Application of AF-SVM based on the Structure of the Machine

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Abstract: The problem of time-consuming in optimization of large complex structures such as grinder, The method of selecting support vector machine parameters based on artificial fish-swarm algorithm and its application, The feasibility of replacing time-consuming finite element analysis for structural optimization is validated. Based on the plane grinder bed, the orthogonal experimental design method was used to select the sample points in the structure parameter space of the grinder bed; The sample point is simulated by ANSYS, and the sample set is produced; By using the better parallelism and the strong global optimization ability of artificial fish swarm algorithm, the optimal parameter combination of SVM is obtained, and the approximate modeling of the grinder bed model is completed. The results show that compared with the traditional finite element method, the method not only significantly improves the computation efficiency, but also has good accuracy.

1 INTRODUTION

The lathe bed is an important supporting part of CNC machine tools ,which has a great influence on the performance of the grinder. In the process of design, it is necessary to have both sufficient strength and light weight, while also taking into account its dynamic characteristics. The traditional design is mainly analyzed and optimized by the finite element model. However, the finite element analysis takes a long time. The iterative calculation of the finite element analysis during the optimization process will increase the time cost of the whole optimization process. It is difficult to carry out multi-scheme analysis and comparison in short time to meet the requirement of rapid scheme demonstration in the initial stage of grinder structure optimization design.

In engineering calculation, in order to save time cost, the approximate model is often introduced instead of the simulation model to calculate and optimize. The approximate model is a mathematical model based on the experimental design method and approximate modelling method ,using the finite input-output parameter pair, the statistical or fitting method, which is the model after the second modeling of the original model. The approximate model can not only reduce the computational time, but also quickly analyze the complexity of the model and the sensitivity of the design variables. At present, there are commonly used response surface methods, neural networks, support vector machines ,etc.

The traditional approximate model method is influenced by the number of samples. Increasing the number of samples can improve the accuracy of the approximate model calculation. However, in practical projects, the number of samples is often limited ,so a more reasonable method is needed to handle the approximate problem in the case of small samples. At present, SVM has been well applied in many fields such as pattern recognition, optimization design, and data mining.

Therefore, this paper will construct an approximate model of the grinder bed based on the support vector machine .on the premise of guaranteeing the rigidity and natural frequency of the grinder bed, it can not only improve the operation speed ,but also improve the overall multidisciplinary optimization design efficiency of the bed body, which provide the technical support for the overall rapid scheme.

2 SVM THEORY

SVM is based on the VC-dimensional theory of statistical learning theory and the principle of structural risk minimization.SVM regression is a generalization of support vector machines in regression estimation of nonlinear systems, it is the concrete realization of the idea of nuclear method, that is, to realize the mapping of input variable to high dimension feature space implicitly by the kernel of estimating inner product in feature space, and then construct linear regression function in high dimensional feature space, and solve the nonlinear problem of original space.

Suppose a set of training sets T={(X_i,Y_i),i = 1, 2,...,n,},where X_i is the input vector of the i-th sample and Y_i is the output corresponding to the i-th sample Function,n is the number of samples.Mapping it to high-dimensional feature space through nonlinear mapping.Its nonlinear regression equation:

$$\mathrm{f}(\mathrm{x}_i) = \mathbf{w} \cdot \varphi(\mathrm{x}_i) + b \tag{1}$$

Where $\varphi(\mathrm{x}_\mathrm{i})$ is the nonlinear mapping of input space Rn to high-dimensional space, $\mathbf{W}$ is the weight vector and b is the offset. The SVM regression equation is based on the structural risk minimization principle, and the number and generalization ability of the support vectors are determined by the insensitive parameter ε, which reflects the sensitivity of the model to the noise contained in the input samples. Regression problem transformation planning problem, consider minimizing, that is:

$$\mathrm{E}(\mathbf{w})=\frac{1}{2}\|\mathbf{W}\|^2 + C \cdot \frac{1}{l}\sum_{\mathrm{i}=1}^{l}\left|y_i - f(\mathrm{x}_i)\right|_{\varepsilon} \tag{2}$$

In the formula, the first item is the confidence risk item ,the role is to flatten the regression function, thereby enhancing the generalization ability ;the second item is the empirical risk item ,in which C is the penalty parameter and controls the degree of penalty over the error ε. When the value of C is small, the allowable error is larger. On the other hand, when the value of C is large, the allowable error is smaller.

