The Cold Rolling Load Distribution of the Nuclear Power Zirconium Alloy Based on the Self-adaptive Particle Swarm Optimization Algorithm

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The cold rolling load distribution of the nuclear power zirconium alloy based on the self-adaptive particle swarm optimization algorithm

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Abstract: Aiming at the problem of load distribution during multi-pass cold rolling of nuclear zirconium alloy strip, the load distribution model with good shape is established by the self-adaptive particle swarm optimization algorithm (SAPSO), considering the main constraint conditions including rolling force, reduction and torque in cold rolling process. Based on the penalty function method transforming the constraint problem into the unconstrained problem, the particle swarm optimization algorithm with adaptive inertia weight factor optimized the load distribution model is developed to improve the local search ability of the particle swarm optimization algorithm. Compared with the existing nuclear zirconium alloy industrial schedule, the simulation results of load distribution based on the SAPSO can keep good shape in multi-pass cold rolling process with the high prediction accuracy. The industrial experiments demonstrate that the proportional crown difference value is consistent, the plate shape flatness is good.

keywords: zirconium alloy; cold rolling; rolling schedule; SAPSO; penalty function

1 Introduction

The zirconium alloy is an important material in the field of the nuclear power zirconium alloy plate and strip, the plate shape is one of the key quality indicators. The zirconium alloy has poor plasticity and small deformation. However, this core

skill is often conducted by rolling technique engineer based on their experience and knowledge, and the quality of plate shape depends on the accuracy of the control system model [1-3]. A reasonable rolling rule is critical for the nuclear zirconium alloy cold rolling process, which can take full superiority of rolling mill equipment potential, reducing the energy consumption and ensure accuracy and quality of plate products. The product quality and productivity effect are the most important factors to evaluate comprehensive engineering level of zircaloy cold multi-pass rolling process. Product quality mainly refers to strip flatness control and production efficiency requires fully bring out mill motor potentiality. The dissimilarity of initial and outcoming proportional crown allowed to vary within the acceptable limit during the actual rolling. In mean time, shape control and plane defect prevention need to meet the requirements of the zirconium alloy plate rolling technology, this paper is based on the actual production data, which combines the rolling theory with the intelligent optimization algorithm to study the load distribution optimization in nuclear power zirconium alloy rolling [4-5].

After a lot of industrial rolling, Xiong et al. [6] showed that the rolling schedule should be designed to ensure proportional crown as the constant, and the rolled piece is not easy to cause wave shape. In the first few passes, due to the large thickness of the rolled piece and the fluctuation of the hot-rolled incoming material need to relax the proportional crown requirements. Chen et al. [7] uses the penalty function method to deal with the constraint conditions and transforms the constrained optimization problem into an unconstrained optimization problem. By setting the optimization variable to a relatively large value that does not meet the constraints, the parameter is automatically discarded in the variable optimization process [8,9]. It is important to study the nuclear power zirconium alloy multi-pass rolling schedule, combined with the artificial intelligence optimization algorithm [10-11]. Chen et al. [12] use the method of the rolling force model self-adaptation and BP neural network to carry out rolling force online forecasting. The accuracy is better than that of purely adaptive or neural network forecasting, and it fully meets the requirements of the rolling mill online rolling. Wei et al. [13] applied the genetic algorithm (GA) to optimize the rolling schedule of four-stand tandem cold rolling mill, binary-coded the exit thickness, and obtained the minimum fitness function through genetic operations such as selection, crossover, and mutation. Srinivas et al. [14] optimized the rolling schedule with the implicit parallelism of the genetic algorithm (GA). Cao et al. [15,16]

use the genetic algorithm (GA) to set the bending force model of a six-high reversible cold rolling mill. Li et al. [17] established a single-stand cold rolling silicon steel load distribution optimization mathematical model based on the particle swarm optimization (PSO) and used the algorithm to achieve the multi-objective load distribution optimization of a single-strand cold rolling mill. The optimization model takes the plate shape control board thickness into account. Sun et al. [18,19] applied the particle swarm optimization algorithm (PSO) to optimize the load distribution of the five-stand cold rolling mill and realized the proportional distribution of rolling force. Wang et al. [20] proposed the improved particle swarm optimization algorithm (IPSO), by judging the fitness variance, which provides an effective method for the optimization of the load distribution of the rolling schedule. This paper uses the self-adaptive particle swarm optimization algorithm (SAPSO) to optimize the nuclear power zirconium alloy cold rolling schedule with the goal of good plate shape [21,22].

