Hot Rolling Scheduling Optimization Problem

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Abstract. In this paper the problem of minimizing the hot rolling time using genetic algorithms of a steel strip is approached. Unlike the traditional approaches in this work the steel chemical composition of the strip is incorporated as a problem parameter allowing the automatically setup of the hot mill for different steels. To validate the approach, a six-stand rolling mill is modeled as an optimization constrained problem. The used set of problem instances were built with realistic data of industrial schedules. In this paper the mathematical model and the instances set are completely described. To evaluate the model quality we present the results obtained with a solution method based on genetic algorithms (GA). The global rolling time obtained solving the modeled problem with a genetic algorithm (GA) is 0.051% better than the industrial time. The generated rolling schedule diminishes the equipment damage risks because it produces softer reductions than the rolling schedule proposed by the manufacturer. Currently we are developing new solution methods using different metaheuristics.

Keywords: genetic algorithm, hot rolling scheduling

1 Introduction

Steel hot rolling is one of the most important metalworking processes in comparison with any other deformation process, aimed to manufacture products of relatively large dimensions (sheets, strips, plates, foils, etc.), at high speeds [1]. The rolling mill reduces the thickness steel slab by rolling two driven work rolls in a mill stand (as we can see in Fig. 1). Due to high operational costs of a rolling mill is not acceptable to setup the rolling schedule in an empirical way.

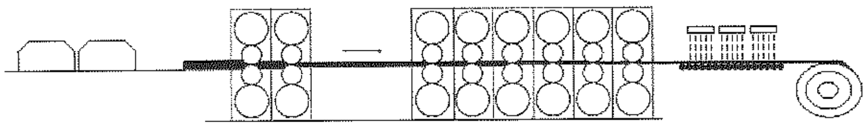

Fig. 1. Hot rolling process

The hot rolling scheduling problem consist in determining the reductions for every rolling pass to obtain the final thickness, considering that the rolling power should be lower than the motor power.

2 Related works

The hot rolling scheduling problem has been the subject of several research works. Nolle & Armstrong propose the optimization of a 7-stand hot rolling mill using simulated annealing (SA) and genetic algorithms (GA) [2]. The goal was to optimize the surface quality of a steel slab. In this work the SA shows a better performance than GA. Oduguwa & Tiwari propose a general methodology to solve problems of sequential processes using GA [3]. The proposal consists in a binary representation of the full set of parameters as a sub-set of strings. An application to multi-pass hot rolling was given, using a multi-objective model. The goal was to maximize the system productivity, optimizing the roll force. Chakraborti [4] applied GA to the problem of minimizing hot rolling time in a reversing mill stand, determining the optimum number of odd passes. In this work the efficiency of GA to calculate a hot rolling schedule, with respect to traditional methods, is demonstrated. Another contribution of Chakraborti [5] was the study of surface profiles of slab rolled. In this case, two objective functions were applied to evaluate the wearing and deflection rolls as the main factors of the variation of the thickness during rolling process. The GA produces good quality solutions with respect to the solutions corresponding to the industrial data [6]. Other approaches to determine hot rolling schedules have been applied as neural network [7, 8], fuzzy logic [9], and finite element methods [10]. Currently the more successfully approach to solve the hot rolling scheduling problem is the genetic algorithm.

In this work the steel chemical composition of the strip is incorporated, as a problem parameter, allowing the automatically setup of the hot mill for different steels. To validate the approach, a six-stand rolling mill is modeled as an optimization constrained problem and a set of industrial instances is used.

3 Hot rolling model

The process parameters to roll the steel are obtained using a rolling model. Fig. 2 shows the hot rolling schedule flowchart to calculate the parameters, for a rolling mill with n deformation passes of the roll stand i.

