A HYBRID SET-UP OPTIMIZATION MODEL FOR TANDEM COLD ROLLING MILL

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Keywords: Hybrid optimization, Real-coded genetic algorithm, Nelder and Mead simplex method, Set-up optimization model, Tandem cold rolling.

Abstract: Set-up optimization of the rolling process involves several parameters that may lead to complex multi objective optimization problem. Also, it is well known that experience is playing a vital role in the selection of operating parameters in rolling mill. This paper presents a combination of two optimization procedure for a multi objective optimization problem. The first optimization phase is based on Nelder and Mead simplex method which focus on balance of power, force and reduction distribution in set-up planning. Then, a real-coded genetic algorithm based optimization procedure applies on the system as an outer loop to optimize energy consumption and productivity. An experimental result of application to five stand tandem cold rolling mill is presented.

1 INTRODUCTION

Process optimization is the discipline of adjusting a process so as to optimize some specified set of parameters without violating some constraint. The most common goals are minimizing cost, maximizing throughput, and/or efficiency. This is one of the major goals in industrial automation systems.

The optimization of manufacturing and product quality is possible when the effect of each process stage and its influence on the process parameters are known as a process model and an advanced architecture of optimization mechanism apply on this model to achieve optimized parameters.

Recently, a lot of attention has been devoted toward advanced techniques of computational intelligence for Process optimization. However it is well known that experience is playing a vital role in modelling and optimization of complex industrial processes (Venkata & Suryanarayana, 2001).

The tandem cold rolling of metal strip is a complex nonlinear multivariable process whose optimization presents significant challenges to the control design.

Set-up optimization and Scheduling for tandem cold mills has been frequently investigated in the last few years, motivated by the benefits they can provide in terms of quality and productivity improvements (Pires, et. al., 2006). Reductions, speeds, tensions and forces, which must be followed by the control loops, form the main part of the mill set-up (Bryant, 1973). Reduction and tension distribution is the major point for set-up calculation that usually obtains by look-up table or some simple formula based on experience. Therefore by this distribution, optimal set-up may not be achieved. Optimal schedules should result in maximized throughput and minimized operating cost (Wang, et al., 2000).

In the present work, recent developments will be discussed concerning to set-up optimization applied to a continues five stand tandem cold mill at Mobarakeh Steel plant in Iran, which, due to more high quality and productivity market demand, was totally revamped in 2004. The proposed algorithm is composed of two step optimization architecture. The first part is an inner loop which calculates stand reductions and inter-stand tensions based on reduction balance, power balance and force balance.

Mirmohammadi M., Haddad H. and Naghavi S. (2009).
A HYBRID SET-UP OPTIMIZATION MODEL FOR TANDEM COLD ROLLING MILL.
In *Proceedings of the 6th International Conference on Informatics in Control, Automation and Robotics - Intelligent Control Systems and Optimization*, pages 49-54
DOI: 10.5220/0002204700490054

For the optimization of the set-up, Nelder and Mead simplex algorithm has been employed. The major goal of this part is to balance of power, force and reduction according to rolling condition and experience. The second part is an outer loop which optimizes rolling productivity by using genetic algorithm. In fact, the outer loop evaluates some coefficient of inner optimization loop to maximize throughput and minimized energy consumption.

The study is organized in the following manner. First, section 2 delivers a brief introduction to the architecture of set-up optimization based on Nelder and Mead simplex algorithm. In section 3, we discuss a productivity optimizer as an outer optimization loop that applies on set-up optimization structure described in section 2. Experimental results are explained in section 4. finally, section 5 presents the main conclusions.

2 PRESET BALANCE MODEL

The structure of the inner loop set-up model is presented in figure 1. The preset balance optimizer receives the power and force of each stand and calculates reductions and tensions. In this work the Bryant model is considered for rolling mill process model (Bryant, 1973).

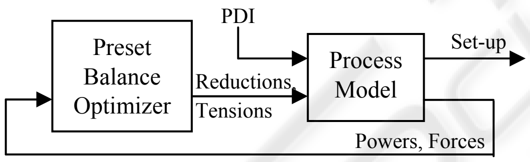

Figure 1: Inner loop set-up model.

