Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2013, Article ID 675381, 8 pages
http://dx.doi.org/10.1155/2013/675381

Research Article

Load Distribution of Evolutionary Algorithm for Complex-Process Optimization Based on Differential Evolutionary Strategy in Hot Rolling Process

Xu Yang,[1,2] Chang-bin Hu,[3] Kai-xiang Peng,[1] and Chao-nan Tong[1]

[1] *Key Laboratory of Advanced Control of Iron and Steel Process, School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing 100083, China*
[2] *Institute for Automatic Control and Complex Systems, University of Duisburg-Essen, Duisburg 47057, Germany*
[3] *Beijing Power Electronics and Motor Drives Engineering Research Center, College of Mechanical and Electrical Engineering, North China University of Technology, Beijing 100144, China*

Correspondence should be addressed to Xu Yang; ustb.yangxu@gmail.com

Received 5 September 2013; Revised 21 October 2013; Accepted 31 October 2013

Academic Editor: Xiao He

Based on the hot rolling process, a load distribution optimization model is established, which includes rolling force model, thickness distribution model, and temperature model. The rolling force ratio distribution and good strip shape are integrated as two indicators of objective function in the optimization model. Then, the evolutionary algorithm for complex-process optimization (EACOP) is introduced in the following optimization algorithm. Due to its flexible framework structure on search mechanism, the EACOP is improved within differential evolutionary strategy, for better coverage speed and search efficiency. At last, the experimental and simulation result shows that evolutionary algorithm for complex-process optimization based on differential evolutionary strategy (DEACOP) is the organism including local search and global search. The comparison with experience distribution and EACOP shows that DEACOP is able to use fewer adjustable parameters and more efficient population differential strategy during solution searching; meanwhile it still can get feasible mathematical solution for actual load distribution problems in hot rolling process.

1. Introduction

With the increasing demand for improving the product quality and control accuracy in hot rolling process, the rolling scheduling problem has become an important issue in the steel industry. According to the principle that nominal motor power should be greater than rolling power, the main purpose of hot rolling scheduling problem consists in determining the final thickness for every rolling pass to set other process parameters [1], such as rolling force and bending force. The key point and object of hot rolling shape/gauge control is the shape control of roll gap, in the sense that the load distribution is the basis of strip shape control. Although the classic load distribution is simple and reasonable, it cannot achieve the most optimal setting to shape control [1, 2].

The hot rolling process has been optimized with rolling theory or heuristics algorithms [3–5]. For example, a differential evolution algorithm with space-adaptive idea is applied to several hot strip mills for the optimal design of scheduling. This algorithm expands or shrinks the search space by certain rules and realizes the automatic search for the suitable space and improves the convergence rate and accuracy [3]. An intelligent method named variable metric hybrid genetic algorithm was introduced to optimize hot strip mills [4]. A genetic algorithm-based optimization was coded and operated for 1370 mm tandem cold rolling schedule. It seems that the performance of the optimal rolling schedule is satisfactory and promising [5]. Although the above load distribution is reasonable, it often requires more adjustable parameters during the search for optimal solution, thereby making influence on coverage speed and search efficiency.

Thus, the major objective pursued in this paper is to formulate a better solution on the rolling scheduling optimization. Based on the evolutionary algorithm for complex-process optimization (EACOP) [6–8], we improve this algorithm within differential evolutionary strategy and utilize it to optimize load distribution of hot rolling. The DEACOP has the flexible structure which is similar to scatter search and employs some elements of scatter search [9] and path relinking [10]. Besides, it makes use of a smaller number of tuning parameters and differential evolutionary strategy among the population members with new strategies. Firstly, according to model's characteristics of load distribution, initial diverse population strategy will be improved with the consideration of latin hypercube uniform sampling. Secondly, differential evolutionary strategy will be presented to replace the original linear combination. Thirdly, a population-update method is introduced to modify the balance between intensification and diversification. Finally, a search intensification strategy called the "go-beyond" to in-depth search is established for enhancement of the efficiency of the local optimal solution. This differential evolutionary strategy can generate broader area around the population members and get better intensification and diversification of population members by the go-beyond strategy.

Based on experimental simulation by actual data in hot rolling process, simulation result shows that the application of DEACOP optimizes the gauge reduction for each rolling pass and gives full play to the upstream rolling mill equipment's ability. Meanwhile, DEACOP algorithm regulates crown index of the downstream mills, so it can further improve the efficiency of plate-shaped regulating.

