PARAMETER OPTIMIZATION OF THE FORGING AND FORMING PROCESS USING PARTICLE SWARM OPTIMIZATION

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Abstract - To find the best process parameters when forging blanks and improve the imperfections of the traditional numerical simulation method, particle swarm optimization (PSO) with excellent problem optimization ability will be used to optimize the parameters. From the perspective of the material itself and the energy saving of forging and forming, the most suitable parameter results can be found using this algorithm. The modeling and simulation of aluminum forging is carried out. The simulation software is used to summarize the action laws of the initial temperature of 440 °C, 460 °C, 500 °C and the forging speed of 3mm/s to 5mm/s. The simulation results are recorded and the standard deviation of the outlet surface temperature is calculated, which are used as the experimental data to establish a support vector machine (SVM) model for further fitting and calculation of the data. Then a multi-objective optimization model is established with the initial temperature and forging speed as variables and the goal of reducing the standard deviation of temperature and energy consumption. PSO is used to further solve the model to find the optimal combination of process parameters to reduce energy consumption and ensure material quality, to achieve the purpose of parameter optimization of forging and forming process. The results show that when the initial temperature is 450 °C and the forging speed is 4.4 mm/s, the material quality can be effectively improved while reducing energy consumption. Compared with the original scheme, the new scheme achieves the purpose of optimizing parameters. It has a great reference for the selection of parameter optimization of the forging and forming process and the application of PSO in the optimization process.

Keywords: Particle swarm optimization, Parameter optimization, Aluminum forging simulation, Standard deviation of temperature.

1. Introduction

With the rapid development of the world economy, energy consumption is serious, and the low conversion rate of various types of energy has been a persistent problem. The advancement of energy utilization restricts the development of the global economy. Reducing energy consumption and increasing output and product quality while economic development is the most urgent problem to be solved at the moment. Taking aluminum production as an example, it is an inevitable trend for aluminum and even all metal materials in the world to ensure the quality of aluminum itself while reducing energy consumption and improving production efficiency by changing process parameters [1].

In the process of aluminum forging, the initial setting of the process parameters directly affects the physical properties of the aluminum itself. However, the essence of forging is a change process of nonlinear forming, which is difficult to measure by traditional methods.

In response to this problem, scientists around the world have used finite meta-technology to simulate the production of aluminum, and to find the change law of parameters such as temperature during the forging process, to improve the production efficiency [2]. However, scientists still do not pay much attention to the energy consumption of forging. Noh and Hwang (2017) divided the energy consumption of forging into ideal, redundant and frictional energy consumption and studied the influence of some process parameters on it. The key factors affecting energy consumption are initially discussed [3]. Deng et al. (2018) studied the temperature field distribution during the forging process by taking advantage of the vibration loading method of the press slide [4]. Malghan et al. (2017) firstly used the particle swarm algorithm (PSO) to simulate the optimization model aiming at reducing the time, cost and energy consumption of production, and obtained some optimal process parameters that meet the basic production conditions [5].

Although the current ordinary numerical simulation calculation method can replace the forging and forming experiments to fundamentally solve the problems of material consumption and energy saving in practice, the time demand of numerical simulation does not match the actual production requirements.

Based on this reason, the simulation software for the forging material and the die is firstly modeled and simulated, and the action law of the initial temperature and the forging speed is recorded, and the standard deviation of the outlet surface temperature is calculated. It is used as the experimental data to set up the support vector machine (SVM) model and perform further fitting calculations on the data. Secondly, a multi-objective optimization model is established with the initial temperature and forging speed as variables and the goal of reducing the standard deviation of temperature and energy consumption. Finally, PSO is used to further solve the model to find the optimal combination of process parameters to reduce energy consumption and ensure material quality.

The purpose is to use a new algorithm to find the optimal parameter combination for forging and forming to achieve the purpose of optimizing energy-consuming materials. It also provides theoretical and data support for future research on optimization parameters of the algorithm.

2. Parameter Optimization of the Forging and Forming Process Using PSO

2.1 Characteristics and Defects of Aluminum Forging and Forming

Since forging and forming came into people's field of vision, aluminum forging has been widely used because of its excellent chemical and physical properties. Forged aluminum alloys have an irreplaceable role in the world such as the infrastructure industry, vehicle manufacturing industry, and high-precision industries [6]. Since the late 1990s, developed countries have begun to study how to reduce costs and optimize performance by improving forging technology. China regards aluminum as a national key research project, and puts the research on the performance and quality of aluminum alloys in the first place, to develop the aluminum industry and aluminum forging technology. The forging and forming of aluminum alloy can improve the basic parameters of aluminum alloy materials by breaking the grains and changing the structure of the aluminum alloy. There are several points that need to be paid attention to in the process of aluminum forging and forming, to greatly improve the quality of aluminum products, as shown in Figure 1a. Aluminum is also prone to five problems during the forging and forming process, as shown in Figure 1b.

