The processing parameters optimisation of UVAM-processed CuNiAl alloy based on surface integrity parameters

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Abstract: The surface integrity of a material has a significant impact on fretting wear performance. Based on the analysis of the material surface integrity, the machining parameters were optimised to obtain the best fretting wear performance of the CuNiAl alloy. First, the effects of ultrasonic vibration-assisted milling (UVAM) processing parameters on the surface integrity of the CuNiAl alloy were studied. Consequently, the relationship between UVAM processing parameters and CuNiAl alloy surface integrity parameters was established through the support vector machine (SVM) model, and it was optimised using the particle swarm optimisation (PSO) algorithm. Finally, the relationship between the surface integrity parameters, processing parameters, and fretting wear performance was established using the PSO-SVM model. The coefficient of determination, mean average error, mean average percentage error, and mean square error of the proposed model were 63.7%, 40.8%, 31.9%, and 52.3% greater than those of the SVM model. The best fretting wear performance was obtained at a spindle speed of 5896 rpm, feed rate of 76 mm/min, and vibration current of 199.5 mA.

Keywords: Fretting wear, UVAM, Surface integrity, SVM

1 Introduction

Surface integrity plays an important role [1-2] in the service performance of machined parts, which has drawn increasing attention in industrial production, especially for products with high reliability [3-4]. The surface quality of machined components is particularly significant while the machining size, structural form, and material properties of the parts are determined [5-6], owing to their significant impact on the fatigue life of the machined components. The fatigue life of parts mainly depends on the surface states, including cracks, defects, and microstructure [7].

Fatigue fracture resistance is mainly determined by the residual stress distribution, surface roughness, and microstructure of the surface integrity [8-9]. It has been shown that under the conditions of monotonic or cyclic stress, most of the fatigue cracks originate at both instances on the surface, and some of them originated at stress concentrations such as inclusions inside the parts [10]. Therefore, the surface integrity of parts has received significant attention, whereas an improvement in the surface quality can improve the ability of parts to resist fatigue crack initiation.

Owing to increasing requirements for the performance and surface integrity of the workpiece, considerable studies [11-13] on surface integrity obtained by different machining techniques for engineering applications have attracted extensive attention and made significant developments in the field of surface integrity.

Axinte et al. [11] aimed at engineering applications of ceramic matrix composite matrices. They attempted to summarise the effects of various conventional machining methods (drilling, milling, and grinding) and non-conventional machining techniques (pulsed laser ablation, abrasive waterjet machining, and electrical discharge machining) on the surface integrity, while considering the complex characteristics of ceramic matrix composites, leading to a comprehensive understanding of the surface integrity for engineering applications. Shokrani et al. [12] reported that cryogenic cooling techniques using liquid nitrogen promote the surface integrity of Ti-6Al-4V titanium alloy used in aviation and medical care, while the surface roughness was reduced by 39% after cryogenic cooling.

Conversely, based on processing methods to the surface integrity, several prediction models [14-16] were established to describe the relationships between processing parameters and surface integrity characteristics, which can predict the surface performance and service performance of machined parts. Shaat et al. [14] proposed a novel surface integrity model to demonstrate the relationships between the surface integrity parameters and vibration behaviours of microbeams. In addition, compared with the Gurtin–Murdoch surface model, the novel model focused on the practical surface characteristics. Wang et al. [15] established an analytical prediction model by combining a dislocation density model and strain-induced martensitic transformation kinetics. This model presents the variation in microstructure, residual stress distribution, and hardness during the process of cylindrical turning. In addition, experiments were conducted to optimise and validate the model.

Several surface engineering methods have been applied to improve the surface integrity of engineering materials, such as shot peening [17], laser texturing [18], surface thermochemical treatments [19], electrodeposition techniques [20], and high-energy beam heat treatments [21]. As a surface engineering technique, ultrasonic vibration-assisted milling (UVAM) can induce compressive residual stress, enhance hardness, and refine the microstructure of machined surfaces [22-24].

