

Multi-objective optimization of process parameters for ultrasonic rolling extrusion of 42CrMo material

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Received: 23 December 2021 / Accepted: 26 January 2023

Abstract. To choose the most suitable method to solve the process parameter optimization of ultrasonic rolling extrusion, the 42CrMo material was taken as the research object. Based on a four-factor five-level orthogonal experiment, the response surface method was used to establish prediction models of the surface roughness, surface residual stress, and work hardening degree. To obtain better Pareto front, resulting in better distribution and convergence of the solution set, the simulated annealing algorithm, particle swarm optimization, second-generation non-dominated sorting genetic algorithm and multi-island genetic algorithm were used to optimize the parameters of ultrasonic rolling extrusion. Comparing the optimization effect with the calculation efficiency, the simulated annealing algorithm is finally selected as the optimization method of the ultrasonic rolling extrusion process parameters, and the optimization parameter domain of the ultrasonic rolling extrusion process is obtained. The optimization model was tested and verified. The results showed that the best optimization effect was achieved after 3000 iterations, and the maximum relative error of the experimental and calculated values for the surface roughness, work hardening degree and residual stress of the optimized 42CrMo material after ultrasonic rolling was controlled within 5%. The established multi-objective optimization model has high accuracy and application value, can realize the optimization of ultrasonic rolling extrusion process parameters.

Keywords: 42CrMo / surface properties / ultrasonic roll extrusion / multi-objective optimization / SA / PSO / NSGA-II / MIGA

1 Introduction

As a medium-carbon low-alloy structural steel, 42CrMo has a high strength, ductility and hardenability, as well as good toughness and fatigue properties [1–3]. Due to its good mechanical properties and relatively low cost, it is widely used to manufacture wind power bearing rings in the wind power field. However, wind turbine bearing rings are subject to high-speed loads for a long time during operation, and the surface is prone to fatigue damage, which affects the service life of the bearing. Only 10% of wind turbine bearings operate normally during their service life, while 90% of bearing failures are related to wearing, flaking, corrosion and friction-induced fractures [4–6]. To improve the surface performance of wind power bearing rings and prolong the service life, surface strengthening technology is usually used to improve the physical and mechanical properties and surface micro-morphology of the surface of the bearing rings [7,8], thereby significantly improving the fatigue life and corrosion resistance of wind power bearing rings.

Ultrasonic rolling extrusion technology is a chipless plastic forming technology that introduces ultrasonic vibration energy into the traditional rolling extrusion processing device so that the tool head vibrates longitudinally at the ultrasonic frequency during horizontal feeding so that the bearing surface produces violent vibrations. Plastic deformation results in residual compressive stress and a work hardened layer on its surface. The residual stress, work hardening degree, and surface roughness reflect the surface properties of the metal materials. A reduction in surface roughness can affect the fatigue strength and wear resistance of metal materials. The generation of residual compressive stress can inhibit the formation of surface microcracks and the degree of work hardening. The improvement can enhance the ability to resist plastic deformation. Ultrasonic rolling extrusion technology is used to strengthen the surface of 42CrMo to improve the surface performance and surface quality of wind turbine bearing rings. In the process of ultrasonic roll extrusion processing, each process parameter affects the surface performance. To analyze the comprehensive interactive influence of each process parameter on the surface roughness, residual stress and work hardening degree and obtain the favorable surface performance of

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42CrMo, it is necessary to perform more target optimization. Therefore, establishing a multi-objective optimization model of 42CrMo surface layer performance to achieve precise control of the residual stress, work hardening degree and surface roughness of 42CrMo and to meet the actual production and processing requirements is an urgent problem to be solved.

In recent years, domestic and foreign scholars have conducted much research on ultrasonic roll extrusion processing. Wang et al. [9] and Liu et al. [10] both performed ultrasonic rolling extrusion fatigue tests on EA4T axle steel and found that the fatigue performance of EA4T axle steel can be improved by the effect of ultrasonic rolling extrusion, where the surface grains are significantly refined. The degree of work hardening and residual compressive stress increase, and the surface roughness decreases, further ensuring the safety and reliability of axle material use. However, as the number of rolling operations increases, excessive plastic deformation causes surface damage and reduces fatigue life. This means that which range the rolling times is located in the surface of the material obtains better performance, which is a common multi-objective optimization problem in engineering applications, but he does not take into account. Wang et al. [11] studied the effect of surface properties on the bending fatigue properties of heavy-duty gear steels. The results showed that the fatigue properties of the 20Cr2Ni4A material treated by ultrasonic rolling have a positive correlation with the surface roughness, surface residual stress and hardness.

Qu et al. [12] studied the effect of ultrasonic surface rolling on the fatigue properties of 25CrNi2MoV steel under different lubricating oil viscosities. The polyalpha-olefin (PAO) was selected as test lubricant, PAO4, PAOmix, and PAO40 were used to represent low, medium and high grade viscosity lubricants. The results showed that the ultrasonic rolling extrusion treatment can significantly refine the surface grains, which is refined to 25 nm and increase the hardness to 547.5 MPa, and produce them on the subsurface. For residual compressive stress, under the action of high-viscosity lubricating oil, an ultrasonic rolling extrusion treatment can effectively improve the fatigue performance. Geng et al. [13] performed ultrasonic rolling on the surface of AZ31B magnesium alloy and found that the surface of AZ31B magnesium alloy produced severe plastic deformation and significantly refined grains. However, as a kind of finishing technology, the workpiece after ultrasonic rolling extrusion is often accompanied by the generation of residual stress and the reduction of surface roughness, and he does not consider it comprehensively.

Ultrasonic surface rolling can improve the integrity of the specimen surface and effectively improve the fatigue resistance of metal materials [14–19]. Among such materials, in order to study the influence of process parameters on the surface roughness of specimens during ultrasonic rolling, Wang et al. [20] established a simulation model through DOFORM software, obtained simulation results using a Box-Behnken design (BBD) type of experimental design, and obtained the predicted values based on simulation results using a response surface

method. In addition, the process parameters were also optimized. Xi et al. [21] used orthogonal experiments to study the influence of the ultrasonic rolling process parameters on the surface quality of the TC4 titanium alloy. The results showed that the ultrasonic rolling extrusion process can significantly improve the physical properties of the surface of TC4 titanium alloy and reduce its surface roughness.

Zheng et al. [22] used the space transformation theory to establish a simulation model of the surface morphology based on the Hertz contact theory and the metal elastoplastic deformation theory to predict the surface morphology of 7075 aluminum alloy treated by ultrasonic roll extrusion and extracted the simulation value calculation and its surface roughness. Xu et al. [23] analyzed the influence of the processing parameters on the residual stress of the ultrasonic rolling bearing surface layer through the ultrasonic rolling extrusion processing test, and the regression model of the ultrasonic rolling extrusion residual stress established compared with the strengthening test, where the relative maximum error was 3.78%. Zheng et al. [24] used ANSYS to simulate the ultrasonic rolling of 7075 aluminum alloy, analyzed the distribution of residual stress through orthogonal experiments.

To study the influence of the ultrasonic rolling extrusion process parameters on surface residual stress, Wang et al. [25] established an ultrasonic rolling dynamic simulation model using ABAQUS software to analyze the distribution of residual stress under different process parameters. The simulation results showed that along the layer, the compressive residual stress in the deep direction first increases and then decreases and then transforms into tensile residual stress. The compressive residual stress increases with increasing static pressure and amplitude. To study the influence of ultrasonic rolling extrusion process parameters on surface residual stress, Jiao et al. [26] used ANSYS software to establish a 12Cr2Ni4A gear steel ultrasonic rolling extrusion simulation model and used a nonlinear curve fitting method to establish a residual stress prediction model. The residual compressive stress on the surface of the 12Cr2Ni4A gear steel treated by ultrasonic rolling increased with increasing static pressure and decreased with increasing spindle speed and feed rate. To analyze the mechanical properties of the surface of the material after ultrasonic rolling, Liu et al. [27] used the nano-indentation method to obtain the load-displacement curve and determine the local microplasticity of the material. They found that the surface yield strength of the material after ultrasonic rolling was very high and was greatly improved.