2. The Gauge and Shape Model

2.1. System Description. In order to determine rolling force of each stand, as well as the other settings, the key point of load distribution is that the exit thickness of each stand should be distributed reasonably. Thus, in this section the optimal load distribution with the consideration of overall performance on shape and gauge is proposed. The optimal load distribution of finishing mill group can be divided into three stages [11–13].

The first phase requires that the 1st stand's reduction should be left some room, as the steel billet's thickness may fluctuate when steel billet goes into rolling mill.

In the second phase, the 2nd and 3rd stands should make full use of equipment power, therefore making the amount of the reduction as large as possible.

In the third phase, the rolling force in the last stage should gradually decrease from the 4th to the last stand, so that the accuracy and performance of the shape and gauge can be synthesized properly. Meanwhile, the relative crown of the last four stands should be equal.

With the consideration of those steps, the objective function is derived as follows, which constructs with the desire of above three stages with DEACOP optimizes load distribution:

$$G = \omega_1 (P_1 - K_1 P_2)^2 + \omega_2 (P_2 - K_2 P_3)^2 + \omega_3 \sum_{i=4}^{7} \left(\frac{\mathrm{CR}_i}{h_i} - \frac{\mathrm{CR}_n}{h_n} \pm \Delta_i \right)^2, \tag{1}$$

where P_i is the rolling force of the ith stand, CR_i and h_i separately represent exit crown and thickness of the ith stand, ω_i denotes weighted coefficient, and Δ_i is the compensation coefficient, which maintain the equality of relative crown from the 4th to the last stand. From the view of engineering, some related variables of rolling process can be restricted, such as $h_{i+1} < h_i$, $0 \le P_i \le P_{\max}$.K_1 and K_2 denote the proportional coefficient about rolling force and both coefficients are changed according to technological condition, where K_1 is set as 0.9 and K_2 is set as 1 in this paper. Apart from the above constraints, the Shohet discriminant [1] about sheet deformation is also necessary. Since the rolling process of hot strip mill is different from the cold rolling, to some extent, Shohet discriminant may relax the requirement of relative crown:

$$-80 \left(\frac{h}{B} \right)^{\alpha} < \left(\frac{C_H}{H} - \frac{C_h}{h} \right) < 40 \left(\frac{h}{B} \right)^{\alpha}, \tag{2}$$

where H, h denote the entry and exit strip thickness, C_H/H and C_h/h separately stand for relative crown of entry and exit, B is the strip width, and $\alpha = 2$ or 1.86.

The main purpose of load distribution system is seeking a set of data h_i, which not only meets the Shohet equation, but also can fulfill those technological conditions. Meanwhile, in order to get the minimum value of objective function, the rolling force model, thickness distribution model, and the temperature model have to be established.

2.2. Rolling Force Model. According to [1], the classic rolling force equation can be expressed as follows:

$$P_i = 1.15 B l_c' Q_P \sigma, \tag{3}$$

$$Q_P = 0.8049 - 0.3393\varepsilon + \left(0.2488 + 0.0393\varepsilon + 0.0732\varepsilon^2\right) \frac{l_c}{h_m}, \tag{4}$$

$$\sigma = \sigma_0 \exp(a_1 T + a_2) \left(\frac{u}{10} \right)^{(a_3 T + a_4)} \times \left[a_6 \left(\frac{e}{0.4} \right)^{a_5} - (a_6 - 1) \left(\frac{e}{0.4} \right) \right], \tag{5}$$

where the subscript i denotes the rolling pass number, B is the strip width, and l_c' denotes the horizontal projection length of contact arc between roll and workpiece. $l_c' = \sqrt{R' \Delta h}$, $R' = R(1 + (16(1 - \nu^2)/\pi E)(P_i / B \Delta h))$, where R is roller radius, R' is roller radius after deformation [12], Δh is the reduction for every rolling pass, ν is Poisson's ratio, and E is Young's modulus. Relative deformation degree and average thickness are denoted as ε and h_m in (4). Deformation resistance introduces (5), where $T = (t + 273)/1000$ and t is rolling temperature. $\varepsilon = \ln(h_{i-1}/h_i)$ and $u = (\nu_i \varepsilon / l_c')$ separately stand for deformation degree and rate about workpiece.