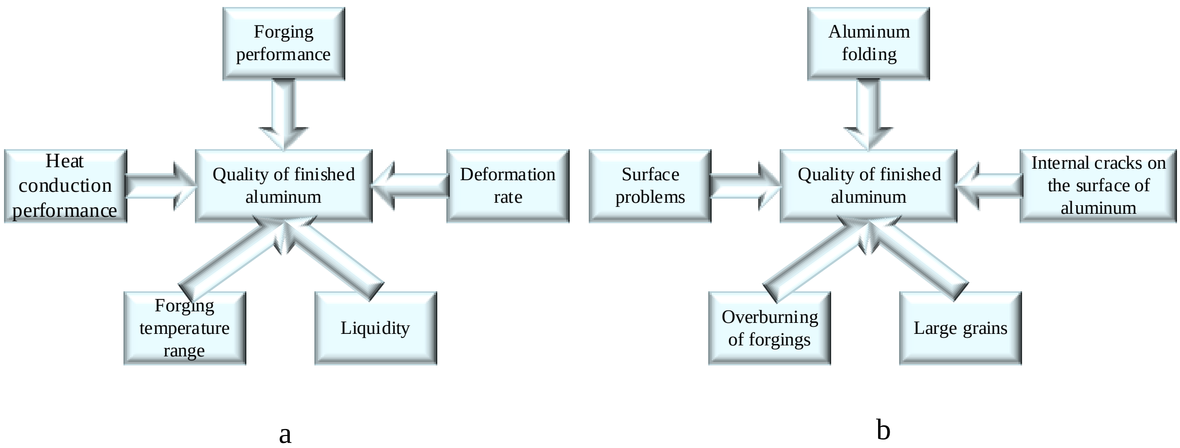


Figure 1: Reasons for affecting process quality (a. Reasons for improving the quality of aluminum; b. Reasons for reducing the quality of aluminum)

2.2 Simulation Software of the Forging Process and the Design and Introduction of Forging Die

(1) Introduction to simulation software of forging and forming process

Deform is used as the simulation software for forgings to simulate the aluminum forging and forming process.

Deform consists of three basic modules, which are a pre-processor for data input and mesh data transfer, a simulation processor for finite meta-analysis, and a post-processor to display the simulation results. Deform can perform data processing on forging and forming and heat conduction coupling, and can also simulate basic heat treatment processes such as annealing, quenching, and shot blasting, and perform property analysis on materials to calculate the hardness distribution of forgings after heat treatment [7].

(2) The design process of forging die

To simulate the forging itself and the corresponding mold of the 3D modeling, Computer Aided Design (CAD) software is used to draw 2D drawings, and import the 2D images into Pro/Engineer (Pro/e) for 3D construction.

Because Pro/e's own die and plate can easily modify and model forgings and dies, the interactive interface between Pro/e and Deform is very stable. To facilitate our research and design, both 3D and 2D models have corresponding import formats. The specific design steps of forging are shown in Figure 2.