The process of set-up calculation consists of power balancing, force balancing and reduction balancing. To balance the power, the required per unit power of each stand should be the same, taken the total available power of the rolling mill as the base power. Thus, the total set-up power should not be greater than the nominal power of the rolling mill. In force balancing the applied forces should be smoothly distributed through the first stands in order to avoid flatness problems. Furthermore, the last stand force is critical due to imposed quality purposes like roughness and flatness. The reduction balancing is based on experience and usually is formed as a look-up table.

The specific tension applied to the strip on each zone should not be greater than one third of the yield strength of the strip on that zone (Bryant, 1973). Furthermore, the distribution of specific tension through the zones should follow the same law as the distribution of reduction through the stands in order to avoid unbalancing of back and front tension on any stand. Also, it is desirable that the stand maximum set-up speed be achieved using the total available power of that stand (Pires, et al., 2006).

To achieve the goals which described we should define a suitable objective function and employ a powerful optimization algorithm. Nelder and Mead simplex method is one of the best algorithm for optimization that is applied in several application related to cold mill set-up optimization.

A detailed description of the simplex method can be found in the work of Pires, et al. (2006). The simplex method, considers the unconstrained minimization of a nonlinear cost function $J = f(x_1, x_2, \ldots, x_n)$ of n variables, without evaluating its derivatives. The minimization step is variable according to the cost function. Briefly speaking, disturbances are introduced in the initial values of x_i and new values of the cost function are calculated, corresponding to each disturbance. Three operations may be accomplished, according to the following steps: reflection, contraction and expansion.

The iterative process is initiated sorting the points x_W, x_N and x_B for which the function has its maximum value J_W, the second maximum value J_N, and the minimum value J_B, respectively.

The average point or centroid x_C is determined finding the average of all points x_i, except x_W. From equation 1 and assuming the minimization step $b = 1$, it results $x = x_R$, known as reflection of x_W with respect to x_C.

$$x = x_C + b(x_C - x_W) \tag{1}$$

The following four cases can then occur:

- If $J_B < J_R < J_N$, then x_W is replaced by x_R and the process is restarted;
- If $J_R < J_B < J_N$, then set $b = 2$ and get $x = x_E$, known as expansion of x_R with respect to x_C. If $J_E < J_B$, x_W is replaced by x_E and a new process is started;
- If $J_N < J_R < J_W$, a contraction is made, generating a vertex $x = x_U$ for which $b = 1/2$. If $J_B < J_U < J_N$, x_W is replaced by x_U and a new process is started;

- If $J_W < J_R$, a contraction with change in direction must be done, generating a vertex $x = x_T$ for which $b = -1/2$. If $J_T < J_W$, x_W is replaced by x_T and a new process is started.

The simplex method requires a starting point not so distant of the optimum point as a condition to converge; the use of empirical laws during initialization or using beta factor algorithm which is described in Pires, et al. (2006) help to reach this objective. From this point, the simplex method calculates the initial cost function and allow for disturbance in reductions and tensions, which result in new values of power, forces and tensions and subsequently in new value for the cost function.

In order to define a suitable objective function for the tandem mill, power, force, reduction and tension were assumed to be the most important variables to form the objective function. Therefore, the objective function was then conceived as:

$$J = k^P \sum_{i=1}^{5} J_i^P + k^F \sum_{i=1}^{5} J_i^F + k^R \sum_{i=1}^{5} J_i^R + \sum_{j=1}^{4} J_j^T \quad (2)$$

Where J_i^P is the power balance cost function, J_i^F is force balance cost function and J_i^R is the reduction balance cost function of stands i = 1, 2, 3, 4, 5, respectively. J_j^T is the tension balance cost function of zones j = 1, 2, 3, 4 between two consecutives stands.

k^P, k^F and k^R present the weight of each cost function of the objective function. We will see later that these coefficients come from the outer optimization loop.