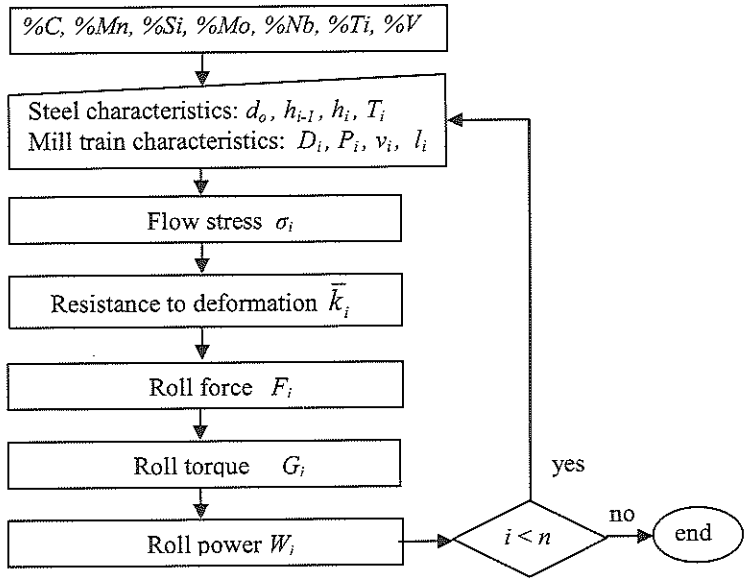

Fig. 2. Hot rolling schedule flowchart.

In this work we use the Hernández model to predict the flow stress of any kind of steel independently of the chemical composition [11-14]. The flow stress parameters include the temperature, the strain, strain rate, grain size and the chemical composition of the rolling steel.

The hot rolling model is used to calculate the flow stress and the resistance to deformation in two steps. The first step uses a stress-strain curve model to calculate the flow stress as follows:

Let

Z_i the Zener-Hollomon parameter in stand i,

$A = (12.19 + 65.58 \cdot \%C - 49.05 \cdot \%Nb) \exp(7.076 \cdot Q)$ and

$Q = 267{,}000 - 253552 \cdot \%C + 1010 \cdot \%Mn + 33{,}620.7 \cdot \%Si + 35{,}651.28 \cdot \%Mo + 93{,}680.52 \cdot \%Ti^{0.5919} + 70{,}729.85 \cdot \%Nb^{0.5649} + 31{,}673.46 \cdot \%V$

where:

%C : percentage weight of carbon.
%Mn : percentage weight of Manganese.
%Si : percentage weight of Silicon.
%Mo : percentage weight of molybdenum.
%Nb : percentage weight of Niobium.
%Ti : percentage weight of Titanium.
%V : percentage weight of Vanadium.

Once the above parameters are determined, the flow stress is calculated using expression (1).

$$\sigma_i = B_i \cdot [1-\exp(-C_i\varepsilon_i)]^{n_i} - B'_i \left\{1-\exp\left[-K_i\left(\frac{\varepsilon_i - a\varepsilon_{p_i}}{\varepsilon_{p_i}}\right)^{m_i}\right]\right\} \quad (1)$$

where:

a : empirical parameter with value 0.95.
ε_i: steel strain in stand i.
ε_p : peak strain for a given steel composition.
Z_i : Zener-Hollomon parameter in stand i .
B , B'_i, K_i, C_i : parameters dependent of Z_i/A.

$$A = (12.19 + 65.58\cdot\%C - 49.05\cdot\%Nb) \exp (7.076E{-}05\cdot Q) \quad (2)$$

$$Q = 267{,}000 - 253552\cdot\%C + 1010\cdot\%Mn + 33{,}620.7\cdot\%Si + 35{,}651.28\cdot\%Mo + 93{,}680.52\cdot\%Ti^{0.5919} + 70{,}729.85\cdot\%Nb^{0.5649} + 31{,}673.46\cdot\%V \quad (3)$$

In the second step, the resistance to deformation [15, 16] is calculated as follows:

$$\bar{k}_i = \frac{1}{\alpha_i}\int_0^{\alpha} \sigma_i d\alpha_i \quad (4)$$

where:

α_i : angle between the steel and the roll in stand i.
σ_i : plane flow stress in stand i.

