Lecture Notes in Computer Science, Vol. 1625, Springer, 1999

Optimum Work Roll Profile Selection in the Hot Rolling of Wide Steel Strip using Computational Intelligence

Lars Nolle[1], Alun Armstrong[1], Adrian Hopgood[1] and Andrew Ware[2]

[1]Faculty of Technology, The Open University in Wales,
Cardiff CF1 9SA UK
lnolle@glam.ac.uk
{D.A.Armstrong, A.A.Hopgood}@open.ac.uk
[2]School of Accounting and Mathematics, University of Glamorgan,
Pontypridd CF37 1DL UK
jaware@glam.ac.uk

Abstract. The finishing train of a hot strip mill has been modelled by using a constant volume element model. The accuracy of the model has been increased by using an Artificial Neural Network (ANN). A non-linear Rank Based Genetic Algorithm has been developed for the optimization of the work roll profiles in the finishing stands of the simulated hot strip mill. It has been compared with eight other experimental optimization algorithms: Random Walk, Hill Climbing, Simulated Annealing (SA) and five different Genetic Algorithms (GA). Finally, the work roll profiles have been optimized by the non-linear Rank Based Genetic Algorithm. The quality of the strip from the simulated mill was significantly improved.

1 Introduction

There is a world-wide 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 task as possible and by optimizing process parameters to maximise efficiency and quality. One of the most critical processes is the hot rolling of the steel strip.

2 Problem Domain

In a rolling mill a steel slab is reduced in thickness by rolling between two driven work rolls in a mill stand (Fig. 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.

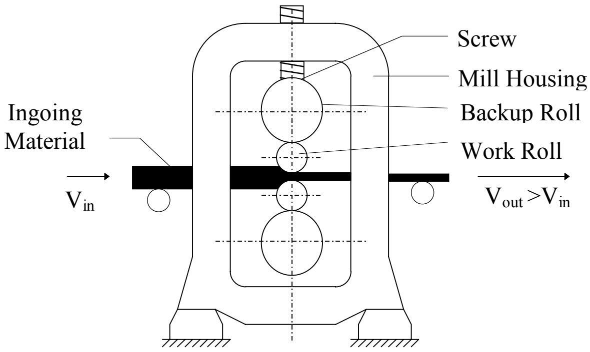


Fig. 1. Layout of a 4-high rolling mill stand.

2.1 Hot 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. Fig. 2 shows a typical hot strip mill train, consisting of a roughing mill (stands R1-R2) and finishing stands (F1-F7).

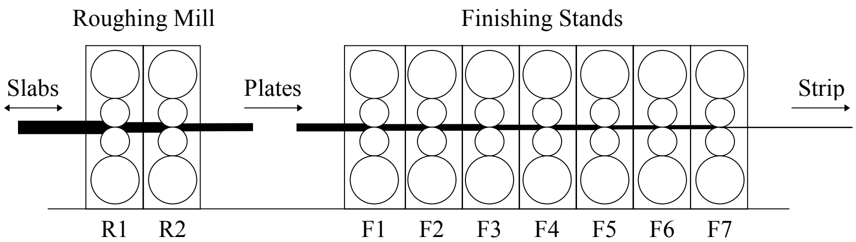


Fig. 2. Hot strip mill train.

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*.

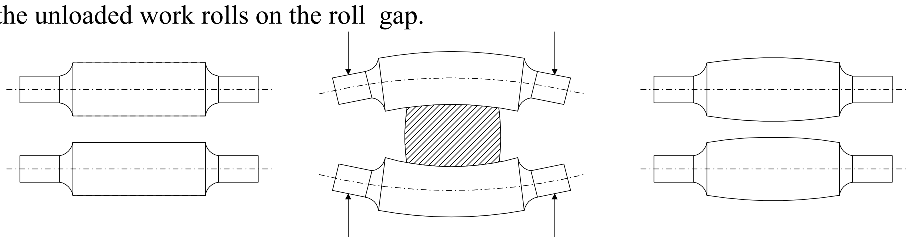
2.2 Strip Quality

Significant quality parameters of steel strip include: *dimensions*, *profile* and *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 [1]. 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 un-coated steel plate, sheet and strip are also defined in European Standard EN 10 051. Tolerances on flatness are also published [2].

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. Fig. 3a shows a pair of cylindrical work rolls. In Fig. 3b 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. Fig. 3c shows the effect of thermal expansion of the unloaded work rolls on the roll gap.



3a. Unloaded rolls. 3b. Loaded cold rolls. 3c. Unloaded hot rolls.

Fig. 3. Factors effecting roll gap.

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. 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 (Fig. 4b).

4a. Flat strip. 4b. Wavy strip

Fig. 4. Flat and wavy strip.

2.3 Bad Shape

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 [3]. Bad shape, latent or manifest, is unacceptable to customers, because it can cause problems in further manufacturing processes.

2.4 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 (Fig. 5).

