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Multi-Objective Optimization of Vortex Disc Process Parameters Based on Neural Network and Genetic Algorithm

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Abstract. In this paper, a multi-objective optimization strategy of production process parameters based on the neural network and genetic algorithm is proposed with an automotive scroll disk as the research object. The forging forming process is numerically simulated by Deform-3D finite element software, with billet temperature, die temperature, and forming speed as optimization variables, and forming load, residual stress, and die deformation as optimization indicators. The nonlinear mapping relationship between variables and indicators is constructed by using the neural network, and the neural network model is optimized based on the genetic algorithm for dynamic optimization of parameters. The most suitable solutions finally obtained in the Pareto frontier set: billet temperature: 460°C, mold temperature: 220.006°C, forming speed: 18.4158 mm/s, when the values of the three optimized indicators are smaller. The solution was experimentally verified and the obtained vortex discs were filled to the brim with no defects, so the process parameters can be applied to actual production processing.

Keywords. Vortex disk, neural network, genetic algorithm, pareto frontier set

1.Introduction

The process of automotive scroll disc forging production line is complex, and most of them still rely on workers' experience to set the production process parameters [1], but with the increasing market requirements for forgings, finding the optimal production process parameters is extremely important in the scroll disc forging production process [2].

In the process of scroll disk production and processing, setting reasonable processing parameters can improve product quality, reduce production costs, and reduce production energy consumption [3], however, the scroll disk production line process is complex, and if only a single objective is optimized with the degree of optimization of other objectives in the manufacturing process is often diminished [4], this approach is very different from the actual needs. Therefore, scholars at home and abroad have conducted a lot of research on the multi-objective optimization of process parameters.

Liu Ganhua used genetic algorithms for multi-objective optimization of process parameters of MIM, which greatly improved the uniformity of volume shrinkage distribution and powder concentration distribution and improved the quality of MIM

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isometric spiral bevel gears [5]. Zhihua Sha used the signal-to-noise ratio method and the gray correlation degree method for multi-objective optimization of extrusion cutting process parameters to obtain a brake disc surface with good braking performance and long service life [6]. Li Feiyi optimized multiple performance criteria of the inlet generator (IG) based on LSTM recurrent neural network by genetic algorithm, which can better represent the time series of realistic probability distribution for the water resources Recovery Facility (WRRF) design and operation to provide a better description of the intake water [7]. Abedzadeh Maafi Rahmat proposed a pareto design method based on multi-objective optimization based fuzzy full state feedback linearized controller (FFSFLC) for spherical wheel system, which was experimentally validated and compared to other algorithms, the hybrid algorithm achieved better results in a shorter time to obtain a better undominated solution of the Pareto frontier [8]. Wang Xiaoguang developed a multi-objective optimization model using genetic algorithm combined with neural network and designed the cross-sectional shape of the thin-walled body beam, and the feasibility of the method was verified after the CSS optimization of the a-pillar of the car frame [9].

In summary, a multi-objective optimization strategy of production process parameters based on the neural network and genetic algorithm is proposed in order to solve the multi-objective optimization of parameters in the production and processing of automotive scroll discs. Firstly, the forging and forming process is simulated by Deform-3D software to obtain the production and processing parameter data; secondly, a neural network is used to fit the numerical simulation results and construct a nonlinear mapping relationship between variables and indicators [10]; finally, a genetic algorithm is used for dynamic optimization of parameters [11] to obtain the optimal solution of process parameters in the Pareto frontier set [12-13]. The accuracy of the numerical analysis is verified by comparing the numerically simulated formed parts with the actual vortex disc forgings obtained from the tests.

2. Optimized solution design

2.1 Selection of process parameters for forging production of vortex discs

Die temperature, embryo temperature and forming speed play a crucial role in forging and forming results. As the raw material of the vortex disc, Al-6061, the chemical composition of the material is shown in Table 1 below. The material has a narrow forging temperature range and is prone to overburning during the forging process, so a suitable embryo temperature can greatly improve the forming quality. The choice of die temperature will affect the performance of the die, which in turn will affect the form of the product. The downward pressure speed of the mold will directly affect the forming speed of the scroll disk. Choosing the right forming speed can improve the internal structure and surface characteristics of the scroll disk, and also improve the stability and accuracy of the system.

The forming load, residual stress and mold deformation are used as predictive parameters for the superiority of the forming performance of the scroll disc.