2.3. Thickness Distribution Model. Consider the following:

$$h_i' = H_0 \exp\left\{\frac{K_{H2} - \sqrt{K_{H2}^2 + 4K_{H1}\phi_i a_n}}{2K_{H1}}\right\}, \quad (6)$$

$$a_n = K_{H1}\left(\ln \frac{H_0}{h_n}\right)^2 + K_{H2} \ln\left(\frac{H_0}{h_n}\right), \quad (7)$$

where h_i' is the experiential thickness value, K_{H1}, K_{H2} denote the site statistics coefficient, ϕ_i is cumulative energy distribution coefficient, H_0 is initial thickness when workpieces go into the first finishing mill, and $h_n$is exit thickness when workpieces go through the last stand.

2.4. Temperature Model. Temperature is an important factor in hot rolling, which can directly impact on the rolling force value of each pass. Equation (8) expresses temperature drop model from roughing exit to finishing entrance, while the next equation denotes slab temperature drop caused by going through finishing mill:

$$T_{F0} = 100\left[\frac{6\varepsilon\delta}{100\gamma c H_0}\tau + \left(\frac{T_{\mathrm{RC}}}{100}\right)^{-3}\right]^{-1/3}, \quad (8)$$

$$T_i = T_w + (T_{F0} - T_w)\exp\left(-K_a \frac{\sum_{j=1}^{i} L_j}{h_n v_n}\right). \quad (9)$$

T_{F0} means entry temperature when slab goes into the first finishing mill. ε is blackness, δ is Boltzmann constant, γ is density, c is specific heat capacity, and τ is the time when strip is transferred from the exit of roughing mill to the entrance of the finishing mill. T_{RC} is steel temperature after strip going through roughing mill.

The exit temperature of each finishing mill is denoted as T_i. T_w is water spray temperature between mills. K_a is cooling coefficient, the interstand distance (L_j) is indicated, and $h_n v_n$ is the product that multiplies exit thickness by rolling speed.

3. Evolutionary Algorithm for Complex-Process Optimization

In this section, the evolutionary algorithm for complex-process optimization based on differential evolutionary strategy (DEACOP) is proposed to solve load distribution problem of the hot rolling scheduling. The DEACOP is innovative strategy embedded in various submethods within the flexible. This algorithm improves path relinking to generate a new combination method which considers a broader area around the population members. Meanwhile DEACOP improves the balance between intensification and diversification with a population-update method. The above strategies can escape from suboptimal solutions and advance the search efficiency. The algorithm consists of five parts: (1) building the initial population, (2) determining similarity solution, (3) differential evolutionary strategy, (4) population update, and (5) deep search feasible solutions. Its principle is to deeply explore new population members near individuals with minimum fitness. The optimization process will be repeatedly executed unless the stop conditions were met.

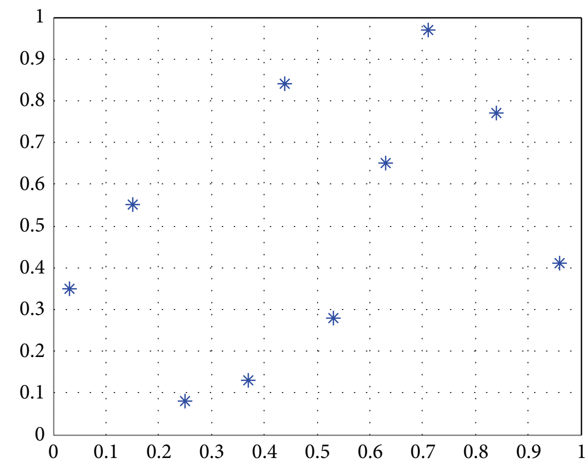

Figure 1: LHS ($H = 10, N = 2$).

3.1. Building the Initial Population. In this subsection a latin hypercube uniform sampling (LHS) is first used to generate the initial population. To illustrate how LHS works, during the following description we will explain the building process of LHS. N is variable dimension that is set as 2; sampling size H is 10. The distribution procedure of LHS is as follows.

3.1.1. LHS Algorithm

(1) Each side of the test area was divided equally into 10 parts, so test area was divided into 10^2 small areas.