Zhang et al. [23] applied the high-speed ultrasonic vibration cutting method to machine a Ti-6Al-4V alloy. They studied the impact of processing parameters on surface integrity as compared to conventional cutting. In addition, they revealed that high-speed ultrasonic vibration cutting techniques improved surface integrity by enhancing hardness, decreasing surface roughness, and inducing compressive residual stress.

Li et al. [24] adopted ultrasonic peening cutting to machine a Ti-6Al-4V alloy and established a theoretical motion model. Compared with conventional cutting, they concluded that specimens with ultrasonic peening cutting exhibited improvements in surface integrity, including the promotion effects on fatigue performance, compressive residual stress, thickness of the deformation layer, and microhardness.

In practical working conditions of naval equipment platforms, during the service of the controllable pitch propeller, fretting wear occurred at the counter surfaces of the blade bearing [25-26]. In addition, fretting wear was the main contributor to the wear failure of the blade bearing. During the working process of the counter surfaces of the blade bearing, the upper and lower contact surfaces were in the reciprocating fretting process, resulting in high demands for the surface integrity of the friction pairs.

However, the variation in surface integrity and its impact on the fretting properties of CuNiAl during the fretting process is yet to be determined.

2 Experimental details

2.1 UVAM process

The ultrasonic vibration-assisted milling technique is characterised by intermittent cutting owing to vibrations of the milling tool [23]. The UVAM device is shown in Fig. 1. The vibration direction of the milling tool is perpendicular to the sample surface. Dry machining tests were conducted using a vertical machining centre (KVC1050N). The ultrasonic vibration generator was connected to the milling tool by applying periodic vibrations to the tool during processing. Previously, the transducer converted electricity to the motions of the ultrasonic vibration generator. The UVAM processing schemes are listed in Table. 1.

2.2 Fretting tests

Fretting tests were performed on a wear test rig (Fig. 2), which was built to simulate the practical working conditions of blade bearings. During the service of the controllable pitch propeller, flat-on-flat torsional fretting wear occurred. The CuNiAl alloy was used as the hub, whereas 42CrMo4 steel was used as the blade carrier during service. The mechanical properties at room temperature are listed in Table. 2. Therefore, in this torsional fretting wear test rig, the CuNiAl alloy was the lower specimen, and the 42CrMo4 steel was the upper specimen in friction pairs. The upper specimen (42CrMo4) was fixed on the upper holder which could not rotate. A torque sensor was connected to the upper holder to record the variation in friction torques (T). Meanwhile, the lower specimen (CuNiAl) was fixed on the lower holder, driven by a stepper motor with a resolution of 0.018°. The rotation angle of the lower holder ranged from 0º to 3º and the rotation frequency was 2 Hz, as determined by the impulse frequency of the stepper motor. In addition, an encoder was used to record the angular displacement amplitude (θ). Practical working conditions were simulated in oil lubrication under a normal load of 86 N, 40000 loading cycles, and an angular displacement of 1.5°. The average values of the results from the three tests were used for subsequent analyses.

2.3 Surface integrity characterisations

For all machined surfaces, the thermal-dimension parameters of the surface topography were measured using an ultra-depth three-dimensional microscope (OLYMPUS, DSX510). An X-ray diffractometer (Cu Kα, x-pert3 powder) was used to measure the residual distribution of the cross-sections. The full width at half maxima was measured, and the conventional $\sin^2\varphi$ method was employed to analyse the value of the residual distribution. The scanning angle ranged from 30° to 90° and the scanning speed was 0.05°/s. To measure the residual stress at different depths below the machined surface, an electrolytic polishing instrument (Struers movipol-3) was employed. The polishing slurry (C_2H_6O: H_3PO_4: H_2O=91: 6: 3) was used for electrolytic polishing to remove successive layers. Corrections for successive layers were also employed.

The hardness distribution along the depth below the sample surface was examined using a microhardness tester (MH-5). Scanning electron microscopy was employed to analyse the microstructures. The grain size was observed using electron backscattered diffraction (EBSD). Previously, the cross-sections of the machined surface were polished using emery sandpapers of different particle sizes (400#, 800#, 1200#, 1500#, 2000#). In addition, samples were prepared through vibration polishing for 6 h, which contributed to the high accuracy of the EBSD experiments. To detect more particles, the step size was set to 1μm.