Table 1. Chemical composition of vortex disc materials (percent)

Materials	Al2O3	Si	Mg	Fe	Cu	Mn	Cr	Zn	Al
6061Al	0	0.80	0.95	0.50	0.30	0.10	0.20	0.09	Residuals

2.2 Overall framework design of the optimization program

The main design idea is to adopt the design process of "numerical simulation - fitting prediction - parameter optimization - experimental verification". Based on Deform-3D, we analyze the forging process and simulate it numerically. A neural network is used to fit the numerical simulation results of Deform-3D and build the prediction model of the objective function. Subsequently, the optimized index Pareto frontier set is obtained by genetic algorithm to obtain the optimized production process parameters. Finally, forging experiments are carried out according to the optimal parameters to verify the reliability of the optimization results.

3. Numerical simulation of forging process based on Deform-3D

Deform-3 The simulation of the forging and forming process is carried out by Deform-3D finite element software to solve the problem of difficult coupling between various factors in the forging and forming process. Taking the vortex disc forming process as an example, the orthogonal test is designed to simulate the forging forming process numerically, and then the numerical simulation results are analysed theoretically to verify the rationality of numerical analysis.

3.1 Orthogonal experimental design

Take the auto air conditioning compressor scroll disk forming process as an example. Design an orthogonal test, set the billet temperature to 400°C~460°C, the mold temperature to 200°C~240°C and the forming speed to 5mm/s~20mm/s. As shown in Table 2.

Table 2. Orthogonal experimental design

Serial number	Embryo Temperature °C	Mold temperature °C	Forming speed mm/s
1	400	200	5
2	420	220	10
3	440	240	15
4	460		20

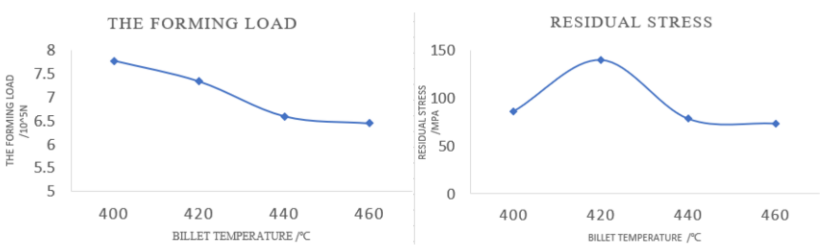
In this orthogonal test, the mold temperature, forming speed and blank temperature are used as input parameters, and the forming load, residual stress and mold deformation are used as predicted parameters. The numerical simulation results are obtained after analyzing the vortex disc forming process by the finite element analysis software Deform-3D simulation using the orthogonal test parameters. The numerical simulation results are shown in Table 3.

Table 3. Experimental design results

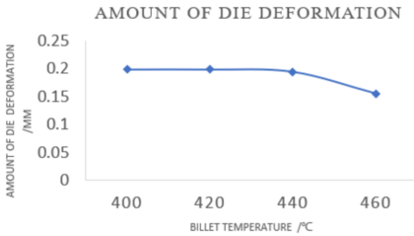
Serial number	Mold temperature °C	Forming speed mm/s	Embryo Temperature °C	Forming load 10^5N	Residual stress MPa	Mold Amount of deformation mm
1	200	5	400	7.13	86.7	0.198
2	200	5	420	7.03	140	0.198
3	200	5	440	6.43	78.9	0.194
4	200	5	460	5.69	73.9	0.155
…	…	…	…	…	…	…
45	240	20	400	7.79	139	0.207
46	240	20	420	7.88	86.9	0.225
47	240	20	440	7.42	67.3	0.210
48	240	20	460	7.31	103	0.199

3.2 Numerical simulation results

Figure 1 shows the effect of billet temperature on the forming results of the scroll disk. From Figure 1 (a), it can be seen that the forming load gradually decreases as the billet temperature rises, which is because as the temperature increases, the fluidity of the metal becomes better and the deformation resistance decreases leading to a decrease in the forming load; in addition, the extra heat generated by friction also raises the billet temperature, which leads to the local overburning phenomenon, causing the grain size to become larger and eventually decreasing the material plasticity. Figure 1 (b) shows that as the billet temperature increases, the maximum residual stress in the forgings increases and then decreases. As the temperature of the billet increases, the temperature difference between the billet and the die becomes larger, forming stress concentration on the surface of the billet, resulting in excessive local stress on the outer surface of the billet and an increase in residual stress; as the temperature continues to increase, the metal flow of the material becomes better and the residual stress will decrease. Figure 1 (c) shows that as the temperature of the billet increases, the deformation of the mold first remains constant and then decreases, which is due to the existence of heat conduction between the billet and the mold, the mold temperature increases and thus the hardness decreases.