Then the rolling forces to deform the steel can be calculated. The constitutive model equations applied in this work have been validated with industrial data [17]. The roll-separating force F can be calculated using different mathematical models, like rolling theories of Sims [18], Cook & McCrum [19] and Alexander & Ford [20], in this work is used the Alexander & Ford model.

The roll force is calculated using:

$$F_i = \frac{X}{4} w \cdot L_i \cdot \left(\pi + z_{a_i}\right) \cdot \bar{k}_i \quad (5)$$

where:

X : parameter with value 1.07
L_i : contact arc between the roll and the steel in stand i.
w : steel width.
z_{ai} : geometrical parameter in stand i.

$\bar{k}_i$: resistance to deformation in stand I, as calculated with (4)

The roll torque is required, applying a variant of equation (1). The model of Alexander & Ford was used [20]. The energy consumption or the rolling work for a given pass can be determined by an empirical expression that takes into account rolling torque. With this formulation, overloading of the main motor can be assessed.calculated using:

$$G_i = 250 \cdot w \cdot R'_i \cdot \Delta h_i \left(\pi + \frac{z_{a_i}^2}{z_{p_i}}\right) \cdot \bar{k}_i \quad (6)$$

where:

R'_i : roll radius with correction plane in stand i.

za_i : geometrical parameter in stand i.
zp_i : geometrical parameter in stand i.
Δh_i: difference between the final and the initial thickness in stand i.

Finally the rolling power can be calculated as follows:

$$W_i = 2\pi \cdot G_i \frac{RPM_i}{60} \quad (7)$$

where:

G_i : roll torque in stand i.
RPM_i = revolutions turns per minute in stand i.

4 Instance description

Industrial data was obtained from the Hylsa Monterrey Company and from the software HSMM of INTEG Process Group [21]. Table 1 shows the chemical compositions of the steels considered in this work. The first column contains the steel identifier. From column two to six are contained the percentage weight of carbon, manganese, silicon, niobium, titanium and vanadium.

Table 1. Chemical composition of steel.

Steels Id.	% C	% Mn	% Si	% Nb	% Ti	% V
1	0.045	0.45	0.069	0.0056	0.002	0.080
2	0.038	0.300	0.009	0.005	0.002	0.002
3	0.082	0.480	0.045	0.036	0.002	0.002
4	0.071	0.758	0.014	0.023	0.013	0.003
5	0.0028	0.170	0.009	0.035	0.035	0.005
6	0.053	0.784	0.010	0.026	0	0

From the industrial data 17 instances were defined, which can be consulted in [22]. Each instance defines the parameters of a different rolling problem. A rolling problem consists in determining the intermediate reductions needed to roll the slab steel and to obtain the final thickness in a 6-stand roll mill. Table 2 shows the parameters included in an instance: the data source, the number rolling stands (n), the instance name, the initial thickness (h_0), the final thickness (h_f), initial width (w) ,chemical composition (%C, %Mn, %Si, %Mo, %Nb, %Ti, %V), and for each rolling stand the roll diameter (D_i), the roll speed (v_i), the temperature (T_i), the grain size (do_i). Also the source of the data is indicated (Hylsa Monterrey or software HSMM of INTEG Process Group)), the motor power (P_i) and the inter-stand distance (l_i) are indicated.

Table 2. Hot rolling scheduling problem instance.