After introducing slack variables ξ_i and ξ_i^*, formula(2) becomes：

$$\left\{\begin{array}{l} \min\limits_{\mathbf{w},\xi_i,\xi_i^*,b} \dfrac{1}{2}\|\mathbf{w}\|^2 + C \cdot \sum\limits_{i=1}^{l}(\xi_i + \xi_i^*) \\ s.t.\ (\mathbf{w} \cdot \varphi(\mathrm{x}_i) + b) - y_i \le \varepsilon + \xi_i \\ \quad \mathrm{y}_i - (\mathbf{w} \cdot \varphi(\mathrm{x}_i) + b) \le \varepsilon + \xi_i^* \\ \quad \xi_i, \xi_i^* \ge 0 \end{array}\right\} \tag{3}$$

By introducing the Lagrange multiplier α and α*,and according to the duality principle, the formula (3)is eventually transformed into the optimization problem:

$$\max W(\boldsymbol{\alpha},\boldsymbol{\alpha}^*) = -\varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{n} y_i(\alpha_i^* - \alpha_i) - \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\mathrm{K}(\mathbf{x}_\mathbf{i} \cdot \mathbf{x}_\mathbf{j}) \tag{4}$$

$$\begin{gathered} \text{s.t.}\ \sum_{i=1}^{n}\alpha_i = \sum_{i=1}^{n}\alpha_i^* \\ 0 \le \alpha_i, \alpha_i^* \le C; i = 1,2,...,n \end{gathered} \tag{5}$$

where K(X_i,X_j) is a kernel function satisfying the mercy condition.

Only part of the α-α* satisfies the non-zero condition, and the data points connected to the partial coefficients are called support vectors. If the number of support vectors isl, the regression equation for the input vector X can be expressed as：

$$\mathrm{f}(\mathrm{x}) = \mathbf{w} \cdot \varphi(\mathrm{x}) + b = \sum_{\mathrm{i}=1}^{1}(\alpha_i - \alpha_i^*)K(\mathbf{x_i},\mathbf{x}) + \mathrm{b} \tag{6}$$

The kernel functions commonly used in SVM include: polynomial kernel function, sigmoid kernel function and radial basis kernel function.

$$K(\mathbf{x_i},\mathbf{x}) = \begin{cases} ((\mathbf{x_i},\mathbf{x})+\mathrm{b})^{\mathrm{d}} & (\textit{polynomial kernel function}) \\ \tanh(\mathrm{k}(\mathbf{x_i},\mathbf{x})+\mathrm{v}) & (\textit{sigmoid kernel function}) \\ \exp\left(\dfrac{-\|\mathbf{x}-\mathbf{x_i}\|}{2\sigma^2}\right) & (\textit{radial basis kernel function}) \end{cases} \tag{7}$$

The choice of kernel function is also an important factor influencing the performance of the support vector machine, and the radial basis function can be well adapted. It has good convergence domain for both low-dimensional spatial data and high-dimensional space. Influence parameters of the approximate model performance of the radial basis kernel function support vector machines The main parameter has penalty parameters C and σ, they need to be optimized.

3 ARTIFICIAL FISH SWARM ALGORITHM

The artificial fish swarm algorithm uses multiple artificial fishes to perform optimization at the same time. The optimal value is chosen as the result of this optimization to achieve parallel operation, so that the artificial fish swarm algorithm can quickly converge to the optimal value, and is insensitive to the given initial value and has the ability of global optimization. Therefore, it is applied to the optimal selection of support vector machine parameters, the optimization objective is to determine the optimal parameter combination (C,σ)to maximize the classification accuracy of SVM.