(a) (b)

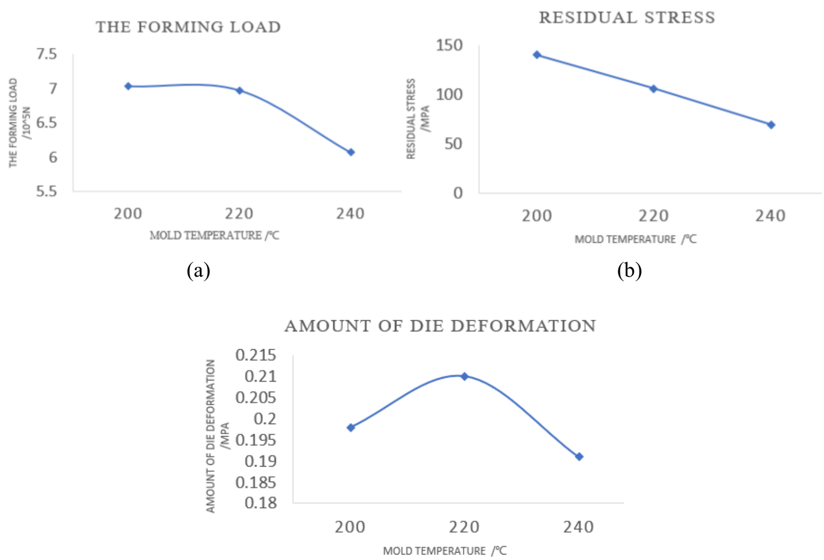


(c)

Figure 1. Influence of billet temperature on forming

(a) Influence of billet temperature on forming load (b) Influence of billet temperature on maximum equivalent stress (c) Influence of billet temperature on mold Deform-3Dation

Figure 2 shows the effect of mold temperature on forming results in the orthogonal test. Figure 2 (a) shows that the forming load decreases as the mold temperature increases and the rate of decrease gradually becomes larger, which is due to the slowing down of heat transfer due to the decrease in temperature difference, which slows down the cooling of the billet and improves the shaping of the billet; in addition, the temperature difference between the mold and the billet decreases as the mold temperature increases, which can relieve the stress concentration phenomenon of the billet. Figure 2 (b) shows that the residual stress tends to decrease as the mold temperature increases, which is due to the fact that increasing the mold temperature will obtain a more stable metallographic organization. Figure 2 (c) shows that the mold deformation tends to increase and then decrease as the mold temperature increases, which is due to the fact that an increase in mold temperature will lead to a decrease in both forming load and forming stress, but the mold hardness will decrease as the mold temperature continues to increase.

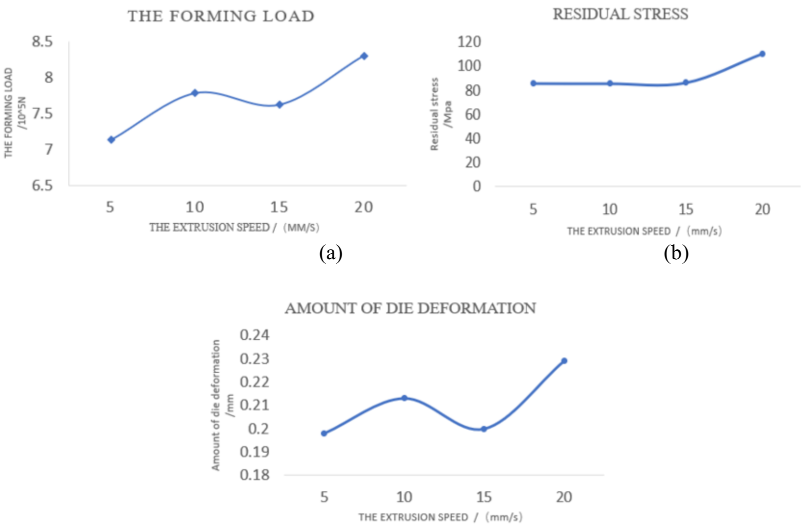


(c)