3. Effects of surface integrity on fretting wear resistance

In essence, fretting wear is a process of repeated reciprocating motions with cyclic loads. Therefore, failure of fretting wear is a process of fatigue failure. Different surface integration processes produce different surface integrity states, which can be critical with regard to the fretting wear properties of the samples. Therefore, flat on flat torsional fretting wear properties are under the comprehensive actions of many surface factors, such as surface topography, residual stress field, microstructure, and hardness distribution, which cannot be controlled by a single factor.

3.1 Fretting wear performance

3.1.1 T-θ curves

T-θ curves provide essential information for the running state of the fretting wear process [25]. Owing to the same experimental fretting conditions, the curve of each sample exhibited the same trend. As shown in Fig. 3, the curves appear in a parallelogram-like shape, revealing that the fretting system operated in the gross slip state. In the gross slip state, the relative displacement of the two contacts occurs in each fretting cycle, which is usually manifested in the dispelling of the matrix of the friction pair and the production of debris. In the inclined part, the contact interface is in partial slip, whereas the friction pairs are in static friction. With an increase in amplitude, the friction is greater than the static friction, and the relative slip occurs. The fretting process enters a relatively stable stage, and the curve shows a straight part, which is less influenced by interference factors such as initial surface roughness and contaminated surface oxide films.

3.1.2 Friction torques

The variation in friction torques during fretting for a typical sample SS 3 is shown in Fig. 4, describing the fretting state in different periods of the fretting process.

At the initial stage of fretting, the friction coefficient is low because of the protection of the contaminated film (such as oxide film and adsorption film) on the contact surface. Subsequently, the contaminated film gradually breaks, the material was in direct contact, and the actual contact area increased [26]. The fretting times required for the rupture and removal of the contaminated film are closely related to the initial working conditions (such as load and displacement amplitude). Owing to surface adhesion and plastic deformation at the contact, the friction rapidly increased.

The continuous hardening of the surface work and the phase transformation of the surface structure of the material increases the surface brittleness of the material, resulting in the peeling of particles [27]. Many particles accumulate on the surface to form a third body layer, which plays the role of solid lubrication. Therefore, the friction coefficient decreased with the transformation from the two-body to the three-body friction system [28].

After a certain number of cycles, fretting was in a relatively stable stage. The surface morphology changes owing to the continuous stripping of particles, and then the wear debris (the third body) was gradually broken and oxidised under the action of fretting extrusion [26]. However, the generation of the third body maintains a dynamic balance with the overflow from the contact surface; thus, the change in the friction coefficient was small.

The average friction torque T_{sta} in the stable period (30000th-40000thcycle) is calculated as follows:

$$T_{sta} = \frac{\sum_{40000}^{30000} T_i}{10000} \tag{1}$$

As seen, SS 3 shows the lowest T_{sta} in the stable period which is 14.7% lower than that of sample UV 1.

3.1.3 Accumulated dissipated energy

The accumulated dissipated energy E_T represents the energy loss in the entire wear process, calculated using the integrals of the friction torque in each cycle:

$$E_T = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} \int_{-\theta}^{\theta} T * \theta \mathrm{d}\theta \tag{2}$$

Sample SS 3 shows a minimum E_T which is 27.5% less than that of the sample without vibration current (UV 1).

3.1.4 Wear scar observations

The wear scar of SS 3 was observed using scanning electron microscopy, as shown in Fig. 7. Under the condition of oil lubrication, the main characteristics of wear scars are furrows and plastic deformation along the direction of relative movement. Cracks and delamination were rarely observed on the worn surface because the lubricating oil film can significantly reduce the shear stress of the friction pair and then inhibit the initiation and propagation of cracks. The low shear strength of the lubricating oil film can reduce the friction resistance, and its high bearing capacity can effectively reduce the adhesion between the metal surfaces. In addition, wear debris is more likely to form three-body friction under the action of an oil film [29]. Under similar processing conditions and the same fretting process, the wear mechanisms of abrasive wear are suitable for all samples.

The wear volume of all the samples was measured using an ultra-depth three-dimensional microscope (OLYMPUS, DSX510). As shown in Fig. 8, sample SS 3 shows a 26.3% promotion effect compared to the sample without a vibration current (UV 1).

