Research on the Optimization of Process Parameters of the Current-Assisted Flow Spinning for 30CrMnSiA Cup-Shaped Part with Different Thickness

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Abstract. A multi-pass current-assisted flow spinning experiment was carried out for the cup-shaped part with different thicknesses. The thickness deviation $\Delta t$, straightness $u$, and roundness $e$ of the spinning parts were selected as the evaluation indexes of forming quality, and the effects of process parameters such as current intensity, preheating time, feed ratio and thinning rate on the forming quality were studied. Based on the genetic algorithm and BP neural network (GA-BP) model, the quality prediction model for the current-assisted flow spinning process was established, and the forming process was optimized by the genetic algorithm (GA). The verification test results are close to the predicted values of the model, in which the maximum error between the predicted value and the test result is about 6%. The results show that the proposed method is useful for the optimization of the current-assisted forming flow spinning process.

1. Introduction
With the excellent properties of fatigue strength and bearing capacity, the alloy structural steels such as 30CrMnSiA are widely used in precision parts and transmission of motion in aerospace, automation equipment, and so on [1]. Due to the poor plasticity (elongation < 20%) of alloy structural steel, it is difficult to deform at room temperature [2]. To meet the needs of manufacturing deep-cup shaped parts with thin-walled, the current-assisted spinning process based on the electroplasticity effect is considered to be one of the most effective methods. The innovative process shows the advantages of low energy consumption, high precision, and microstructure control [3]. There is a positive correlation between the electroplasticity effect and the section current density [4]. Thus, as a kind of local loading continuous forming process [5], the contact area between roller and metal is small. The current-assisted spinning process can make full use of the advantages brought by the significant improvement of material formability with electroplasticity. The forming process is a complicated nonlinear large deformation process, which is influenced by the coupling of the electro-plastic effect and the thermal effect. Therefore, the key point of published papers is to establish a direct correlation model between the forming quality and many process parameters, and to realize the control of the quality.

At present, lots of research were carried out to focus on optimization of the forming process by using a different methodology. For example, Fan Wenxin et al. established the grey GM (0, 3) prediction model of yield strength [6], tensile strength, and Brinell hardness of connecting rod bush respectively with spinning process parameters as system-related factors, which can provide optimization basis for spinning parameters. Liu Donglei et al. optimized the molding process based on
response surface methodology and improved genetic algorithm [7]. Based on the current-assisted deep drawing spinning forming experiment, Xu xiao et al. constructed a response surface analysis model to obtain the optimized process parameters for current-assisted drawing spinning [8]. However, there are few related studies on optimization of current-assisted flow spinning process. With the development of artificial intelligence technology, automatic optimization algorithms such as BP neural network, genetic algorithm, etc. are beginning to use in the optimization of the forming process [9, 10]. For highly nonlinear systems, BP neural network model can accurately obtain the output of extreme points. But for the problem of multiple extreme points, BP neural network model is easy to fall into a local minimum. The genetic algorithm can search the global range, and does not rely on gradient calculation. It can optimize the initial weight and threshold of the BP neural network, so that the BP neural network obtains a better result [11].

To obtain the optimal process parameters of the current-assisted flow spinning process, this study carried out the experiments of the current-assisted flow spinning process and the experimental values of forming quality were acquired. On this basis, the GA-BP method was used to predict the forming quality and the genetic algorithm was used to obtain the optimized process parameters. Then, the forming test was carried out to verify the accuracy of the optimization model. Finally, the qualified cup-shaped parts with thin-walled was produced.

2. Experiment procedure

2.1. Experimental scheme

In this study, current density $I$, preheating time $t_{0}$, feed ratio $f$, and thinning rate $\Psi$ of different spinning passes are selected as the main experimental factors [8]. According to the capability of the equipment, the range of current intensity $I$ is 1100-1300A, the range of preheating time $t_{0}$ is 40-80s, and the range of feed ratio $f$ is 0.4-0.8mm/r. As shown in Fig. 1, in this study, the cup-shaped part with 2mm wall thickness is thinned to the stepped part with 0.4mm wall thickness (zone I) and 0.7mm wall thickness (zone II), respectively. Therefore, in the multi-pass flow spinning scheme, the final thinning pass is to reduce the thickness of 0.7mm to 0.4mm (zone I), while keeping the thickness of the zone II unchanged. The thinning rate of first-pass ranges from 25% to 45%, while the thinning rate before 0.7mm wall thickness is approximately uniform. Therefore, the obtained schemes of the multi-pass thinning rate are shown in Table 1. When the first pass thinning rate range from 25% to 35%, it needs to be formed in four passes. When the thinning rate of the first pass is 40% to 45%, three passes of spinning are required. An orthogonal experiment scheme with 4 factors and 5 levels is established, as shown in Table 2. The letter of $D$ represents the multi-passes thinning rate scheme of flow spinning.