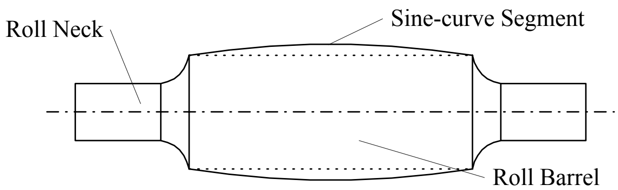
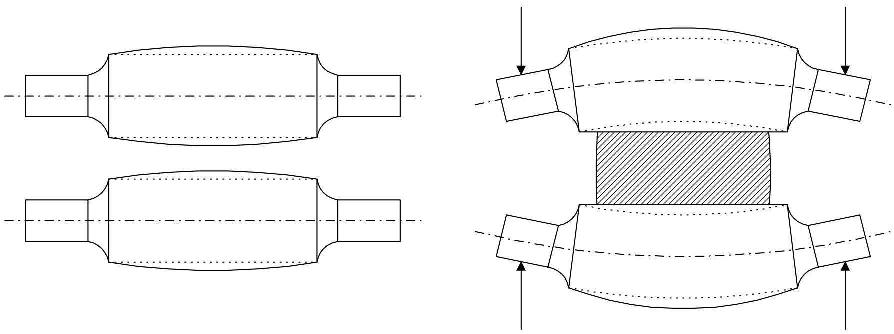


Fig. 5. Initially ground profile.

Fig. 6 shows how the initially ground camber can compensate for the combined effects of bending and expansion.



6a. Unloaded rolls

6b. Loaded, hot rolls

Fig. 6. The combined effect of bending and thermal expansion compensated by initial roll camber.

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.

2.5 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 (Fig. 7).

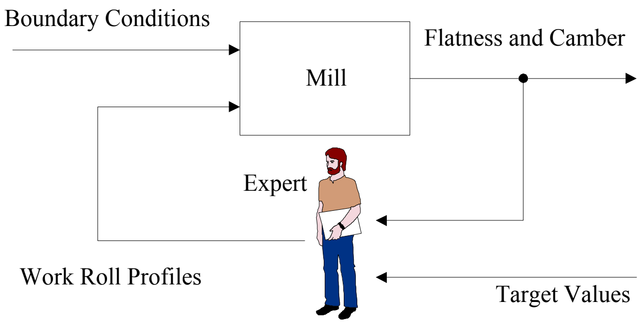


Fig. 7. Iterative optimization of work roll profiles by rolling mill expert.

Due to the lack of accurate model equations and auxiliary information, like derivatives of the transfer function of the mill train, traditional calculus-based optimization 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.

2.6 Optimization of Work Roll 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.

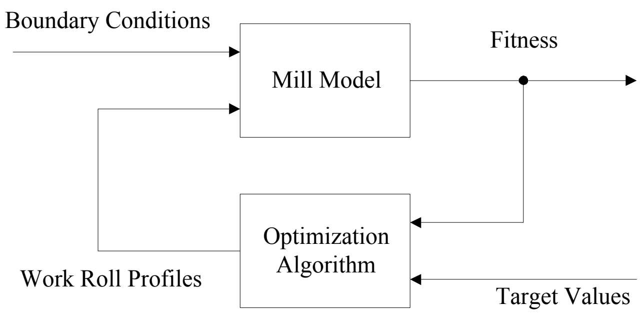


Fig. 8. The optimization loop.

Any unscheduled interruption of strip production leads to considerable financial loss. The use of unsuitable roll profiles can seriously damage the mill train. One solution is to simulate the mill and then apply experimental optimization algorithms. Fig. 8 shows the closed optimization loop, containing the mill model and an optimization algorithm.

2.7 Summary

To survive in an aggressive global market, producers of steel strip need to optimize their rolling process. A major selling factor is the quality of the shape of the steel strip, which in turn depends heavily on the loaded roll gaps. These roll gaps are functions of the initially ground work roll profiles, thermal expansion of the work rolls, roll bending, roll wear and elastic deformation of the mill housings [4]. The required initial ground profiles cannot be readily calculated by conventional methods. Due to the very high operating costs of a wide hot strip mill, it is not usually economically a feasible option to determine experimentally the optimum roll profiles for a particular rolling program. One solution is to simulate the mill and apply experimental optimization algorithms.

3 Modelling the Rolling Mill Train

In the past, the accuracy of analytical mill models has been increased by on-line adaptation to certain process parameters [5]. More recently, Artificial Neural Networks (ANN) have been used successfully to compensate for model errors [6], or for modelling the complete transfer function of a mill [7]. In this research, an ANN has been used to adapt a model to the hot strip mill, using sample data kindly supplied by Thyssen Krupp.

3.1 Constant Volume Element Model

The simulation (developed using C++) models the finishing train of a hot strip mill consisting of seven mill stands. It is based on constant volume elements. Each steel slab consists of $m \times n$ elements (Fig. 9).