Due to the lack of references on zirconium alloy plate and strip rolling, the rolling theory and intelligent optimization algorithm are combined to optimize its load distribution. In accordance with the production line of nuclear zirconium alloy, the objective function is the good flatness, and the constraint conditions include rolling force, reduction and torque in cold rolling process. Furthermore, the penalty function method transforming the constraint problem into the unconstrained problem. To minimize the influence of the step changed weight coefficients on the strip flatness, a model is proposed to solve this problem by the SAPSO. Finally, the optimization performance of the model is evaluated by comparison with the traditional solution. The actual industrial test is further investigated to verify the effectiveness of the SAPSO rolling schedule.

2. Objective function and related mathematical models

The proportional crown principle is a good method to determine whether the strip can meet the demand of flatness and good plate shape. The rolling force is important factor in establishing the load distribution model. In the optimization algorithm design of the nuclear zirconium alloy load distribution, the objective function of multi-pass cold rolling of zirconium alloy is established, which aims to control the proportional crown during the rolling process. The objective function of

the zirconium alloy rolling schedule is based on the self-adaptive particle swarm optimization algorithm (SAPSO) to achieve the goal of good plate shape.

2.1Mathematical models of cold rolling force

In this work, the nuclear power zirconium alloy used is Zr-4 alloy. The chemical composition of Zr-4 alloy is more than 95% Zr, 1.2–1.7% Sn, and less than 0.3% Fe and 0.1–0.14% oxygen. The rolling force is related to many factors [9]. During the production process, the main factors that affect the rolling force are the properties of the rolled material, the exit thickness, the reduction rate, and other factors. The friction coefficient is the main factor affecting the rolling force prediction model of the nuclear power zirconium alloy.

According to the measured parameters on-site, the particle swarm optimization algorithm (PSO) is used to regress parameters that are difficult to determine in the friction coefficient model. The friction coefficient is regarded as the correction value of determining process parameters. The sum of square errors of the friction coefficient model (in Eq. (1)) is the objective function which is reverse obtained by regression of the measured parameters and the actual rolling force.

$$J_2 = \sum_{i=1}^{n} \left(\mu_{\mathrm{i}} - f_{\mathrm{i}} \right)^2 \tag{1}$$

The regression model of the friction coefficient is shown in follow Eq. (2).

$$f = (-0.5700 + 5.8241h - 23.1075\varepsilon) \frac{20.6763}{1.0 + N_{\mathrm{r}} \cdot 5.1705} \tag{2}$$

Where, μ_{i} is the friction coefficient was calculated by the i pass; f_{i} is the actual friction coefficient of the i pass; N_{r} is the number of rolled steel coils after roll change; Where h is the exit thickness (mm); ε is the reduction rate; a_0, a_1, a_2, a_4 and a_5 are the regression coefficients of the model. The friction coefficient obtained from the reverse calculation by the Particle Swarm Optimization algorithm (PSO), and the corresponding parameters of the algorithm are given in Table 1.

Table 1 The parameters of the PSO

Parameter	Particle dimension	Iteration steps	Initial particle number	Upper bound of weight $\omega_{\max}$	Lower bound of weight $\omega_{\min}$	Learning coefficient c_1	Learning coefficient c_2
value	1	300	200	1.2	0.2	2	2

Therefore, the Bland-Ford Hill model is used as the cold rolling force prediction model of the nuclear power zirconium alloy. Among then, the deformation resistance model must consider the work hardening in all previous pass rolling processes, using the hardening model [23]. shown in Eq. (3).

$$\begin{cases} F = BL_c^{'}KK_TQ_p \\ K = 403+1.85569e^{5.68614\varepsilon^{0.09931}} - 28.4029e^{-2758.41756\varepsilon^{2.28922}} \\ Q_p = 1.1666 + 7.3755\varepsilon f\sqrt{1-\varepsilon}\sqrt{\dfrac{R^{'}}{h}} - 23.3456\varepsilon \\ f = 0.0407+0.3875\mathrm{h} - 1.1707\varepsilon \end{cases} \tag{3}$$

Where F is the rolling force (kN); B is the width of strip (m); K_T is the tension influence coefficient; τ_f is the front tension stress (MPa); τ_b is the post tensile stress (MPa); Q_p is the external friction stress state coefficient; a , b , c are the coefficients to be estimated; K is the deformation resistance (MPa), $K = 1.15\sigma$; $L_c^{'}$ is the length of contact arc after roll flattening, and the Hitchcock formula is used to calculate. Δh is the reduction (mm), $\Delta h = h_1 - h_0$; R' is the flattening radius of roll (mm); R is the original radius of the work roll (mm); c_0 is the roll flattening coefficient, which is generally taken as 2.2×10^{-5}.