To study the effect of ultrasonic surface rolling on the fretting fatigue behavior of Ti-6Al-4V alloy, Liu et al. [28] conducted an ultrasonic rolling test on Ti-6Al-4V alloy on a lathe, and the results showed that the ultrasonically treated Ti. The surface hardness of 6Al-4V alloy is significantly higher than that of untreated specimens. Additionally, the fretting fatigue limit increased by 72.7%, which can effectively inhibit the occurrence of surface cracks. Zhang et al. [29] studied the microstructure and mechanical properties of 17-4PH stainless steel treated by ultrasonic rolling. The microstructure was observed by

X-ray diffraction and scanning electron microscopy, the surface of the 17-4PH stainless steel treated by ultrasonic rolling forms a deformed layer composed of nano-level grains, and the hardness is significantly improved. The hardness of a deformed layer composed of nano-level crystal grains was significantly improved. Yao et al. [30] established a neural network prediction model for the physical and mechanical properties of the surface layer of an ultrasonic rolling extrusion bearing ring through orthogonal experiments and analyzed the influence trends of various process parameters on the surface mechanical properties. The results showed that the average relative error between the predicted value of the residual stress on the surface of the bearing ring and the test value is 3.9%, and the relative error of the degree of work hardening is 3.31%.

Scholars all focus on the research on the properties of a single surface layer of ultrasonic rolling extrusion, including surface roughness, residual stress or work hardening degree, etc. At the same time, it is not common to analyze the properties of the three surface layers of the specimen after ultrasonic rolling extrusion processing. Moreover, the properties of the surface layer after ultrasonic rolling extrusion are often restricted and influenced by each other, and the properties of the surface layers cannot be optimized at the same time. A multi-objective optimization algorithm needs to be used to optimize the process parameters. There are many kinds of multi-objective optimization algorithms, including particle swarm algorithm, NSGA-II, simulated annealing algorithm and so on. It is particularly important to choose which optimization method is more suitable for the optimization of ultrasonic rolling extrusion process parameters.

Therefore, scholars have conducted much research on ultrasonic rolling extrusion processing to obtain better surface performance; however, there are few studies that have been presented on the optimization of 42CrMo ultrasonic roll extrusion process parameters through multi-objective optimization algorithms. To obtain a better Pareto front, resulting in better distribution and convergence of the solution set, it is necessary to conduct in-depth research on the optimization of ultrasonic rolling extrusion processing parameters. In this paper, the surface roughness, work hardening degree and residual stress models are established by the response surface method, and the significance of the model was tested. This shows that the established second-order regression equation has a good fit and small error and can be used for multiple surface performances, SA, PSO, NSGA-II and MIGA were used to optimize the parameters of ultrasonic rolling extrusion. Comparing the optimization effect with the calculation efficiency, the simulated annealing algorithm is finally selected as the optimization method of the ultrasonic rolling extrusion process parameters, and the optimization parameter domain of the ultrasonic rolling extrusion process is obtained. The optimization model was tested and verified.

2 Materials and methods

The test piece is 42CrMo bar material after quenching and grinding. The size of the test piece is $\Phi 50 \text{ mm} \times 300 \text{ mm}$,

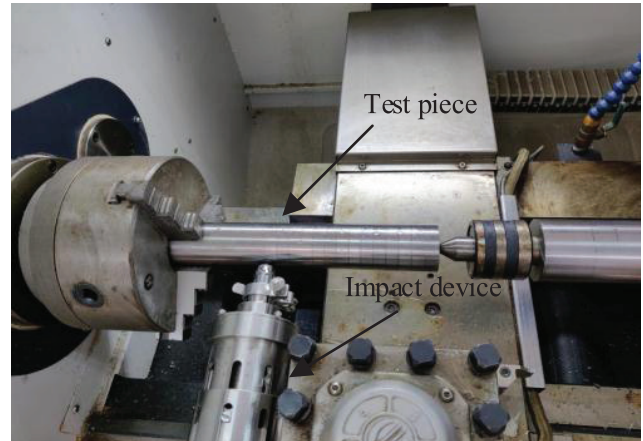


Fig. 1. Ultrasonic rolling extrusion process.

and the hardness is 630 HV. The processing length of each group of cylindrical bars is 20 mm. The test piece is shown in Figure 1, and its main chemical composition is shown in Table 1.

Four factors (speed n , feed speed v , amplitude A , static pressure F) five-level $L_{25} (5^4)$ orthogonal test design method for sample placement, three evaluation results are surface roughness, work hardening degree, residual stress, Get 25 sets of test results. The level factor settings are shown in Table 2.

Ultrasonic rolling extrusion process is shown in Figure 1. Ultrasonic rolling extrusion equipment is consisting of an ultrasonic generator, transducer, horn, and rolling extrusion head. The ultrasonic rolling extrusion processing test is carried out on the ZAK4085DI CNC machine tool. The surface roughness (R_a) of the specimen is measured by the MarSurf VD 280 Profiler, Which measurement range is between $0.025\text{--}12.5 \mu\text{m}$, and the error range is between -5% to $+5\%$. The surface hardness of the specimen is measured by the HVS-1000A microhardness meter; The residual stress (RS) of the surface layer of the test piece is measured by the Xstress3000 X-ray stress instrument. The test selects the test voltage of 30 kV, the current of 7 mA and the Cu target K_α ray to irradiate the surface of the test piece, the radiation area is 1 mm^2 , and the $\sin 2\phi$ method was selected to measure the surface residual stress. The value of the ϕ angle is 0° , 45° , and three points are taken on the same test piece to measure, and then the average value is obtained.

During the ultrasonic rolling extrusion process, due to the action of the static pressure of the rolling head and the ultrasonic impact force, the surface layer of the test piece undergoes severe plastic deformation and local grain refinement, resulting in the occurrence of work hardening (N_H). It can improve the hardness and strength of the surface layer of the material, but excessive work hardening will reduce the plasticity and toughness of the surface layer of the material. In order to evaluate the severity of the work hardening phenomenon, the work hardening degree is selected as the evaluation parameter, and its calculation

Table 1. Chemical composition of 42CrMo test (mass fraction %).

C	Mn	Cr	Mo	Si	Ni	Fe
0.37	0.77	0.98	0.21	0.15	0.04	97.44

Table 2. Processing parameters of orthogonal test.

Number	Rotating speed $n/(r/min)$	Feed rate $v/(mm/min)$	Amplitude $A/\mu m$	Static pressure F/N
1	130	15	5	200
2	250	25	10	280
3	340	30	15	350
4	490	40	20	480
5	630	55	25	600

formula is shown in equation (1).

$$N_H = \frac{H_v}{H_{v0}} \times 100\%, \quad (1)$$

where N_H is the degree of work hardening (%); H_v is the surface hardness after processing; H_{v0} is the surface hardness of the substrate.

3 Results

Through the orthogonal test of four factors and five levels, the following experimental results are obtained, the test results are shown in Table 3.

Use the response surface method shown in equation (2) to establish the mathematical relationship between surface performance and various process parameters [31]. Based on the test results in Table 3, models of the surface roughness, residual stress, and work hardening degree are established

$$R_a(RS, N_H) = \beta_0 + \sum_{i=1}^n \beta_i w_i + \sum_{i=1}^n \sum_{j=1, i < j}^n \beta_{ij} w_i w_j + \sum_{i=1}^n \beta_{ii} w_i^2 + \varepsilon \quad (2)$$

where β_0 is the constant term coefficient; β_i is the first-order coefficient; β_{ij} and β_{ii} are the quadratic term coefficients; w_i and w_j are influencing factors; and ε is the error.

To evaluate the accuracy of the established model, the analysis of variance (ANOVA) of the model is required, and the results are shown in Tables 4–6, where N/A indicates that F value is not applicable.

The ANOVA of the surface roughness, residual stress and work hardening degree of ultrasonic rolling extrusion processing specimens in Tables 4–6, which show the second-order regression model F of the surface roughness, residual stress and work hardening degree; the corresponding values are 244.69, 213.57, 154.97, $F > F_{0.05}$, $P < 0.0001$, respectively, indicating that the second-order regression model equations for surface roughness, residual stress, and work hardening degree are highly effective. The R^2 values of the model are 95.70%, 97.96%, 96.33%, respectively,

indicating that it is highly significant at the 95% confidence level. The established model value has a high correlation with the test value, the fit is good and the error is small.

Figures 2a–2c show the residual distribution of surface roughness, residual stress, and work hardening degree, and most of the sampling points are located near the reference line, which means that the test results are consistent with the predicted values. The residuals of the surface performance in the regression model follow a normal distribution, indicating that the established multi-objective mathematical model is more accurate.

4 Discussion

Four common optimization algorithms including simulated annealing method, particle swarm optimization algorithm, NSGA-II algorithm and multi-island genetic algorithm were used to optimize the parameters of ultrasonic rolling extrusion process of 42CrMo material. The process parameter domains of different optimization algorithms (SA, PSO, NSGA-II, MIGA) were analyzed, and the optimal process parameter domain of ultrasonic rolling extrusion was determined by comparing the calculation efficiency and calculation accuracy.