A volume element is reduced in thickness by the effective roll gap. If the thickness is greater then 8mm, all elements of a segment are taken to expand equally in length. Extra materiel is taken to result in spread, i.e. extra width of the element (Fig. 10a). If the thickness becomes less than 8mm, all the extra material is taken to produce extra length (Fig. 10b), and hence waviness (Fig. 10c).

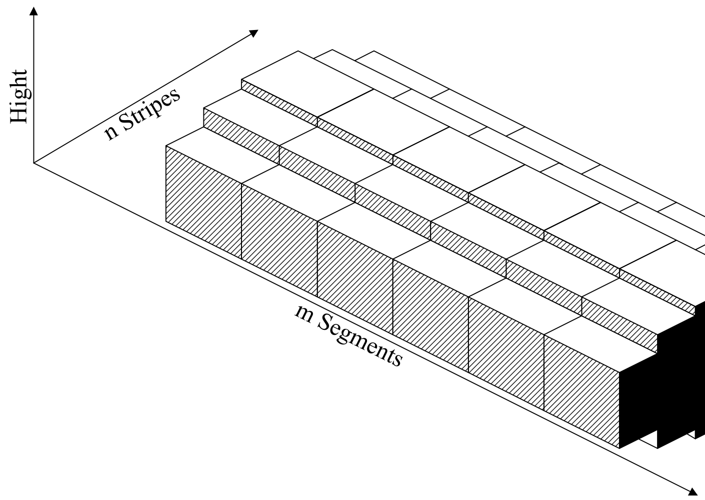
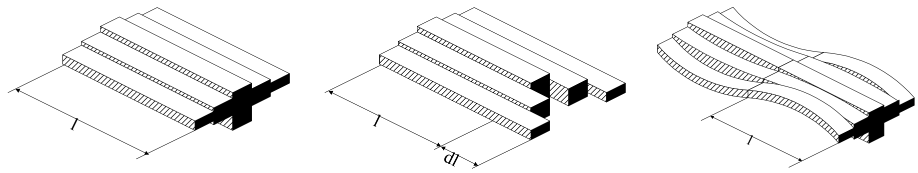


Fig. 9. Simulated steel slab.



10a. Spread and elongation. 10b. Elongation. 10c. Wavy strip.

Fig. 10. Elongation of a strip segment.

The degree of flatness f of stripe *i* was calculated as follows:

$$f(i) = \frac{dl_i}{l} \cdot 10^5 \text{ [I-Units]}. \tag{1}$$

3.2 Mill Stand Model

Fig. 11 shows the model used to calculate the effective roll gap of a single stand. The roll force has been calculated by means of a formula found empirically by *Ekelund* [8] and subsequently corrected by an Artificial Neural Network, that has been trained with actual process data derived from a commercial hot strip mill. The roll deflection due to bending stress and shear stress has been calculated by using a set of equations published by *Winkler* [9]. The thermal crown of the work rolls has been calculated by the means of the formula stated by *Wusatowski* [10]. Finally, equally distributed random numbers in the interval [-0.001mm,+0.001mm] have been added to the calculated strip thickness values in order to simulate non-deterministic influences, like inaccuracies in measurement devices etc. For the same reason, random numbers in the interval [-5 I-Units, +5 I-Units] have been added to the flatness values. The simulation also comprises a PI-controlled thickness control loop (Fig. 12).

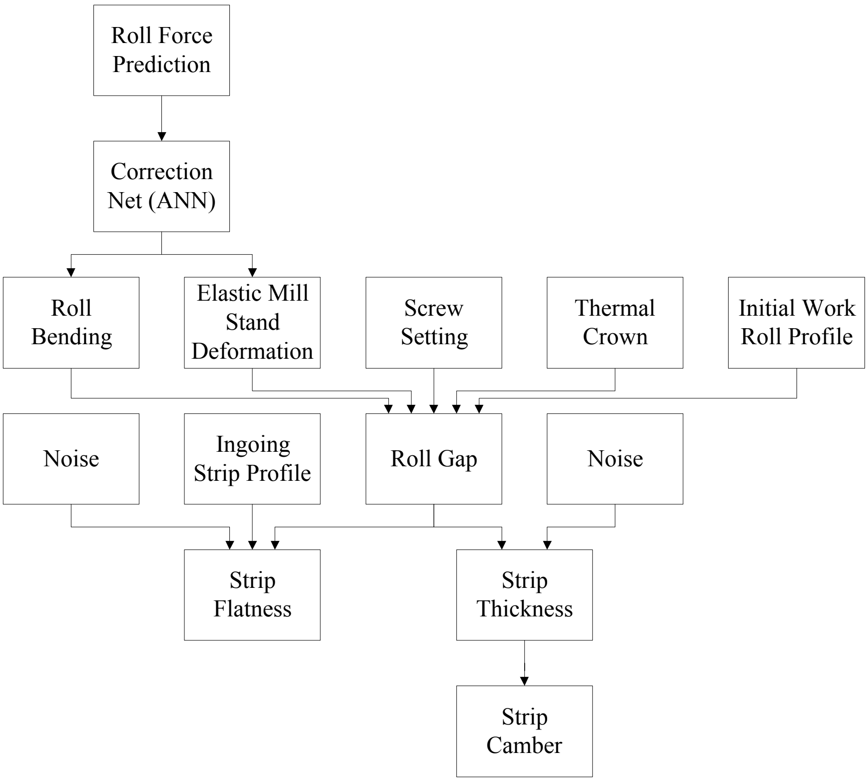


Fig. 11. Mill Stand Model.