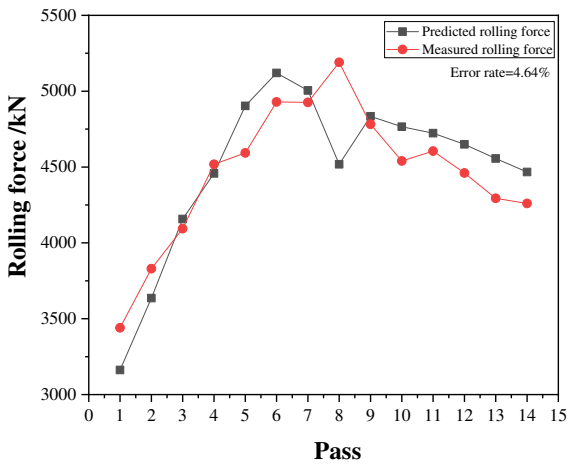

Fig.1 Industrial tests verification of the cold rolling force model for zirconium alloy

According to Fig.1, the average prediction accuracy of the cold rolling force model is 95.36%, the average prediction error rate of rolling force per pass is 4.64%. It found that the error rate increases significantly during the eighth pass. Considering of the pressure sensor output the rolling force measuring error and data acquisition error, it will affect the actual prediction value of the rolling force. In the cold rolling force prediction of Zr-4 alloy, the error rate of more than 60% rolling force will be controlled below 5%. Therefore, the rolling force model established by this method, which has good calculation accuracy and can be applied for industrial control of the zirconium alloy cold rolling production process. Meanwhile, the model can preset the cold-rolled scheme for zirconium alloy, and the industry test results are satisfactory.

2.2 Objective function

According to on-site situation, the equipment has a lot of rolling passes. To obtain a good shape of the plate with a high precision proportional crown model, the objective function can be adjusted to be suitable for the actual situation. According to the paper (Jiao et.al [24]), to ensure the proportion crown of each pass in the rolling process is the constant, and the rolling force and exit thickness meet a linear relationship, we take the good shape as the load distribution objective function. That is shown in Eq (4-5).

$$\frac{F_i - F_{i+1}}{F_i - F_{i+1}} = K_P \frac{\Delta}{H} \tag{4}$$

$$F(x)=\min\sum_{i=1}^{n-2}\left(\frac{F_i-F_{i+1}}{h_i-h_{i+1}}-\frac{F_{i+1}-F_{i+2}}{h_{i+1}-h_{i+2}}\right)^2 \tag{5}$$

F_i is the rolling force at pass i, kN; h_i is the outlet thickness at pass i, mm.

The reduction rate of each stand, the total rolling force, and rolling torque are limited to the corresponding maximum values due to the design limits imposed by manufacturers of the rolling mill and electrical drive motors. The constraint can be described as $\varepsilon_i \le \varepsilon_{i\max}$, $F_i \le F_{i\max}$, $M_i \le M_{i\max}$. Where, $\varepsilon_{i\max}$ is the allowable maximum reduction rate of each stand, $F_{i\max}$ is the allowed maximum rolling force for each stand, kN, $M_{i\max}$ is the maximum rolling torque allowed for each stand, $\mathrm{kN\cdot m}$.

3.Optimization of the load distribution model by the self-adaptive particle swarm optimization algorithm (SAPSO)

The self-adaptive particle swarm optimization algorithm (SAPSO) optimized the load distribution of the nuclear power zirconium alloy with the goal of good plate shape. [25,26]. The zirconium alloy rolling process, there are more than 60 passes. The load distribution process optimization takes 19 passes as an example for research and analysis. The thickness of the incoming zirconium alloy plate is 3.56mm, the exit thickness of the plate is 2.2mm, and the width of the zirconium alloy plate is 540mm.

3.1 Basic particle swarm optimization

PSO algorithm is an optimization algorithm based on the random intelligence optimization algorithm. Assuming that the size of the particle population is n, the particle is randomly distributed in the N dimension space, and the individual extremum and the population extremum are continuously updated to make it close to the position of the global optimal particle. Updating the position and velocity of the particle and calculating the fitness value. By comparing the fitness value of each particle, the better fitness value is assigned to the individual extremum and the population extremum, until the condition of iteration number is satisfied. Then

output the optimal position of the population, and update the formula of the velocity and position of the particle. The formula is expressed as Eq. (6).

(6)

Where $v_{ij}(t)$ is the particle velocity, i is the iteration number, w is the inertia weight, $pbest_{ij}(t)$ is the individual extremum, $gbest_{ij}(t)$ is the population extremum, $x_{ij}(t)$ is the particle position (the limit value of each pass reduction), M is the search dimension, c_1 and c_2 is the acceleration factor.

3.2 Self-adaptive weights particle swarm optimization algorithm (SAPSO)

The basic PSO algorithm has the advantages of fast convergence speed and simple structure. However, the population diversity of this algorithm disappears quickly in the later stage of the search. It is easy to fall into a local minimum value and difficult to jump out of the local minimum. The increase and decrease of the inertia weight have a greater impact on the global search ability and local search ability of the particle swarm algorithm. Therefore, setting a reasonable inertia weight has always been the focus of promoting the particle swarm optimization algorithm for fast and efficient optimization.