3.2 Surface topography

Surface topography has a direct impact on the contact area between parts and the external environment, physical, and chemical properties of the surface, and indirectly influences the force, local stress concentration, and fatigue properties of materials [30-32].

Surface roughness refers to the microscopic geometric features of peaks and valleys with little spacing on the machined surface, which is a key geometric characteristic parameter of surface topography [33].

As regards the microscopic mechanism, during the fatigue process, cracks initiate at the free surface of the sample or structure. An increase in the surface roughness value leads to stress concentration at the machined texture grooves on the outer surface, pushing the nucleation of cracks, which is detrimental to the fatigue limit.

The surface morphology is characterised by continuous adjacent notches, and the undulating surface morphology results in a stress concentration. Conventionally, surface roughness influences the fatigue life of specimens because of the microscopic stress concentration coefficient K_t [34]:

$$K_t = 1 + n\frac{R_a}{\rho}\frac{R_y}{R_z} \tag{3}$$

$$\begin{aligned} R_a &= \frac{1}{l}\int_0^l \left|z(x)\right| \mathrm{dx} \\ R_y &= \left|z_{\max} - z_{\min}\right| \\ R_z &= \frac{1}{5}\left[\sum_{i=1}^{5}(z_i)_{\max} + \sum_{j=1}^{5}\left|(z_j)_{\min}\right|\right] \end{aligned} \tag{4}$$

where ρ is the radius of curvature of the valley profile, n is the surface state (n=1 for shear loading and n=2 for tension loading), and z represents the height distribution on the machined surfaces. Measurements of R_a, R_y, R_z, ρ, and calculation of K_t were performed using an ultra-depth three-dimensional microscope (OLYMPUS, DSX510). K_t for all samples are shown in Fig. 6. An increase in ultrasonic current from 0 to 200 mA leads to a 47.8% decrease in K_t compared to UV 1. The lowest K_t value was obtained at FR 1.

For UVAM processing, the ultrasonic current provided vibrations that were perpendicular to the sample surface to the milling tool, resulting in a concave texture on the sample surface. The three-dimensional surface topography of the ultrasonic current specimens is shown in Fig. 10. The surface morphologies of all the samples were measured at the same reference height. The concave dimples become deeper when the ultrasonic current was greater. Therefore, fluctuations increased.

For sample UV 1 which is processed without the current, scallop height and defects such as casting pores and inclusions have detrimental effects on the stress concentration coefficient of the surface. Assuming a given ultrasonic current, the transient high-frequency shock wave of the milling cutter produces severe plastic deformation on the sample surfaces, which can partially seal or eliminate some defects, thus densifying the structural layer on the surface of the sample. Consequently, the effects of micro-hole and slag inclusion defects on the stress concentration coefficient of the samples were improved. Meanwhile, as shown in Fig. 6, variations in the feed rate and spindle speed had no significant effects on K_t. As the spindle speed increased, the stress concentration coefficient showed a slow decreasing tendency. The feed rate resulted in a slow increase in the stress concentration coefficient.

3.3 Residual stress field

As a major parameter of surface integrity, residual stress is closely related to the fatigue life and service performance of parts [35-36]. The influence of residual stress on the fatigue limit of parts depends on the magnitude, compressive or tension, distribution, and stress state.

During the UVAM process, the surface layer is subjected to the impact of the milling cutter owing to ultrasonic vibration. The surface material yielded and plastic deformation occurred. Meanwhile, the core material remained unchanged, which restricted the deformation of the surface material. Therefore, compressive residual stress was generated in the surface material of the UVAM-processed samples. The compressive residual stress generated in the surface material of the part delayed the initiation of fatigue cracks and decreased the propagation of existing cracks, leading to an improvement in fatigue life [37].

The residual distributions of SS 1 and UV 1 along the depth are shown in Fig. 11. In the UV1 sample, the residual stress is the tensile stress, whereas the residual stress field in the SS 1 sample presents a compressive stress distribution. After UVAM, the residual stress along the depth direction of the sample changed from tensile to compressive stress. The first measuring point of the residual stress is at a surface layer depth of 0.025 mm, which is considered as the surface residual stress.