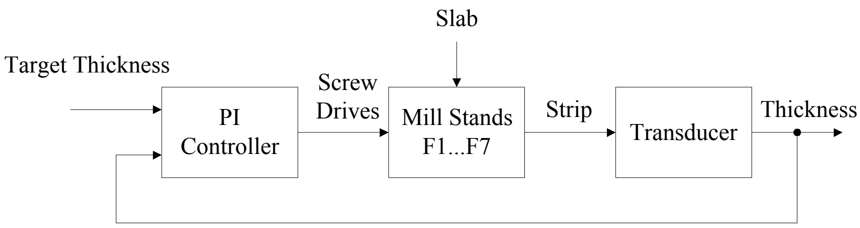


Fig. 12. Thickness control loop.

3.3 Use of an Artificial Neural Network to Correct the Predicted Roll Force

The most important parameter in the process model is "roll force". It has the greatest influence on the effective roll gap and thence on the accuracy of the model calculations. Due to a lack of satisfactory roll force models, the predicted roll forces are usually approximations of the reality. Therefore an Artificial Neural Network has been used as a synthesis network [11] to correct the predicted roll force.

The experiments were carried out on a 233 MHz Pentium PC with 64 Mb RAM using the *LINUX 2.0.29* operating system, running the well known neural network package *SNNS v4.1*, developed at the *Institute for Parallel and Distributed High Performance Systems (IPVR)* of the University of Stuttgart, Germany.

A three layer feed-forward network was used [12][13] and trained by a standard back-propagation algorithm (η=0.2, d=0.0) [14]. The number of hidden units was calculated to be 9 by the mean of *Kolmogorov's theorem* [15].

The input parameters for the network were: strip temperature, strip width, thickness reduction and the predicted roll force. The network output was the corrected roll force. The training set and the test set each contained 49 samples.

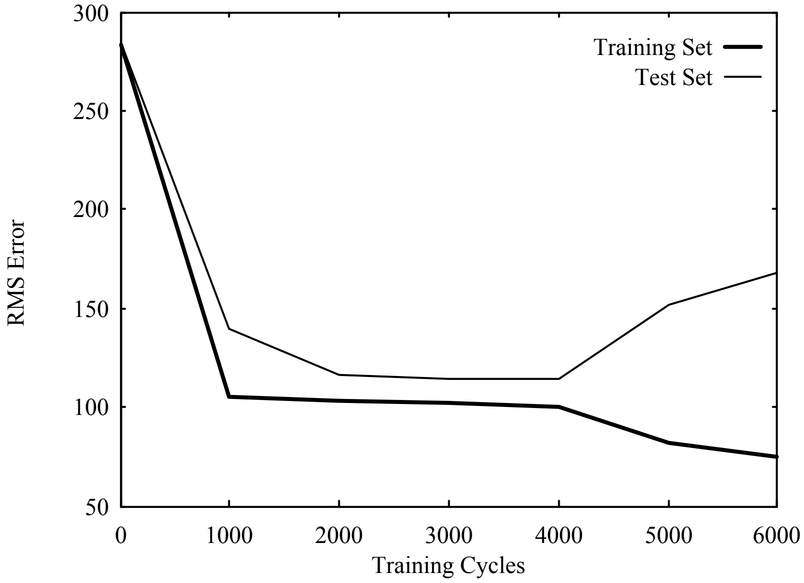


Fig. 13. The development of the RMS error during the training phase.

Fig. 13 shows the development of the RMS-error for the training set and the verification set (test-set) during training. It can be seen that the RMS-error for the verification set reaches a minimum after approximately 4000 training cycles. It is considered that the network has been trained optimally after 4000 cycles.

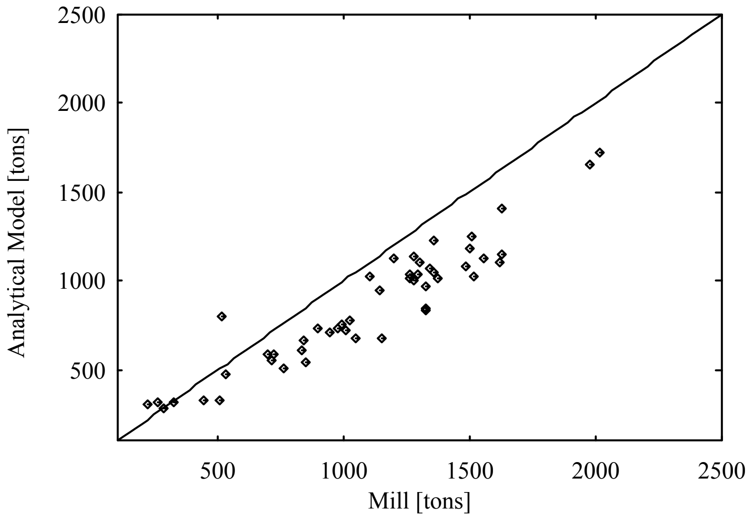


Fig. 14. Correlation between predicted roll force and real roll force.

