Multi-Object Optimization of Titanium Alloy Milling Process using Support Vector Machine and NSGA-II Algorithm

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***Abstract* — Titanium alloys are widely used in aviation fields, the processing quality of this materials is affected by the milling force. In order to guarantee machining quality, improve production efficiency and reduce cost, the cutting parameters of the titanium alloy should be carefully selected. In this paper: i) the Titanium Alloy Ti6Al4V milling process is analyzed by finite element method, ii) a milling force prediction model is established based on Support Vector Machine (SVM), and iii) we propose an optimization design methodology based on SVM and NSGA-II for Titanium Alloy milling process cutting parameters. The results show that this methodology has good performance in finding satisfying Pareto solutions, and thus can be used in finding the machining process optimum parameters with applications to other material processing fields.**

Keywords - Titanium Alloy; SVM; NSGA-II algorithm; multi-object optimization

I. INTRODUCTION

Titanium alloy materials have such excellent characteristics as high temperature resistance, high strength, good abrasion resistance, good corrosion resistance and so on, and they widely used in aerospace, automotive, rail transport, chemical, petroleum, medical and other fields [1]. At the same time ,titanium alloy materials have such characteristics as low elastic modulus, low thermal conductivity and serious work hardening ,etc. it is a difficult processing material, so, the study processing in particular milling performance and optimization of process parameters of titanium alloy have important practical significance for improving machining efficiency and quality control, reducing manufacturing cost and promoting application of titanium alloys by studying titanium alloy processing.

At present, many scholars at home and abroad have made a lot of research for technological parameter optimization for high speed milling of titanium alloys, Andre F.H.L et al. took the machining efficiency to be the optimization goal, and adopted the genetic algorithm to study the optimization of milling parameters [2]. Sardifias R.Q et al. took cutting force, surface roughness and machining cost as the optimization goal, established multi-objective optimization model and studied the optimization of milling parameters [3]. Zain Arjun et al. used the neural network prediction model and genetic algorithm to predict and optimize the surface roughness of titanium alloys milling components [4]. Ozel T et al. used finite element model to set up 3D finite element model of Ti6Al4V, analyzed influence of different processing parameters on cutting force, and predicted surface roughness [5]. Domestic scholars Chen Jianling et al. made maximal production efficiency and minimum consumption rate of cutter life be the goal, established the titanium alloy milling parameter optimization model and used ENSGA-Ⅱ for multi-objective optimization [6]. Yang Yinfei et al. established milling force prediction model of titanium alloy thin-walled work piece, and used the regression analysis method to get the milling force prediction formula, and verified milling force prediction model through milling test and finite element simulation [7]. Wang Haiyan et al. put forward multi-object genetic algorithm based on Pareto, and took material removal volume and tool life to be the optimization goal and optimize spiral milling parameters [8].

At recent, the optimization methods mostly adopted empirical formula as the optimization function, few methods adopted the response surface method or neural network model prediction method, all of that exist the problem of insufficient model precision and the optimization solution is local optimization solution.

Support Vector Machine (SVM) is a kind of effective method based on the basis of statistics VC dimension theory and structural risk minimum principle and is used to solve non-parametric regression modeling problems such as small sample, strong nonlinearity, high dimension and local minimal point[9], which has very strong generalization ability. A large number of examples show that support vector regression machine has better regression performance than the common response surface, Kriging model and the neural network model.

This paper use the support vector machine (SVM) surrogate model technology to optimize the milling parameters of Titanium alloy, take material removal rate and tool life to be the optimization goal, take cutting force, surface roughness to be constraint conditions and use the NSGA - II algorithm optimization to study multi-objective optimization of milling parameters.

II. Finite Element Method for Ti6Al4V

Ti6Al4V titanium alloy is taken to be research object, it can be found that milling performances of Ti6Al4V material mainly include machining efficiency, surface quality and manufacturing cost, that is concretely expressed in the size of the cutting force, surface roughness, tool life and material removal rate and other performance indicators. Under the circumstance of certain process conditions, the main factors that affect these indicators include cutting speed, load of every tooth, milling depth and milling width. Therefore, we will respectively use test and finite element theory to study the influence of different processing parameters for the performance indicators.

Carbide-tipped tool is used in this test, hook angle is 10°, relief angle is 7°, blunt round radius r of cutting edge is 0.001 mm, titanium alloy material property parameter density is 4.45g/cm3, elastic modulus is 103 GPa, heat conduction coefficient is 6.8 W/m·K, specific heat capacity is 611J/kg·K, Poisson's ratio is 0.3, milling force need use dynamic load testing sensor to obtain, the value of surface roughness use roughness tester Mitutoyo Surftest SJ - 310 to obtain, material volume of milling in per unit time is taken to be material removal rate [10], tool wearing capacities are taken to be measurement parameters of tool wear, wear size is used to measure tool life. In order to decrease times of test, we chose multi-factor orthogonal experiment design method to carry on sample stationing, adopted L16(4^4) orthogonal table to test and obtained 16 sets of test results [7].