This paper adopts the objective function when minimizing the surface roughness and maximizing the work hardening degree and residual compressive stress through a multi-objective optimization. Because the surface residual stress is compressive stress, the result obtained by the model is negative; therefore, when establishing a multi-objective optimization model, the residual stress is minimized. According to the optimization principle of the simulated annealing algorithm, the optimal value is found to be the value of the objective function. Therefore, a negative sign is added before the degree of work hardening and the minimum value is found. The expression of the multi-objective optimization model is shown in equation (3).

$$\begin{cases} \text{Min}[R_a \quad (n.v.A.F)] \\ \text{Min}[-NH \quad (n.v.A.F)] \\ \text{Min}[RS \quad (n.v.A.F)] \end{cases} \quad (3)$$

Table 3. Orthogonal test results of ultrasonic rolling extrusion.

Number	n /(r/min)	v /(mm/min)	$A/\mu\text{m}$	F/N	$R_a/\mu\text{m}$	RS/MPa	$N_H/\%$
1	130	15	5	200	0.665	-901	1.083
2	130	25	10	280	0.524	-983	1.105
3	130	30	15	350	0.456	-1031	1.123
4	130	40	20	480	0.382	-1113	1.138
5	130	55	25	600	0.333	-1153	1.142
6	250	15	10	350	0.536	-1028	1.117
7	250	25	15	480	0.435	-1092	1.132
8	250	30	20	600	0.382	-1160	1.153
9	250	40	25	200	0.559	-940	1.135
10	250	55	5	280	0.539	-939	1.093
11	340	15	15	600	0.432	-1151	1.143
12	340	25	20	200	0.614	-937	1.137
13	340	30	25	280	0.519	-1012	1.142
14	340	40	5	350	0.524	-971	1.096
15	340	55	10	480	0.424	-1064	1.123
16	490	15	20	280	0.586	-997	1.142
17	490	25	25	350	0.500	-1053	1.151
18	490	30	5	480	0.493	-1038	1.103
19	490	40	10	600	0.415	-1116	1.126
20	490	55	15	200	0.597	-907	1.122
21	630	15	25	480	0.477	-1121	1.155
22	630	25	5	600	0.471	-1082	1.107
23	630	30	10	200	0.671	-898	1.103
24	630	40	15	280	0.553	-979	1.122
25	630	55	20	350	0.479	-1019	1.134

Table 4. Analysis of variance of surface roughness.

Factor	Freedom	Sum of squared deviations	Mean square deviation	F
Regression	14	0.177577	0.012684	244.69
Error	10	0.000518	0.000052	N/A
Sum	24	0.178096	0.012736	N/A

On the premise of meeting the safety requirements in the processing process, combined with the actual conditions of CNC machine tools, ultrasonic rolling extrusion processing test equipment, etc., appropriate process parameters are selected, and the range of ultrasonic rolling extrusion processing parameters is set, as shown in equation (4):

$$s.t. \begin{cases} 130 \text{ r/min} \leq n \leq 630 \text{ r/min} \\ 15 \text{ mm/min} \leq v \leq 55 \text{ mm/min} \\ 5 \mu\text{m} \leq A \leq 25 \mu\text{m} \\ 200 \text{ N} \leq F \leq 600 \text{ N} \end{cases} \quad (4)$$

4.1 Multi-objective optimization of ultrasonic rolling extrusion process parameters based on SA

The idea of simulated annealing (SA) is derived from the process of decreasing the annealing temperature of solids.

This process has much in common with the genetic algorithm; that is, new solutions are generated by mutation to replace old solutions [32]. The simulated annealing algorithm is easier than the genetic algorithm because it compares only one solution at a time in the design space, while the genetic algorithm compares a set of solutions (a population). In addition, the simulated annealing algorithm does not have to consider complex crossover situations, which can save a considerable number of design steps. In the case of the few variables in this experiment, the simulated annealing algorithm is better than the particle swarm algorithm and genetic algorithm.

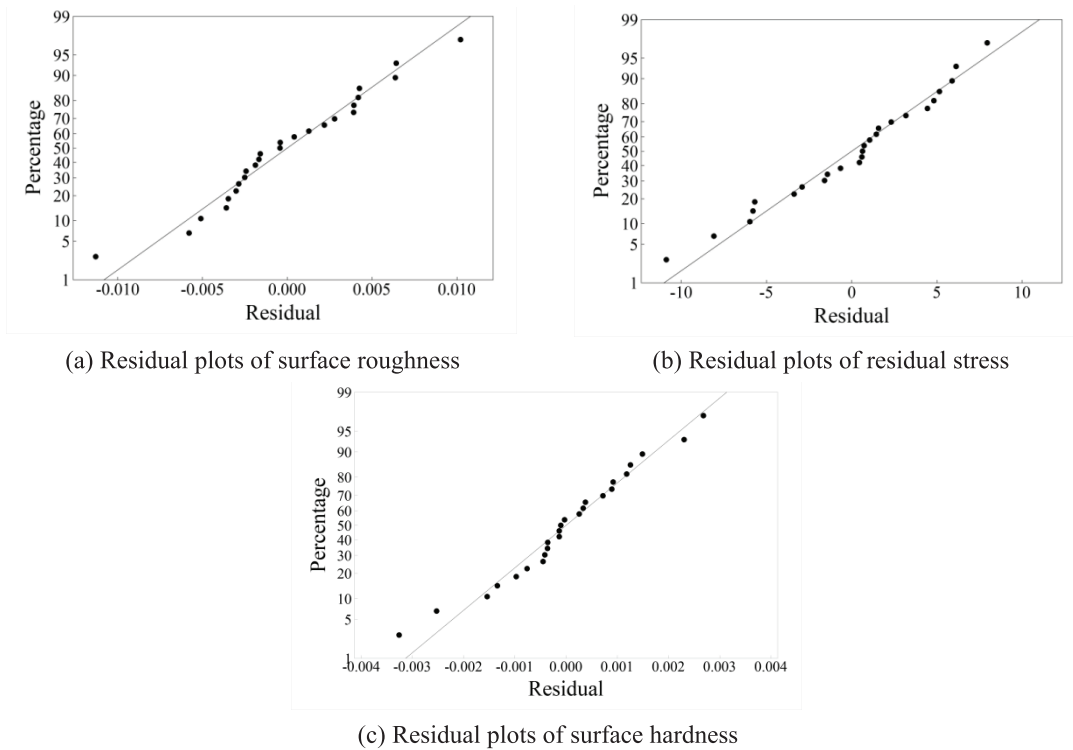
According to the principle of solid annealing, the internal energy of the solid is expressed through the value of the objective function and the temperature is expressed through the control parameter. Taking the initial value as the starting point, a new solution is randomly generated, and the difference between the new solution and the

Table 5. Analysis of variance of residual stress.

Factor	Freedom	Sum of squared deviations	Mean square deviation	F
Regression	14	160880	11491.4	213.57
Error	10	538	53.8	N/A
Sum	24	161418	11545.2	N/A

Table 6. Analysis of variance of surface hardness.

Factor	Freedom	Sum of squared deviations	Mean square deviation	F
Regression	14	0.009462	0.000676	154.97
Error	10	0.000044	0.000004	N/A
Sum	24	0.009506	0.00068	N/A

**Fig. 2.** Residual plots of surface performance.

objective function of the initial solution is considered to determine whether to accept the new solution. If it is acceptable, the initial solution is replaced by the new solution. The above iteration process is repeated. When the temperature drops, the system gradually tends to balance to find the optimal solution.

According to the Metropolis criterion [33] for judging whether the new solution is the optimal solution, the criterion is shown in equation (5).

$$p = \begin{cases} 1 & E_b \leq E_a \\ \exp\left(\frac{E_a - E_b}{kT}\right) & E_b > E_a \end{cases} \quad (5)$$

If the energy E_b of the new solution is smaller than the energy E_a of the initial solution, according to the Metropolis criterion, the new solution is regarded as the current optimal solution. If the energy E_b of the new solution is greater than the energy E_a of the initial solution, there is a certain probability that the new solution is regarded as the optimal solution. In contrast, the initial solution is regarded as the current optimal solution.

The annealing start temperature is set to T_0 , the termination temperature is set to T_f , the cooling coefficient is set to β , and the Markov chain length is set to L_k and rand is set to a random value in (0,1). The optimization principle of the simulated annealing algorithm is shown in Figure 3.

