms (GA), Simulated Annealing (SA) and Differential Evolution (DE), a system is confronted with a random input vector and its response is measured. This response is then used by the optimisation algorithm to tune the input vector in such a way that the system produces the desired output or target value in an iterative process.

The following section describes the Self-Organising Migration Algorithm (SOMA). SOMA is a stochastic optimisation algorithm that is modelled after the social behaviour of co-operating individuals [7]. It was chosen because it was proven that the algorithm has the ability to converge towards the global optimum [8].

SOMA is a stochastic optimisation algorithm that works on a population of candidate solutions in loops - so called *migration loops*. The population is initialised randomly at the beginning of the search. In each loop, the population is evaluated and the solution with the highest fitness becomes the leader *L* (Figure 11). Apart from the leader, in one migration loop, all individuals will traverse over the input space into direction of the leader (Figure 12):

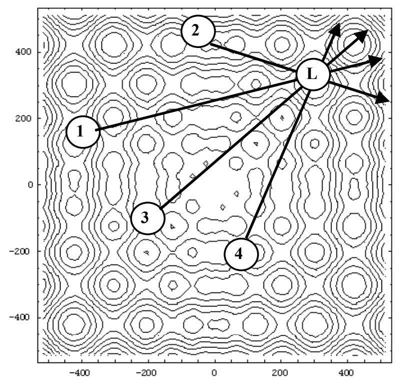


Figure 11 – *2D example: positions of individual before migrating.*

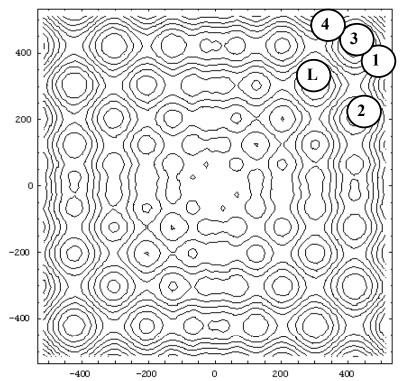


Figure 12 – *2D example: positions of individuals after migration loop.*

An individual will travel a certain distance (called Path Length) towards the leader in *n* steps of defined length. If the path length is chosen to be greater than one, then the individual will actually over shot the leader. This path is perturbed randomly.

3.2.1 Perturbation

Mutation, the random perturbation of individuals, is an important operation for evolutionary strategies (ES). It ensures the diversity amongst the individuals and it also provides the means to restore lost information in a population. Mutation in SOMA is different compared to other ES strategies. SOMA uses a PRT parameter to achieve perturbation. This parameter has the same effect for SOMA as mutation has for GA. It is defined in the range [0, 1] and is used to create a perturbation vector (PRTVector) as follows:

$$if\ rnd_j < PRT\ then\ PRTVector_j = 1\ \ else\ 0\,, \quad j = 1,\ldots,n_{param} \quad (2)$$

The novelty of this approach is that the PRTVector is created before an individual starts its journey over the search space. The PRTVector defines the final movement of an active individual in search space.

The randomly generated binary perturbation vector controls the allowed dimensions for an individual. If an element of the perturbation vector is set to zero, then the individual is not allowed to change its position in the corresponding dimension.

Figure 13 shows an example of a candidate solution *Individual 1* that would make a number of steps towards *Leader L* without perturbation. With the perturbation vector [0,1] it is only allowed to move in *y* direction.

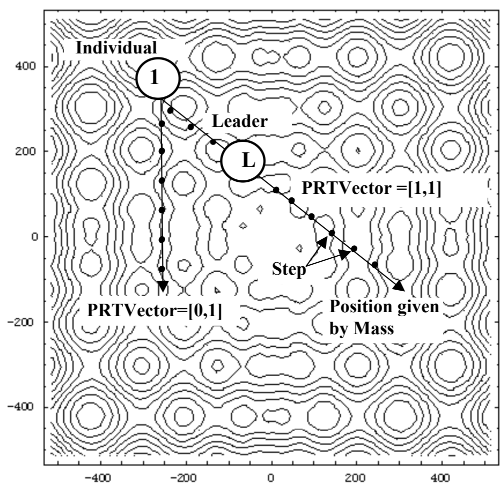


Figure 13 –*Perturbation in SOMA.*

3.2.2 Generating New Candidate Solutions

In standard ES the *Crossover* operator usually creates new individuals based on information from the previous generation. Geometrically speaking, new positions are selected from an *N* dimensional hyper-plane. In SOMA, which is based on the simulation of cooperative behaviour of intelligent beings, sequences of new positions in the *N* dimensional hyper-plane are generated. They can be thought of as a series of new individuals obtained by the special crossover operation. This crossover operation determines the behaviour of SOMA. The movement of an individual is thus given as follows:

$$\vec{r} = \vec{r}_0 + \vec{m}\, t\, \vec{PRTVector} \tag{3}$$

where:

$\vec{r}$:	new candidate solution
$\vec{r}_0$:	original individual
m:	difference between leader and start position of individual
t:	$\in$ [0 , Path length]
PRTVector:	control vector for perturbation

It can be observed from Eq. (3) that the PRTVector causes an individual to move toward the leading individual (the one with the best fitness) in *N-k* dimensional space. If all *N* elements of the PRTVector are set to 1, then the search process is carried out in an *N* dimensional hyper-plane (i.e. on a *N+1* fitness landscape). If some elements of the PRTVector are set to 0 then the second terms on the right hand side of equation equal 0. This means those parameters of an individual that are related to 0 in the PRTVector are 'frozen', i.e. not changed during the search. The number of frozen parameters "*k*" is simply the number of dimensions which are not taking part in the actual search process. Therefore, the search process takes place in a N-*k* dimensional subspace.

4 EXPERIMENTAL RESULTS

SOMA has been applied 50 times in order to find the optimum set of profiles. In the rolling program there were 14 different slabs, therefore the average fitness for this 14 slabs had to be calculated.

The control parameter settings have been found empirically: 40 migration loops were carried out by 20 individuals. The path length was chosen to be 2.0 , the step size was 0.31 and PRT was 0.1.

From Table 1 it can be seen that the average fitness achieved during the experiments was 0.96499526 out of 1.0. The small standard deviation indicates that in most of the searches the same optimum has been found, i.e. the algorithm has converged towards the global optimum. The algorithm needed on average 4418 fitness evaluations until it reached that optimum.

	Fitness	Fitness Evaluations
Average	0.96499526	4417.7
Standard Deviation	0.000304117	164.3509498

Table 1 – *Search results.*

Table 2 shows the strip quality achieved using the original specification, Table 3 shows the strip quality achieved using the best set of profiles found by SOMA during the experiments.

	Average	Standard Deviation
Crown error [mm]	0.06363165	0.03021786
Flatness edge [I-Units]	13.23412214	14.93880901
Flatness quarter [I-Units]	32.64022143	40.98805286
Flatness middle [I-Units]	22.2865	52.16940555

Table 2 – *Strip quality with original profiles.*

	Average	Standard Deviation
Crown error [mm]	0.023995157	0.026874573
Flatness edge [I-Units]	2.510596429	7.042907048
Flatness quarter [I-Units]	29.20729071	41.96476839
Flatness middle [I-Units]	26.86778571	53.90688005

Table 3 – *Strip quality with best solution found by SOMA.*

Table 4 shows the improvement achieved by using the optimised set of profiles. It can be seen that the average crown error was reduced dramatically by 62.3% and the corresponding standard deviation by 11.1%. The strip flatness at the edges was improved by 81.0 %, the flatness in the quarter line by 10.5%. Only the average flatness in the middle of the slabs has decreased by 20.6%.

	Average [%]	Standard Deviation [%]
Crown error	62.3	11.1
Flatness edge	81.0	52.9
Flatness quarter	10.5	-2.4
Flatness middle	-20.6	-3.3

Table 4 –*Improvement of strip quality.*

5 CONCUSIONS

In this research, a Self-Organising Migration Algorithm (SOMA), a heuristic optimisation algorithm, has been used to find optimum profiles for a simulated rolling mill. The profiles were not only optimised for one particular slab, but for a whole rolling program, which is required for a real rolling mill.

The resulting strip quality produced using the profiles found by the optimisation algorithm and the quality produced using the original specifications were compared. It was shown that the best set of profiles found by SOMA clearly outperformed that of the original set. The average percentage improvement for crown error and fitness values is 33.3% compared to the original values. Therefore, SOMA has been applied successfully to the optimisation problem described in the paper.

In future work, the performance of other optimisation algorithms will be compared with that of SOMA in this problem domain.

Biography

Lars Nolle graduated from the University of Applied Science and Arts in Hanover in 1995 with a degree in Computer Science and Electronics. After receiving his PhD in Applied Computational Intelligence from The Open University, he worked as a System Engineer for EDS. He returned to The Open University as a Research Fellow in 2000. He joined The Nottingham Trent University as a Senior Lecturer in Computing in February 2002. His research interests include: applied computational intelligence, distributed systems, expert systems, optimisation and control of technical processes.

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