For UVAM samples, the surface is subjected to impacts perpendicular to the surface, forming a work-hardening layer. Because of the high-speed vibration impact of the milling cutter, the surface material yielded partially. Plastic deformation occurred in some areas below the surface layer. The core material was still elastic, which restricted the deformation of the surface material. Therefore, residual compressive stress is generated in the surface layer of the material. The material surface is furthest from the core and is least restricted by the core material. Therefore, in the first stage, the residual compressive stress increased and reached a peak with an increase in the layer depth. When the layer depth further increased, the influence of work hardening transmitted from the surface decreased, and the residual stress decreased until it disappeared in the core. Under the same UVAM conditions with ultrasonic currents, the compressive stress was distributed in all samples except the sample without ultrasonic currents (UV 1).

To evaluate the intensity of residual stress in different samples, the average residual stress in the residual stress field $\overline{\sigma_{rs}}$ was used:

$$\overline{\sigma_{rs}} = \frac{1}{l}\int_0^l |\sigma_{rs}| \mathrm{dx} \tag{5}$$

where l denotes the length of the residual stress field. The length of the residual stress field l differs for different samples. As seen in Fig. 8, among the three main processing parameters, the ultrasonic current has the most significant influence on the residual stress. The increase in ultrasonic current from 50 to 200 mA resulted in a 30.1% promotion effect on the residual stress.

Meanwhile, the feed rate had no significant influence on the residual stress. Regarding the spindle speed, the sample with a spindle speed of 6000 rpm showed 6.8% promotion effects compared to the sample with a spindle speed of 3600 rpm. With an increase in spindle speed from 4800 rpm to 6000 rpm, the average residual stress $\overline{\sigma_{rs}}$ is almost the same, indicating that the positive effects were caused when the spindle speed is approached saturation.

3.4 Hardness

The hardness distributions of UV 1 and UV 2 are shown in Fig. 12, indicating the typical distribution characteristics of all the samples. Apparently, higher hardness distribution and deeper hardened layer occurred in UV 2 than in UV 1. After UVAM processing, work-hardening effects occurred below the surface layer, leading to microstructure fibrosis and grain breakage. The grains of the surface layer were refined, and the hardness and strength of the surface material were improved. Simultaneously, the plasticity and ductility of the core were retained. The fatigue strength and wear resistance of the material were effectively improved. Under the action of cyclic loads, the surface hardening layer prevented the dislocation line from extending to the surface, thus delaying the generation of fatigue cracks.

To evaluate the intensity of hardness in different samples, the average hardness in the surface-hardened layer $\overline{H_v}$ was used:

$$\overline{H_v} = \frac{1}{l}\int_0^l |H_v| \mathrm{dx} \tag{6}$$

As seen in Fig. 13, the ultrasonic current has a positive effect on hardness with a maximum of 12.3% promotion compared to the sample without ultrasonic current (UV 1). In addition, with an increase in ultrasonic current, the promotion effects decreased gradually.

The spindle speed had a positive effect on the hardness. The increase in spindle speed contributed to more severe plastic deformation and work-hardening effects. As regards the feed rate, the improved effects were less severe. The sample with a feed rate of 80 mm/min showed 4.2% improved effects compared to the sample with a feed rate of 60 mm/min.

3.5 Grain size

The mechanical properties of materials, such as hardness, strength, and wear resistance, are influenced by the grain size from the surface to the interior; thus, the analysis of surface integrity is complex.

The grain size was the main factor that influenced the hardness intensity. The variation trend of grain size is consistent with the hardness. The UVAM treatment is a process of energy transfer. Under the combined actions of complex multi-directional impact loads, severe plastic deformation occurred on the surface layer, resulting in a rapid increase in the dislocation density. Subjected to the reciprocating motion of the milling tool, large-sized grains gradually break up along with the formation of numerous small-angle grain boundaries. Small-angle grain boundaries continuously absorb dislocation energy and gradually transfer to large-angle grain boundaries. New grains were continuously formed, and grain refinement effects were gradually realised. The degree of grain refinement depends on the deformation mechanism, whereas the deformation mechanism and the number of grains are derived from the type of main phase lattice.