At the same time, we chose Johnson-Cook model to be constitutive model and built up the finite element model for Ti6Al4V ,as shown in figure 1.

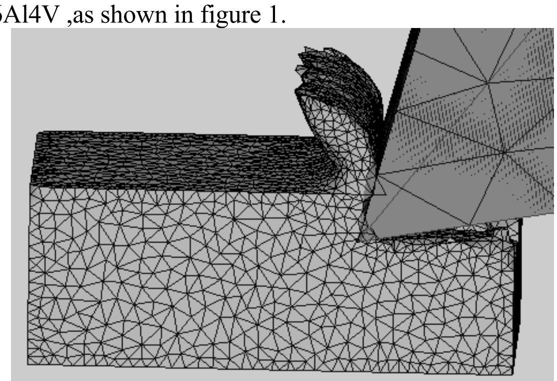

Figure 1. Fig.1 Titanium Alloy finite element model

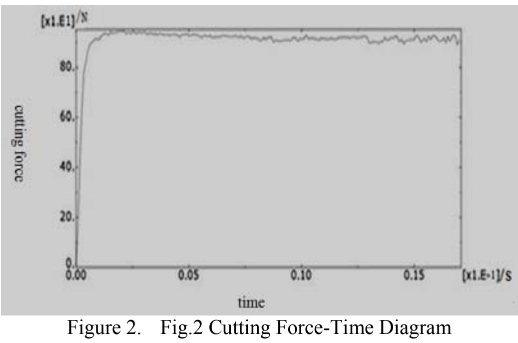

Figure 2. Fig.2 Cutting Force-Time Diagram

By calculation and analysis, the time-dependent curve of milling force under the given milling parameters is obtained as shown in figure 2, it can be seen that the cutting force increase amplitude is large because of the influence of cutting vibration at the beginning of milling, after turn into plastic milling, cutting force decreases and verge on stabilization soon, because node continuously separate, milling force continuously appear small scale fluctuation, we take the average values which have been stable as the milling force.

In order to verify effectiveness of finite element method, we compared 16 sets of computation with test data, as shown in Table1,relative errors were within 8%, it illustrated that computations are exact and effective.

III. Support Vector Machine (SVM) surrogate model

Consider a sample set defined as:

$$D = \{(x_i, y_i) \mid i = 1,2,\cdots,l\}$$

therein, $x_i \in R^n$ is n dimensions input sample, $y_i \in R$ is output sample. The basic theory that SVM is used for regression algorithm is realized through training samples, and using regression function $f(x) = w \cdot x + b$ to fit the relationship between input sample and out sample.

TABLE I. Training Samples

Order	Cutting Speed (m/min)	Load Of Every Tooth / m/min	Milling Depth / mm	Milling Width / mm	Cutting Force /N	Cutting Force Testing/N
1	100	0.06	1.4	11	406	404
2	80	0.14	1.4	5	120	126
3	120	0.02	1.4	8	190	193
4	60	0.1	1.4	14	413	416
5	60	0.06	1	8	298	296
6	120	0.14	1	14	478	473
7	80	0.02	1	11	139	145
8	100	0.1	1	5	273	267
9	60	0.14	0.6	11	374	380
10	120	0.06	0.6	5	236	237
11	80	0.1	0.6	8	182	186
12	100	0.02	0.6	14	87	89
13	100	0.14	0.2	8	131	135
14	80	0.06	0.2	14	35	39
15	120	0.1	0.2	11	131	128
16	60	0.02	0.2	5	29	31

Through importing nonnegative relaxation factors ξ_i , ξ_i^* , fitting problem of function is translated into following optimization problem.

$$\min \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{1}$$

$$\text{S.T.} \quad \begin{aligned} & y_i - w\cdot x_i - b \le \varepsilon + \xi_i \\ & w\cdot x_i + b - y_i \le \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \ge 0 \quad i = 1,2,\cdots n \end{aligned} \tag{2}$$

$\varepsilon > 0$ expresses necessary fitting precision, which is relative to noise level. C>0 controls penalty degree of the sample that went beyond error ε. we can get following form by using duality principle of optimization method.

$$\max \quad \begin{aligned} & W(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle x_i, x_j\rangle \\ & + \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)y_i - \sum_{i=1}^{n}(\alpha_i + \alpha_i^*)\varepsilon \end{aligned} \tag{3}$$

$$\text{S.T.} \quad \begin{aligned} & \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ & 0 \le \alpha_i, \alpha_i^* \le C \quad i = 1,2,\cdots n \end{aligned} \tag{4}$$

SVM fitting function can be obtained from Eq.(3,4):

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{5}$$

Therein, $K(x_i, x_j) = \phi(x_i)\phi(x_j)$ expresses kernel function, inner product of kernel function is used to solve nonlinear regression problem in high-dimension characteristic space.

