Study on loading path optimization of internal high pressure forming process

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Abstract. In the process of internal high pressure forming, there is no formula to describe the process parameters and forming results. The article use numerical simulation to obtain several input parameters and corresponding output result, use the BP neural network to found their mapping relationship, and with weighted summing method make each evaluating parameters to set up a formula which can evaluate quality. Then put the training BP neural network into the particle swarm optimization, and take the evaluating formula of the quality as adapting formula of particle swarm optimization, finally do the optimization and research at the range of each parameters. The results show that the parameters obtained by the BP neural network algorithm and the particle swarm optimization algorithm can meet the practical requirements. The method can solve the optimization of the process parameters in the internal high pressure forming process.

1. Introduction
Because of its light weight, good rigidity and less forming process, internal high pressure forming parts have been widely used in the production of automobile parts and components [1]. According to statistics, about 30% of the parts of the car body can be manufactured by internal high-pressure forming process. In the early 1980s, western countries began to study the forming technology of internal high pressure. By 1990s, internal pressure forming technology has begun to be widely used in the automotive field. Internal high pressure forming is a new plastic forming technology for tube forming under this background [2].

The quality of internal high pressure forming is related to many factors, such as the material and size of the pipe, the quality of the mould, the friction coefficient between the tube and the die and the loading path of the forming process [3]. In order to obtain qualified parts, researchers have carried out a great deal of research on the factors that affect forming [4]. Studies have shown that, after solving the material, mold and friction and other factors, there must be a suitable loading path to get high-quality forming parts [5]. Therefore, it is important to find a method to calculate and optimize the loading path to improve the forming quality, reduce the reject rate and reduce the production cost of internal high pressure forming parts [6].

Loading path has great impact on the quality of parts during the processing. How to get the optimal loading path is a central issue which always been researched by domestic scholars and foreign scholars [7]. Now the common method has theoretical calculations and numerical simulation. Internal high pressure forming process is so complicated that the result which is required by theoretical calculation is inaccurate. Because theoretical calculations need certain assumption and predigestion. The theory of numerical simulation is that use finite element software to simulate forming process [8]. It needs to adjust the input variables constantly to require the optimal loading path, and the results finally
obtained are not an accurate result but a similar result. In response to these problems, the article propose a new method which gets the input parameters and the output by finite element software firstly, then calculates the mapping relationship between the input parameters and the output by BP neural network, finally uses the particle swarm optimization to optimize and get the optimal loading path.

2. Basic theories
Neural network is an algorithm which can simulate brain’s physical function, and it has strong ability of logical operation and linear approximation. It includes computer, physics, mathematics, biology and other disciplines, and has broader prospect compared with mathematical modeling. BP neural network is a multilayer feed forward networks which is trained by error back propagation algorithm. Its basic theory is that input layer neurons receive input information, the middle layer deal with and convert message, and the output layer neurons calculate and export processing results. When the actual output has larger mistake compared with the expected result, BP neural network begin doing back-propagation. The algorithm adjusts constantly the network’s weights and threshold to adjust the mistake to the appropriate extent [9].

Particle swarm optimization (PSO) is an intelligent algorithm which is proposed by simulating the phenomenon of bird predation. It is proposed by J. Kennedy and R. C. Eberhart in 1995. For introducing simple speed-die placement method and global searching tactics, particle swarm optimization avoids complex genetic manipulation and has higher searching efficiency and convenient performance. In recent years, particle swarm optimization has been widely used machinery, electricity, chemical industry and other fields to solve global extreme, integer programming, multi-objective optimization and other issues [10].

3. Test and simulation
3.1. Select design variables
Tube’s internal high pressure forming process is affected by many factors, yielding pressure $P_1$, forming pressure $P_2$, finishing pressure $P_3$ and axial feeding $\Delta l$ is the four most important parameters. These parameters can be calculated by such formula.

$$P_1 = \frac{2 \cdot t_0}{D_0 - t_0} \cdot \sigma$$

(1)

$$P_2 = \frac{2 \cdot t_0}{D_0 - t_0} \cdot \sigma_b$$

(2)

$$P_3 = \frac{2}{\sqrt{3}} \cdot \sigma_f \cdot \left[ \ln \left( \frac{r_b}{r_b - t_0} \right) \right]$$

(3)

$$\Delta l = \frac{\int_0^l f(x)dx}{R} \cdot \Delta H$$

(4)

In the formula, $D_0$ is tube’s diameter, $t_0$ is the tube’s initial thickness, $D_p$ is the tube’s forming thickness, $r_b$ is the mode’s minimum fillet, $f(x)$ is the forming tube’s profile curve, $R$ is the tube’s initial radius, $\Delta H$ is the forming tube’s height of branch tube, $\sigma_y$ is the tube’s yielding limit, $\sigma_b$ is the tube’s strength limit, $\sigma_f$ is the tube’s flowing stress.

