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The Optimization of Finishing Train Based on Improved Genetic Algorithm

Hongxia Liu*, Xin Chen, Rongyu Li
Electronics and Information Engineering, Nanjing University of Technology, Nanjing, China
*Corresponding author, email: lhx_cec@126.com

Abstract

The central issue of finishing train is that we should distribute the thickness of each exit with reason and determine the rolling force and relative convexity. The optimization methods currently used are empirical distribution method and the load curve method, but they both have drawbacks. To solve those problems we established a mathematical model of the finishing train and introduced an improved Genetic Algorithm. In this algorithm we used real number encoding, selection operator of a roulette and elitist selection and then improved crossover and mutation operators. The results show that the model and algorithm is feasible and could ensure the optimal effect and convergence speed. The products meet the production requirements.

Keywords: *steel rolling, load distribution, improved genetic algorithm*

1. Introduction

In rolling production process, the optimization problem of train finishing load distribution is very important. The optimization methods currently used are empirical distribution method and the load curve method [1], but they both have drawbacks. The empirical distribution method is simple and reliable, but it would cause the inequality of each assembling unit and cannot self-adapt online. The model of the load curve method is simple but requires a lot of measured data and complex calculations to complete.

In this paper we take the shape, thickness and load balancing into account and established the mathematical model of the finishing train and introduced an improved Genetic Algorithm for Load Distribution Model. This algorithm is based on the mathematical model we established. Then we use it to do the simulation experiment. The results show that the model and algorithm is feasible.

2. The Mathematical Model of the Finishing Train

The main aim is distributing the thickness of each exit. At the same time, we should take the shape into account to ensure that the striped steel meets production requirements.

An important issue of the model is to determine the objective function [2]. We consider a model with $n\,(3<n<10)$ frames. We will divide the whole process into three phases. The former two phases should maximize the amount of reduction and keep loading balanced. The third phase should reduce the amount of reduction and keep the shape optimal.

The objective function:

$$J = J_1 + J_2 + J_3 \tag{1}$$

$$J_1 = \min\{(P_1 - K_1 P_2)^2\} \tag{2}$$

J_1 ensures that we fully use the facilities.

$$J_2 = \min\{(P_2 - K_2 P_3)^2\} \tag{3}$$

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J_2 ensures that the load balancing has been kept.

$$J_3 = \min\{\sum_{i=4}^{n}(\frac{CR_i}{h_i} - \frac{CR_n}{h_n} \pm \Delta_i)^2\} \quad (4)$$

J_3 ensures that the shape has been well optimized.

In the formula P_i is rolling force of i-th frame. K_1, K_2 is scale factor, in this paper $K_1 = 0.9$, $K_2 = 1$; $\frac{CR_i}{h_i}$ is the relative convexity of the strip after getting through the i-th frame. $\frac{CR_n}{h_n}$ is the relative convexity of the end product, Δ_i is the optimal adjustment variable.

So the last objective function is:

$$J = \min\{(P_1 - K_1P_2)^2 + (P_2 - K_2P_3)^2 + \lambda\sum_{i=4}^{n}(\frac{CR_i}{h_i} - \frac{CR_n}{h_n} \pm \Delta_i)^2\} \quad (5)$$

λ is the weight coefficient.

Constraints:

$$0 \le P_i \le P_{\max} \quad (6)$$

$$0 \le M_i \le M_{\max} \quad (7)$$

$$h_{i+1} \le h_i \quad (8)$$

$P_{\max}$, $M_{\max}$ is the maximum rolling force and rolling moment for a single device. h_i is the thickness of the strip after getting through the i-th frame.

3. The Improved Genetic Algorithm

The Genetic Algorithm is a stochastic global optimization algorithm [3]. It not only has strong global search capabilities and the ability to solve problems, but also has a simple generic and robust, suitable for parallel processing, etc. But it has two significant drawbacks: First, prone to premature, second, due to selection and hybridization and mutation operator role in making some excellent gene fragment prematurely lost. To solve these problems, the standard Genetic Algorithm has been improved and successfully applied to the model in this paper [4].

Encoding:

The currently used encoding are binary encoding, Gray encoding, letter encoding and real number encoding [5]. In this paper we use a real number encoding. Compared with other encoding, real number encoding is with a high precision and search range.

Fitness function:

In traditional Genetic Algorithm fitness function and the objective function is a linear relationship, and even in some simple models the objective function can be used directly as a fitness function. However, this approach has several disadvantages: (1) In the early stage the maximum fitness value and the minimum fitness value is likely to vary greatly, it is easy to eliminate many of the individual gene fragments containing excellent information, and makes the destruction of pre-population diversity. (2) In the late stage in the algorithm the difference of fitness value between individuals is very small, making the ability to search the global optimal solution [6] reduced.