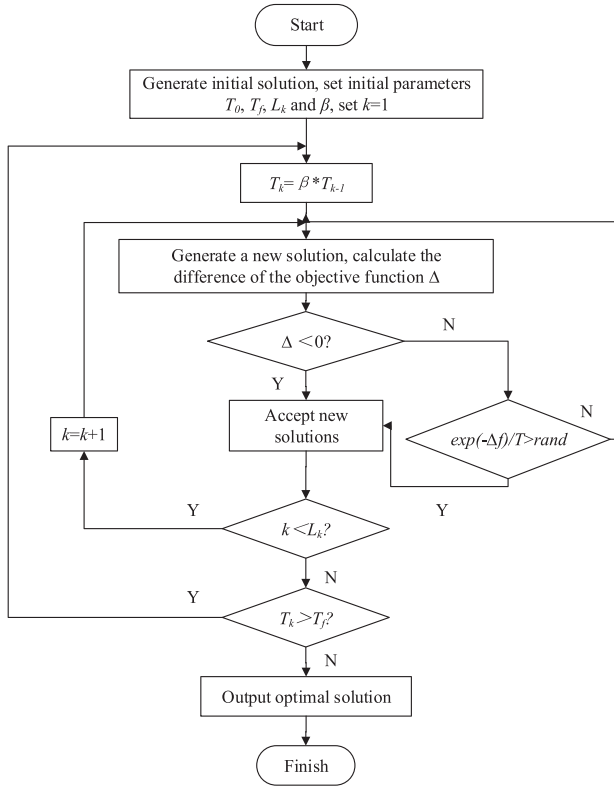


Fig. 3. Operation flow chart of SA.

When the optimization target dimension is not high and the problem is relatively simple, the maximum number of iterations for this optimization is set to 3500, the check convergence interval is set to 5, the relative rate of the quenching loss function is set to 1, and the simulated annealing threshold magnification is set to 1000. The threshold power exponent is set to 2.

The simulated annealing algorithm is used to optimize ultrasonic rolling extrusion process parameters, and the corresponding optimal surface performance parameter domain is obtained. The optimization results under different iteration times are shown in Figure 4. The figures intuitively reflect the entire process of the initial population from the initial iteration to the final convergence, and the optimal solution set is obtained. Figure 4a shows the optimization result for 500 iterations. The randomly generated particle population begins to converge to a smaller feasible solution space, but it is not continuous. Figure 4b shows the optimization result for 1000 iterations. Figures 4c–4e show the optimization results for 1500 to 2500 iterations. Compared to the optimization results for 1000 iterations, the particles at this time show a gradual convergence trend with L-shaped, and the number of optimal solutions is greatly increased. The distribution is relatively uniform; Figure 4f shows the optimization result for 3000 iterations. At this time, the particles are more concentrated in the optimal solution sets, the convergence trend is good, the optimal frontier obtained is smoother, and the optimal solution distribution is even. Figure 4g shows the optimization results for 3500 iterations. Compared with the results for 3000 iterations, the particle convergence effect at this

time is somewhat divergent, and the improvement in the convergence effect is not obvious. To increase the calculation efficiency, the number of iterations is set to 3000.

It can be seen from the figure that in the optimization process, when the surface roughness decreases, the work hardening degree decreases, and the residual compressive stress first increases and then decreases; when the work hardening degree increases, the surface roughness becomes larger and the residual pressure The stress first becomes larger and then becomes smaller. Therefore, the surface roughness, the degree of surface work hardening and the surface residual compressive stress are mutually restricted and affect each other. The improvement of one performance will lead to the decrease of the other performance, and the three cannot reach the optimal at the same time, so only A group of relatively optimal can be selected from it. It is easier to obtain the optimal solution when the speed and feed rate are smaller, and the amplitude and static pressure are larger.

4.2 Multi-objective optimization of ultrasonic rolling extrusion process parameters based on PSO

PSO was first proposed by Kennedy, Eberhart and others in 1995. It originated from the predation behavior of birds, and found Pareto solution according to the snatch and cooperative predation among birds. Using the method of evolutionary computing, the PSO algorithm selects particles to search for the optimal solution in the space, and there is no crossover and mutation in the genetic algorithm. Compared with the genetic algorithm, it is simpler and easier, and there are not many parameter settings.

In particle swarm optimization, the optimal solution of each optimization problem is equivalent to a bird in the search space, called a particle, and each particle has its own position. Assuming that q particles form a population, each particle represents a solution within the range, and its own fitness is calculated through the objective function [34]. When searching for a new solution, the individual optimal solution and the population optimal solution are used as benchmarks to change the position and velocity of the particle itself. As shown in Figure 5, clearly express how the particle position changes.

The equation of particle refresh speed is shown in equation (6), and the equation of refresh position is shown in equation (7) [35].

$$v_{mn}(t+1) = \omega v_m(t) + c_1 r_1 [p_{mn}(t) - x_{mn}(t)] + c_2 r_2 [p_{gn}(t) - x_{mn}(t)] \quad (6)$$

$$x_{mn}(t+1) = x_{mn}(t) + v_{mn}(t+1) \quad (7)$$

where random values between 0 and 1 are represented by r_1 and r_2 . c_1 is the self-learning factor, and c_2 is the social learning factor. x_{mn} represents the position of the particle numbered m in n dimensions, and v_{mn} represents the velocity of the particle numbered m in n dimensions. p_{mn} represents the best position of the individual when searching for food, and p_{gn} represents the best position of the population when searching for food. ω is the inertia weight.

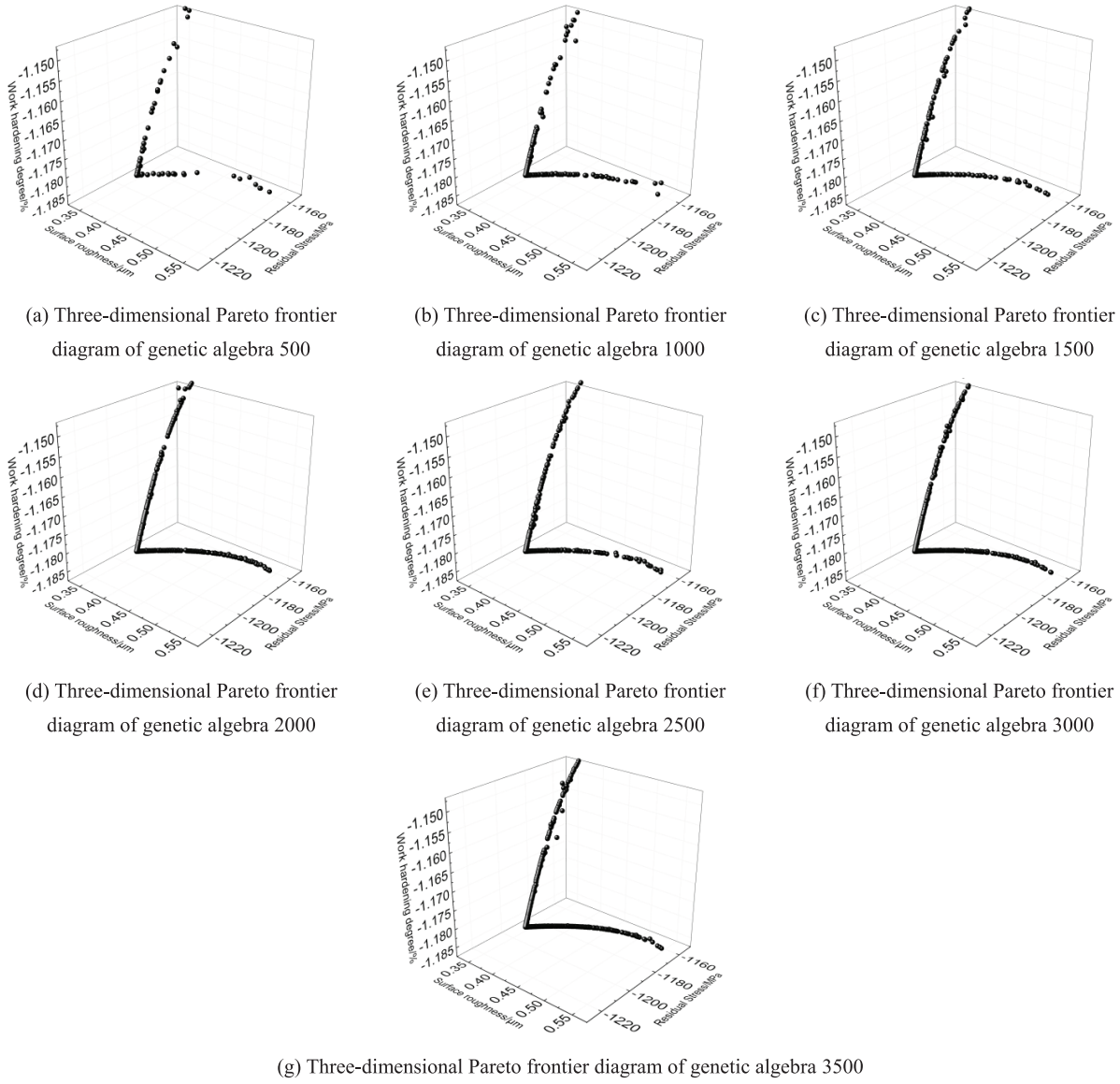


Fig. 4. Three-dimensional Pareto frontier diagram obtained by SA.