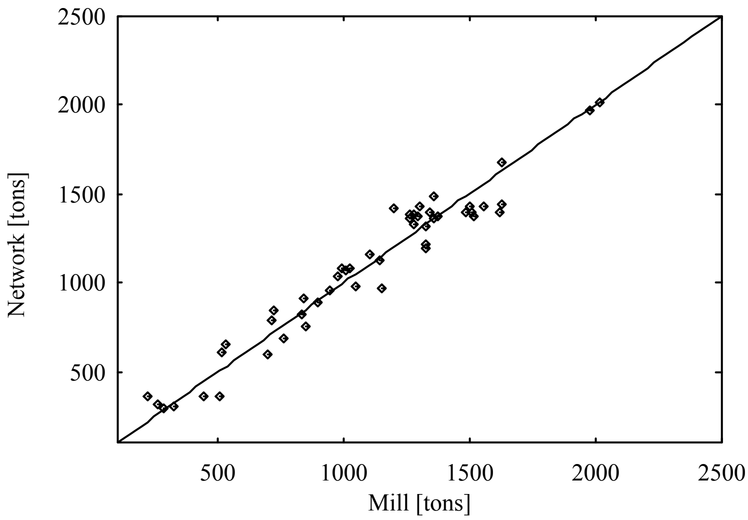


Fig. 15. Correlation between network output and real roll force for the test set.

The RMS error has been reduced from 283.15 I-Units to 100.12 I-Units and the correlation factor r has been increased from 0.9402 to 0.9723 by using the synthesis network.

3.4 Discussion

This model is a compromise between accuracy and computational costs. In order to keep the computation time within an acceptable range, for use together with Genetic Algorithms, the following assumptions were made:

- No roll flattening (roll flattening can be neglected during the hot rolling of steel strip),
- symmetrical roll gap, i.e. strip centralised,
- balanced inter-stand tension,
- constant roll force distribution over the roll barrel.

4 A Non-linear Rank Based Genetic Algorithm

For standard GAs, the selection probability of one individual depends on its absolute fitness value compared to the rest of the genepool. For Rank Based GAs [16] (Fig. 15), the selection probability of one individual depends only on its position in the ranking and is therefore disconnected from its absolute fitness value.

Baker [16] has shown, that Rank Based GAs have better performance for small genepool sizes. He used a linear selection function, but he also proposed the development of non-linear selection functions as well. During this research, such a non-linear selection function has been developed (Equation 2).

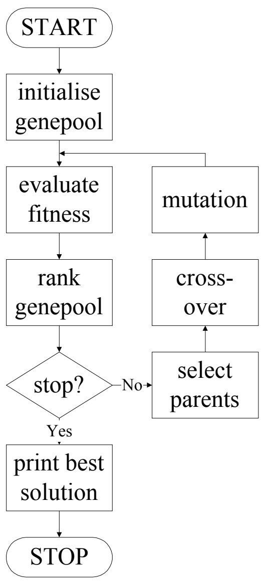


Fig. 16. Flow chart of a standard Rank Based Genetic Algorithm.

$$n(x,c) = ceil\left[\frac{N}{1-\frac{1}{e^{c}}} \cdot \left(1-\frac{1}{e^{c \cdot x}}\right)\right] \tag{2}$$

where:

n: Individual chosen from the current genepool to join the mating pool,
N: number of individuals in genepool,
x: equally distributed random number [0, 1],
c: constant which controls the non-linearity of the function,
ceil(a): function returning the smallest integer that is not less than its argument *a*.

Note: in contrast to the original Rank Based GA, the best individual becomes the highest rank in this case. The degree of non-linearity can be controlled by changing the constant *c*. This allows on-line adaptation of the algorithm. For example, *c* could be adjusted to the ratio (on-line performance/off-line performance). Fig. 17 shows the graphical representation of the function where c=3.0.