We use MATLAB software, take the data of Table 1 to be training sample to study support vector machine (SVM), and carry on examining, through comparing milling force predicted values of established support vector machine (SVM) model with its experimental values, the correlation curve of predicted values and experimental values of milling force is shown in Fig.3.

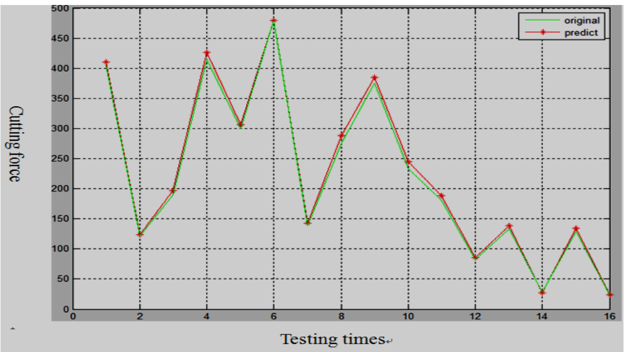

Figure 3. Comparison between True Value and from SVM

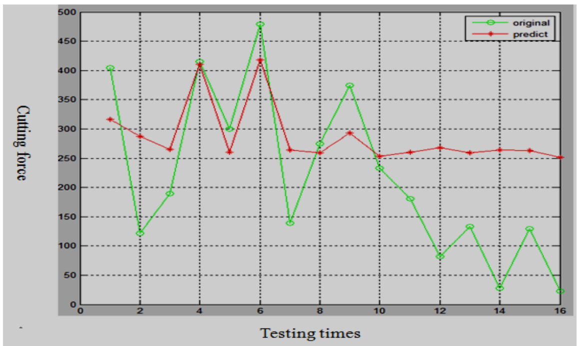

Figure 4. Comparison between True Value and from BPNN

From Fig.3 it can be seen that test values and predicted value's results of SVM model have the consistent change tendency. In order to illustrate the accuracy of support vector machine (SVM) model, we use the same samples to train the BP neural network (BPNN) model and get the correlation curve of BPNN model cutting force predicted values and experimental values as shown in Fig.4. The figure shows that the SVM model's predicted values and experimental values have more obvious effect of fitting, and that is better than BPNN model.

Table 2 is the correlation table of the predicted values of SVM model, predicted values of BPNN model and experimental values, it can be seen that the relative error of SVM model is within 5%, but the relative error of BPNN model's some local predicted values is large, it illustrates milling force prediction model which is based on the SVM and built in small sample and high dimension have higher precision and more effective.

TABLE II. PREDICTED VALUE ACCURACY COMPARISON BETWEEN SVM AND BPNN

order	Experimental Values /N	SVM Predicted Values /N	Relative Error /%	BPNN Predicted Values /N	Relative Error /%
1	406	410.6	1.13	316.6	22.0
2	120	124.5	3.75	167.9	39.9
3	190	196.1	3.21	237.1	24.8
4	413	426.9	3.36	410.6	0.58
5	298	306.3	2.78	260.1	12.7
6	478	478.1	0.02	418.2	12.5
7	139	142.6	2.59	161.5	16.2
8	273	288.9	4.98	259.5	4.9
9	374	385.1	2.97	293.3	21.6
10	236	244.8	3.72	253.5	7.4
11	182	188.5	3.57	259.7	42.7
12	87	85.6	1.60	97.3	11.8
13	131	136.9	4.50	159.2	21.5
14	35	33.3	4.86	51.6	47.4
15	131	134.7	2.82	162.9	24.3
16	29	29.9	3.10	36.7	26.5

According to the same method, we constructed the SVM surrogate model of removal rate, tool life and surface roughness.