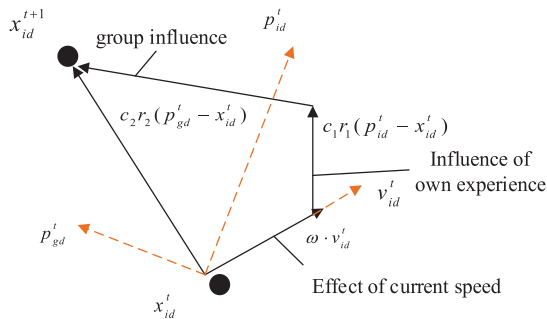


Fig. 5. Updated diagram of particle position.

The flowchart of the particle swarm algorithm is shown in Figure 6, and the algorithm steps are:

- Initialize the velocity and position of particles whose population size is m .
- Solve the fitness of all particles.
- Compare the current fitness of all particles with the best position $pbest$ it has experienced. If the current fitness is good, update the current fitness and use it as $pbest$, otherwise, keep it unchanged.
- Compare the current fitness of each particle with the best position $gbest$ experienced globally. If the current fitness is better than the best position $gbest$ experienced globally, update the fitness of the natural position to $gbest$.

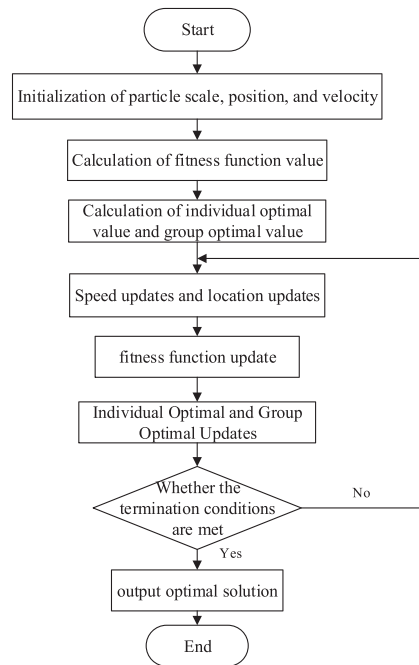


Fig. 6. Operation flow chart of PSO.

Update the current velocity and position of the particle according to equation (6) and equation (7).

- According to whether the desired fitness is reached or the maximum number of iterations is reached, if any condition is met, record the current fitness as the optimal solution, and end the algorithm, otherwise return to step (2), and continue to run the particle swarm in a loop iteration algorithm.

The influence of the number of particles on the search for the global optimal solution is not very large. Usually, the number of particles between 20 and 60 can find good Pareto optimal solution, and the number of particles for complex nonlinear problems can be up to 100. When the optimization target dimension is not high and the problem is relatively simple, to reduce the optimization time, the population size can be set to 30.

The inertia weight indicates the degree to which the speed of the particle is affected by the original speed at the moment. The proper choice of w can effectively avoid falling into the local optimal solution and obtain the global optimal solution. A small value of w can enhance the local search ability, and a large value of w can enhance the global search ability. Determine the inertia weight w suitable for this ultrasonic rolling extrusion parameter optimization to be 0.8.

The number of iterations of the particle swarm algorithm will affect whether the optimization results will eventually converge. However, the number of iterations is not as large as possible, meaninglessly increasing the number of iterations will only increase the computational load of the computer and prolong the solution time. According to the optimization of ultrasonic rolling extrusion of 42CrMo material, the maximum number of iterations is set to 7000.

The particle swarm algorithm was selected to optimize the ultrasonic rolling extrusion process parameters, and the corresponding optimal surface performance parameter domain was obtained. Obtained Pareto front diagram is shown in Figure 7, which clearly shows the whole process from the initial iteration to the final convergence of the initial population, and the optimal solution set of Pareto is obtained. When the number of iterations is 2000, the particles are chaotically distributed in the space, and the number of Pareto optimal solutions obtained is small and sporadically distributed at the lower end of the frontier. In the process of iterating from 3000 times to 6000 times, the convergence effect is gradually good, the obtained particle distribution becomes smoother and smoother, and the number of optimal solutions is more and more uniform, but when iterating 7000 times, the work hardening degree is [114.5%, 115%], the particles appear superimposed, and with the increase of the number of iterations, no new optimal solution can be searched, and the solution with residual stress of -1151.94 Mpa, surface roughness of $0.361 \mu\text{m}$ and work hardening degree of 114.5% is always found. Repeated search in the process can not escape the local optimal solution. When the number of iterations is 8000, obtained three-dimensional Pareto solution appears discontinuous in the degree of work hardening [118%, 118.5%], and the convergence effect is not good.

Similarly, in the optimization process of particle swarm optimization, when the degree of work hardening increases, the surface roughness increases instead, and the residual compressive stress first increases and then decreases. When the surface roughness decreases, the degree of work hardening decreases, and the residual compressive stress shows a trend of increasing first and then decreasing. The three evaluation indexes of the surface performance of ultrasonic rolling extrusion cannot be the best at the same time. Compared with the simulated annealing algorithm, the optimization effect of particle swarm algorithm is not good.

4.3 Multi-objective optimization of ultrasonic rolling extrusion process parameters based on NSGA-II

The NSGA was first proposed by Srinivas. It is innovative from the traditional genetic algorithm. Compared with the traditional GA, it first performs non-dominant sorting on each solution, and then operates according to the sharing mechanism. The solutions solved by NSGA have various sex, and prevent premature convergence. However, the algorithm takes a long time to calculate, and the calculation is complicated, and the shared parameter σ needs to be specified in the calculation process, and there is no suitable method to determine the value of σ . To this end, Deb et al. proposed the second-generation non-dominated sorting genetic algorithm (Non-Dominated Sorting Genetic Algorithm II—NSGA-II) based on the NSGA, which introduced the methods of crowding distance calculation and crowding distance sorting [36], in the solution process, the non-dominated sorting is performed first, and then the optimal solution is determined according to the calculation of the crowding distance.