(2) (1, 2, ..., 10) is randomly ordered to (7, 5, 6, 9, 2, 4, 1, 8, 10, 3) and (7, 9, 3, 8, 6, 2, 4, 10, 5, 1). They are arranged in a matrix as follows:

$$A = \begin{bmatrix} 7 & 5 & 6 & 9 & 2 & 4 & 1 & 8 & 10 & 3 \\ 7 & 9 & 3 & 8 & 6 & 2 & 4 & 10 & 5 & 1 \end{bmatrix}^T. \quad (10)$$

Column of the matrix, such as (7,7), (5,9), (6,3) ... (3,1), is fixed on 10 rectangles.

(3) A sample was randomly selected in each small rectangle, and then sampling group was composed of 10 samples. The result about LHS works is shown in Figure 1.

Through LHS procedure, an initial set Pop of Psize diverse vectors is generated, whose size is set as 10 × Nvar (Nvar is defined as a number of variables which need to be optimized). Meanwhile high-quality solution set *Pop1* is composed in terms of better fitness. Its number is $b1$. Diversity set *Pop2* (its size is *b2*) includes individual selected randomly from the remaining *m*−*b1* vectors in Pop. According to the above completion strategy, the population size is $b = b1 + b2$. McKay et al. [14] pointed out that the total average received LHS than a simple random sampling mean has smaller total variance.

```
for i = 1 to b
  for j = i to b
    if d(x_i, x_j) = ||x_i − x_j|| ≤ dist  then one of two solutions will be replaced with random solution within the search space.
    else
      until the end of the loop
    endif
  endfor
endfor
```

Algorithm 1: Check for solutions similarity algorithm.

3.2. Check for Similarity Solution. The purpose of similarity determining is to help escape from (possible) local optimal area. Algorithm 1 checks for duplicity with Euclid distance in the population before performing the next subsection (combination method). If the Euclidean distance between the two solutions is less than set value *dist*, then one of two solutions will be replaced with random solution within the search space. Otherwise, reserve two solutions and continue to the next judge.

3.3. Differential Evolutionary Strategy of Population. In the traditional EACOP, the reference set was usually based on linear combination method, which has advantage in some aspects. Unfortunately, there is difficult to solutions of complex issue. Thus, an improved differential variation method was introduced as follows:

$$M_i^{t+1} = X_i^t + F\left(\left(X_{r1}^t - X_i^t\right) + \left(X_{r2}^t - X_{r3}^t\right)\right), \tag{11}$$

where M_i^{t+1} is individual set after variation, X_{r1}^t is the current best individual populations, and F is scaling factor. $(X_{r1}^t - X_i^t)$ item was used in this strategy in order to increase the algorithm coverage speed. Meanwhile $(X_{r2}^t - X_{r3}^t)$ was introduced as disturbance, which can make difference for each variation individual, therefore maintaining the population diversity.

Besides, the crossover strategy is used for better evolutionary effects. After the crossover operation on X_i^t and M_i^{t+1}, thereby generating the new individual C_{ij}^{t+1}. The crossover strategy equation can be expressed as follows:

$$C_{ij}^{t+1} = \begin{cases} M_{ij}^{t+1}, & \text{rand} \le \text{CR} \\ X_{ij}^t, & \text{rand} > \text{CR} \end{cases} \quad j = 1, 2, \ldots, n, \tag{12}$$

where CR can be defined as crossover probability factor between 0 and 1 and rand is uniform random number in the same interval.

3.4. Population Update. As described in the combination method, we incorporate each member of the reference set with the rest $b - 1$ members, resulting in $b - 1$ new solution. Best quality solutions among new solutions were chosen and compared with their parent, if their value is better than the parent, and then the latter is replaced in the population. The principle of population regeneration is that new solutions are generated along with the path formed by the parent superrectangular.

3.5. Deep Search Feasible Solutions. By the previous steps, the new population members are surrounded by hyperrectangle in accordance with update strategy. For enhancing the search intensification to exploit better feasible solutions, the evolutionary algorithm has implemented *go-beyond* strategy which consists in exploiting promising directions. *Go-beyond* strategy (Figure 2) means that new solution is created in the light of direction defined by the child and its parent (Algorithm 3).