IV. SVR BASED ON NSGA-II

A. NSGA-II

The NSGA-II algorithm is put forward by K. Deb and other scholars to solve the shortcomings of NSGA [11], the improvements are mainly manifested in three aspects: the first is the rapid non-dominated sorting method was put forward, which reduced computational complexity of the algorithm. The second is the crowding degree and the crowding degree comparison operator that is used to replace the NSGA's fitness sharing strategy that need specify sharing radius is used as the victory standard of same grade comparison after rapid order, it make the Pareto solution set uniformly distributed and keeps the diversity of the population. The third is the introduction of elite strategy, which expand the sample space, it make the parent population and its progeny population combine and produce the next generation population through common competition. That is good for keeping the good parent individuals into next generation and makes the best individual retain through hierarchically depositing all individuals of population.

NSGA-II algorithm adopts the following methods to achieve: first of all, it randomly initializes population P0 with N individuals, make all the individuals sort according domination relationship and assigns a fitness value. Then, the population P0 is carried on selection, and use crossover and mutation genetic operators to produce offspring population Q0. When entering t-th generation, combining the parent population Pt and the offspring population Qt to be a populations Rt with 2N individuals, next, populations Rt is rapidly non-dominantly sorted, producing a series of non-dominated set and calculating crowding degree, the better N individuals are inherit to the next generation Pt+l according to the principle that crowding degree selects operator, and thus get a new generation of the parent population. Finally, the new generated parent population Pt+l is carried on genetic operators (selection, crossover and mutation) operation, and produce new offspring population Qt+1 with N individuals, algorithm enter the generation t+1. Recycling until convergence or evolving to the specified maximum evolution algebra.

Because of high efficiency and good astringency of NSGA-II algorithm, it specially fits multi-objective problem solution in engineer.

B. SVM based on NSGA-II

The optimization design method based on SVM and NSGA-II put forward in this paper is coupling of experiment design, the SVM and the NSGA-II algorithm. At first, using experiment design to choose suitable experimental scheme, sample points are obtained through experiment or numerical simulation, and then building support vector regression machine predicted model with automatic parameter optimization function. Prediction is taken to be objective function or constraints of optimization, and combined with other constraints to establish multi-objective optimization model. Finally, using NSGA-II program to calculate optimum value of the optimization model. The algorithm process based on the SVM and NSGA-II as shown in Diagram 5.

1) Test design: screening variables with important influence degree as design variables, selecting experiment design method, through experiments and numerical calculation, obtaining the training sample.

2) Construct the SVM prediction model: aiming at the objective function and constraint function without explicit function expression, it needs be approached through constructing high precision support vector regression machine prediction model. If the approximation precision of prediction model does not satisfy the requirement, the optimal results of each iteration is taken as new training sample, updating model, improving the model accuracy.

3) NSGA-II multi-objective optimization: it uses the NSGA-II to search optimization problems based on the SVM prediction model in design space, and uses the distribution uniformity and diversity of Pareto solution set to evaluate the quality of Pareto solution set, if it satisfies the requirement, Pareto solution set is output; if it doesn't satisfy the requirement, increasing population and maximum evolution algebra, returning to step 2, and carrying on optimization solution again.

4) According to preference information, selecting satisfied solution.

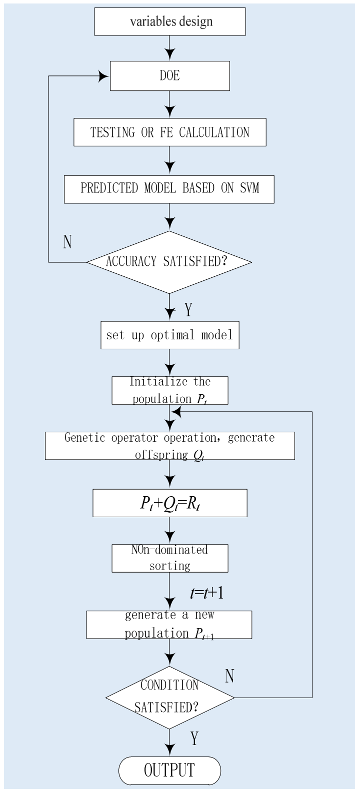

Figure 5. Algorithm Flow of Framework Based on SVM-NSGA-II

V. OPTIMIZATION OF MILLING MACHINING PARAMETERS BASED ON SVM AND NSGA-II ALGORITHM

The optimization goals of titanium alloy milling include material removal rate, processing efficiency, tool life and so on, all of that are related to machining parameters. This paper take the material removal rate and tool life as the optimization goal, which separately use $f_1(X)$ and $f_2(X)$ to express, take milling force, surface roughness R_a of component and machine own conditions as constraints, and take four machining parameters including milling speed v, each tooth feed rate z, milling depth a_r and milling width a_l as optimization variables, which use $X=(x_1, x_2, x_3, x_4)$ to express, the optimization model is expressed as

$$\max F(X) = (f_1^*(X), f_2^*(X))$$

$$\text{s.t.}\quad \begin{aligned} & g_1^*(X) \le F_{\max} \\ & g_2^*(X) \le R_{\max} \\ & g_j(X) \le 0 \\ & X = [x_1, x_2, x_3, x_4]^T \in [X_{\min}, X_{\max}] \end{aligned} \qquad (6)$$