Researching on the self-adaptive weights particle swarm optimization algorithm (SAPSO). The fitness of the particle swarm is used to judge the pros and cons of the particles. For particles with better fitness, the algorithm should be made to perform a fine search for the poor neighboring areas around them, that is, to appropriately reduce the inertia weight. For particles with poor fitness, it indicates that their location is not good. Jump out of the surrounding area where the modified particles are located, and perform a global search, that is, increase the weight value. Adjust the inertia weight as follow Eq. (7).

$$\begin{cases} f_{avg} = \text{sum}(f_i)/\text{N} \\ f_i > f_{avg} \ , w = w - (w - w_{\min})\text{g}\left|\dfrac{f_i - f_{avg}}{f_{best} - f_{avg}}\right| \\ f_{avg} < f_i < f_{best} \ , w = w \\ f_i < f_{best} \ , w = 1.5 - \dfrac{1}{1 + \exp(-\left|f_{best} - f_{avg}\right|)} \end{cases} \tag{7}$$

3.3 The penalty function method based on SAPSO algorithm

The penalty function for establishing the objective function of nuclear zirconium alloy cold-rolled flatness is in Eq. (8).

$$Const = F_k \sum_{i=1}^{n} \{\min[0, F_i]\}^2 + M_k \sum_{i=1}^{n} \{\min[0, M_i]\}^2 + \varepsilon_k \sum_{i=1}^{n} \{\min[0, \varepsilon_i]\}^2 \tag{8}$$

F_k M_k ε_k are the larger values of rational numbers. The rolling force F_i, rolling torque M_i and reduction ratio ε_i of each stand can be calculated according to the follow Eq. (9).

$$\min[0, X_i] = \frac{|X_i - X_{i\max}| + (X_i - X_{i\max})}{2} \tag{9}$$

According to industry process requirements, considering the influence of pass reduction on the properties of rolling mill and zirconium alloy materials, the zirconium alloy cold rolling adopts a small reduction rate, and the single pass reduction rate does not exceed 10%. In the continuous tracking test in the single stand reversible cold rolling mill, the maximum rolling force is 5500kN. When it exceeds this value, the rolling process is likely to be unstable. Table 2 shows the parameter settings in the particle swarm algorithm. The calculation results of each passed parameter of the optimized load distribution shown in Table 3.

Table 2 The adaptive particle swarm optimization of nuclear power zirconium alloy rolling schedule parameters

parameters	Particle dimension	Initial particle number	Iteration number	Learning coefficient c_1	Learning coefficient c_2
value	19	200	300	2	2

Table 3 The calculation results of each pass parameter of the optimized load distribution

parameters	Upper limit of particle	Lower limit of	Particle speed limit	Particle velocity	Weight upper	Weight lower

	position yp_{max}	particle position yp_{min}	v_{max}	lower limit v_{min}	bound ω_{max}	bound ω_{min}
value	0.1	0.01	0.001	-0.001	1.2	0.2