Figure 2. Influence of die temperature on forming

(a) Influence of die temperature on forming load (b) Influence of mold temperature on equivalent force (c) Influence of mold temperature on mold Deform-3Dation

Figure 3 shows the effect of forming speed on forming results in the orthogonal test. Figure 3 (a) shows that as the forming speed increases, the forming load increases, then decreases, and then increases again, which is due to the fact that as the forming speed increases, the work-hardening phenomenon will occur in the billet, which hinders the metal flow and thus the forming load increases. At the same time, as the forming speed increases, the contact time between the billet and the mold decreases, the uneven stress distribution on the surface of the billet slows down, and the forming load decreases. Figure 3 (b) shows that the maximum residual stress tends to increase significantly as the forming speed increases, which is due to the fact that when the forming speed is too large, part of the billet will not be deformed in time due to the presence of friction when it is in contact with the mold, which eventually generates stress concentration. Figure 3 (c) shows that with the increase of forming speed, the mold deformation rises, then falls and then rises again, which is due to the fact that too slow speed will lead to excessive heat transfer, while increasing the forming speed, the equivalent force on the mold increases, leading to an increase in mold deformation.



(a) (b) (c)

Figure 3. Influence of extrusion speed on forming

(a) Influence of extrusion speed on forming load (b) Influence extrusion velocity on equivalent force (c) Influence of extrusion speed on mold Deform-3Dation

4. Functional model building and parametric multi-objective optimization

Compared with Deform-3D numerical simulation, neural network modeling can significantly improve the computational efficiency and ensure computational accuracy, which can be used to establish a function model through neural networks to predict the production results of the production line in real time. Firstly, the function model is established by neural network, and the calculation results of the function model are compared with the Deform-3D numerical simulation results to verify the accuracy of the neural network model.

In addition, a non-dominated ranking genetic algorithm (NSGA-II) combined with a constructed neural network model is used to dynamically find the optimal process parameters in the pareto frontier for multiple factors of the vortex disk machining and feed back to the physical entity. In addition, to verify the optimization results, Deform-3D is used to validate the optimization results at the end of this paper.

4.1 Neural network-based function model building

The neuron is mainly composed of four major parts: weight, summation mechanism, activation function, and threshold, as shown in Figure 4. The weights are used to assign weights to the input signals, the summation is used to accumulate the weighted numbers, the activation function is used to enable the neural network to fit the nonlinear system, and finally the threshold is used to adjust the computational bias.

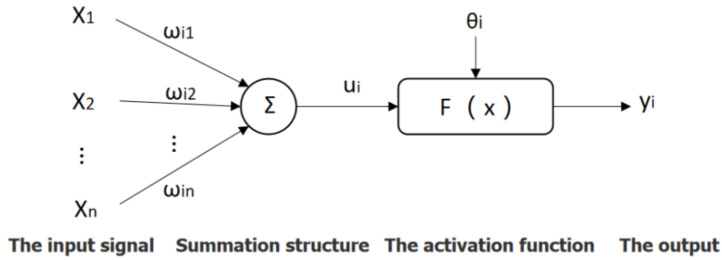


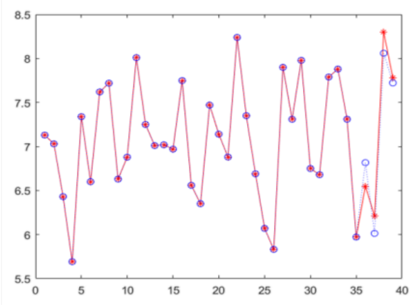
Figure 4. Simple neural network model

The neural network model is constructed in MATLAB using the results of Deform-3D numerical simulations. The input layer of the neural network function model is the production process parameters, and the output layer is the target parameters. In this paper, the input layers are billet temperature, mold temperature, and forming speed, and the output layers are forming load, residual stress, and mold deformation.

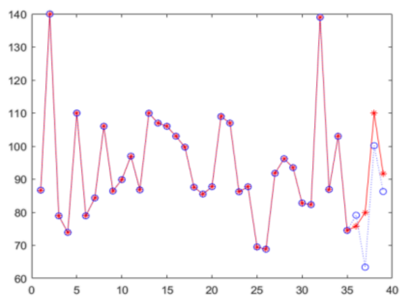
The structure of the neural network is then set. In the paper, the number of hidden layers of the neural network is set to 3 layers, the number of units in the first hidden layer is 20, the number of units in the second hidden layer is 12, the activation function is 2/(1+e^(-2x))-1, the output layer is linear output, and the gradient descent method is used for fitting to obtain the function model.