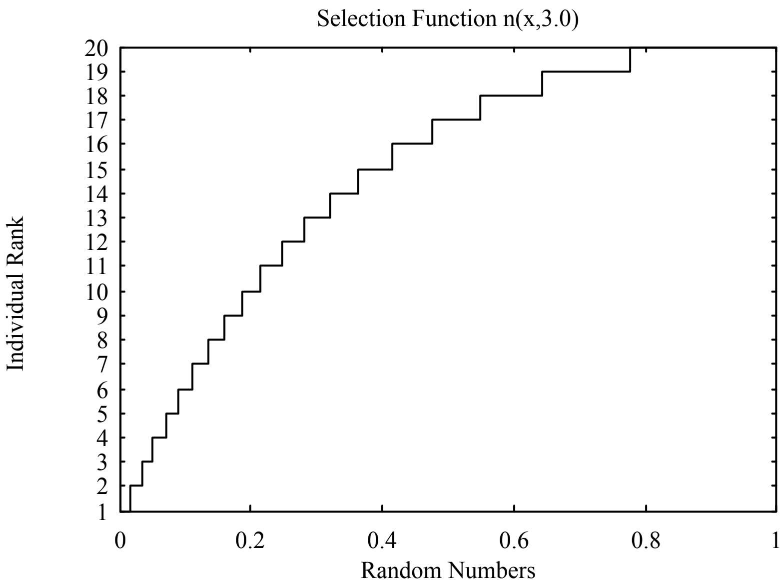


Fig. 17. Graphical representation of the non-linear selection function.

For c=0.2, the selection probability of an individual i is similar to the selection probability using the standard linear selection with e=1.1 (Fig. 18). Fig. 19 shows how the selection probability of an individual i depends on its rank for greater values of c.

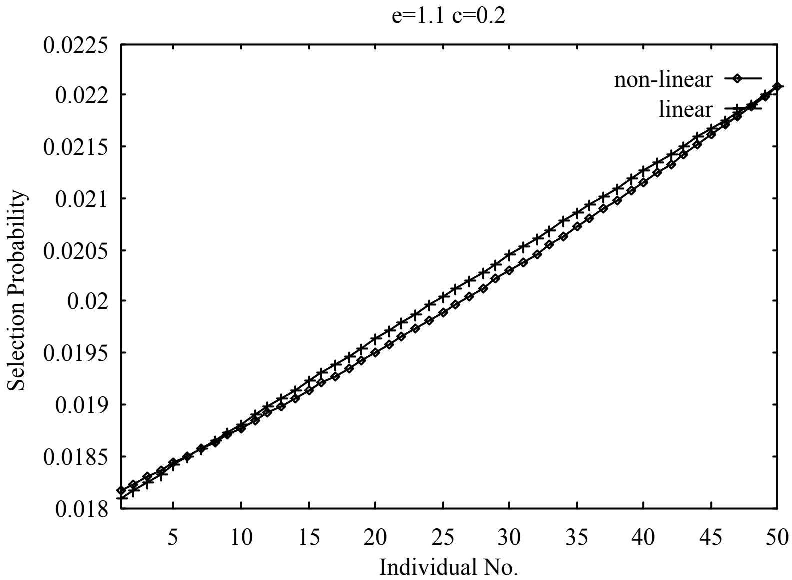


Fig. 18. For c=0.2, the selection probabilities are almost equal for linear and non-linear selection.

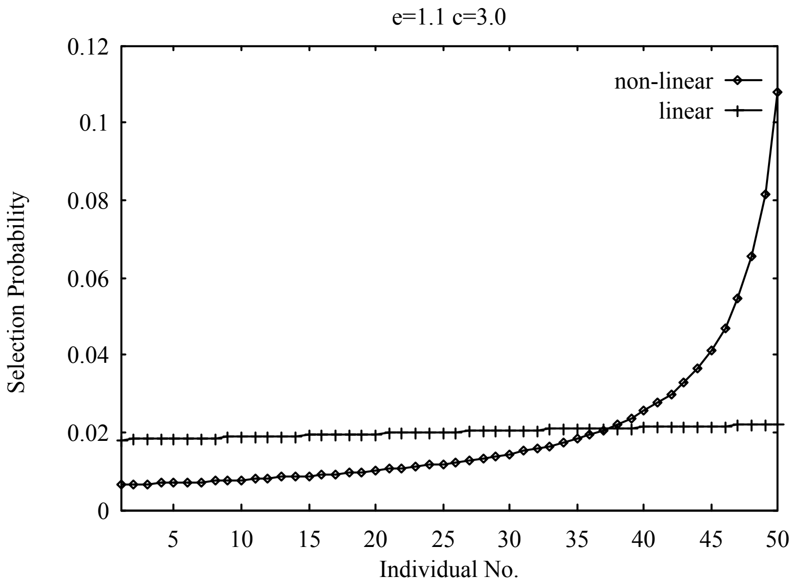


Fig. 19. Larger values of c (e.g. c=3.0) increase the selection probability of the fitter individuals in the genepool.

5 Comparison of Methods

Using the mill simulation, nine different Experimental Optimization Algorithms have been evaluated for the optimization of the work roll profiles. Details are given in table 1.

Table 1. Optimization methods used for the evaluation.

No.	Algorithm	Parameters
1	Random Search	./.
2	Hill Climbing	./.
3	Simulated Annealing	T_0= 0.2, T_t=0.99T_{t-1}, t_{step} =50
4	GA with Tournament Selection	μ=40, p_c=0.6, p_m=0.01, ζ=2
5	GA with Fitness Proportional Selection	μ=40, p_c=0.6, p_m=0.01
6	GA with SUS Selection	μ=40, p_c=0.6, p_m=0.01
7	Rank Based GA with linear selection function	μ=40, p_c=0.6, p_m=0.01, e=1.2
8	Rank Based GA with non-linear selection function	μ=40, p_c=0.6, p_m=0.01, c=3.0
9	Adaptive Rank Based GA with non-linear selection	μ=40, p_c=0.6, p_m=0.01, c=(average fitness/best fitness)

(Note: one-point cross-over has been used for all GAs.)