The cost function of power, force, reduction and tension are given by

$$J_i^P = K_i^P \left(\frac{P_i - \frac{P_i^{\max} + P_i^{\min}}{2}}{\frac{P_i^{\max} - P_i^{\min}}{2}} \right)^{N_i^P} \quad (3)$$

$$J_i^F = K_i^F \left(\frac{F_i - \frac{F_i^{\max} + F_i^{\min}}{2}}{\frac{F_i^{\max} - F_i^{\min}}{2}} \right)^{N_i^F} \quad (4)$$

$$J_i^R = K_i^R \left(\frac{R_i - \frac{R_i^{\max} + R_i^{\min}}{2}}{\frac{R_i^{\max} - R_i^{\min}}{2}} \right)^{N_i^T} \quad (5)$$

$$J_i^T = K_i^T \left(\frac{T_i - \frac{T_i^{\max} + T_i^{\min}}{2}}{\frac{T_i^{\max} - T_i^{\min}}{2}} \right)^{N_i^T} \quad (6)$$

N_i^P, N_i^F, N_i^T and K_i^P, K_i^F, K_i^T are exponents and coefficients of cost functions of power, force and tension, respectively. The maximum and minimum limits for power ($P_i^{\max}$ and $P_i^{\min}$), force ($F_i^{\max}$ and $F_i^{\min}$), reduction ($R_i^{\max}$ and $R_i^{\min}$), and tension ($T_i^{\max}$ and $T_i^{\min}$), are normally defined based on the process analyst knowledge. The objective function is strongly penalized if $P < P^{\min}$ or $P > P^{\max}$ for power and also there is the same situation for force, reduction and tension.

The algorithm described above is executed several times until a minimum value for the cost function is reached. The criterion for stopping this process is the number of iterations or a given incremental reduction of cost function between two consecutive iterations. Consequently one set of reduction and tension distribution will be achieved that will be used in other set-up values calculation.

3 HYBRID SET-UP MODEL

In section 2, the optimization was done to balance the main parameters of rolling but it doesn't guarantee to maximize throughput and efficiency. So in this paper, we present an additional optimization loop as an outer loop using genetic algorithm to optimize energy consumption and rolling speed.

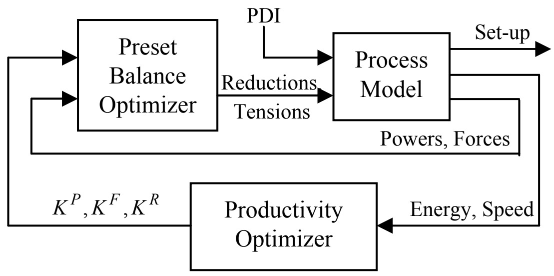

Figure 2: Hybrid set-up model.

Figure 2 shows the structure of hybrid optimization method. The required energy and rolling speed are feedback parameters from process model and is used in productivity optimizer. The outputs of this optimizer are k^P , k^F and k^R which is used as coefficients of objective function in balance optimization. To minimize energy consumption and maximize rolling speed we consider the objective function as:

$$J = \sum \left(\alpha . E + \beta (v_{\max} - v)^2 \right) \tag{7}$$

In this equation, E demonstrate required energy consist of reduction and tension energy and evaluate by rolling energy model. The parameter v is the maximum allowable rolling speed corresponding to reduction distribution and power of motors.

Genetic algorithms (GAs) are gradient free parallel-optimization algorithms that use a performance criterion for evaluation and a population of possible solutions to search for a global optimum. These structured random search techniques are capable of handling complex and irregular solution spaces (Setnes & Roubos, 2000). GAs are inspired by the biological process of Darwinian evolution where selection, mutation, and crossover play a major role. Good solutions are selected and manipulated to achieve new and possibly better solutions. The manipulation is done by the genetic operators that work on the chromosomes in which the parameters of possible solutions are encoded. In each generation of the GA, the new solutions replace the solutions in the population that are selected for deletion.