4.2 Neural network model evaluation

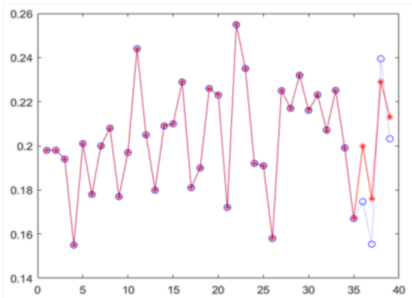
As shown in Figure 5 below, the first 44 points in the algorithm as the training array, the last 4 points as the test array, the test array that is not involved in the neural network model training; after bringing the test data into the neural network model it can be seen that the maximum error between the results calculated using the neural network and the test array is not more than ten percent, so the model has some reference significance.



(a)



(b)



(c)

Figure 5. Evaluation of function model

(a) forming load error (b) equivalent stress error (c) Mold Deform-3Dation error

4.3 Parametric multi-objective optimization

Traditional optimization methods generally convert multi-objective functions into single-objective functions, but with the development of industrial technology, the traditional method of converting multi-objective into single-objective can no longer meet the demand, so it is especially important to use intelligent multi-objective optimization methods. The so-called intelligent multi-objective optimization method is to solve the multi-objective optimization problem by multi-objective optimization method without reducing to the single-objective solution. The advantages of this type of method over traditional optimization methods are: (1) through one operation, the intelligent algorithm can obtain a set of solutions; (2) the search process of the intelligent algorithm for the optimal solution is more stochastic, i.e., the greater the probability of finding the optimal solution; (3) the intelligent algorithm does not have many limitations for the objective function, while the traditional methods have stronger limitations for the objective function, such as usually requiring the objective function when linearly continuous.

The methods of multi-objective optimization are genetic algorithm, particle swarm algorithm, ant colony algorithm, etc. The most commonly used non-dominated sorting genetic algorithm is used in the paper, and the specific process is shown in Figure 6. The concept of Pareto optimal solution is also involved in conducting the numerical study of the legacy algorithm, and the appropriate effective solution is selected in the pareto frontier set as shown in Figure 7.