To solve these problems, we introduce a sequence-based fitness function:

$$eval(x_i^{'}) = \beta(1-\beta)^{i-1},\ i = 1,2...m; \tag{9}$$

$\{x_i^{'}\}$ is obtained by sorting the the objective function value of $\{x_i\}$. $\{x_i\}$ are individuals of the population. m is the population size.

The advantage of such improved is to ensure population diversity and decrease selection pressure early in the algorithm; in the latter part of the algorithm relative increase selection pressure and accelerate the convergence.

Selection operator, crossover operator and mutation operator:

Selection operator: In this paper we use a roulette and elite selection [7] model. Roulette selection is an approach Proposed by Professor J. H. Holland to select individual according to fitness randomly. Individual is copied depends on the individual fitness. The basic idea of elite selection is that if the fitness of the best individual in the next generation is less than the current population fitness of the best individual, copy the current best individual to the next generation directly and replace the worst individual in the next generation.

This strategy not only ensures the population diversity of the next generation, but also ensures that the current generation of the best individual retained to the next generation.

crossover operator: In this paper, the arithmetic crossover operator is used, in the form below:

X_A^t, X_B^t are two parent individuals in t-generation, of which:

$$X_A^t = [X_A^{(1)t}, X_A^{(2)t} ... X_A^{(i)t} ... X_A^{(n)t}],\ X_B^t = [X_B^{(1)t}, X_B^{(2)t} ... X_B^{(i)t} ... X_B^{(n)t}];$$
$$X_A^{(i)t}, X_B^{(i)t} \in (a^{(i)}, b^{(i)}),\ X_A^{(i+1)t}, X_B^{(i+1)t} \in (a^{(i+1)}, b^{(i+1)})$$

The two new individuals resulting from the crossover operator are:

$$X_A^{t+1} = \alpha X_A^t + (1-\alpha) X_B^t,\ X_B^{t+1} = \alpha X_B^t + (1-\alpha) X_A^t \tag{10}$$

α is a random number, $0 < \alpha < 1$; The solution produced from this method is between the range of the two parent individuals, ensuring no feasible solution.

mutation operator: In this paper we use non-uniform mutation operator, the operating procedures are:

During the $X = x_1 x_2 ... x_k ... x_n$ to $X^{'} = x_1 x_2 ... x_k^{'} ... x_n$ non-uniform mutation operation, if a gene mutation point value range is $[U_{\min}^k, U_{\max}^k]$, the new gene value is determined by the following:

$$x_k^{'} = x_k + \Delta(t,z),\ random(0,1) = 1; \tag{11}$$

$$x_k^{'} = x_k - \Delta(t,z),\ random(0,1) = 0; \tag{12}$$

$$\Delta(t,z) = z \times [random \times (1 - t/T)]^{\beta} \tag{13}$$

In the Formula $z = U_{\max}^k - U_{\min}^k$, $random$ is a random number from (0, 1), t is current generation, T is the total generation, β is the parameter for the system.

4. Simulation

In this paper the data used is collected from the scene. Experimental steels are high-quality carbon structural steel 20. The material width: B_0 =1050 mm; the material thickness: H_0 =30 mm; end production thickness: 3.5 mm; aiming convexity: CR_n =0.012 mm; the frame number: n=7. The remaining parameters are in Table 1.

Table 1. Remaining Parameters

frame / parameter	F1	F2	F3	F4	F5	F6	F7
Work roll diameter[mm]	800	800	800	760	760	760	760
Support roll diameter[mm]	1570	1570	1570	1570	1570	1570	1570
Motor rated power[kw]	7600	7600	7600	7600	7350	7350	5000
Motor rated speed[m/s]	1.74	2.82	4.33	5.97	7.36	8.56	9.55

In the experiment, the parameters of the algorithm are: population size M=50, Maximum generation: T=200, Crossover probability P_c =0.8, Mutation probability P_m =0.01. The results of the experiment are given in Table 2 and Table 3. The thickness contrast curves for h_i are shown in Figure 1. The relative convexity contrast curves are shown in Figure 2.