5.1 Fitness-function

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 2). To avoid a division by zero, one been added to the denominator. The theoretical maximum value of this objective function is 1.0, but, due to the non-deterministic influence of the simulated measurement devices, the target maximum of this function is 0.994. The lowest acceptable value is 0.969

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

where:

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.

5.2 Experimental Results

Each algorithm has been applied 50 times. In order to allow for a fair comparison of the different algorithms, the measure *"guess"* has been introduced rather then using *"generation"*. One *guess* equals one model calculation, e.g. a GA with a genepool containing 50 individuals carries out 500 guesses in 10 generations. Each run has been allowed 400 guesses. Table 2 gives the results for the average fitness found by each method. Table 3 gives the average number of guesses taken by the method to find the best result during one run.

Table 2. Fitness results.

Method	Average Fitness	Standard Deviation
Random Walk	0.93261044	0.07308076
Hill Climbing	0.93091918	0.071281203
Simulated Annealing	0.9766379	0.033922189
GA Tournament	0.9608671	0.031718002
GA Roulette Wheel	0.98206098	0.012783254
GA SUS	0.98624604	0.005983528
linear Rank Based GA	0.983616	0.008452708
non-linear Rank Based GA	0.98894954	0.006316525
Adaptive Rank Based GA	0.98897732	0.006726639

Table 3. Guesses results.

Method	Average Number of Guesses	Standard Deviation
Random Walk	2097.76	1191.972736
Hill Climbing	2721	854.9758321
Simulated Annealing	2472.24	983.4050707
GA Tournament	2412	1364.96692
GA Roulette Wheel	2655.2	1146.248967
GA SUS	2809.6	941.3688687
linear Rank Based GA	2366.4	1165.528276
non-linear Rank Based GA	2683.2	939.1907937
Adaptive Rank Based GA	2760.8	899.0694509

5.3 Discussion

It can be seen, that the variation in the average number of guesses is not significant, while there are considerable differences in the achieved average fitness (Fig. 20).

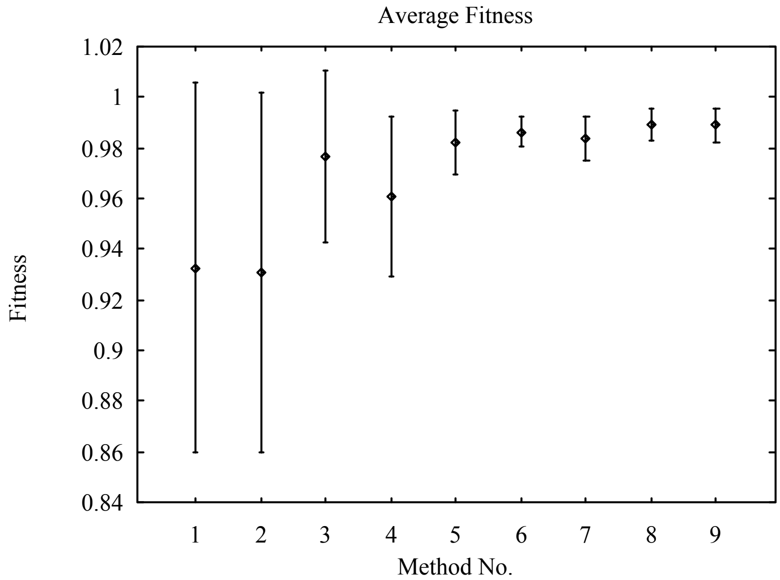


Fig. 20. Experimental Results. The dots represent the achieved average fitness, the error bars represent the standard deviation.

In this problem domain, Rank Based GAs clearly out-perform Random Walk, Simulated Annealing [17][18], and fitness proportional GAs.

The adaptive version of the non-linear Rank Based GA (method 9) shows no significant improvement compared to the non-adaptive one. Therefore, the ratio (best fitness/average fitness) is not appropriate to calculate *c*. It should be investigated whether other ways of calculating *c* lead to better results.

The second best method is SA. Interestingly, Hill Climbing has been declassified to Random Search due to the non-deterministic disturbance of the (simulated) measurement equipment.

6 Optimum Work Roll Profiles

For the final optimization, the non-linear Rank Based GA was selected. The genepool contained 40 individuals of 42 bit length. Uniform cross-over [19] was used with a cross-over probability of 0.6. The mutation probability was 0.01 and *c* has been chosen to be 3.0.

Table 3 shows the simulation results for a typical rolling program using the original work roll profiles and the profiles found by the GA after 63 generations. The target crown was 0.031 mm. The required flatness values were 0 I-Units, the (simulated) inaccuracy of the flatness transducer was ± 5 I-Units.