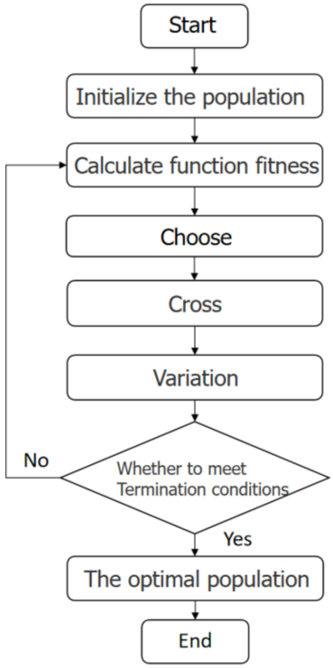


Figure 6. Flow chart of simple genetic algorithm

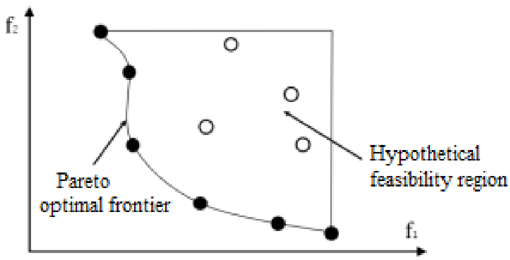


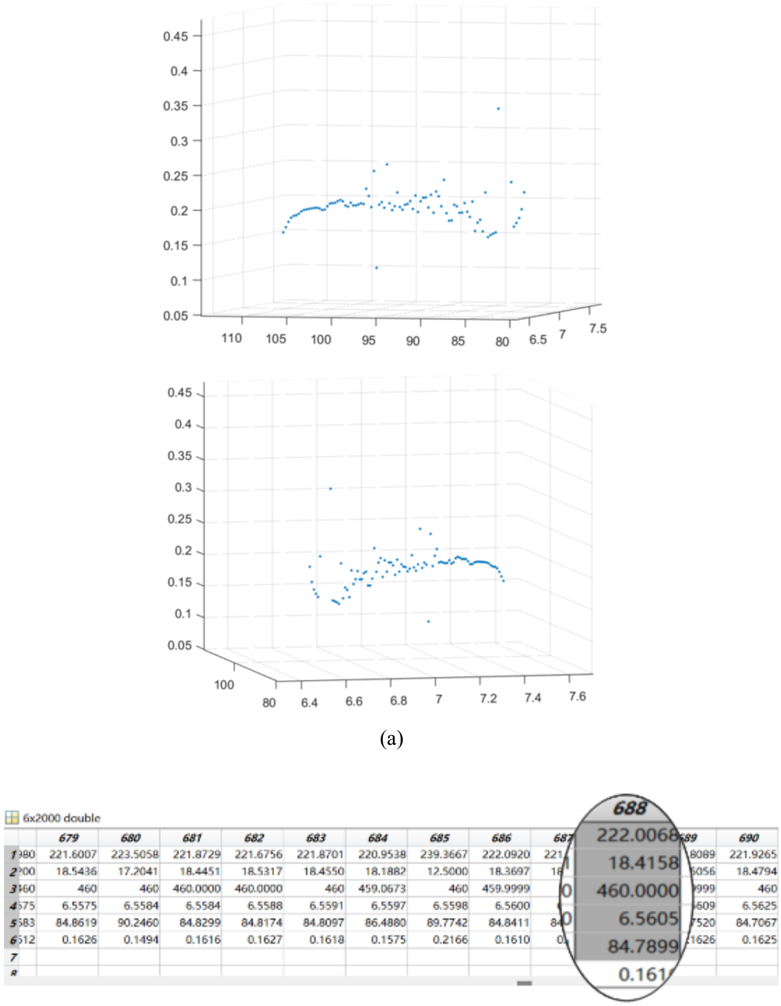
Figure 7. Pareto optimal frontier

In this paper, the number of iterations is set to 1000, and the number of populations is set to 1000 groups. Individuals of the parent generation and the mother generation provide a part of their own genes according to a certain probability, and form offspring after crossover, and in order to prevent falling into the local optimal solution, mutation is used to make the numbers at any position into random numbers within a reasonable range, and then the function model is brought into the genetic algorithm, and through calculation, non-dominated sorting is performed according to the merits of the results, and some individuals are eliminated and the good ones are selected to enter the next cycle.

After the optimization is completed, the three objectives are placed on the coordinates for display, as shown in Figure 8 (a). Each point on the Pareto front in the Figure is a Pareto optimal solution, and behind each point corresponds to the relevant process parameters, which can be fed back to the physical entity for field selection of the optimal results.

4.4 Evaluation of genetic algorithm results

To verify the rationality of the optimization results of the genetic algorithm, the optimal production process parameters shown in Figure 8 (b) are used as an example to validate the model.



(a)

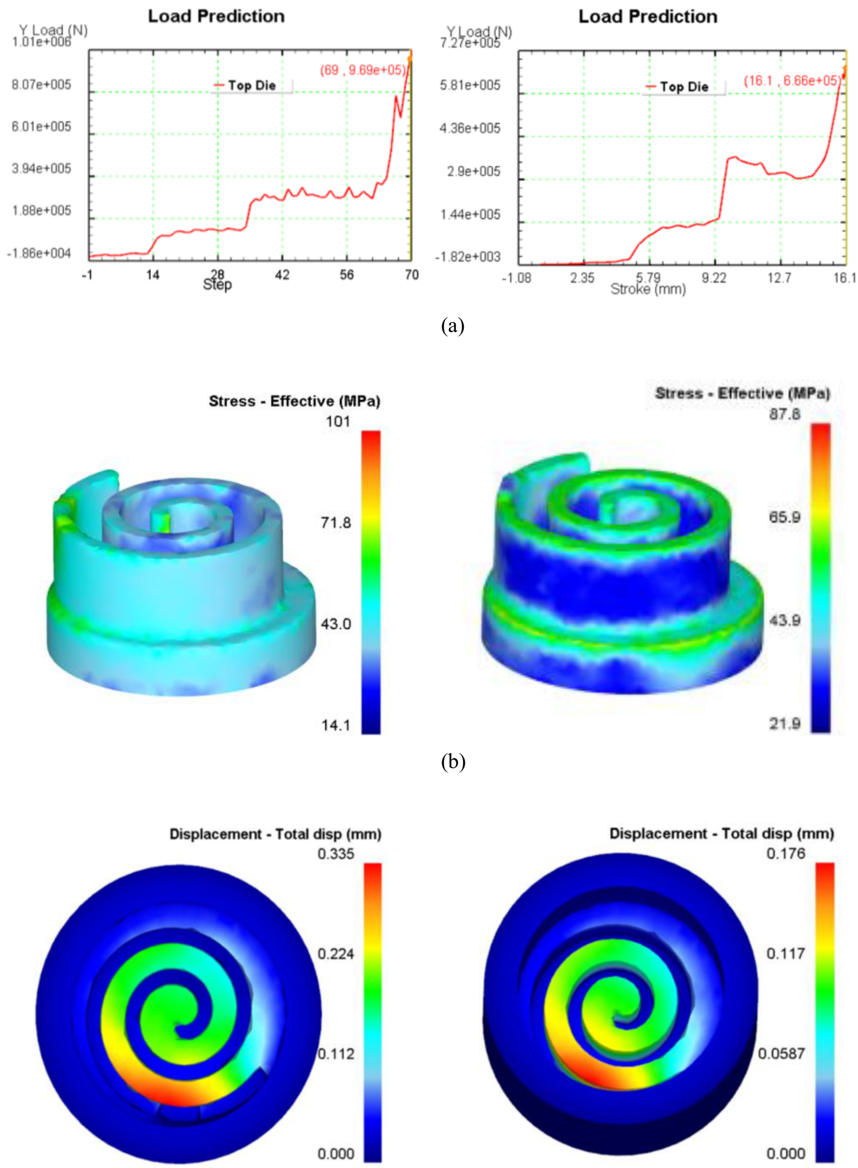
(b)