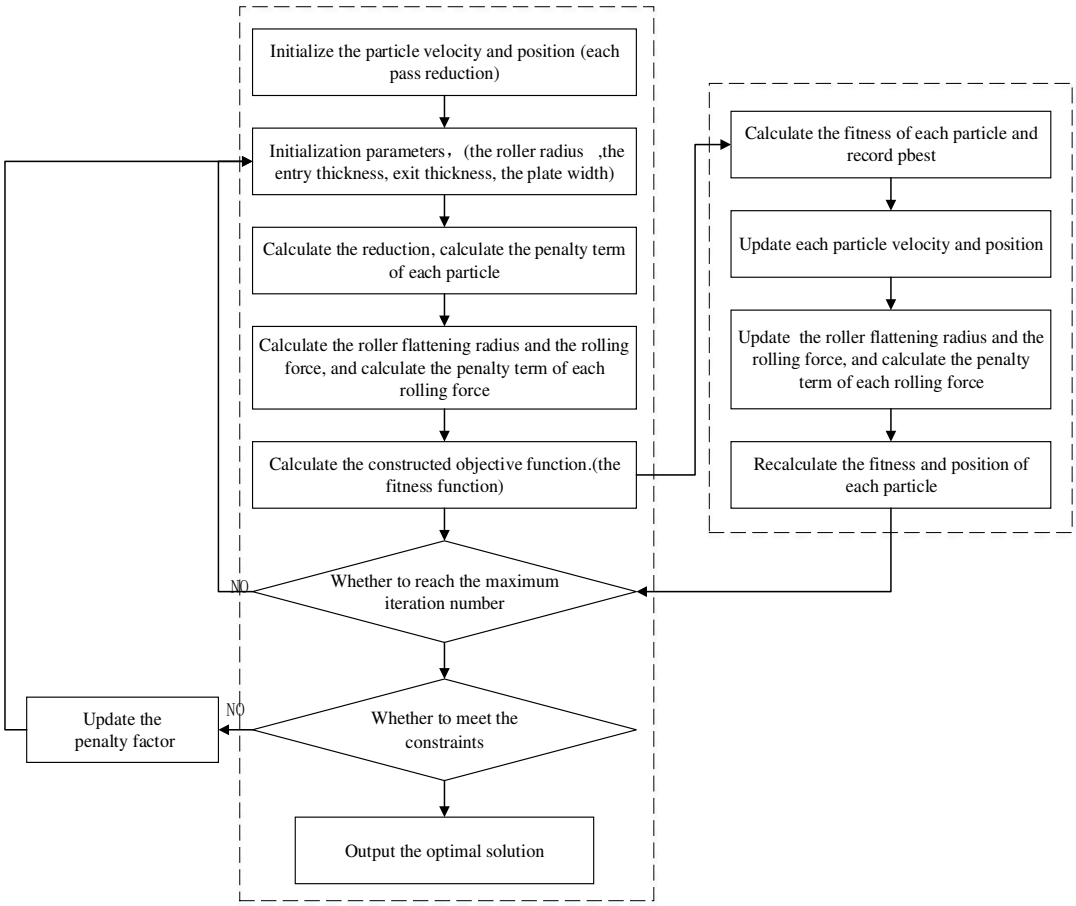

Fig.2 Flow chart of the load distribution for zirconium alloy cold rolling based on the self-adaptive particle swarm optimization (SAPSO)

From the penalty function method based on SAPSO algorithm, we can see Fig.3, which is the optimization results used to calculate the rolling process parameters of each pass. In Fig.3(a-c), we can find that the exit thickness curve of cold rolling load distribution of nuclear power zirconium alloy with good plate shape shows a concave curve. The reduction in each pass gradually decreases, and the rolling force first increases and then gradually decreases. From the third pass, the rolling force and exit thickness meet the objective function of good shape. The iterative calculation of the

extreme value of the objective function in the optimization calculation process is shown in Fig.3(d), the extreme value of the objective function after optimization is $fF_{\min} = 36.57$. By the above analysis, the model could keep the good shape in the multi-pass reversing cold rolling process and the high prediction accuracy.

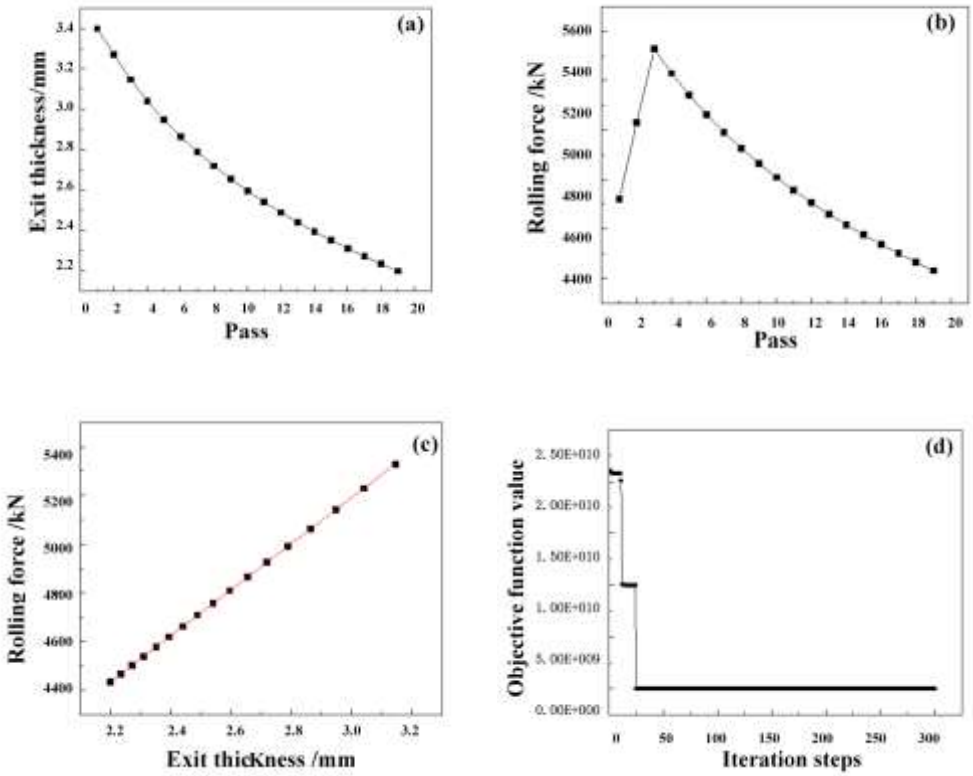

Fig 3. (a) The exit thickness curve (b) the rolling force curve (c)the rolling force and the exit thickness curve (d) the curve of objective function value during optimization calculation

3.4 Optimization results and discussion

The following is a comparative analysis of the original zirconium alloy cold rolling schedule and the new load distribution based on SAPSO. Among them, J-1-1, J-1-2, and J-1-3 are zirconium alloy plates rolled under the original rolling process. The new one needs to rely on established the rolling model by the on-site collected production parameters under the original technology. The exit thickness curve and the rolling force comparison curve are illustrated in Fig.4.