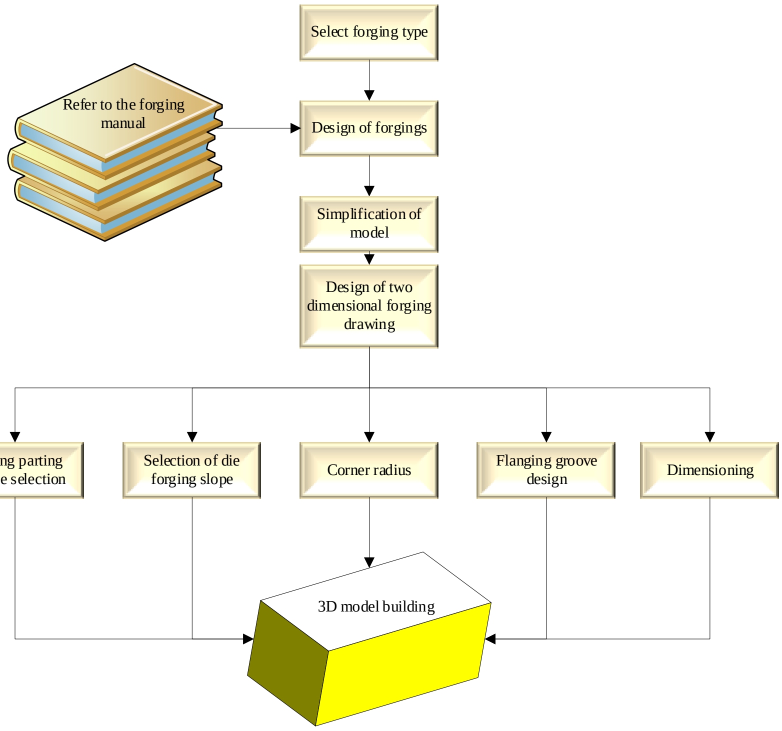


Figure 2: The design process of forging die

Figure 2 shows the specific design process of the forging die. The simplification of the shape and size of the forging can reduce the amount of calculation and time. The unique structural characteristics of the forging are not simplified.

The selection of the sub-surface film of the subsequent forging, the determination of the forging drawing and other details can be referred to the forging design manual.

6063 aluminum alloy hollow tube is used. The specific data of the billet is the diameter of 90mm, the length of 250mm, and the inner diameter of the extrusion cylinder of 96mm. The hollow circular tube produced has an outer diameter of 60 mm, an inner diameter of 56 mm and a wall thickness of 2 mm [8]. Subsequent forging simulations will be carried out according to the data of the aluminum alloys in Table 1 into the simulation software.

Table 1: Performance parameters of 6063 aluminum alloy

Performance parameters	AA6063
Elastic Modulus (MPa)	4.0×10^4
Density (kg/cm^3)	2.7×10^3
Poisson’s ratio	0.333
Heat transfer coefficient between the aluminum rod and die (m^2·K)	3000
Heat conduction system (W/(m·K))	198
Specific heat (J/(kg·K))	900

2.3 Simulation of Forging Process

To meet the design requirements, forgings with uniform grain distribution need to determine the specific forging process.

The process ideas are shown in Figure 3:

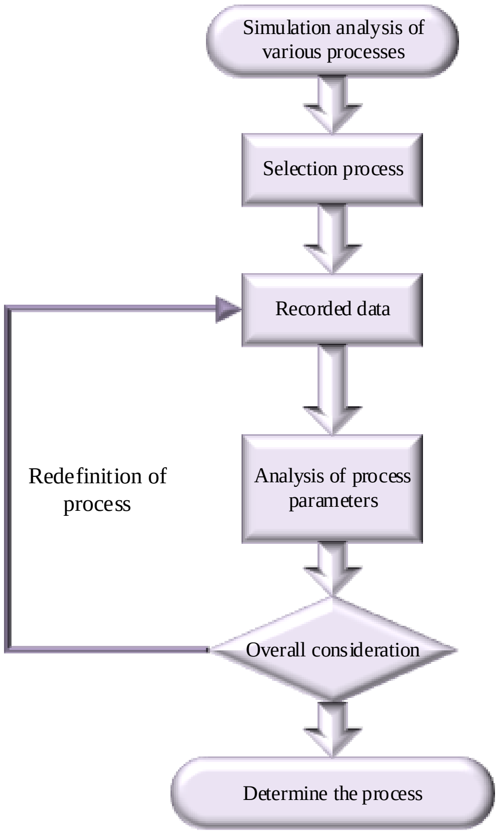


Figure 3: The research flow of the process

In Figure 3, Deform is used to perform finite element simulation on the designed aluminum alloy die for forgings, and then the relevant quality parameters and process parameters are counted according to the data of Deform. The relationship is analyzed between the two to summarize the rules. Considering the influence of process parameters on energy consumption, the forging process is determined.

Numerous studies have found that the forging speed and the deformation resistance of aluminum are the two parameters that have the greatest impact on energy consumption. Among them, the deformation capacity of aluminum is related to temperature, and the forging speed is inseparable from the performance of aluminum and the production efficiency of aluminum. The forging speed and the initial temperature of the billet are mainly selected as the process parameters optimized for simulation experiment research. The quality and quality of the forging process can generally be judged by judging the uniformity of the outlet temperature of the material, and if the difference of the outlet temperature is too large, the internal structure of the steel will be deformed and the mechanical properties will change [9]. Only when the outlet temperature is controlled between +10°C and -10°C, can the influence of the forging process parameters on the energy consumption of the forging process be studied. The standard deviation of temperature is selected as an important benchmark for judging the quality of aluminum. The specific expression of the standard deviation of temperature is shown in equation (1):

$$\Delta T=\sqrt{\frac{\sum_{i=1}^{n}(T_i-\bar{T})^2}{n}} \tag{1}$$

In equation (1): a total of n nodes are selected. T_i is the temperature of the node corresponding to the exit surface of the steel. $\bar{T}$ represents the average T of the node corresponding to the exit surface of the aluminum.