Deep search step is shown as follows: firstly, create a new solution x_{child} in hyperrectangle which is generated by a pair of solutions (x_i, x_j) and estimate if fitness value $f(x_{\text{child}})$ outperforms parent fitness value $f(x_i \text{ or } x_j)$ (x_i, x_j is selected after deciding which of them is combined with other $b - 1$ population individuals). If $f(x_{\text{child}}) > f(x_i$ or $x_j)$, new solution x_{Nchild} is created according to *go-beyond* strategy over again. Now once more the program determines if $f(x_{N\text{child}})$ is greater than $f(x_{\text{child}})$; if the result holds, determine update solution $x_{NN\text{child}}$ with *go-beyond* strategy again. In the end, last subsection D is introduced to make $x_{NN\text{child}}$ replace one of x_i or x_j.

3.6. Optimization Process of DEACOP. According to description about above five parts subsection, all of subsections will be integrated to build an evolutionary algorithm. Optimization steps of DEACOP are shown as follows.

Step 1. Set initial parameters that include variable dimension vars, P_{size}diverse vectors of the initial set (normally $P_{\text{size}} = 10 \times \text{vars}$), the number of high-quality solution *b1*, and random set size *b2*. Initial population whose size b is the sum of *b1* and *b2*. To escape from suboptimal solution, the number of consecutive iterations T_{stick} is defined as a vector. $T_{\text{stick}} = [T_1, T_2, \ldots, T_b] = [0, 0, \ldots, 0]$. T_{change} is denoted as logo whether get suboptimal solution.

Step 2. This step uses a latin hypercube uniform sampling to generate initial set of diverse solutions. But the set should meet constraint condition about optimization problem.

Step 3. Check for similarity solutions. This step uses Algorithm 2 to test the diversity of population.

Step 4. Make differential evolutionary computation in reference to the actual individuals of concentration.

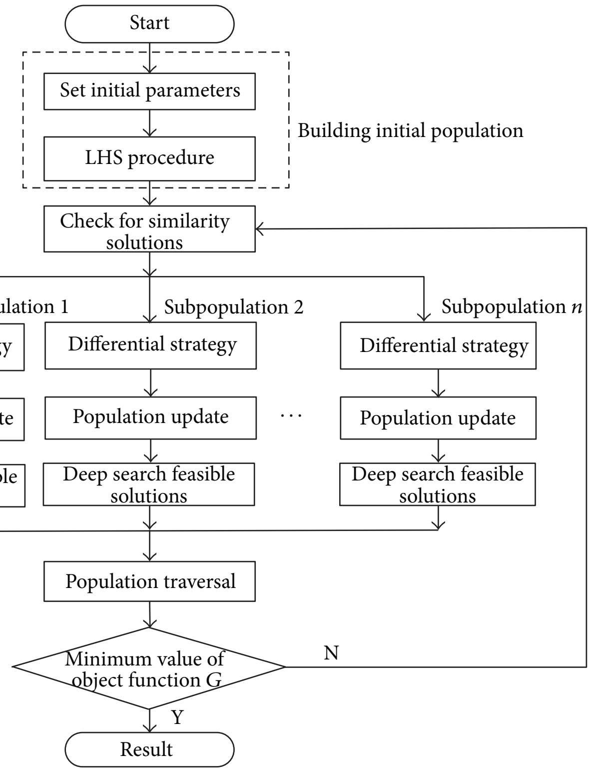

Figure 2: The flow chart of DEACOP.

$$
\begin{array}{ll}
\textit{if} & f(x_{\text{new}}) < f(x_{\text{parent}}) \\
& \quad x_{\text{parent}} = x_{\text{new}} \\
\textit{endif} &
\end{array}
$$

Algorithm 2: Population-update algorithm.

Step 5. Associate population-update strategy with *go-beyond* strategy. If the quality of child x_{child} that is generated with combination method outperforms its parent x_i, then *go-beyond* strategy is used to further exploit solution intensification. Otherwise, *go-beyond* strategy is not performed.

Step 6. Escape from suboptimal solution. If the parent x_i is replaced by the child, then the number of consecutive iterations T_i is reset as 0; otherwise $T_i = T_i + 1$, and estimate whether $T_i \geq T_{\text{change}}$. If the result is affirmative, x_i will be substituted by the random one of the remaining $P_{\text{size}} - b$ members.

Step 7. Repeatedly perform Step 4–Step 6 until all members of population come through this process.