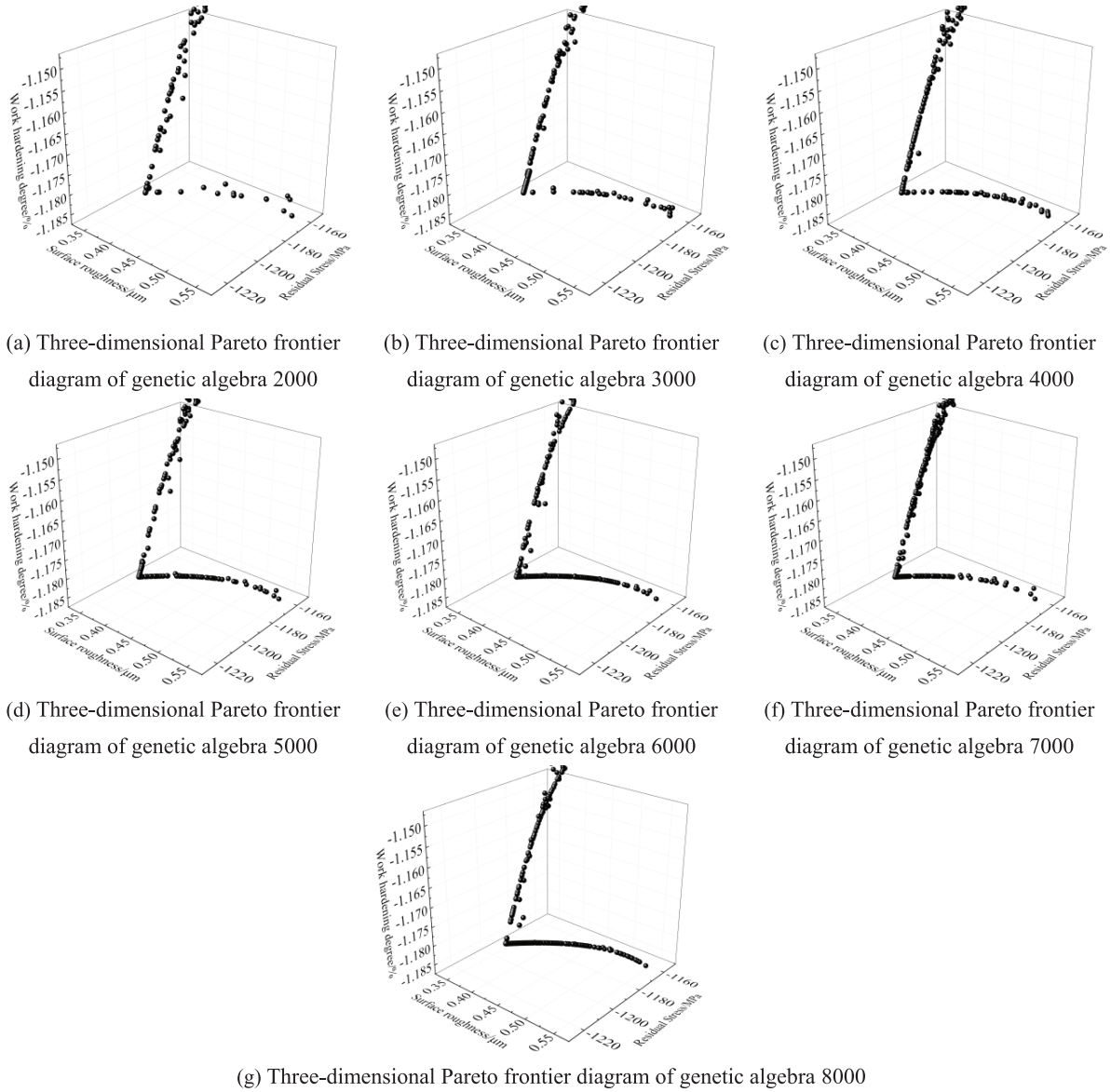


Fig. 7. Three-dimensional Pareto frontier diagram obtained by PSO.

The crowding degree calculation introduced by NSGA-II refers to the density of the surrounding individuals in the search space. As shown in [Figure 8](#).

In NSGA-II, judging whether a calculated solution is Pareto optimal solution according to the two criteria of non-dominated sorting and crowding distance. Suppose that for the solution e and the solution t , Compared with the non-dominated levels of the two solutions firstly, the solution with a higher non-dominated level is selected as Pareto optimal solution. If two solutions have the same level of non-dominance, their crowding distances are compared. The solution with large crowding distance will be selected as the Pareto optimal solution.

The flowchart of NSGA-II is shown in [Figure 9](#).

– The parent population appears, non-dominated sorting is performed, and the offspring population is generated through inheritance.

- Aggregate the parent population and the child population to generate a new population. Perform non-dominated sorting on all individuals in the new population to obtain the non-dominated frontier.
- Calculate the crowding degree of Pareto solutions of each layer, and sort them according to the crowding degree distance from large to small, and select the excellent Pareto solutions as the new parent population.
- Select, cross, and mutate the newly selected parent population.
- Test the population obtained in step (4), and stop when the number of iterations reaches the set maximum number of iterations. If the maximum number of iterations is not reached, repeat step (3) and step (4) until the optimal solution of Pareto is obtained. set.

NSGA-II was used to optimize the process parameters of ultrasonic rolling extrusion, and the corresponding

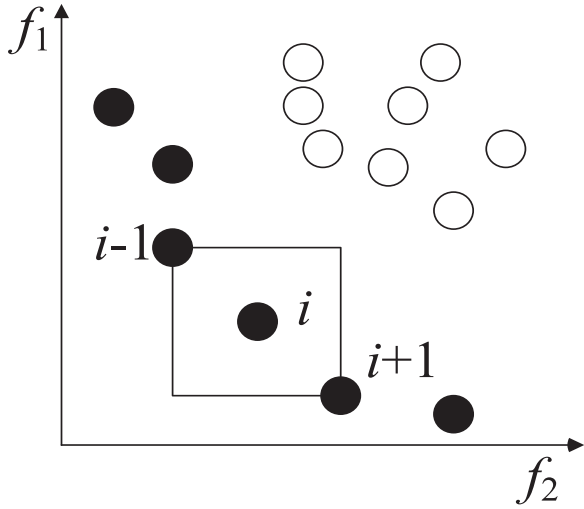


Fig. 8. Individual crowded distance.

optimal surface performance parameter domain was obtained. The optimization results under different iteration times are shown in Figure 10. The figure clearly shows the whole process of the initial population from the initial iteration to the final convergence, and the optimal solution set is obtained. Figure 10a shows the optimization results of 600 iterations. The Pareto optimal solution set of work hardening degree is widely distributed, but from the surface roughness and residual stress, the Pareto optimal solution set does not cover the entire value space; Figure 10b is Pareto solution set when iterating 1200 times, the solution set at this time has a wider distribution range than 600 times, but optimal Pareto solution set obtained is not continuous; Figures 10c–10e are the iteration 2400, compared with the optimization result of 1200 iterations, Pareto optimal solution set from times to 4800 times, Pareto solution at this time spreads more and more continuously in the space, tends to gradually converge, but still produces an accumulation effect at the upper end of the frontier. Still searching for optimization, the convergence effect is not good; Figure 10f is Pareto optimal solution at 6000 iterations, and the obtained solution set is smooth and uniform. Figure 10g shows Pareto optimal solution set at 7200 iterations. Compared with the solution at 6000 iterations, the improvement is not significant. Compared with the simulated annealing algorithm, the effect of NSGA-II iteration 6000 times is similar to that of simulated annealing 3000 times, but the number of iterations is doubled, and the efficiency is not high.

4.4 Multi-objective optimization of ultrasonic rolling extrusion process parameters based on MIGA

Multi-Island Genetic Algorithm (MIGA) was first proposed by M. Kaneko of Doshisha University in Japan and others. It is improved by parallel distribution processing on the basis of traditional genetic algorithm, and has more advantages in design space. Good global search capability [37].

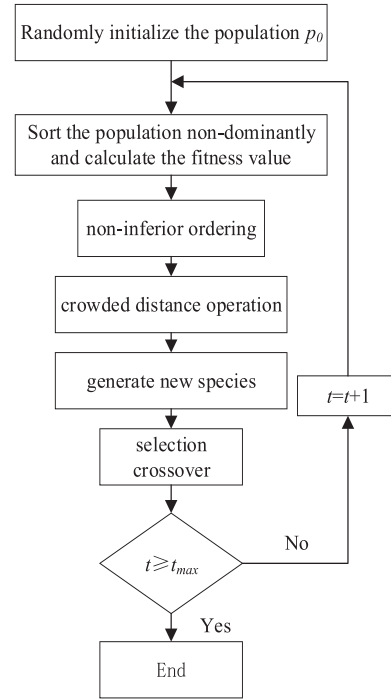


Fig. 9. Operation flow chart of NSGA-II.

The principle of the multi-island genetic algorithm is shown in Figure 11. It is based on the traditional genetic algorithm, which divides a large population into several sub-populations, and these sub-populations are vividly called “islands”. Operations such as selection, crossover, mutation, etc. take place on each island. The optimal individuals are screened out from each island to the remaining islands, and then operations such as selection, crossover, and mutation are performed. This behavior maintains the diversity of the population, improves the global search ability, and avoids falling into local optimality in traditional genetic algorithms. solution problem.

The algorithm flowchart of the multi-island genetic algorithm is shown in Figure 12.

The optimization steps of the multi-island genetic algorithm are:

- Generate a parent population.
- Find the fitness of each individual in the population.
- According to the calculated fitness, select individuals to offspring through genetic operations.
- The crossover operator is completed by the probability P_a .
- The mutation operator is completed by the probability P_y .
- If the maximum number of iterations is not reached, go back to step (2), and if it reaches the next step.
- Obtain Pareto solution with the best fitness for the objective function.

In this optimization, the subpopulation size is set to 10, the number of islands is set to 10, the maximum population size is set to 100, the crossover probability P_a is set to 0.08, the mutation probability P_y is set to 0.08, and the inter-island mobility rate is set to 0.3.