2.4 The Process of Multi-objective Optimization of Process Parameter

After using the Deform analysis to summarize the effect of the initial temperature of the blank and the forging speed on the forging, the optimization of the process parameter combination still requires a lot of calculation to meet the production requirements. However, the number of computations of numerical simulation is too large and time-consuming, which cannot match the production requirements. To find the rules between the forging process parameters and the energy and material loss, the PSO will be used to record and learn the existing data and then conduct the search experiment to achieve the purpose of optimizing parameters or even finding the best parameter combination [10].

The process of multi-objective calculation and optimization of process parameters is shown in Figure 4:

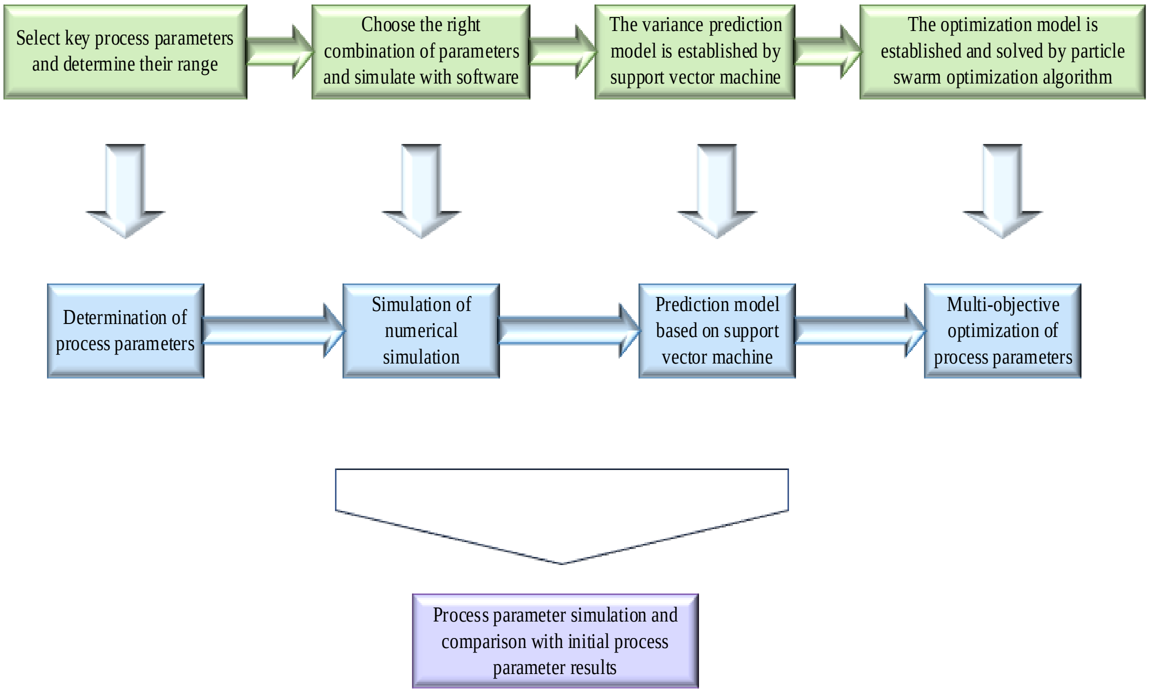


Figure 4: The process of multi-objective calculation and optimization of process parameters

The forging speed and the initial temperature of the billet are selected by the process parameters, its value (value within the specified value range) is changed into 9 process combinations, and then the conventional method to simulate the forging model is used, the simulation results are recorded and the standard deviation of the outlet surface temperature is calculated. The standard deviation of the outlet surface temperature is taken as the experimental data, a SVM model is established to further fit and calculate the data, and a functional relationship is constructed to express the relationship between the outlet surface temperature and the energy consumption of forging. Forging speed, billet initial temperature and energy consumption and multi-objective optimization model of profile parameters are set. The optimal solution will be further obtained by PSO [11]. Then the simulation experiment is carried out on the optimal parameter target, and finally the target of PSO of forging and forming process parameters is achieved.

In the field of machine learning, SVM is a learning method that is different from neural network (NN) learning. Compared with NN learning, SVM is more suitable for regression problems, such as no local minimum and strong generalization ability, the topology grid structure does not need to be pre-established and other advantages [12].