Figure 8. Optimization will analyze the results

(a) Optimal solution (b) Optimal process parameters

The optimal process parameters after optimization were numerically simulated using the finite element analysis software DEFORM-3D, and the obtained results were compared with the optimized results of the genetic algorithm for verification.

The numerical simulation results of the finite element analysis software DEFORM-3D are shown in Figure 9. The maximum error is less than ten percent. Comparing the forming load, residual stress and mold deformation before and after the optimization, we can see that the forming load is reduced from 969kN to 666kN, the residual stress is reduced from 101Mpa to 87.8Mpa, and the mold deformation is reduced from 0.335mm to 0.176mm.



(c)

Figure 9. Verification of optimization results

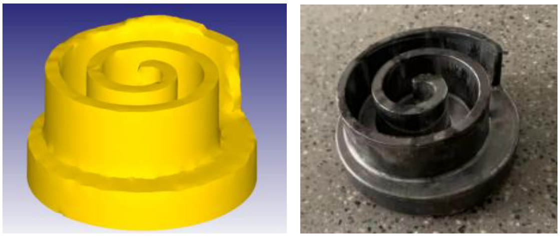
(a) forming load before and after optimization

(b) residual stress before and after optimization

(c) Mold Deform-3Dation before and after optimization

4.5 Experimental verification of numerical results

The numerical analysis results were subjected to corresponding precision die-forging process experiments to verify the reliability of the numerical optimization results. The billet was heated to 460°C using a heating furnace and extruded and formed using a 200T forging press. Figure 10 shows the numerical simulation of the formed part (a) and the physical object obtained from the forming experiment (b). It can be seen that the test results are in good agreement with the simulation results, and the vortex discs are all filled to the brim without defects such as folding, cracks and crush injuries.



(a) (b)

Figure 10. Verification of finite element simulation results

(a) Scroll simulated forming parts (b) actual product precision die forgings

5. Conclusion

1.Deform-3D analysis shows that as the billet temperature rises, the forming load gradually decreases, the maximum residual stress in the forging increases and then decreases, and the die deformation first remains unchanged and then shows a decreasing trend. As the die temperature increases, the forming load decreases, the residual stress decreases, and the die deformation first increases and then decreases. As the extrusion speed increases, the maximum residual stress rises.

2. After training, the maximum error between the prediction result of the neural network model and the test array does not exceed ten percent, which indicates that the model has certain reference significance.

3. After the optimization of genetic algorithm, the forming load decreases from 969kN to 666kN, the residual stress decreases from 101Mpa to 87.8Mpa, the die deformation decreases from 0.335mm to 0.176mm, the corresponding die temperature is 222°C, the billet temperature is 460°C, and the forming speed is 18.4158mm/s. The results of forging experiments show that the vortex discs are all filled full. There are no defects such as folding, cracks and crush injuries.

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