We consider real-coded GAs. Binary coded or classical GAs are less efficient when applied to multidimensional, high-precision or continuous problems. The bit strings can become very long and the search space blows up. Furthermore, central processing unit (CPU) time is lost to the conversion between the binary and real representation. Other alphabets like the real coding can be favourably applied to variables in the continuous domain. In real-coded GAs, the variables appear directly in the chromosome and are modified by special genetic operators. Various real-coded GAs were recently reviewed in Herrera and Lozano (1998).

The chromosome representation determines the GA structure. We encode the parameters of outer loop in a chromosome as Eq. (8) where $l = 1, \cdots, L$ and L is the size of chromosomes population.

$$S_l = [K_{Pl}, K_{Fl}, K_{Rl}] \tag{8}$$

The selection function is used to create well-performing chromosomes which have a higher chance to survive. The roulette wheel selection method is used to select n_C chromosomes for operation.

Two classical operators, simple arithmetic crossover and uniform mutation and four special real-coded operators are used in the GA. These operators have been successfully applied in the work of Setnes and Roubos (2000) and Michalewicz (1994).

For crossover operations, the chromosomes are selected in pairs. In Simple arithmetic crossover two chromosomes are crossed over at the random position. Whole arithmetic crossover creates a linear combination of two chromosomes as:

$$\begin{aligned} S_v^{t+1} &= r.S_v^t + (1-r).S_W^t \\ S_w^{t+1} &= r.S_w^t + (1-r).S_v^t \end{aligned} \tag{9}$$

In this section, $r \in [0,1]$ and is a random number. Heuristic crossover is another kind of a pair chromosomes combination such that:

$$\begin{aligned} S_v^{t+1} &= S_v^t + r.\left(S_w^t - S_v^t\right) \\ S_w^{t+1} &= S_w^t + r.\left(S_v^t - S_w^t\right) \end{aligned} \tag{10}$$

For mutation operations, single chromosomes are selected. In Uniform mutation a random selected element is replaced by a random number in the range of element. Multiple uniform mutations is uniform mutation of n randomly selected elements and in Gaussian mutation all elements of a chromosome are mutated such that a random number drawn from a Gaussian distribution with zero mean will be added to each element.

In this paper the chance that a selected chromosome is used in a crossover operation is 95% and the chance for mutation is 5%. When a chromosome is selected for crossover (or mutation) one of the used crossover (or mutation) operators are applied with equal probability. The search space of elements in chromosomes is determined in the range between 0 and 1.

4 EXPERIMENTAL RESULTS

As an experimental work, we implemented the described algorithm on five stand tandem mill of Mobarakeh Steel plant, Iran. In the first step, the Preset Balance Model was implemented to produce optimal set-up values based on objective function presented in Eqs. (2)-(6) by using the values for the

Table 2: Optimization results using Preset Balance Model and Hybrid Set-up Model.

	Preset Balance Model						Hybrid Set-up Model					
	Red. (%)	Tens. (ton)	Speed (mpm)	Force (ton)	Power (kw)	Energy (kwh/t)	Red. (%)	Tens. (ton)	Speed (mpm)	Force (ton)	Power (kw)	Energy (kwh/t)
Zone 0		13	273					13	288			
Stand 1	28.8			865	1724	4.29	32.4			949	2656	6.26
Zone 1		25.9	383					22.7	427			
Stand 2	28.4			890	4560	11.35	26.7			1074	4560	10.74
Zone 2		19.4	535					18.85	582			
Stand 3	26.1			854	4487	11.18	24			846	4300	10.12
Zone 3		16.83	723					16.82	766			
Stand 4	21.1			876	4481	11.15	20.1			795	4375	10.29
Zone 4		16.72	917					16.95	957			
Stand 5	5.36			570	1831	4.58	7			623	2103	4.95
Zone 5		2.86	969					2.85	1029			
Total						42.55						42.36

coefficients and exponents adjusted for each stand that are presented in Table 1. Adjustment of these coefficients has been done by focus on a regular distribution of reductions, power and forces based on rolling situation and experience.

Table 1: Exponents and coefficients of cost functions.