Industrial Data: Hylsa		$n = 6$		Name: hyl001.txt		
$h_0 = 48$ mm		$h_f = 3.8$ mm		$w = 991$mm		
%C=0.053, %Mn=0.784, %Si=0.017, %Mo=0, %Ti = 0, %Nb = 0, %V = 0						
Roll Pass No.	1	2	3	4	5	6
D_i (mm)	752	764	758	492	456	474
v_i (m/s)	0.81	1.43	2.21	3.38	4.57	5.54
T_i (°C)	1010	987.64	964.25	942.7	927.32	908.27
d_{0i} (μm)	400	100	80	60	40	20
P_i (kW)	7000	7000	7000	7000	7000	7000
l_i (m)	3.5	3.5	3.5	3.5	3.5	

5 Formulation of the optimization problem

Given an instance of the hot rolling scheduling problem, the goal is to determine the intermediate thicknesses $h_1, \ldots, h_{n-1}$ to minimize the total rolling time:

$$t = \sum_{i=1}^{n} t_i$$

To calculate the total rolling time t, the process time in each stand is added, to calculate the total rolling time. The rolling time in each stand is calculated adding the contact time between the roll and the steel, and the time to take the steel from one stand to another, taking into account the roll radius R_i, roll peripheral speed v_i, inter-stand distance l_i, initial thickness h_i, and final thickness h_{i-1} (Fig. 3).

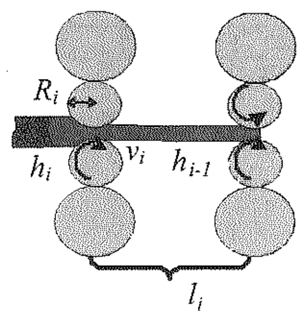

Fig. 3. Parameters to calculate the rolling time in a pass.

The rolling time in a stand can be calculated as follows:

$$t_i = \frac{\sqrt{\Delta h_i \cdot R_i} + l_i}{v_i} \tag{8}$$

where:

R_i : roll radius in stand i.
l_i : inter-stand distance

v_i : roll speed in stand i.
Δh_i: $h_{i-1} - h_i$

The problem includes the following two constraints:

1. In every rolling stand a reduction will be applied until the final thickness is obtained. Each intermediate thickness should be lower than the previous one:
$$h_0 > h_1 > h_2 > h_3 > h_4 > h_5 > h_f$$
2. To get the reduction in a rolling stand, a rolling power is applied. The rolling power should be lower than the motor power:
$$W_i < P_i \qquad \text{for } i = 1 \dots 6$$

6 Industrial rolling time calculation

For each kind of steel there is a rolling schedule given by the machine manufacturer. The rolling schedule proposes to the machine operator the reductions that must be applied to rolling the slab steel. These reductions are a suboptimal solution of the problem, but it is a good empirical solution. We use the instance parameters, the rolling schedule proposed by the manufacturer and the expression (8) to calculate the total industrial rolling time. Table 3 shows the reductions configuration for the steel specified in the Hylsa Monterrey instance and the rolling time calculated with expression (8) in each stand.

Table 3. Total industrial rolling time

Rolling stand No.	D_i mm	v_i m/s	l_i m	Stand exit thickness, mm		Rolling time,s
				h_0	48	
1	752	0.81	3.5	h_1	26	4.433
2	764	1.43	3.5	h_2	14.3	2.494
3	758	2.21	3.5	h_3	9.31	1.603
4	492	3.38	3.5	h_4	6.03	1.043
5	456	4.57	3.5	h_5	4.55	0.769
6	474	5.54		h_f	3.8	0.0024
			Total industrial rolling time:			10.3444

The total industrial rolling time will be the reference time to compare the rolling time obtained with the solution methods.

7 Experimental results

In this section the experimental results of the model evaluation are described. The experiments were carried out with Microsoft Windows Server 2003 for Small Business, dual Xeon CPU 3.06 GHZ, 3.87 GB RAM and the compiler C++.

To evaluate the quality of the proposed model, the rolling time obtained solving the modeled problem with a genetic algorithm (GA) and the industrial time calculated using the rolling schedule proposed by the manufacturer were compared for each of the 17 considered instances. Each instance was solved 30 times to obtain the average results. The genetic algorithm uses SBX crossover, uniform mutation and population with feasible and unfeasible individuals and was configured using 40% of crossover, 50% of mutation, a population of 100 individuals and 100 generations.