2.5 Multi-objective Optimization based on PSO

When carrying out multi-objective optimization of the forging and forming process, it is not difficult to find that the quality of the profile will be lost when the energy consumption of the forging is targeted. Similarly, if the energy consumption of forging is optimized with the target of profile quality, there will be a larger increase. The Pareto optimal solution is used to explain the energy consumption of forging and the quality of the unit shape [13]. The set is regarded as the optimal solution of multi-objective optimization, and the specific solution in the set will be selected as the optimal solution according to the specific requirements of the environment. For the forging process, the most important criterion for judging the quality of the profile is the uniformity of the outlet temperature, that is, the standard deviation of the outlet surface temperature. Therefore, the standard deviation of the outlet surface temperature and the energy consumption of forging are chosen by the optimization objective, and a multi-objective optimization model is established, as shown in equations (2) and (3):

$$\min: \Delta T(\Delta t, t, v), E_{total}(\Delta t, t, v)$$

$$E_{total} = E_t + W_d + \sum_{i=1}^{7} W_{S_i} + \lambda_k \left(W'_d + \sum_{i=1}^{7} W'_{S_i} \right) = f_E(\Delta t, t, v) \tag{2}$$

$$\Delta T=\sqrt{\frac{\sum_{i=1}^{n}(T_i-\bar{T})^2}{n}}=f_{\Delta T}(\Delta t,t,v) \tag{3}$$

In equations (2) and (3), ΔT is the temperature difference. E_{total} is the total energy consumption of deformation. W is the frictional power loss. T_i is the temperature of the selected node on the outlet surface of the profile. T represents the average temperature of the selected node on the outlet surface of the profile. n is the number of nodes selected.

The flow chart of optimization of forging and forming process of PSO is shown in Figure 5:

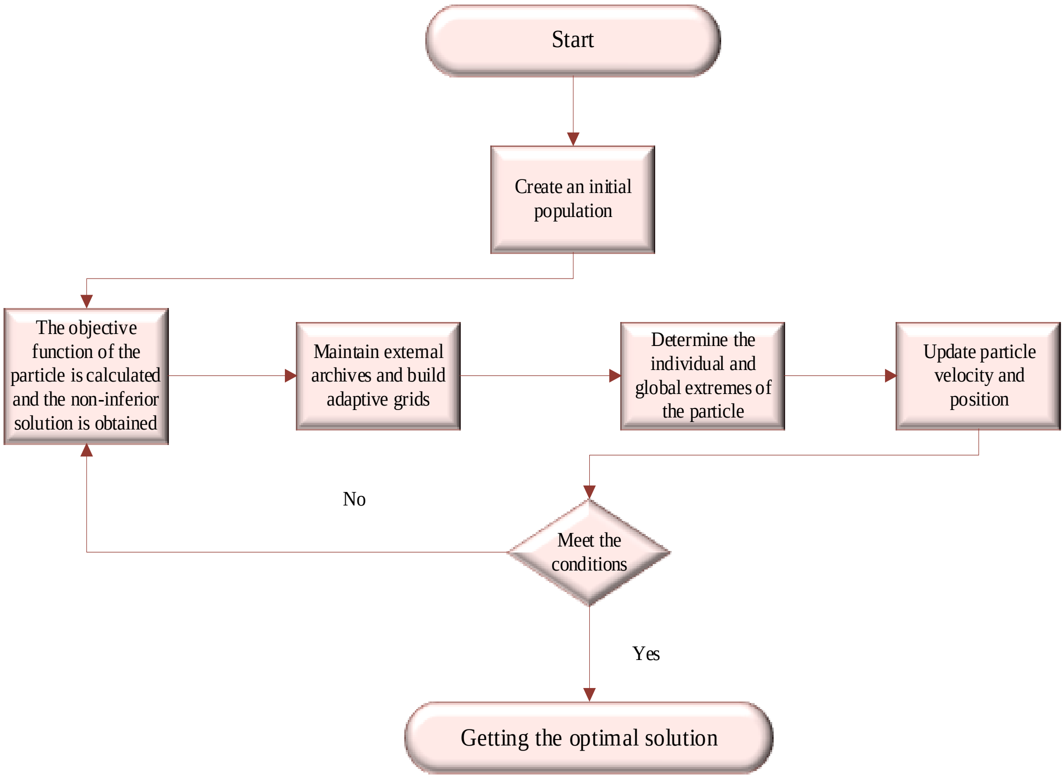


Figure 5: The flow chart of optimization of forging and forming process of PSO

Firstly, when initializing, particles one by one are randomly assigned until the particles of the entire population are copied. It should be emphasized that to determine the maximum diversity of the population, the decision vector should be homogenized first, and there is only one assignment process in the sub-intervals it divides. Secondly, it is to construct the grid. Since the optimization objective includes the energy consumption of forging and the mean square error of the temperature of the outlet surface, the space is selected to be gridded [14]. The calculation method of the t-th dimension target width of the grid is shown in equation (4):

$$\Delta f_1=\frac{\max f_1^i-\min f_1^i}{K_1},\Delta f_2=\frac{\max f_2^i-\min f_2^i}{K_2} \tag{4}$$

In equation (4), K represents the number of grids in the t-th dimension. Δf_1 and Δf_2 mean the first and second dimensions of energy consumption of forging and the standard deviation of the outlet surface temperature on the width.