![Figure 1. Cup-shaped parts with different thickness.](image)

2.2. Experimental result

As shown in Fig.1, the key dimension of the cup-shaped part is wall thickness with 0.4mm and 0.7mm. Besides, the roundness and straightness of the sidewall are also important indexes to evaluate the forming quality for cup-shaped parts. Therefore, four indexes of straightness $u$, roundness $e$, thicknesses deviation $\Delta t_1$ in zone I, and $\Delta t_2$ in zone II are selected for study. Thickness deviation $\Delta t$ is the difference between the measured data and the design value. Roundness $e$ represents the degree that the cross-section of the part is close to the theoretical circle. Straightness $u$ refers to the allowable
variation of the measured line relative to the ideal line. The calculations of the thickness deviation, roundness and straightness can be written as Eq. (1)-(3). The measured points of the parts are shown in Fig. 2. There are eight measured generatrices in the circumferential direction, and each generatrix has nine measured points uniformly.

\[ \Delta t = \sum_{i=1}^{M \times N} (t_i - t_0) / (M \times N) \]  

(1)

\[ e = \sum_{k=1}^{K} \left( \Delta r_k^{\text{max}} \right) / K \]  

(2)

\[ u = \sum_{n=1}^{N} \left( \Delta r_n^{\text{max}} \right) / N \]  

(3)

where \( t_i \) is the thickness of measured points, \( t_0 \) is the design value of thickness; \( N \) is the number of measured points in the circumferential direction; \( M \) is the number of axial measured points in a different zone. \( \Delta r_k^{\text{max}} \) is the maximum difference of radius at the specified axial position; \( \Delta r_n^{\text{max}} \) represents the maximum difference of radius at the same generatrix. \( K \) is the number of measured points in the axial direction. The experimental results are shown in Table 3.

### Table 1. Multi-pass thinning rate scheme

| Code | First pass /% | Second pass /% | Third pass /% | Fourth pass /% |
|------|---------------|----------------|---------------|----------------|
| ①   | 25.00         | 32.00          | 31.37         | 42.86          |
| ②   | 30.00         | 30.00          | 28.57         | 42.86          |
| ③   | 35.00         | 26.92          | 26.32         | 42.86          |
| ④   | 40.00         | 41.67          | 42.86         | /              |
| ⑤   | 45.00         | 36.36          | 42.86         | /              |

### Table 2. Factors and levels

| Levels | \( I / \text{A} \) | \( \text{th} / \text{s} \) | \( f / (\text{mm/r}) \) | Thinning rate scheme |
|--------|-------------------|---------------------|---------------------|---------------------|
| -2     | 1100              | 40                  | 0.4                 | ①                   |
| -1     | 1150              | 50                  | 0.5                 | ②                   |
| 0      | 1200              | 60                  | 0.6                 | ③                   |
| 1      | 1250              | 70                  | 0.7                 | ④                   |
| 2      | 1300              | 80                  | 0.8                 | ⑤                   |