The accumulated of the average execution time required for solving each instance is 42.62 cpu sec. The accumulated of the average execution time required for the GA to get the best solution is 23.62 cpu sec. While the average of the improvement percentage in the rolling time respect to the industrial time is 0.051%.

Table 4 shows the rolling schedule proposed by the manufacturer, and the rolling schedule generated by the GA for the Hylsa Monterrey instance. In both cases we can see the exit thicknesses and the rolling time in each stand.

Table 4. Rolling schedules for a 6-stand roll mill.

Roll pass	Manufacturer proposed			GA generated		
	Exit thickness (mm)		Industrial rolling time (sec)	Exit thickness, (mm)		Rolling time, (sec)
	h_0	48		h_0	48	
1	h_1	26	4.433	h_1	36.67	4.401
2	h_2	14.3	2.494	h_2	22.52	2.498
3	h_3	9.31	1.603	h_3	13.57	1.610
4	h_4	6.03	1.043	h_4	8.23	1.046
5	h_5	4.55	0.769	h_5	5.80	0.771
6	h_f	3.8	0.0024	h_f	3.8	0.0039
	Total time :		10.3470	Total Time:		10.3317

Figure 4 shows the typical differences that were observed between the rolling schedules proposed by the manufacturer and the genetic rolling schedules generated for a given instance. In the graph, the rolling time and the thickness reductions for each one of the six stands are showed.

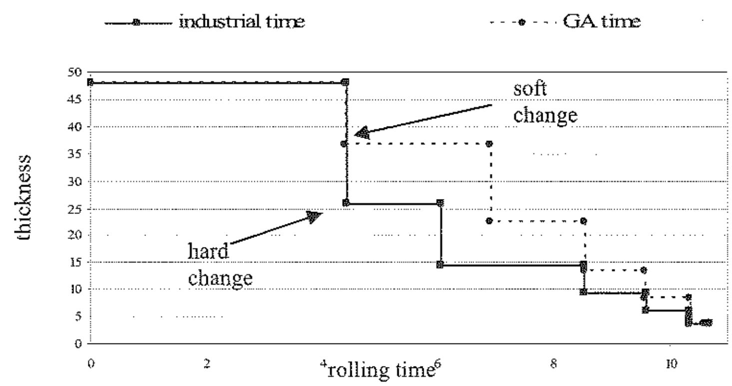

Fig. 4. Comparison of rolling schedule obtained with the GA vs the industrial schedule

As we can see the global rolling time obtained solving the modeled problem with a genetic algorithm is 0.051% better than the industrial time. Additionally the rolling schedule generated produces softer reductions than the rolling schedule proposed by the manufacturer. This characteristic of the solutions generated using the proposed model, diminishes the equipment damage risks.

8 Conclusions

In this work the problem of minimizing the hot rolling time was approached. Unlike the traditional approaches, the steel chemical composition is incorporated as a problem parameter allowing the automatically setup of the hot mill for different steels. To validate the approach a six-stand rolling mill is modeled as an optimization constrained problem. The mathematical model and the instances set were completely described. The used instances were built with realistic data of industrial schedules. The suboptimal industrial rolling time was used as the reference time to evaluate the solution methods performance. Also we present the results obtained using a solution method based on genetic algorithms. The global rolling time obtained solving the modeled problem with a genetic algorithm is 0.051% better than the global industrial time. Additionally the generated rolling schedule using the model diminishes the equipment damage risks because it produces softer reductions than the rolling schedule proposed by the manufacturer.

Currently we are developing new solution methods using different metaheuristics.

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References

1 G.E. Dieter et al. (2003) Chap 16-Rolling, Handbook of Workability and Process Design, ASM International, Materials Park, Ohio.