To evaluate the intensity of the grain size in different samples, the grain size was characterised by EBSD at a step size of 0.5 μm. To prepare the EBSD specimen, samples were cut along the cross-section to observe the microstructure in the plastic deformation layer. After grinding with sandpaper 400#, 800#, 1200#, 1500#, and 2000#, the EBSD specimens were subjected to mechanical and vibration polishing to meet the testing standards required by the EBSD experiments. The test region was within 100 μm from the edge. The distribution of grain size in the UV 2 and EBSD observations is shown in Fig. 14. As seen, fine particles are prone to distribution at the edge area, which results from the microstructure transformation produced by UVAM processing.

The grain sizes of all the samples are shown in Fig. 15. According to the Hall-patch model, the grain size has a significant impact on hardness. From Fig. 13, it can be concluded that the effects of the spindle speed, feed rate, and ultrasonic current on grain size are consistent with those of hardness, which is in good agreement with the Hall-patch theory.

4. PSO-SVM

In the friction and wear process, the relationship between machining parameters and wear volume is difficult to accurately solve using a definite theoretical model, which is complex and difficult to describe nonlinear relationships [38-39]. Support vector machines (SVM) are mainly used to learn historical data to establish a nonlinear model between assembly quality parameters and assembly quality characteristics, and finally realise the prediction of assembly quality characteristics. However, when using an SVM to predict the friction and wear characteristics, its prediction accuracy is related to the selection of SVM parameters, and the selection of these parameters is not guided by any definite rule.

4.1 SVM

SVM is a machine learning method based on statistical learning theory [38]. It is considered the most effective method of solving small samples and nonlinear regressions. It maps the sample data to a high-dimensional space through a kernel function for linear regression processing. In 1995, Cortes and Vapnik formally proposed a major achievement in machine learning and SVMs. Statistical learning theory (SLT) is the theoretical basis of SVM, which aims to solve machine-learning problems in small sample cases. In this study, an SVM algorithm is used for prediction, with UVAM processing parameters as input and wear volume as output.

The classification accuracy of SVM is still influenced by the hidden layer activation function G (x), which mainly includes the binary activation function, linear activation function, sigmoid function (also known as S-type activation function), and radial basis function. The commonly used activation functions are as follows:

1) A binary activation function refers to a function that binarizes the sample data through certain changes, and it is expressed as follows:

$$G(x_i) = U(x_i) \tag{7}$$

where $U(x_i)$ is the jump function.

2) Linear activation function:

$$G(x_i) = ax_i + b, a > 0, b > 0 \tag{8}$$

3) Sigmoid function:

$$G(x_i) = \tanh(ax_i + b), a > 0, b > 0 \tag{9}$$

4) Radial basis function:

$$G(x_i) = \exp\left(-\frac{\left\|x_j - b_j\right\|^2}{2\sigma^2}\right), \sigma > 0 \tag{10}$$

Assume that the sample data feature vector is $\{x_i, y_i\}$, where x_i represents the input parameters which are UVAM processing parameters (the spindle speed, feed rate, and vibration current) and y_i represents the output parameter which is the wear volume.

The y_i value corresponding to x_i is predicted by solving the function $f(x)$. Thus, the linear function of the SVM is

$$f(x) = \omega \cdot x + b \tag{11}$$

where ω is a weight variation and b is the linear function coefficient.

The relaxing factors ξ_i, $\hat{\xi}_i$, and the penalty factor C are introduced. The optimisation problem can be expressed as:

$$\min R\left(\omega, \xi_i, \hat{\xi}_i\right) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}\left(\xi_i + \hat{\xi}_i\right) \tag{12}$$

$$\text{s.t.}\begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \hat{\xi}_i \\ \xi_i \ge 0, \hat{\xi}_i \ge 0, i = 1, 2, \cdots, m \end{cases} \tag{13}$$

where ε is insensitive loss function and R is the loss function.