Figure 2. Selection of measuring points
Table 3. Experimental scheme and results

| Label | I (A) | t (s) | f (mm·r⁻¹) | D (%) | Δt₁/mm | e/mm | u/mm | Δt₂/mm |
|-------|-------|-------|-----------|-------|---------|------|------|---------|
| 1     | 1300  | 60    | 0.6       | 35    | 0.026   | 0.341| 0.443| 0.03    |
| 2     | 1150  | 70    | 0.7       | 30    | 0.043   | 0.248| 0.322| 0.046   |
| 3     | 1250  | 70    | 0.7       | 40    | 0.025   | 0.473| 0.614| 0.028   |
| 4     | 1250  | 50    | 0.7       | 40    | 0.032   | 0.376| 0.488| 0.036   |
| 5     | 1200  | 60    | 0.6       | 25    | 0.029   | 0.206| 0.267| 0.034   |
| 6     | 1150  | 70    | 0.5       | 30    | 0.034   | 0.143| 0.185| 0.039   |
| 7     | 1100  | 60    | 0.6       | 35    | 0.065   | 0.265| 0.314| 0.068   |
| 8     | 1200  | 80    | 0.6       | 35    | 0.040   | 0.294| 0.382| 0.042   |
| 9     | 1250  | 70    | 0.5       | 40    | 0.028   | 0.240| 0.312| 0.031   |
| 10    | 1200  | 60    | 0.8       | 35    | 0.038   | 0.396| 0.514| 0.042   |
| 11    | 1200  | 40    | 0.6       | 35    | 0.042   | 0.274| 0.326| 0.045   |
| 12    | 1250  | 70    | 0.5       | 30    | 0.017   | 0.232| 0.278| 0.021   |
| 13    | 1250  | 50    | 0.5       | 30    | 0.020   | 0.226| 0.271| 0.023   |
| 14    | 1200  | 60    | 0.6       | 45    | 0.055   | 0.289| 0.346| 0.056   |
| 15    | 1200  | 60    | 0.6       | 35    | 0.049   | 0.239| 0.286| 0.051   |
| 16    | 1250  | 50    | 0.7       | 30    | 0.033   | 0.297| 0.356| 0.036   |
| 17    | 1200  | 60    | 0.4       | 35    | 0.030   | 0.131| 0.157| 0.034   |
| 18    | 1150  | 50    | 0.7       | 30    | 0.036   | 0.130| 0.156| 0.038   |
| 19    | 1200  | 60    | 0.6       | 35    | 0.049   | 0.239| 0.286| 0.052   |
| 20    | 1150  | 50    | 0.5       | 30    | 0.029   | 0.122| 0.146| 0.033   |
| 21    | 1200  | 60    | 0.6       | 35    | 0.049   | 0.239| 0.286| 0.051   |
| 22    | 1150  | 70    | 0.5       | 40    | 0.048   | 0.169| 0.202| 0.052   |
| 23    | 1200  | 60    | 0.6       | 35    | 0.049   | 0.239| 0.286| 0.051   |
| 24    | 1150  | 70    | 0.7       | 40    | 0.061   | 0.312| 0.343| 0.065   |
| 25    | 1150  | 50    | 0.7       | 40    | 0.052   | 0.243| 0.267| 0.055   |
| 26    | 1200  | 60    | 0.5       | 35    | 0.049   | 0.239| 0.286| 0.051   |
| 27    | 1250  | 70    | 0.7       | 30    | 0.021   | 0.454| 0.499| 0.024   |
| 28    | 1150  | 50    | 0.5       | 40    | 0.054   | 0.136| 0.149| 0.056   |
| 29    | 1250  | 50    | 0.5       | 40    | 0.024   | 0.226| 0.248| 0.027   |

3. Prediction of quality and optimization of process parameter

3.1. Prediction model of forming quality based on GA-BP algorithm

The calculation flow of the BP neural network model optimized based on the genetic algorithm is shown in Fig.3. The structure of BP neural network includes network layers and transfer function. In this paper, the input layer, hidden layer, and output layer were used to realize nonlinear mapping relationships. The optimal value of the hidden layer node is 9 in the usual BP model. The BP model takes wall thickness deviation, roundness, and straightness as output variables. The transfer function of logsig was selected as the hidden layer. Finally, the BP neural network structure of 4-9-1 was established, and the linear transfer function of purelin was used as the transfer function for the output layer node.
Figure 3. GA-BP algorithm.

According to the network structure of 4-9-1, there were 45 weights and 6 thresholds. The individual coding length of the genetic algorithm was 51 [12]. The selection strategy based on fitness proportion was used, and the probability of individual being selected is calculated according to Eq. (4).

\[
F(x_i) = \frac{f(x_i)}{\sum_{i=1}^{40} f(x_i)}
\]  

(4)

where \(f(x_i)\) is the fitness value of individual \(x_i\). \(F(x_i)\) is the chosen probability of individual. Generally, the crossover probability is between 0 and 1. In this paper, the single-point crossover method and the discrete mutation algorithm were selected. The crossover probability was selected as 0.7 and the mutation rate is selected as 0.01. The input parameters included current intensity, preheating time, feed ratio, and the thinning rate. The output variables were thickness deviation \(\Delta t_1\) in zone I, roundness \(e\), straightness \(u\), and thickness deviation \(\Delta t_2\) in zone II, respectively. The function \(\text{trainlm}\) was used as the learning function. The maximum number of training times was set as 100000, while the training accuracy was 0.00001. The initial population was set to 50, and the evolution algebra was 75.