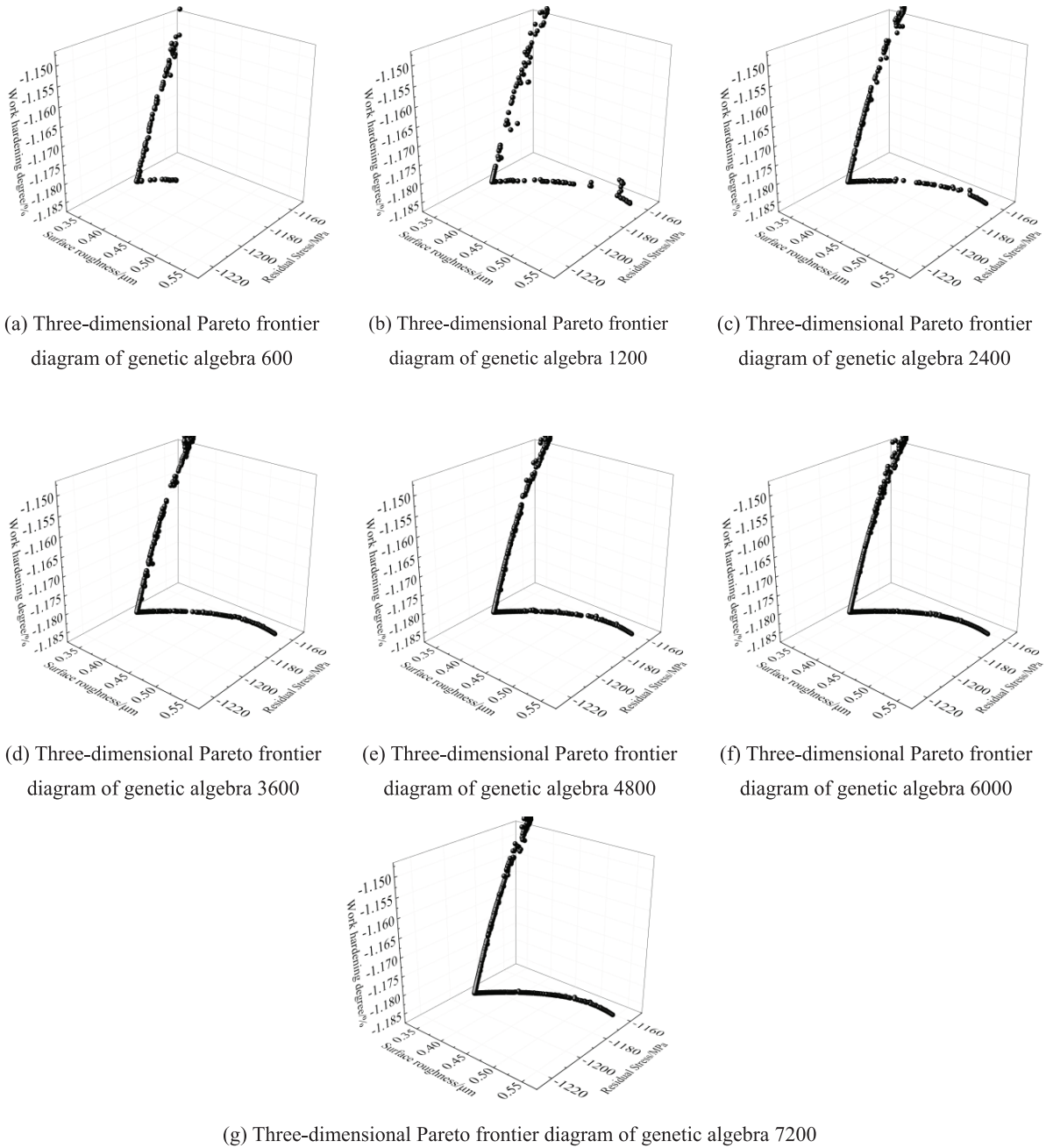


Fig. 10. Three-dimensional Pareto frontier diagram obtained by NSGA-II.

The multi-island genetic algorithm was selected to optimize the process parameters of ultrasonic rolling extrusion, and the corresponding optimal surface performance parameter domain was obtained. Figure 13 shows Pareto fronts under different iterations. The figure clearly shows the whole process of the initial population from the initial iteration to the final convergence, and the optimal solution set is obtained. Comparing three-dimensional Pareto frontier graphs with 4000–10,000 iterations, it can be seen that no matter the number of iterations, the optimal solution set of Pareto obtained by the multi-island

genetic algorithm is not continuous, showing an uneven “granular” distribution, and Pareto optimal solution set does not tend to be smooth and continuous as the number of iterations increases. It can be seen that compared with the previous simulated annealing method, particle swarm algorithm, and NSGA-II, the optimization effect of the multi-island genetic algorithm is not good, three-dimensional Pareto front is interrupted, the particle convergence effect is not smooth, the particle distribution is uneven, and the number of iterations is relatively high Too much, not very efficient.

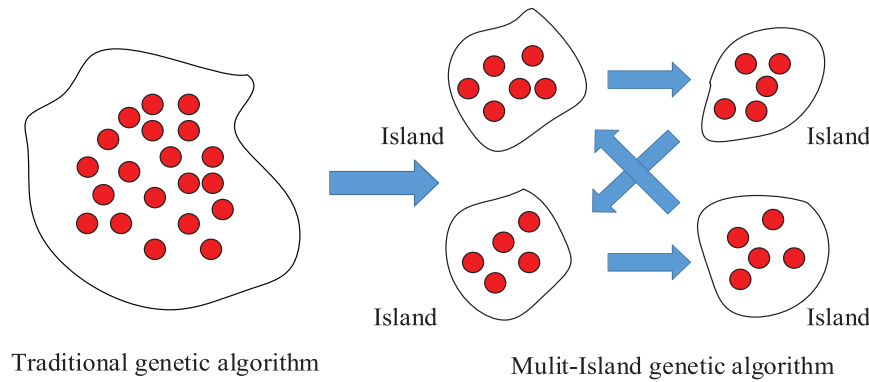


Fig. 11. Schematic diagram of multi-island genetic algorithm.

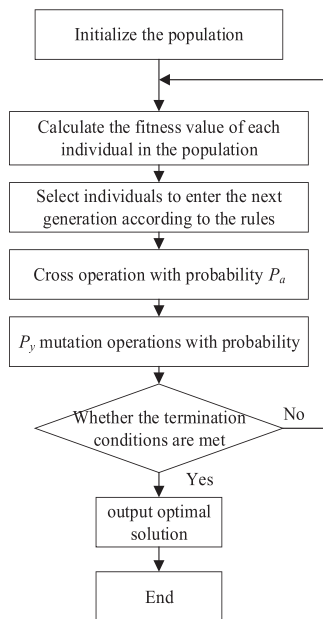


Fig. 12. Operation flow chart of MIGA.

4.5 Comparison of different optimization methods

Comparing with the optimized parameter domains obtained by the four optimization algorithms, the simulated annealing algorithm has the best optimization effect, and obtained Pareto frontier graph has the most uniform particle distribution, better convergence effect, and smoother solution. Pareto solution obtained by the particle swarm optimization algorithm is discontinuous in the middle, and Pareto obtained at both ends of the optimization range overlap. Compared with the SA algorithm, Pareto optimal solution optimized by NSGA-II has a similar effect. The solution set is evenly distributed and the front is smooth. However, compared with the simulated annealing algorithm, it takes 6000 iterations to achieve the effect of the simulated annealing algorithm 3000 times. NSGA-II has a long optimization time and low efficiency. The number of iterations of the multi-island genetic algorithm is too large, and the result of the obtained Pareto frontier solution is not good, the efficiency is not high, and the accuracy is not good. Comparing with the optimization effect

and combining the calculation efficiency, the simulated annealing algorithm was selected as the optimization method of ultrasonic rolling extrusion process parameters.

Pareto optimal solution solved by the simulated annealing algorithm, and the optimized process parameter domain is shown in Table 7. The evaluation indexes of the surface properties restrict and influence each other. The optimal processing parameters of the ultrasonic rolling extrusion are obtained from the solution: the amplitude is 22–25 μm , the rotational speed is 130–160 r/min, and the static pressure is 580 N to 600 N. When the feed speed is 15–19 mm/min, the corresponding surface layer performance parameters range: the surface roughness is 0.430–0.451 μm , the work hardening degree is 117.1–118.2%, and the residual stress is –1210 MPa to –1220 MPa.

To verify the reliability and validity of the optimization results, it is necessary to perform experimental verification on the process parameter domain optimized by the simulated annealing algorithm. Table 8 shows some of the optimal process parameters and surface performance evaluation parameter values obtained by the simulated annealing algorithm optimization. The optimized values of Group 1, Group 3, Group 5, Group 7 and Group 10 in the optimized optimal processing parameter domain were randomly selected for experimental verification.