Then the density of the particles in the grid is calculated, and the calculation method of the number of the corresponding particle in the grid is shown in equation (5):

$$\left(\mathrm{int}\left(\frac{f_1^i-\min f_1^i}{\Delta f_1}\right)+1,\mathrm{int}\left(\frac{f_2^i-\min f_2^i}{\Delta f_2}\right)+1\right) \tag{5}$$

The generation of non-inferior solutions is unavoidable. When PSO is performed, non-inferior solutions will be generated in a single cycle, and the external files responsible for storing non-inferior solutions will also interfere with the operation efficiency of PSO. The external file is truncated, and the impact of the external file storing the non-inferior solution on the algorithm is controlled by setting the upper and lower limits of the file size [15].

The optimal solution is in the generated non-inferior solution, and the optimal solution cannot be determined when the particle swarm optimizes. The method of calculating the global extreme value $P_{g,d}(t)$ of the selected particle i can be described by equation (6):

$$S_i=\{A_{k,t}|A_{k,t}\in A_t,A_{k,t}\succ P_{i,d}(t)\} \tag{6}$$

In equation (6), A represents the file set; all values in the file set that are better than the individual extreme value $P_{i,d}(t)$ of particle i will be stored in the set S_i. In the final result, if the number of global extrema is greater than that, the particle with the smallest density is selected, and if the density is equal, one of them is selected.

The flying direction and speed of each update particle will also be jointly determined according to the individual extreme value and the global extreme value. The method of updating the particle is shown in equations (7) and (8):

$$v_{i,d}(t+1)=\omega v_{i,d}(t)+c_1\times rand()\times(P_{i,d}(t)-x_{i,d}(t))$$
$$+c_2\times rand()\times(P_{i,d}(t)-x_{i,d}(t)) \quad (7)$$

$$x_{i,d}(t+1)=x_{i,d}(t)+v_{i,d}(t) \quad (8)$$

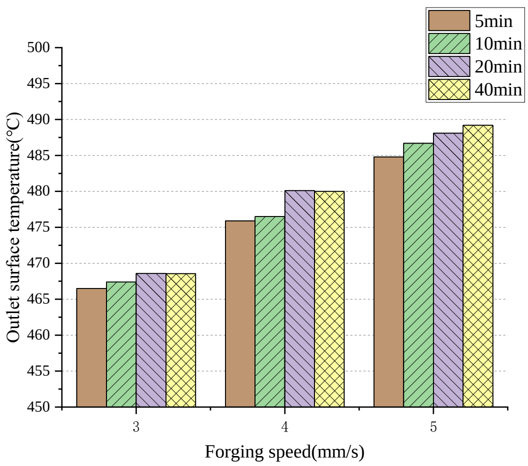
In equations (7) and (8), c means the learning factor. ω represents the inertia weight. The value range of $rand()$ is between 0 and 1. x is the corresponding position at the t-th iteration. v represents the corresponding speed.

The final calculated $P_{g,d}(t)$ is the optimal solution selected from the non-inferior solutions.

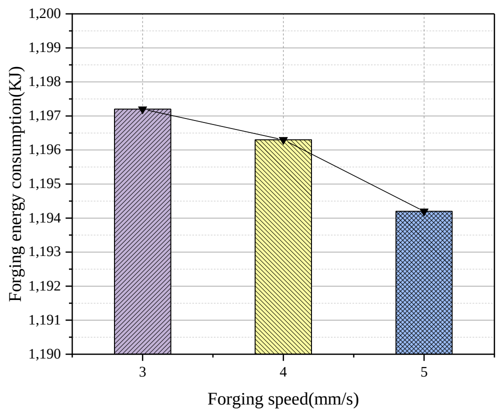
3. Analysis of Experimental Results

3.1 Analysis of Simulation Results

Different forging speeds are used as variables in the simulation because the surface, microstructure and production speed of the forgings are directly affected by them. The initial temperature t of the simulated forging is set to 460 °C, the die and forging temperature is set to 430 °C, and the temperature difference between the forging head and the tail is set to 20 °C. The process parameters of different forging speeds are simulated by simulation software, and the histogram of temperature change at the outlet surface of the forging material is derived. The forging speeds are selected as 3mm/s, 4mm/s, 5mm/s, and the time nodes are 5min, 10min, 20min, and 40min for horizontal comparison, as shown in Figure 6a. Then, according to the established model of energy consumption, the energy consumption is calculated during the forging process under different forging speeds, as shown in Figure 6b:



a



b

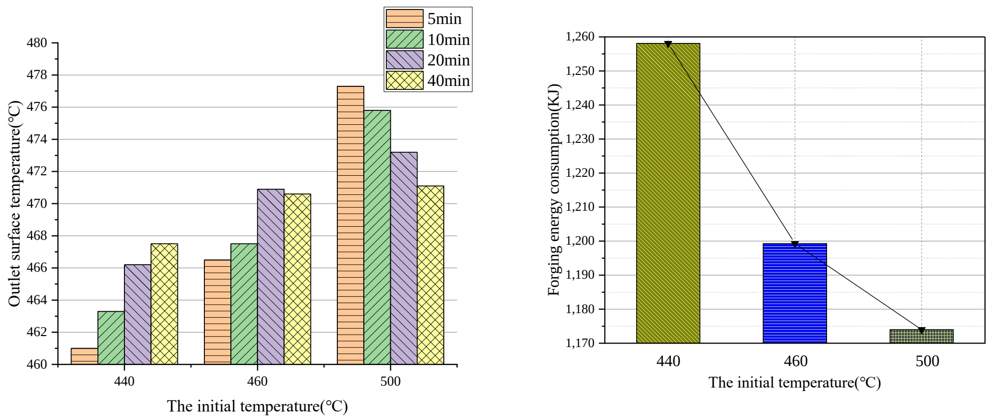
Figure 6: Experimental results under different forging speeds (a. The temperature of the outlet interface under different forging speeds; b. Energy consumption value under different forging speeds)

Through the lateral comparison of Figure 6a, it shows that at the same time point, the higher the forging speed is, the higher the outlet surface temperature increases, and the lower the forging speed is, the lower the temperature increase is. On the one hand, it is because the forgings are deforming while releasing heat (including friction heat). On the other hand, the forging speed increases, the residence time of the forging in the die decreases, the heat exchange time between solids decreases, and the heat diffusion is incomplete, resulting in the continuous increase of the outlet temperature of the forging. However, as the forging continues, the outlet temperature increases very little at 20min and 40min, because the heat lost by the heat exchange between the die and the forging is offset by the heat generated by the friction and deformation of the forging, and the outlet temperature also tends to remain unchanged. In addition, it is not difficult to find that the faster the forging speed is, the faster the forging will be formed, which directly affects the production efficiency of the forging.

Figure 6b indicates that the energy consumption decreases with the increase of the extrusion speed. Although the anti-deformation force increases with the increase of the speed, the increase of the forging speed leads to the reduction of heat exchange, and the temperature residue on the forging tends to reduce the deformation resistance. The energy consumption for forming is also reduced. When calculating the standard deviation of the outlet surface temperature to measure the quality of the aluminum, it is found that the variance first decreases and then increases, indicating that the extrusion speed within an appropriate range can make the temperature of the outlet surface uniform and improve the quality of the aluminum.

Then the initial temperature of the forging is taken as a variable to observe change of the outlet surface temperature, and the initial temperature is set to be 440 °C, 460 °C, and 500 °C, respectively. The forging speed is controlled unchanged, and the time points of 5min, 10min, 20min, and 40min are selected to obtain the change rule, as shown in Figure 7a.

According to the energy consumption model, a histogram of energy consumption values at different initial temperatures is established, as shown in Figure 7b:



a b

Figure 7: Experimental results under different initial temperature (a. Outlet surface temperature under different initial temperatures; b. Energy consumption value under different initial temperatures)

Figure 7a shows that the temperature of the outlet surface of the forging with an initial temperature of 440 °C starts to rise suddenly and then slows down after 20 minutes. The main reason is that the heat energy generated by the temperature of the forging in the die is much greater than the heat energy lost by the heat exchange, so that the residual heat of the forging is retained and the temperature of the outlet surface rises directly. As the temperature of the forgings increases, the heat exchange between the forgings and the die increases, the heat loss and the heat generated are offset, and the tendency of temperature increase slows down in the later stage of forging.

When the initial temperature is 460 °C and 440 °C, the temperature change curves of the outlet face are similar. In contrast, the temperature of the outlet surface of the forging with an initial temperature of 500°C drops significantly. it is because the temperature difference between the die and the forging is too large, and the heat loss from heat exchange also increases, the temperature drops in the later stage of forging, the lost heat is offset with the generated heat, and the downward trend slows down.