Step 8. Until stopping criterion is met, go into Step 3.

In order to clarify this algorithm procedure, a flow chart was shown in Figure 2.

Table 1: Set parameters for optimization.

Model parameters	Value	DEACOP parameters	Value
B/mm	1520	$b1$	10
H_0/mm	35.3	$b2$	10
h_n/mm	5.9	P_{size}	70
T_{RC}/°C	1061	T_{change}	20
CR_n/mm	0.016	r	10^{-4}
n	7	ITTM	150

4. DEACOP Application and Results Analysis

4.1. Set Initial Parameters and Optimization Steps. In order to validate the effectiveness of DEACOP optimization for load distribution of the hot rolling, Q235 Steel was used for simulation experiments. The parameters load distribution was listed in Table 1, including the width of strip steel B, initial thickness of workpiece H_0, finish product thickness h_n, exit temperature of roughing mill T_{RC}, objective crown CR_n, and the number of stands n. Moreover, parameters in DEACOP include the number of population b (including the number of high-quality solutions $b1$ and the number of random solutions $b2$), the size of initial set P_{size}, the number of dropping into suboptimal region T_{change}, radius of suboptimal region r, and iteration times of optimization ITTM.

Table 2: Comparison of rolling force distribution.

Methods	Variables (/KN)						
	P_1	P_2	P_3	P_4	P_5	P_6	P_7
Classic	22438.8	20054.3	24530.9	17842.8	12593.2	12170	8941.5
EACOP	20356.8	22629.6	22048.6	17446.9	15130.7	12136.4	9184.9
DEACOP	21845.7	23648.4	23646.4	15963.3	13472.2	9813.8	9148.4

Table 3: Relative crown of each stand.

Methods	Variables ($\times 10^3$)						
	CR_1/H_1	CR_2/H_2	CR_3/H_3	CR_4/H_4	CR_5/H_5	CR_6/H_6	CR_7/H_7
Classic	1.4	1.7	3	3.1	2.6	2.9	2.8
EACOP	1.2	1.9	2.6	2.9	3.1	2.9	2.8
DEACOP	1.2	1.9	2.6	2.9	2.9	2.8	2.8

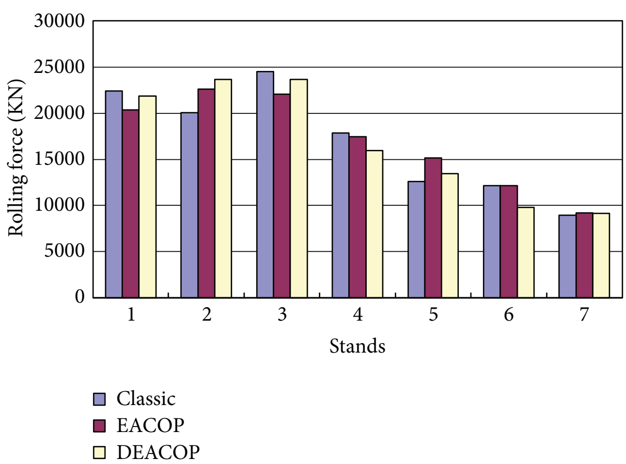

Figure 3: Comparison of rolling force distribution.

The process of DEACOP algorithm optimization for load distribution of the hot rolling is shown as follows.

Step 1. The load distribution model considering flatness is established based on the actual production process parameters.

Step 2. First of all, thickness value h_i' can be obtained according to experiential load distribution (6). Variables optimized are determined as Δoh_i, so exit thickness optimized is denoted as $h_i = h_i' + \Delta oh_i$.

Step 3. Use DEACOP to optimize mathematic model of load distribution. According to constraint condition of modeling details, the process parameters which are calculated by optimizing variable must satisfy actual production requirements.

Step 4. Until stopping criterion is met, go back to Step 3.

4.2. Simulation and Discussion. In this part, we have considered three methods for optimizing load distribution, including, experience distribution, EACOP, and DEACOP. Meanwhile, the results generated through those algorithms were compared and analyzed. Under constraints conduction and objective function, as we can notice that top three stands' reduction must be as large as possible. For the desire of rolling force, the first stand rolling force P_1 is expected as 90% of the second stand rolling force P_2, and P_2 should be equal to the third stand rolling force P_3. In addition, the purpose of optimization should guarantee integrated performance of shape and gauge control system, so the object function desires that rolling force of the last four stands should be descended one by one, and relative crown remains consistent as far as possible. The calculation results about rolling force distribution as well as relative crown of each stand were simulated separately by Matlab Platform, and the results are shown in Tables 2 and 3.