Table 2. Results of Empirical Distribution

frame / parameter	Thickness in the entrance [h/mm]	Thickness in the exit [h/mm]	Rolling force [P/KN]	Relative convexity [CR/h($\times 10^{-3}$)]
F1	30.00	24.11	18100	2.35
F2	24.11	16.55	13500	2.47
F3	16.55	12.68	14820	3.78
F4	12.68	9.55	15180	4.29
F5	9.55	6.84	9240	4.04
F6	6.84	5.52	8460	4.75
F7	5.52	3.50	6530	3.70

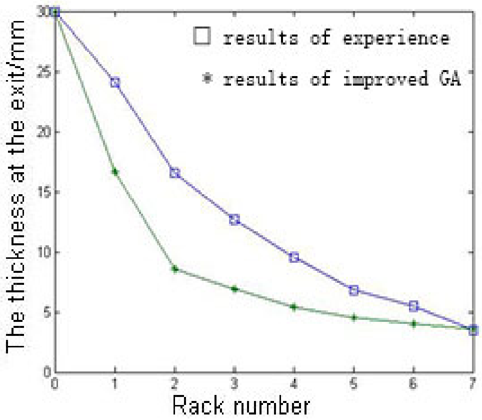

Figure 1. Thickness Contrast Curve for h_i

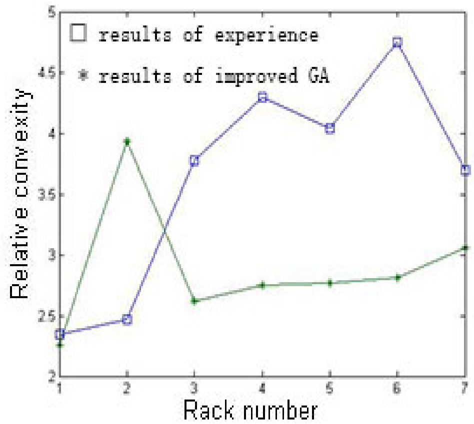

Figure 2. Relative Convexity Contrast Curve

From the simulation results we can see the result of improved Genetic Algorithm is superior to the results obtained from empirical distribution: The thickness of exit and the rolling force of each frame are more reasonable. The first few frames can have a sufficiently large amount of reduction, and the later frames can keep the shape optimal to meet the production requirements.

Table 3. Results of Improved Genetic Algorithm

frame / parameter	Thickness in the entrance [h/mm]	Thickness in the exit [h/mm]	Rolling force [P/KN]	Relative convexity [CR/h($\times 10^{-3}$)]
F1	30.00	16.62	18239	2.26
F2	16.62	8.56	21380	3.93
F3	8.56	6.92	10320	2.62
F4	6.92	5.38	8260	2.75
F5	5.38	4.50	6590	2.77
F6	4.50	3.96	5780	2.81
F7	3.96	3.51	5260	3.06

5. Conclusion

In this paper, the traditional Genetic Algorithm premature convergence, and the result is not a global search for optimal solutions as well as the late evolutionary disadvantages such as low efficiency has been improved, and we successfully applied it to the finishing train optimization allocation model. The improved Genetic Algorithm in global convergence and convergence speed has been greatly improved. And by comparing the experience distribution method commonly used with the graph, we show that improved Genetic Algorithm has a great advantage when dealing with complex issues.

References

[1] ZL Cui. Design and Implementation about the Optimization of the Rolling Schedules Based on Improved Genetic Algorithms. Master Thesis. Shandong: Shandong University. 2007.

[2] K Lua, J Croweroft, M Pias, et al. A Survey and Comparison of Peer-to-peer Overlay Network Schemes. *Communication Surveys & Tutorials, IEEE.* 2005; 7(2): 72-93.

[3] JH Holland. Building Blocks, Cohort Genetic Algorithms, and Hyperplane-defined Functions. *Evolutionary Computation.* 2000; 8(4): 373-391.

[4] C Lv, QL Zhao, LZ Liu etc. Optimization of Hot Strip Mill Load Distribution. *Iron and Steel Research.* 2001; 13(1): 26-29.

[5] F Xhafa, X Herrero, et al. Evaluation of Struggle Strategy in Genetic Algorithms for Ground Stations Scheduling Problem. *Journal of computer and system sciences.* 2013; 79: 1086–1100.

[6] YH Li, SS Ning etc. A JIT Production Planning Model and Algorithm for Rolling Mills. *Control Engineering.* 2004; 11(4): 321-324.

[7] J Suzuki. A Markov Chain Analysis on Simple Genetic Algorithm. *IEEE Trans on Systems, Man and Cybernetics.* 1998; 25(4): 655-699.

[8] Y Zhu, C Dovrolis, M Ammar. Dynamic Overlay Routing Based on Available Bandwidth Estimation: A Simulation Study. *Computer Networks The International Journal of Computer and Telecommunications Networking.* 2006; 50(6): 742-762.

[9] E Afzalan, M Joorabian. Emission, Reserve and Economic Load Dispatch Problem with Non-smooth and Non-convex Cost Functions Using Epsilon-multi-objective Genetic Algorithm Variable. *International Journal of Electrical Power & Energy Systems.* 2013; 52: 55-67.