Taking the temperature of the same forging truncated outlet surface to calculate the standard deviation of the temperature, it is found that the blasting forging speed is constant, and the standard deviation of the temperature will also increase with the increase of the initial temperature. The increase in the initial temperature of the surface results in a non-uniform temperature distribution at the outlet interface, which affects the quality of the material. Therefore, the initial temperature should be lower than 500 °C.

Figure 7b expresses that with the gradual increase of the initial temperature, the residual heat of the forging increases and the energy consumption decreases significantly, so the increase of the initial temperature within a certain range is conducive to saving energy consumption.

3.2 Results of the Experimental Model of Multi-objective Optimization

The obtained forging process parameters are counted, and the fitting model made by combining the forging energy consumption and the standard deviation of temperature is used as a function of the PSO, and it is easy to obtain the Pareto optimal solution, as shown in Figure 8a.

The simulation software is used to simulate and compare with the initial scheme. The comparison results are shown in Figure 8b:

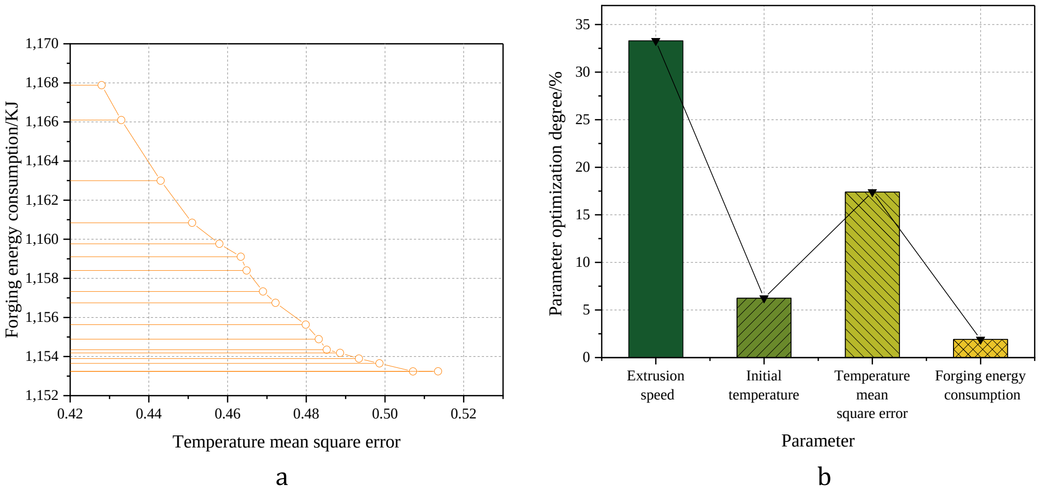


Figure 8: The final result of parameter optimization (a. Pareto optimal solution set; b. Comparison results of parameter optimization)

In Figure 8a, the learning factor c is set to 2. The maximum and minimum weights are set to 0.4 and 0.9 respectively, the number of particle swarms is set to 70, and the number of iterations is 400. Combined with Figure 8b, the optimal solution is obtained as the extrusion speed of 4.5mm/s, and the initial temperature is 450 °C. On the basis of the results, the simulation software is used to simulate and compare with the original scheme. It represents that compared with the initial scheme, the standard deviation of the temperature has decreased from 0.585 to 0.483, a decrease of about 17.4%, indicating that the quality of the material has been significantly improved. Meanwhile, the energy consumption of forging is also reduced from 1177KJ to 1154.8KJ, a decrease of 1.9%.

4. Conclusions

Firstly, the modeling and the simulation of aluminum forging are carried out. The simulation software is used to summarize the action law of initial temperature and forging speed. The simulation results are recorded and the standard deviation of the outlet surface temperature is calculated to further fitting calculations. Secondly, a multi-objective optimization model is established with the initial temperature and forging speed as variables and the goal of reducing the standard deviation of the temperature and energy consumption. Finally, the PSO is used to further solve the model to find the optimal process to reduce energy consumption and ensure the quality of materials, to achieve the purpose of optimizing forging and forming process parameters. The results show that the obtained optimized solution can reduce the standard deviation of temperature by 17.4% and the energy consumption by 1.9% compared with the initial solution, which achieves the purpose of optimizing parameters. However, only some parameters of the process are selected for optimization, and more parameters can be considered in the future, and the energy consumption can be recalculated. Besides, the energy transfer of the forging press is not considered, and the subsequent research can further consider the energy consumption of the forging press. It is of great significance for the selection of parameter optimization of the forging and forming process and the application of PSO in the optimization process.

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