The subject of this test is a stainless steel tube. Its material is SS304, length is 200 mm, thickness is 1.5 mm, diameter is 20 mm. we want to get a four-way tube whose diameter is 20 mm and branch’s height is 20 mm through internal high pressure forming. By the formula (1) to (4) and parameter in the
Table 1, we can get the curve about the relationship between the axial feeding and time (Figure 1) and the curve about the relationship between the internal pressure and time (Figure 2).

Table 1. Parameter list

| $t_0$  | $D_0$ | $D_p$ | $r_b$ |
|-------|-------|-------|-------|
| 1.5 mm | 20 mm | 20 mm | 5 mm  |
| $\sigma_s$ | $\sigma_b$ | $\sigma_f$ | $\Delta H$ |
| 205 MPa | 520 MPa | 625 MPa | 20 mm |

Figure 1. Relationship between the axial feeding and time

Figure 2. Relationship between internal pressure and time

This article make yielding pressure $P_1$, forming pressure $P_2$, finishing pressure $P_3$ and axial feeding $\Delta l$ as the design variables, and according to the calculation result set each variable’s range: $30 \leq P_1 \leq 50, \ 50 \leq P_2 \leq 90, \ 100 \leq P_3 \leq 200, \ 50 \leq \Delta l \leq 70$.

3.2. Training BP neural network

When we want to evaluate a four-way tube’s quality by internal high pressure forming, we often analyze branch tube’s height $\Delta H$, the minimum thickness of the tube $T_{\text{min}}$ and the maximum thickness of the tube $T_{\text{max}}$. The article takes these parameters as BP neural network’s output variables and takes yielding pressure $P_1$, forming pressure $P_2$, finishing pressure $P_3$ and axial feeding $\Delta l$ as the input variables. According to Empirical formula $m = \sqrt{m_1 + m_2 + a}$, we set hidden layer’s number of the nodes to 5. In the formula, $m_1$ is the number of input layer and $m_2$ is the number of the output layer. $a$ is a constant whose range is from 1 to 10. According to these factors, we can get a model of BP neural network which has 3 layers.

We random select 40 sets of data from the range of input parameters. Then we use finite element software-DYNAFORM to simulate these parameters and get the corresponding output data. We make 21 sets of data of them as BP neural network’s training sample, make others as BP neural network’s training sample examining sample. The training result is as shown in Figure 3 and Figure 4. From Figure 3 and Figure 4, we can know that this BP neural network’s forecasting accuracy is very well.
4. Simulate the loading path

In this article we will simulate branch tube’s height $\Delta H$, the minimum thickness of the tube $T_{\text{min}}$ and the maximum thickness of the tube $T_{\text{max}}$, it is a Multi-objective optimization problem. In order to simulate these three parameters same time, we need to make them into an entirety. In this article we describe them with formula (5).

$$f(x) = 0.1\Delta H + t_{\text{min}} - t_{\text{max}}$$ (5)

The value of the $\Delta H$ is 10 times compared with the value of the $T_{\text{min}}$ and $T_{\text{max}}$, so we set the modulus of $\Delta H$ to 0.1 in order to make these parameters in the same order of magnitude. The value of $\Delta H$ and $T_{\text{min}}$ is the smaller the better, but the value of $T_{\text{max}}$ is the bigger the better, so we set the symbol of $T_{\text{max}}$ to minus.

The process of optimizing loading path can be divided into 3 steps.

Step 1: initialize the parameters of particle swarm optimization; make the input parameters mapping a group of particles and initialize speed and position of particle.

Step 2: calculate the output parameters by trained BP neural network, and then calculate value of the objective function.

Step 3: judge whether the value are function’s the optimal solution or whether the number of iterations have attained to the maximum. If meet the condition, the value is the expecting result. If don’t meet the condition, renew the speed and position of particle and go to the step 2.

Optimization results are shown as Figure 5. In the figure, the blue points indicate all particles’ position in the internal high pressure forming process, the red points indicate each generations of particles’ optimal position. When the function get the optimal result, $P_1$ =30.8599, $P_2$ =74.959, $P_3$=12.1239, $\Delta l$=59.5066. We make the required value of the parameters into the DYNAFORM to simulate, and the result is shown as Figure 6. From the Figure 6 we can see that the branch tube’s height $\Delta H$ is 19.95 mm and the minimum thickness of the tube $T_{\text{min}}$ is 1.167 mm and the maximum thickness of the tube $T_{\text{max}}$ is 3.079 mm, all results entirely reached the expected target.

5. Conclusions

(1) Using BP neural network to simulate tube’s internal high pressure forming process can solve that tube’s internal high pressure forming process has so many factors that it can’t be described by mathematical model.

(2) Particle swarm optimization make the work of searching optimal loading path more simple and convenient and freed the craft workers from complex work which need to be calculate and simulate. Obtained many optimal solution can offers several options to craft workers.
(3) In the test, we need experience to select weighting factor of the objective function’s parameters and set parameters of particle swarm optimization. Different selecting method has different effect on the result of the test. How to select all parameters scientifically is the key to further research.

Figure 5. Optimization process of PSO

Figure 6. Simulating result

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