According to reference with the constraints conduction and objective function in actual rolling process, Figure 3 shows optimization effect of rolling force. For top three stands, all the results optimized by DEACOP are greater than those optimized by EACOP and classic optimization. As for the empirical distribution, the conclusion cannot meet the characteristics of objective optimization function because P_1 and P_2 are not equal. Meanwhile, the last four rolling forces which empirical distribution configure cannot be in accord with objective function neither, while rolling force allocated by DEACOP and EACOP is in line with in turn reduced law. Besides, as we can see from Table 4, the relative crown of the last four mill stands almost maintains the same by DEACOP algorithm, which perfectly meets the demand on rolling schedule that the relative crown of the last four stands should be equal.

The thickness distribution of every stand is shown in Table 4. Since the values of DEACOP optimization fully meet the requirements of objective function based on gauge control system, a similar experiment was made to verify its better results in strip shape optimization curve; the data of DEACOP in Table 4 was curved with the consideration of Shohet discriminant criterion, which is useful to determine whether shape has met requirements. As shown in Figure 4, the relative crown difference between entrances and exits which is optimized by DEACOP does not exceed the scope

for $i = 1$ *to* b
  $Expl = 0$
  $A_{\text{change}} = 1$
  for $j = 1$ *to* 2
    $x_{\text{parent}} = x_i$ or x_j
    if $f(x_{\text{child}}) < f(x_{\text{parent}})$
      The hyper-rectangle direction defined by x_{parent} and x_{child} is $[a, b] = \left[x_{\text{child}} - \dfrac{x_{\text{parent}} - x_{\text{child}}}{A_{\text{change}}}, x_{\text{child}}\right]$
      $x_{\text{parent}} = x_{\text{child}}$
      $x_{\text{child}} = x_{N\text{child}}$
      $A_{\text{change}} = A_{\text{change}}/2$
    endif
  endfor
endfor

Algorithm 3: Go-beyond strategy algorithm.

Table 4: Thickness distribution of each stand.

Methods	Variables (/mm)						
	h_1	h_2	h_3	h_4	h_5	h_6	h_7
Classic	24.9662	18.3946	12.7358	9.7047	8.0254	6.718	5.9
EACOP	25.8395	18.2928	13.1485	10.0799	8.04719	6.7393	5.9
DEACOP	25.2135	17.3832	12.1914	9.5458	7.797	6.7361	5.9

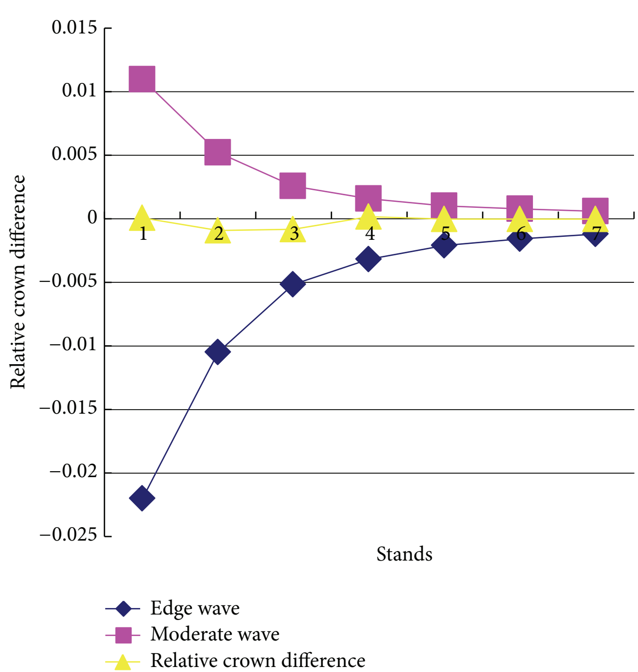

Figure 4: Judgment with Shohet formula.

of moderate wave and edge wave and has a larger margin. Conclusions show that Shohet discriminant verifies the reliability of the experimental results.