To further compare the experimental results with the optimized results, the relative error between the experimental value and the calculated value of the surface properties of ultrasonic rolling extrusion was obtained. It is concluded that the maximum relative error of the surface roughness of the specimen after ultrasonic rolling extrusion is 3.58%, the maximum relative error of the work hardening degree is –4.88%, and the maximum relative error of the residual stress is –4.75%, Pareto optimal solution set obtained by simulated annealing optimization is better, and the distribution and convergence of the solution set are better. The comparison between the optimization results and the test results is shown in Table 9.

5 Conclusions

This paper studies the simulation annealing method optimization of 42CrMo material ultrasonic roll extrusion process parameters. Taking 42CrMo as the research object, based on four-factor five-level orthogonal experiment, the response surface method was used to establish the models

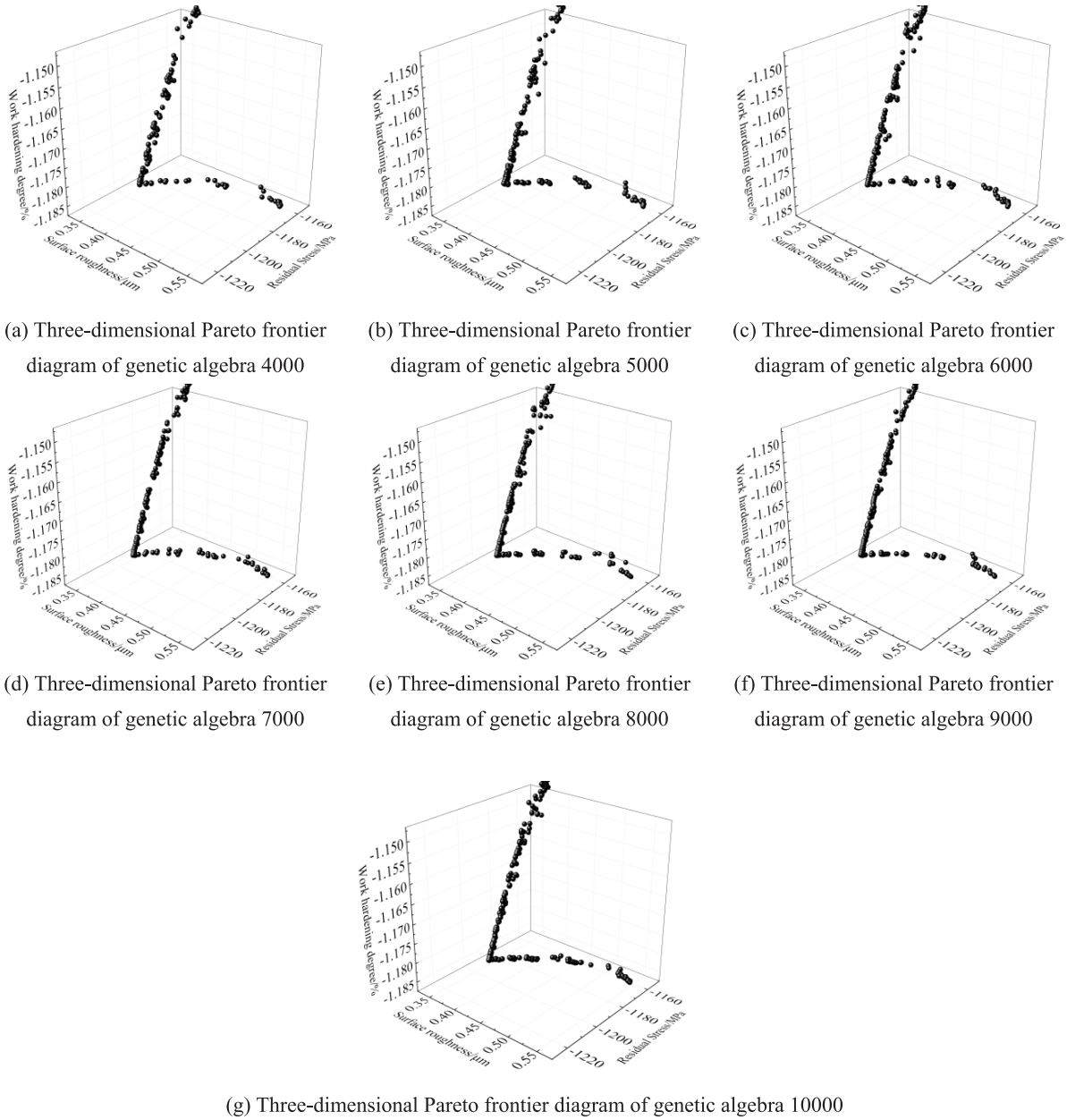


Fig. 13. Three-dimensional Pareto frontier diagram obtained by MIGA.

Table 7. Optimal parameter fields.

$n/(r/min)$	$v/(mm/min)$	$A/\mu m$	F/N	$R_a/\mu m$	$N_H/\%$	RS/MPa
[130, 160]	[15, 19]	[22, 25]	[580, 600]	[0.430, 0.451]	[117.1, 118.2]	[-1210, 1220]

of surface roughness, surface residual stress, and work hardening degree; to obtain a better Pareto front, resulting in better distribution and convergence of the solution set, SA, PSO, NSGA-II, MIGA were used Multi-objective optimization of the surface performance of ultrasonic rolling extrusion, SA is used to solve the optimal parameter window set, and experimental verification is carried out to verify the reliability and rationality of the optimization results. The following conclusions are drawn:

– The evaluation indexes of surface layer performance mutually restrict and influence each other, and the optimal processing parameter domain obtained by solving is: speed [130 r/min, 160 r/min], feed speed [22 mm/min, 25 mm/min], amplitude [15 μm , 19 μm], static pressure [580 N, 600 N], the corresponding surface performance parameter domain: surface roughness [0.430 μm , 0.451 μm], work hardening degree [117.1%, 118.2%], residual stress [-1210 MPa, -1220 MPa].

Table 8. Multi-objective optimization results.

Number	n /(r/min)	v /(mm/min)	$A/\mu\text{m}$	F/N	$R_a/\mu\text{m}$	$N_H/\%$	RS/MPa
1	130	15	25	600	0.431	-1217.45	117.566
2	132	18	23	590	0.435	-1213.74	117.343
3	135	15	24	596	0.432	-1216.48	117.577
4	138	17	23	593	0.436	-1213.67	117.414
5	142	16	22	586	0.434	-1215.13	117.591
6	144	19	25	587	0.431	-1212.54	117.628
7	146	15	22	586	0.435	-1214.38	117.601
8	152	16	23	580	0.450	-1210.37	117.935
9	155	16	22	600	0.443	-1217.64	118.097
10	160	15	25	597	0.438	-1212.01	118.212

Table 9. Comparison of optimization results and test results.

optimized value	$R_a/\mu\text{m}$ Test value	Relative error	optimized value	$N_H/\%$ Test value	Relative error	optimized value	RS/MPa Test value	Relative error
0.431	0.447	3.58%	117.566	112.1	-4.88%	-1217.45	-1185	-2.74%
0.432	0.445	2.92%	117.577	122.5	4.02%	-1216.48	-1198	-1.54%
0.434	0.445	2.47%	117.591	112.3	-4.71%	-1215.13	-1160	-4.75%
0.435	0.424	-2.59%	117.601	120.7	2.57%	-1214.38	-1167	-4.06%
0.438	0.430	-1.86%	117.628	113.4	-3.73%	-1212.01	-1253	3.27%

– The maximum relative error of the surface roughness of the optimized ultrasonic rolling extrusion is 3.58%, the maximum relative error of the work hardening degree is -4.88%, and the maximum relative error of the residual stress is -4.75%, indicating that the optimized result can be used in the actual manufacturing of engineering.

Data availability

All the code/data used in this paper can be obtained upon request to the corresponding author.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

Financial support

This work was supported by the National Natural Science Foundation of China (U1804145) and National key research program (2018YFB2000405). The authors would like to sincerely acknowledge all the support.

Author contributions

HW provided ideas, reviewed the overall process for the work, and wrote the majority of the paper. XW provided the optimization,

made the figures, and revised the paper. PW and QZ performed the optimizations and experiments.

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Cite this article as: X. Wang, H. Wang, P. Wang, Q. Zhu, Multi-objective optimization of process parameters for ultrasonic rolling extrusion of 42CrMo material, *Mechanics & Industry* **24**, 6 (2023)