To facilitate the solution, Lagrange multipliers are introduced to transform the quadratic programming problem into a dual problem:

$$\max Q(\alpha, \hat{\alpha}) = \sum_{i=1}^{m} y_i(\hat{\alpha}_i - \alpha_i) - \varepsilon(\hat{\alpha}_i + \alpha_i) - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}(\hat{\alpha}_i - \alpha_i)\left(\hat{\alpha}_j - \alpha_j\right) x_i^{\mathbf{T}} x_j \tag{14}$$

$$\text{s.t.}\begin{cases} \sum_{i=1}^{m}\left(\hat{\alpha}_i - \alpha_j\right) = 0 \\ \alpha_i \ge 0, \hat{\alpha}_i \le C \end{cases} \tag{15}$$

where Q is the loss function of the Lagrange coefficient, $\hat{\alpha}_i$, α_i, $\hat{\alpha}_j$,and α_j are the Lagrange multipliers. By solving Equation above, the SVR function model can be written as:

$$f(x) = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i) K(x_i, x) + b \tag{16}$$

where $K(x_i, x)$ is the kernel function.

4.2 Particle swarm optimisation algorithm

Particle swarm optimisation (PSO) algorithm is a swarm intelligent optimisation algorithm [40]. Each particle in the swarm represents a possible solution to the optimisation problem, and the particle characteristics are represented by three indexes: position, speed, and fitness value. In N-dimensional space, particle positions are expressed as $X_i = (x_1, x_2, \cdots, x_n)$, and flight speed is expressed as $V_i = (v_1, v_2, \cdots, v_n)$. Each particle has a fitness value that is determined by an objective function. In each iteration, the particle updates its speed and position through the individual extremum and group extremum.

$$\begin{cases} v_i = \omega v_i + c_1 r_1 \left(p_{besti} - x_i \right) + c_2 r_2 \left(g_{besti} - x_i \right) \\ x_i = x_i + v_i \end{cases} \tag{17}$$

where v_i is the velocity of the particle, x_i is the current position of the particle, p_{besti} indicates that the particle is the individual optimal value, g_{besti} indicates the global optimal value of the particle swarm, r_1 and r_2 are random numbers between (0, 1), c_1 and c_2 are learning factors, usually c_1 = c_2 = 2, and ω is an inertia factor. The larger the value, the stronger the global search ability and the slower the convergence; the smaller the value, the stronger the local search ability and the faster the convergence.

4.3 PSO-SVM model

The parameters of the SVM were optimised using the PSO algorithm to obtain the wear prediction model based on SVM [41-42]. The program flowchart is shown in Fig. 16. First, the original dataset of the assembly parameters was obtained. After cross-validation, the basic parameters of the PSO-SVM model were initialised. Using the mean square error (MSE) as the optimisation objective function value, the current fitness value of each particle was calculated and compared, and the individual and global extreme values were updated. The velocity and position of the current particle were updated, whether the number of iterative optimisations was determined, and the optimal penalty parameters and kernel function parameters to determine the optimal position were output [42]. Finally, the optimal penalty parameters and kernel function parameters were transmitted to the SVM model training to construct the optimal PSO-SVM prediction model.

4.4 Prediction case of fretting wear volume for UVAM samples based on surface integrity parameters

To provide sufficient samples for the algorithm, there are 48 groups of samples, and some original data are shown in Table 2.

In this section, owing to the characteristics of small samples, the six-fold cross-validation method is used to divide the training and test sets and evaluate the established model. The performance evaluation indexes of the regression model mainly include the mean absolute error (MAE), MSE, mean absolute percentage error (MAPE), and the coefficient of determination (R^2).

MSE, MAE, and MAPE can be expressed as:

$$\begin{aligned} MSE &= \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i\right)^2 \\ MAE &= \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i\right| \\ MAPE &= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i}{y_i}\right| \end{aligned} \tag{18}$$

where y_i represents the prediction value and y_i is the actual value. However, it is difficult for MAPE, MAE, and MSE to measure the effects of the model when the equivalent dimensions differ. To effectively evaluate the fitting effect of the model, R^2 is used to characterise the quality of fitting through the change of data, which can be expressed as:

$$R^2 = 1 - \frac{SSE}{SST}$$
$$SSE = \sum_{i=1}^{n}\left(y_i - y_i\right)^2 \quad (19)$$
$$SST = \sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2$$

where y_i represents the prediction value, y_i is the actual value, and $\overline{y_i}$ is the mean value. R^2 normally ranged from 0 to 1. The closer it is to 1, the stronger the explanatory ability of the variables of the equation to the results, and the model fits the data better.