Using MATLAB toolbox for training, the predictive value and experimental data of cup forming quality based on the GA-BP model are as shown in Fig. 4. The coefficient of determination \(R^2\) of all items is not less than 0.95, and the average deviation (A.D.) is about 3%-4%. The results show that the accuracy of the predictive model is high.

3.2. Optimization of forming process parameters based on genetic algorithm

Based on the quality prediction model in the previous section, the forming quality data under different process parameters were obtained. The genetic algorithm model was used to select the optimal process parameters. The algorithm flow was shown in Fig. 5.
The three quality indexes of wall thickness deviation, roundness and straightness are interrelated. Therefore, the optimized quality indexes cannot take the minimum value at the same time. The most important dimension of the cup-shaped part was the thickness deviation, so that the optimization objective was to minimize the sum of the wall thickness deviation $\Delta t_1 + \Delta t_2$, while the roundness $e \leq 0.15\text{mm}$ and the straightness $u \leq 0.15\text{mm}$. The optimization model was expressed as Eq. (5).

The MATLAB toolbox was used to optimize the forming process. When the termination conditions were met, the parameters of the last generation population were the optimal solution. The fitness curve in the optimization process was shown in Fig. 6, and the optimal process parameters and quality prediction were shown in Table 4.

![Figure 4. Comparison of predicted value and experimental data of forming quality.](image)

| $I$/A | $t_0$/s | $f$/mm/r | $\Psi$/° | $\Delta t_1$/mm | $e$/mm | $u$/mm | $\Delta t_2$/mm |
|-------|--------|---------|---------|----------------|-------|-------|--------------|
| 1211.8 | 63.58  | 0.411   | 29.87   | 0.016          | 0.107 | 0.143 | 0.021        |

$$
\text{min } F(\Delta t) = 0.5(\Delta t_1 + \Delta t_2) \\
\text{s.t. } 1100 \leq I \leq 1300, 40 \leq t_0 \leq 80 \\
0.4 \leq f \leq 0.8, 0.25 \leq \psi_f \leq 0.45 \\
e \leq 0.15, u \leq 0.15
$$
The trial production of the cup-shaped part was carried out to verify the optimization effect, as shown in Fig. 6. The process parameters obtained from the theoretical optimization were rounded for the experiment. The current intensity was set to 1200A and preheating time was equal to 60s. Feed ratio and the first thinning rate were 0.40mm/r and 30%. The comparison between the experimental value and the predicted value of the GA-BP model was shown in Table 5. The relative error of all values less than 10%. The spun workpiece manufactured under optimized parameters was shown in Fig. 7 (a), and the cup-shaped part with different thickness after polishing and trimming was shown in Fig. 7 (b). The test results show that the optimization model obtained in this study can use to the optimization of the spinning process for cup-shaped parts.

| objectives | Experimental value | Predicted value | Relative error |
|------------|--------------------|-----------------|---------------|
| $\Delta t_1$ | 0.016              | 0.016           | 0.0%          |
| $x$        | 0.114              | 0.107           | 6.1%          |
| $u$        | 0.149              | 0.143           | 4.0%          |
| $\Delta t_2$ | 0.020             | 0.021           | -5.0%         |

Figure 7. Cup-shaped parts with different thickness.

4. Conclusion
(1) The GA-BP model of the 4-9-1 structure has a high predictive ability for the forming quality of the current-assisted flow spinning process. The coefficient of determination of all items is not less than 0.95, and the average deviation is about 3%-4%, which shows that the high accuracy of the predictive model.
(2) The global better process parameters based on the GA optimization algorithm are $I=1211.8\, \text{A}$, $t_{sg}=63.58\, \text{s}$, $f=0.411\, \text{mm/r}$, $\Psi_{\text{n}}=29.87\%$. The reliability of the optimization model is proved by the validation test. The relative error between the test results and the predicted value is less than 6%.

(3) The cup-shaped part with different wall-thickness is formed by the optimized process parameters. The results indicate that the optimization methodology combined with the BP-GA prediction model and genetic algorithm is applicable to the optimization of the current-assisted flow spinning process.

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