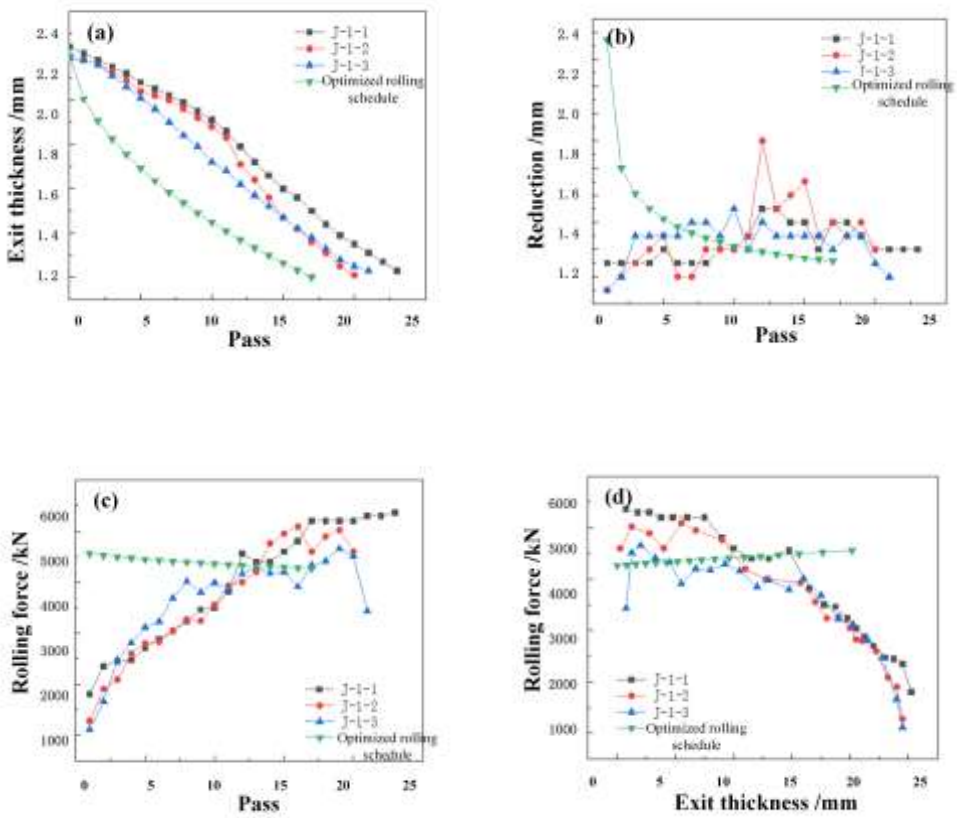

Fig 4. The comparison of empirical and the optimized schedule

Fig. 4 shows, the new rolling schedule of nuclear power zirconium alloy with good plate shape reduces the number of rolling passes of the original deformation system, shortens the rolling time and rolling energy consumption, and improves the rolling efficiency. Fig.4(a) shows the exit thickness of each pass of the original zirconium alloy shows a convex curve decreasing, while the new rolling schedule is showing a concave curve decreasing at each pass. Fig. 4(b) shows the rolling force of each pass under the original rule shows an upward trend, while the new deformation system that shows a downward trend, which meets the requirements of the strip pressure conditions for the material uniformly deformation. Fig 4(c-d) shows the load distribution of original zirconium alloy, the rolling force of each pass has no obvious relationship with the exit thickness, they are opposite to each other. Under the new rolling schedule, the rolling force and the thickness of each stand satisfy the objective function of the good rolling shape.

4.Industrial experimental verification

The practical industrial experiment is further study to verify the effectiveness of

the SAPSO for rolling schedule. According to the nuclear power zirconium alloy cold rolling production line, formulating the rolling schedule based on the self-adaptive particle swarm optimization algorithm. The cold-rolled zirconium alloy rolling process was tested on-site. Continuous tracking test collects data of five zirconium alloy plates. the numbers are U-1, U-2, U-3, U-4，and U-5. The main rolling specifications and corresponding parameters of the five plates are illustrated in Table 4.