2 L.Nolle, et al. (2002) Simulated Annealing and Genetic Algorithms Applied to finishing mill optimisation for hot rolling of wide steel strip International Journal of Knowledge-Based Intelligent Engineering Systems, 6 (2): 104-111,

3 V.Oduguwa and A. Tiwari (2004). Sequential Process Optimisation Using Genetic Algorithms. Lecture Notes in Computer Science. Springer. Berlin, pp. 782-791,

4 N. Chakraborti, and A. Kumar (2003) The Optimal Scheduling of a Reversing Strip mill: Studies using Multipopulation Genetic Algorithms and Differential evolution, Materials and Manufacturing processes, 18 (3): 433-445.

5 N.Chakraborti et al. (2006). Optimizing Surface Profiles during Hot Rolling: A Genetic Algorithms Based Multi-objective Optimization, Practical Approaches to Multi-Objective Optimization, Comp. Mat. Sci., 37: 159-165,

6 N.Chakraborti (2004). Genetic algorithms in materials design and processing, Int. Mat. Rev., 49 (3-4): 246-260,

7 A. Gorni (1992). The Application of Neural Networks in the Modeling of Plate Rolling Process, JOM-*e*

8 L. Nolle et al. (1999). Optimum Work Roll Profile Selection in the Hot Rolling of Wide Steel Strip using Computational Intelligence, Lect. Notes in Comp. Sci., 1625: 435.

9 C. Pataro and H. Herman (1999). Direct determination of sequences of passes for the strip rolling by means of fuzzy logic rules. Proc. 2d. Conf. on Intell. Proc. and Manuf. of Mat., IPMM. pp. 549.

10 R. Shivpuri and S. Kini (1998). Application of Fuzzy Reasoning Techniques for Roll Pass Design Optimisation. Proc. 39th Mech. Work and Steel and Symp. on New Metal Form. Proc. pp. 755.

11 S. F. Medina and C. A. Hernández (1996). General Expression of the Zener-Hollomon Parameter as a Function of the Chemical Composition of Low Alloy and the Microalloyed Steels. Acta Metall. et Mater., 44 (1): 137-148.

12 S. F.Medina and C. A.Hernández (1996). The Influence of Chemical Composition on Peak Strain of Deformed Austenite in Low Alloy and Microalloyed Steels. Acta Metall. et Mater. 44(1): 149-154.

13 C. A. Hernández et al. (1996). Modelling Austenite Flow Curves in Low Alloy and Microalloyed Steels. Acta Metall. et Mater. 44 (1): 155-163.

14 S. F. Medina and C. A. Hernández (1996). Modelling of the Dynamic Recrystallization of Austenite in Low Alloy and Microalloyed Steels. Acta Metall. et Mater., 44(1): 165-171.

15 Z.Wusatowski (1969). Fundamentals of Rolling, Pergamon Press.

16 W.Roberts (1983). Hot Rolling of Steel, CRC.

17 C. A. Hernández and J. E. Mancilla (2003). Evolución de los precipitados en un acero microaleado al Nb fabricado por laminación directa. Informe técnico sobre estudios metalúrgicos y por MET en planchones de acero 7095. HYLSA Monterrey. Com. privada.

18 R. B. Sims (1954). The Calculation of Roll Forces and Torque in Hot Rolling Mill, Proc. AIME 168 (6): 191-200.

19 P. M.Cook and A. W.McCrum (1958). The Calculation of Load and Torque in Hot Flat Rolling, Reporte B.I.S.R.A., Londres.

20 H. Ford and J. M. Alexander (1963). Simplified Hot-Rolling Calculations, J. Inst. Met. 92: 397-404.

21 HSMM Rel. 3.0. INTEG process group, inc., AISI/DOE Technology (2006).

22 F. K. Espriella (2008). Optimización mediante algoritmos genéticos: aplicación a la laminación en caliente. Master Thesis. Instituto Politécnico Nacional.