	Std.1	Std.2	Std.3	Std.4	Std.5
K_i^P	1	1	1	1	1
N_i^P	18	18	18	18	10
K_i^F	0.001	0.001	0.001	0.001	1
N_i^F	18	18	18	18	18
K_i^R	1	0.1	0.1	0.1	1
N_i^R	10	10	10	10	10
K_i^T	1	1	1	1	-
N_i^T	5	5	5	5	-

For the second phase, the hybrid set-up model with proposed objective function in Eq. (7) was implemented. We apply a real-coded GA with the population size (L) equal to 20 and $n_C = 5$ for operation in each iteration. The chance of crossover operation is 95% and for mutation is 5%.

The values summarized in Table 2 show the final result of set-up calculation according to the preset balance model in the right side and hybrid set-up model in the left side of table.

By using preset balance model, the balance of power, force and reduction is obtained after approximately 100 iteration but the maximum obtained speed value will be 969 (m/min) while the total required energy is equal to 42.55 (kwh/t).

The implementation of the hybrid set-up model produced, as shown in the right part of Table 2, a significant improvement for the global performance. The rolling speed will increase to 1029 (m/min) and the required energy will decrease to 42.36 (kwh/t). However the balance of power, force and reduction is a little changed but we can obtain more throughputs by using less energy that provide higher productivity.

5 CONCLUSIONS

In this paper we have described a hybrid optimization procedure for set-up generation of tandem cold rolling mill. In order to complexity of rolling process and the role of experience in this process, we should solve a multi objective problem to calculate optimum set-up values. So, we has presented a hybrid algorithm consists of two optimization model.

The preset balance optimization model is based on Nelder and Mead simplex method which optimizes the balance of power, force and reduction of stands. The simplex method, considers the unconstrained minimization of a nonlinear cost function, without evaluating its derivatives. By using empirical laws and beta factor algorithm we can find starting point not so distant of the optimum point which helps us to reach the optimum solution in a few iteration.

The hybrid set-up model appears as an outer loop which minimizes the energy consumption and maximizes rolling speed through evaluation of coefficient of objective function related to preset balance model.

The optimization algorithm used in this model is based on Genetic algorithm and to increase the efficiency and decrease the processing time, we have proposed a real-coded genetic algorithm which employs some special kind of crossover and mutation operation to reduce the calculation time.

The proposed optimization approach was successfully applied to five stand tandem cold rolling mill, located at mobarakeh steel plant of Iran. Experimental results show that the obtained set-up leads to high quality and productivity in the tandem cold mill.

REFERENCES

Pires, C. T. A., Ferreira, H.C., Sales, R.M., and Silva, M.A., (2006) 'Set-up optimization for tandem cold mill: A case study', *Journal of Materials Processing Technology,* vol. 173, pp.368-375, ELSEVIER Press.

Setnes, M., Roubos, H., (2000) 'GA-Fuzzy Modelling and Classification: Complexity and Performance', *IEEE Transactions on Fuzzy Systems,* vol. 8, no. 5, October, pp. 509-522.

Michalewicz, Z., (1994) *Genetic Algorithms + Data Structures = Evolution Programs*, 2nd edition, New York: Springer-Verlag.

Herrera, F., Lozano, M. and Verdegay, J. L., (1998) 'Tackling real-coded genetic algorithms: Operators and tools for behavioural analysis', *Artificial Intelligence Rev.*, vol. 12, pp. 265–319.

Venkata, R.N., Suryanarayana, G., (2001) 'A set-up model for tandem cold rolling mills', *Journal of Materials Processing Technology*, vol. 116, October, pp. 269-277, ELSEVIER Press.

Wang, D. D., Tieu, A. K., De Boer, F.G., Yuen, W. Y. D., (2000) 'Toward a heuristic optimum design of rolling schedules for tandem cold rolling mills', *Engineering Applications of Artificial Intelligence*, vol. 13, August, pp. 397-406, ELSEVIER Press.

Bryant, G. F., (1973) *Automation of Tandem Mills,* London: Iron and Steel Institute.