Table 4. Zirconium alloy plate standard in the cold rolling industrial test

Number	U-1	U-2	U-3	U-4	U-5
Material thickness /mm	3.9	3.874	3.797	3.93	3.9
Exit thickness /mm	2.273	2.207	2.207	2.3	2.23
Plate width/mm	526	526	526	526	526
Pass number	22	20	18	20	20

Five groups of data were collected by continuous tracking test in the industrial rolling test site. Five plates were rolled according to the optimized load distribution principle. However, this core skill is often conducted by rolling technique engineer in accordance with their experience and knowledge. the technological parameters of five plates would frequent changes during the service period [27,28]. The rolling speed is constant at 10m/min, and the low-speed rolling is adopted. The bending force is not used in the rolling process.

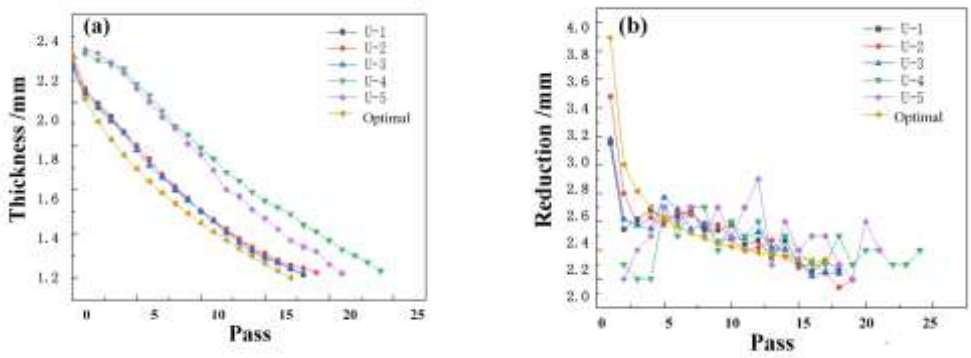

Fig.5 Curves of thickness and reduction of each pass

The curve trend in the figure is in line with the optimization goal. It can be seen from the thickness curves of each pass in Fig. 5 (a) that compared with the U-1 plate,

the other four plates better meet the optimized thickness curve of the rolling schedule outlet. Fig.5 (b), show each pass reduction curve, the pass reduction fluctuation of three pieces plate (U-1, U-4and U-5) is more intense, but plates (U-2and U-3) rolling is more stable.

4.1 Comparative analysis of crown

Considering the rolling condition of the zirconium alloy strip, C25 and C40 are selected as the analysis of crown. According to the continuous tracking test of five groups of rolling pieces on the spot, the cross-sectional geometry of the relevant cross-section is collected, and the crown values of each pass are calculated. The analysis is as follows.

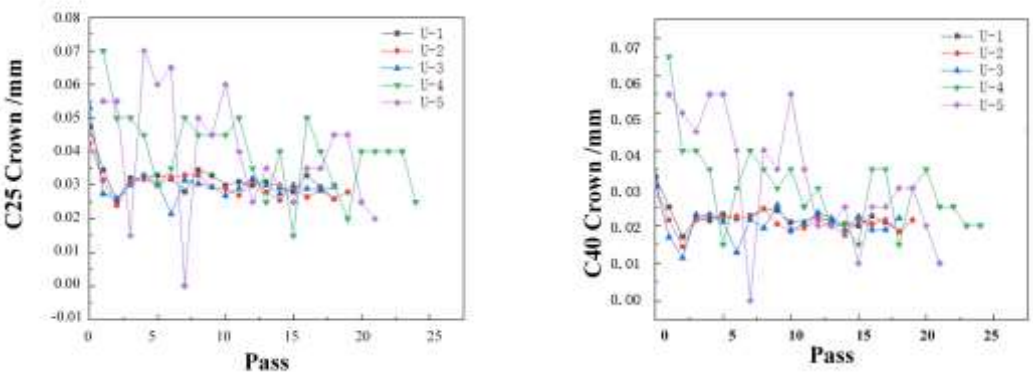

Fig.6 Crown curves of C25 and C40

According to Fig.6, the crown variation curves of five groups data were collected by continuous tracking test. the crown values of each pass showed a downward trend. The crown changes of U-1, U-4, and U-5 plates were relatively intense, and the crown changes of U-2 and U-3 plates were relatively flat. the C40 crown curve of each pass also conforms to the C25 crown change trend, and the crown change of U-2 and U-3 plates tends to be gentler.

4.2 Comparative analysis of proportional crown

Proportional crown is an important parameter to measure the wave shape in the rolling process of plate and strip. To control plate flatness in the cold rolling process. The original process and optimized rolling schedule were compared and analyzed. According to the field continuous tracking test, collecting five groups of data and plotting the variation curve of proportional crown difference of each pass, as shown in Fig. 7.