4.4.1 PSO-SVM model and SVM model results

The spindle speed, feed rate, and vibration current were taken as the input of the model, and the wear volume of the fretting process was taken as the output to establish the prediction model. In the PSO algorithm, the particle number was N =24, the maximum number of iterations $T_{\max}$=100. The value of the penalty factor C ranged from 2^{-5} to 2^{15}. The error threshold was 0.001. The kernel function parameter σ ranged from 2^{-15} to 2^{3}. Inertia factor ω =0.8, c_1 =0.5, c_2=0.5. As seen in Table 3, R^2 for PSO-SVM is higher than that of SVM, indicating that the fitting effects of the PSO-SVM model are better than those of SVM. In addition, MAE, MSE, and MAPE for PSO-SVM are smaller than those of SVM. Therefore, a higher satisfactory prediction precision was obtained through the PSO-SVM model.

4.4.2 Prediction of surface integrity parameters

In practical production processes, it is not easy to directly measure the surface integrity parameters of materials, and the surface integrity parameters have a significant impact on the fretting wear properties of materials. Therefore, in this section, the model from machining to surface integrity parameters is established based on a previous analysis of the influence of the machining parameters on the surface integrity parameters. The prediction of the surface integrity parameters using the machining parameters was realised.

Based on the comparison above, the PSO-SVM model was selected for the prediction of surface integrity parameters (stress concentration coefficient, residual stress, grain size, and hardness, respectively). The spindle speed, feed rate, and vibration current were taken as the inputs of the model, and the surface integrity parameters (stress concentration coefficient, residual stress, grain size, and hardness, respectively) were taken as the outputs to establish the prediction model. The results are presented in Table 4.

4.4.3 Prediction of wear volume through the processing and surface integrity parameters

To predict the wear volume in the actual production process with higher satisfactory prediction precision, the machining parameters combined with the predicted surface integrity parameters were used as input parameters for the PSO-SVM model. In the PSO-SVM model, the processing parameters were taken as input. The predicted surface integrity parameters were obtained from the PSO-SVM model in 4.4.2.

As shown in Table 5, the prediction effect is poor. The evaluation indexes in Table 4 indicate that the prediction of hardness is inaccurate. Therefore, the poor prediction effect may result from the inaccurate prediction of hardness. As follows, the hardness is removed from the input parameters. Taking the processing parameters and predicted grain size, residual stress, and stress concentrate coefficient as input parameters, the results are shown in Table 6. It shows better performance evaluation indexes of R^2, MAE, MSE, and MAPE for promotion effects of 20.6%, 49.8%, 74.8%, and 51.3%, respectively. The lowest wear volume was obtained at the spindle speeds of 5896 rpm, a feed rate of 76 mm/min, and a vibration current of 199.5 mA. Therefore, the best fretting wear performance of the UVAM-processed CuNiAl alloy was obtained at a spindle speed of 5896 rpm, a feed rate of 76 mm/min, and a vibration current of 199.5 mA.

5. Conclusion

1) The UVAM-processed CuNiAl alloy showed high fretting wear performance. Compared to the sample without a vibration current, sample SS 3 shows 26.3%, 27.5%, and 14.7% promotion effects in wear volume, the accumulated dissipated energy and the friction torques, respectively.
2) Fretting wear properties are under the comprehensive actions of surface integrity parameters such as surface topography, residual stress field, grain size, and hardness distribution.
3) Compared with the SVM model which directly predicts the fretting wear performance using machining parameters, the evaluation indexes: R^2, MAE, MAPE, and MSE were increased by 20.6%, 49.8%, 74.8%, and 51.3%, respectively.
4) The best fretting wear performance of the UVAM-processed CuNiAl alloy was obtained at a spindle speed of 5896 rpm, feed rate of 76 mm/min, and vibration current of 199.5 mA.

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