Table 4. Improvement by optimized work roll profiles.

Parameter	Target value	Old profiles	New profiles	Improvement
Strip crown [mm]	0.031	0.081	0.032	98 %
Flatness edge [I-Units]	0	5	3	40 %
Flatness quarter [I-Units]	0	205	29	86 %
Flatness middle [I-Units]	0	287	1	99 %

It will be observed, that it has prove possible to reduce the profile error from 61.73% to 3.13% and the mean flatness error from 165.67 I-Units to 11.00 I-Units.

7 Conclusions

The accuracy of an analytical mill model has been considerably improved by using Artificial Neural Networks to compensate for the model error. For this particular optimization problem, Nine Experimental Optimization Algorithms have been compared. A non-linear Rank-Based Genetic Algorithm gave the best performance. Hence, this algorithm was selected and used to optimize the work roll profiles in the simulated hot strip mill. The quality of the strip profile and flatness from the simulated mill was significantly increased.

It has been demonstrated that Genetic Algorithms are capable of solving optimization problems of physical systems, even if these systems have non-deterministic behaviour, provided adequate models of these physical systems are available.

Acknowledgements

The financial support of this research by *Metrology Systems Wales, UK* is gratefully acknowledged. The authors also wish to thank the management of *Thyssen Krupp Stahl AG, Bochum* for supplying the process data, and in particular Dr.-Ing. Ingolf Jäckel for his help and advice.

References

1. Wilms, Vogtmann, Klöckner, Beisemann, Rohde: Steuerung von Profil und Planheit in Warmbreitbandstraßen, Stahl u. Eisen 105 (1985) Nr. 22, pp 1181-1190
2. Hensel, Poluchin: Technologie der Metallformung, Deutscher Verlag für Grundstoffindustrie, Leipzig, 1990

3. Sheppard, Roberts: Shape Control and Correction in Strip and Sheet, International Metallurgical Reviews 1973, Vol. 8, pp 1-17
4. Emicke, Lucas: Einflüße auf die Walzgenauigkeit beim Warmwalzen von Blechen und Bändern, Neue Hütte, 1. Jg. Heft 5, 1956, pp 257-274
5. Takashi, Satou, Yabuta: Adaptive Technology for Thickness Control of Finisher Set-up on Hot Strip Mill, ISIJ International, Vol. 35 (1995), No. 1, pp 42-49
6. Ortmann, Burkhard: Modernisierung der Automatisierungssysteme der Warmbreitbandstraße bei Voest-Alpine Stahl Linz, Stahl u. Eisen 115 (1995) Nr.2, pp 35-40
7. Nolle, Armstrong, Ware: Optimisation of Work Roll Profiles in a 2-hight Rolling Mill Stand by Means of Computational Intelligence, Proc. of the 4th Int. Mendel Conf., Brno, 1998, pp 277-284
8. Hensel, Arnold, Thilo Spittel: Kraft- und Arbeitsbedarf bildsamer Formgebungsverfahren, VEB Deutscher Verlag für Grundstoffindustrie, Leipzig, 1978
9. Winkler W.: Theoretische Untersuchungen über die Einflüße, welche die Stärkenunterschiede beim Warmwalzen von Breitstreifen bestimmen, Dr.-Ing. Dissertation, TH Achen, 1943
10. Wusatowski, Zygmunt: Fundamentals of Rollling, Pergamon Press Ltd, Oxford, London, Edinburgh, 1969
11. Portmann, Lindhoff, Sorgel, Gramckow: Application of neural networks in rolling mill automation, Iron and Steel Engineer, Feb. 1995, pp 33-36
12. Hornik Stinchcombe, White: Multilayer Feedforward Networks are Universal Approximators, Neural Networks, Vol. 2, 1989, pp 359-366
13. Hornik: Approximation Capabilities of Multilayer Feedforward Networks, Neural Networks, Vol. 4, 1991, pp 251-257
14. Picton, Phil: Introduction to Neural Networks, The MacMillian Press LTD, 1994
15. Sprecher, D.: On the Structure of Continuous Functions of Several Variables, Transaction of the American Mathematical Society, Vol. 115, 1964, pp 340-355
16. Baker: Adaptive Selection Methods for Genetic Algorithms, Proc. on an Int. Conf. on GA's and Their Application, Hilldsdale, 1985, pp 101-111
17. Kirkpatrick, S., C.D. Gelatt, Jr., M. P. Vecchi: Optimization by Simulated Annealing, Science, 13 May 1983, Vol. 220, No. 4598
18. Metropolis, A., W. Rosenbluth, M. N. Rosenbluth, H. Teller, E. Teller: Equation of State Calculations by Fast Computing Machines, The Journal of Chemical Physics, Vol. 21, No. 6, June 1953
19. Syswerda: Uniform Crossover in Genetic Algorithms, Proceedings of International Conference on Genetic Algorithm 1989 (ICGA'89), pp 2-9