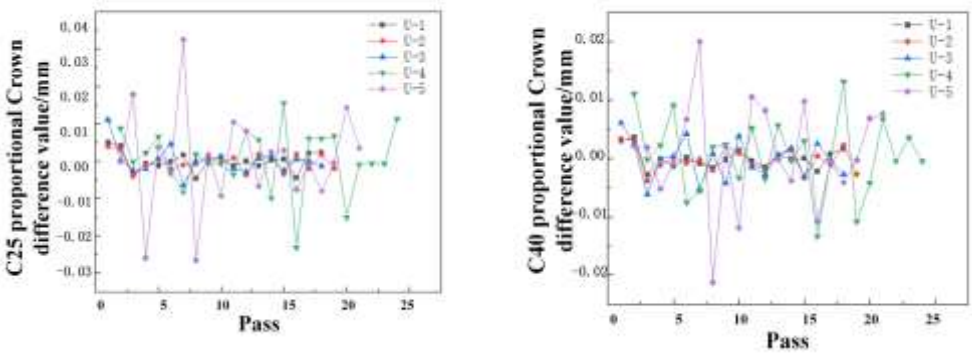

Fig. 7 The difference value of proportional crown

From Fig.7, on-site continuous tracking test acquisition process parameters. C25and C40 percentage crown difference curve can be seen. Compared with other plate rolling, the difference value of U-2 and U-3plate rolling proportion crown change small. To further analyze the difference and quantify proportional crown, the mean and variance of the proportional crown of the above plates are calculated respectively, and the closeness to zero is observed. The calculation results are shown in Fig. 8. The variances of plates U-2 and U-3 are 9.72e-06 and 8.06e-06, respectively, which are smaller than those of the other three plates. The mean value of the proportional crown difference value is close to zero. And the calculation variance fluctuation is small.

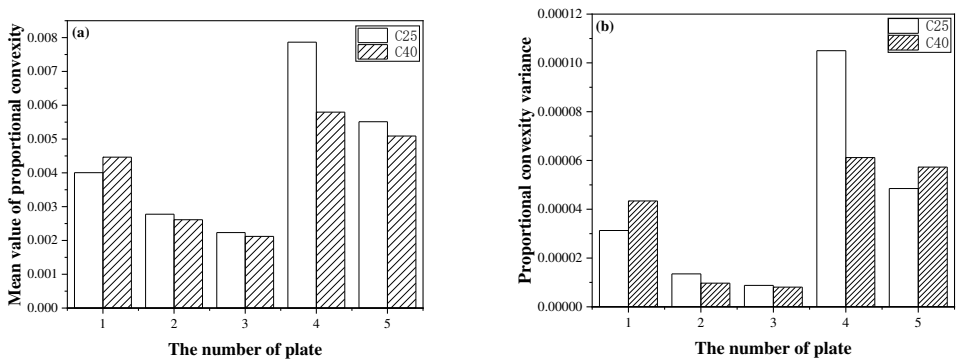

Fig 8 Mean and variance of C25 and C40 proportional convexity difference value

According to the industrial experiment, compared with the traditional process specification, the advantages of the optimized process specification are mainly reflected in the following three aspects. Firstly, shorten the number of rolling passes, improve the rolling efficiency, and the rolling production is more stable when applied to engineering practice. Secondly, the optimized process schedule does not produce an

obvious wave shape during rolling production, and the proportional crown value is constant. Based on the above analysis, the optimized process from theory to practice has verified the superiority of the design results, and the shape quality can be improved.

5. Conclusion

To satisfy the premise of good pressure and flatness conditions during the cold rolling of nuclear power zirconium alloy, the objective function of multi-pass nuclear power zirconium alloy cold rolling with the good plate shape was established.The constraint conditions including rolling force, reduction and torque in cold rolling process. Based on the penalty function method transforming the constraint problem into the unconstrained problem.

The self-adaption particle swarm optimization algorithm (SAPSO) is optimized the goal of good shape of the nuclear power zirconium alloy. The optimized model can keep good shape in multi-pass cold rolling process with the high prediction accuracy. The industrial experiments demonstrate that the number of rolling passes is reduced, the mean value of the proportional crown difference value is close to zero, and the variance fluctuation of the proportional crown difference value is small.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval

The authors claim that they are non-life science journals and there are no ethical issues.

Consent to participate

The authors claim that they agree to participate.

Consent for publication

The authors claim that they agree to publish.

Availability of data and material

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Authors' contributions

Cao Jian-guo: Conceptualization, Supervision, Project administration.

Cao Yuan: Investigation, Validation, Writing - Review & Editing.

Wang Tao: Investigation, Theoretical analysis, Validation, Writing - Original Draft.

Wang Lei-lei: Investigation, Validation, Writing - Review & Editing.

Luo Qian-qian: Supervision, Resources, Validation.

Zhang Peng-fei: Supervision, Resources, Validation.

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