5. Conclusions

In this paper, The DEACOP which has a flexible frame structure embedding in various submethods has been introduced. This algorithm was presented to optimize the rolling schedule and show its superior ability of global searching. Moreover, it can not only escape from suboptimal solutions, but also advance the search efficiency.

According to the experimental results within actual data in hot rolling process, the DEACOP still can get feasible and better mathematical solution and validate the real-time application even by fewer adjustable parameters, which is more suitable for the actual load distribution problems. With this algorithm, the optimized rolling schedule can make full use of the upstream finishing mill equipment which controls top three stands' reduction and improves the total rolling consumption. The rolling force of the last four stands which control exit thickness can be used as an important means of shape control. Therefore, the improvement of efficiency in plate-shaped regulating by DEACOP is recommended as an important issue for further investigation.

Acknowledgments

The authors gratefully acknowledge the support by the National Natural Science Foundation of China (61074085, 51205018), China Postdoctoral Science Foundation Funded Project (2012M510321), and Fundamental Research Funds for the Central Universities (FRF-TP-12-104A, FRF-SD-12-008B). The authors heartily appreciate the data support from Ansteel Company in Liaoning Province, China. Meanwhile, great thanks also go to former researchers for their excellent work, which gives great help for our academic study.

References

[1] Y. K. Sun, *The Model and Control of Cold and Hot Strip Mill*, Metallurgical Industry Press, Beijing, China, 2010.

[2] Y. Wang, J. Liu, and Y. Sun, "Immune genetic algorithms (IGA) based scheduling optimization for finisher," *Journal of University of Science and Technology Beijing*, vol. 24, no. 3, p. 339, 2002.

[3] F. Yao, W.-D. Yang, M. Zhang, and Z.-D. Li, "Improved space-adaptive-based differential evolution algorithm," *Control Theory and Applications*, vol. 27, no. 1, pp. 32–38, 2010.

[4] H.-J. Li, G.-D. Wang, J.-Z. Xu, and X.-H. Liu, "Optimization of draft schedules with variable metric hybrid genetic algorithm during hot strip rolling," *Journal of Iron and Steel Research*, vol. 19, no. 8, pp. 33–36, 2007.

[5] J.-M. Yang, H.-J. Che, F.-P. Dou, and T. Zhou, "Genetic algorithm-based optimization used in rolling schedule," *Journal of Iron and Steel Research International*, vol. 15, no. 2, pp. 18–22, 2008.

[6] J. A. Egea, R. Martí, and J. R. Banga, "An evolutionary method for complex-process optimization," *Computers and Operations Research*, vol. 37, no. 2, pp. 315–324, 2010.

[7] J.-T. Tsai, J.-H. Chou, and W.-H. Ho, "Improved quantum-inspired evolutionary algorithm for engineering design optimization," *Mathematical Problems in Engineering*, vol. 2012, Article ID 836597, 27 pages, 2012.

[8] J.-Y. Wu, "Solving constrained global optimization problems by using hybrid evolutionary computing and artificial life approaches," *Mathematical Problems in Engineering*, vol. 2012, Article ID 841410, 36 pages, 2012.

[9] M. Laguna and R. Marti, *Scatter Search: Methodology and Implementations in C*, Kluwer Academic Publishers, Boston, Mass, USA, 2003.

[10] F. Glover, M. Laguna, and R. Marti, "Scatter search and path relinking: foundations and advanced designs," in *New Optimization Techniques in Engineering*, G. C. Onwubolu and B. V. Babu, Eds., Springer, Berlin, Germany, 2004.

[11] H.-D. Yang and J.-Q. E, "An adaptive chaos immune optimization algorithm with mutative scale and its application," *Control Theory and Applications*, vol. 26, no. 10, pp. 1069–1074, 2009.

[12] X. Yang and C. N. Tong, "Coupling dynamic model and control of chatter in cold rolling," *Journal of Dynamic Systems, Measurement and Control-Transactions of the ASME*, vol. 134, no. 4, Article ID 041001, 8 pages, 2012.

[13] V. B. Ginzburg, *Flat-Rolled Steel Processes. Advanced Technologies*, CRC Press, New York, NY, USA, 2009.

[14] M. D. McKay, R. J. Beckman, and W. J. Conover, "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics*, vol. 21, no. 2, pp. 239–245, 1979.