Where, $f_1^*(X)$, $f_2^*(X)$, $g_1^*(X)$, $g_2^*(X)$ respectively express the predicted values of material removal rate, tool life, milling force and surface roughness. $F_{\max}$ is allowable maximal milling force, which is related to machine power. $R_{\max}$ is allowable maximal value of surface roughness. $g_j(X)$ is the j_{th} conventional constraint.

The parameter setting of NSGA-II algorithm as: population scale is 50,evolution algebra is 300, crossover operation probability is 0.9, mutation operation probability is 0.1.

Pareto sets as shown in Fig.6. BC part points is taken as satisfied solution set. The detail table information of Pareto solution of BC part is shown in Table 3, it can be seen:

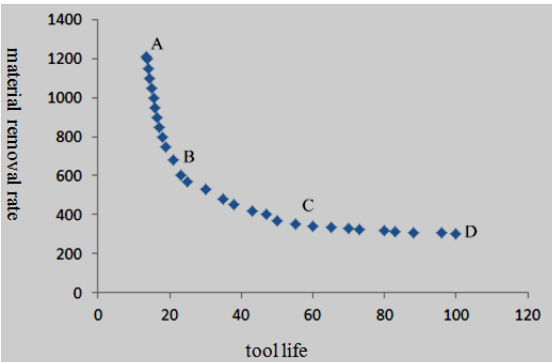

Figure 6. Optimization Result Pareto Solutions

Material removal rate and tool life are closely related to the size of milling speed, with milling speed increase, material removal rate increases, processing efficiency improve, but tool life obviously shorten. Each tooth feed rate keep change within small scope because of limit of constraint conditions, which has some influence for material removal rate and tool life and obviously influence on roughness value, each tooth feed rate is larger, roughness value is smaller, surface quality is better. Milling depth has larger influence on the material removal rate, with milling depth increases, material removal rate increased significantly. Milling width mainly keep near maximum, the main reason is that the milling width has little impact on the tool life; Surface roughness obviously decreases when milling speed is bigger, therefore, milling speed can be suitably improve to improve surface quality and production efficiency. In the process of titanium alloy milling processing, technology personnel can combine with the enterprise actual to consider machining efficiency, tool cost and machining quality and determine a set of best milling parameters, a set of suggest parameter is proposed as: milling speed x_1=88.7m/min, each tooth feed rate is 56.6mm/min, milling depth is 0.85mm, the milling width is 13.6mm.

TABLE III. TAB.3 PARTIAL PARETO SOLUTIONS

order	x_1/ m/min	x_2/ mm/min	x_3/ mm	x_4/ mm	R_a/ μm	$f_1(X)$ /mm^3/min	$f_2(X)$ /min
1	91.3	57.3	1.06	13.9	0.58	763	20.3
2	89.5	52.5	0.92	13.9	0.59	680	22.6
3	88.7	56.6	0.85	13.6	0.57	607	25.5
4	86.3	49.4	0.79	13.8	0.58	569	25.1
5	78.9	50.3	0.78	13.5	0.62	533	29.7
6	76.2	48.9	0.78	13.7	0.62	487	35.2
7	75.1	47.1	0.76	13.9	0.61	462	38.9
8	74.8	45.3	0.74	13.7	0.64	427	43.3
9	72.6	45.8	0.72	13.9	0.64	401	46.4
10	69.7	43.2	0.71	13.6	0.63	366	49.8
11	68.5	41.7	0.68	13.8	0.64	305	51.6

VI. CONCLUSION

(1) In Ti6Al4V titanium alloy processing process, the relative error of the milling force which used finite element method to calculate and the test value is within 8%, the numerical calculation can more accurately simulate machining process, and replace test methods to reduce design cost.

(2) In the circumstance of small sample, high dimension, support vector regression machine surrogate model prediction accuracy is high, and it has higher precision than the other surrogate model like neural network when it applied to titanium alloy milling performance.

(3) The optimization method based on support vector regression machine and the NSGA - II algorithm, it can get satisfied Pareto solutions when it used to solve the optimization problem of titanium alloy milling parameter, technology personnel can flexibly select milling parameters according to the preference of production efficiency, machining cost and machining quality and it provide a new technological method for parameter optimization of material processing, it has good generalization value.

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