Artificial fish is the virtual entity of a fish, which encapsulates its own parameters and a series of behaviors, and the effect of these parameters on the final result, can accept the environment stimulus information, and make corresponding activities, Its environment consists of the solution space of the problem and the state of other artificial fish, its behavior depends on its state and the state of the environment in the next moment, and it also affects the environment through its own activities, which affects the activities of other artificial fishes. The artificial fish swarm algorithm has the following fourbasicbehaviors:(1)foraging-behavior,(2)clustering-behavior,(3)rearend-behavior(4)random-behavior.

(1)Foraging-behavior is a kind of activity that imitates fish tending to food, and can be considered to be the direction of action by perceiving the amount of food or food concentration in the water by sight or taste. In the design algorithm, it can be described as:

①Artificial Fish X_i randomly selects a state X_j in its field of vision.

$$X_j = X_i + V_{isual} * Rand() \tag{8}$$

② Calculated the objective function value of $X_i$and X_j respectively Y_i and Y_j,if found to be better Y_j, then X_i to X_j direction move one step.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|} * Step * Rand() \tag{9}$$

③Otherwise, X_i continues to select the state X_j in its field of vision to determine whether to meet the forward conditions ,and after trying Try−number times repeatedly, it still does not meet the forward conditions, then execute random behavior.

The artificial fish individual state $X=(X_1,X_2,...,X_n)$ (where$X_i(i=1,2,...,n)$ is the optimization variable),artificial fish vision is Visual, Rand() is a random function that is a random number in the interval(0,1).Step for artificial fish move stride length.

(2)Clustering-behavior is the simulation of a large number or a small number of fish aggregations, collective foraging and avoidance of predators, which is a form of survival that they formed during the evolution process. There are two rules to follow in the fish cluster: One is to move as close to the center of the neighboring partner as possible, and the other is to avoid overcrowding. In the design algorithm, it can be described as：

①Artificial Fish X_i searches for the number of partners in the current field ($d_{ij}<V_{isual}$) N_f and central location X_c, If $Y_c/N_f>\delta Y_i$,it indicates that the position of the partner center is better and less congested ,then X_i moves one step toward the center of the partner.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\left\| X_c - X_i^t \right\|} * Step * Rand() \tag{10}$$

②Otherwise, foraging behaviour .

The total number of artificial fish is N, congestion factor is δ, the distance between artificial fish individual i,j,$d_{ij}=|X_i-X_j|$.

(3)Rearend-behavior is to imitate when a certain fish or a few fishes finds food, the fish in the vicinity of them will follow, resulting in a behavior that the fish in the more distant place will follow. In the design algorithm, it can be described as：

①Artificial Fish X_i searches for the best partner X_j of function Y_j in the partner of current field of Vision ($d_{ij}<V_{isual}$).If $Y_j/N_f>\delta Y_i$,indicating that the optimal partner's surroundings are less crowded,X_i moves one step towards partner X_j:

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|} * Step * Rand() \tag{11}$$

②Otherwise, foraging behavior.

(4)Random-behavior is a default behavior of simulating fish foraging behavior, which refers to the artificial fish moving randomly in the field of vision. When food is found ,it moves fast in the direction that food is gradually increasing. In the design algorithm, it can be described as：

①Artificial fish X_i randomly move one step to reach a new state：

$$X_i^{t+1} = X_i^t + V_{isual} * Rand() \qquad (12)$$

4 APPROXIMATE MODEL VALIDATION

Determine The approximate model flow of the grinder bed is established by the artificial fish-swarm algorithm. See Figure 1.

The whole process can be roughly divided into the following steps:

(1)using orthogonal design to generate parameters, then through finite element analysis, the design variables and structural responses of each analysis are recorded, respectively, as experimental samples.

(2)Setting and initializing parameters of AF and SVM, respectively.

(3)Through the sample data, SVM training based on artificial fish swarm algorithm and establish an approximate model to find the optimal target value, determine the optimal parameter combination of SVM.

(4)Contrastive analysis of results with traditional finite element analysis.

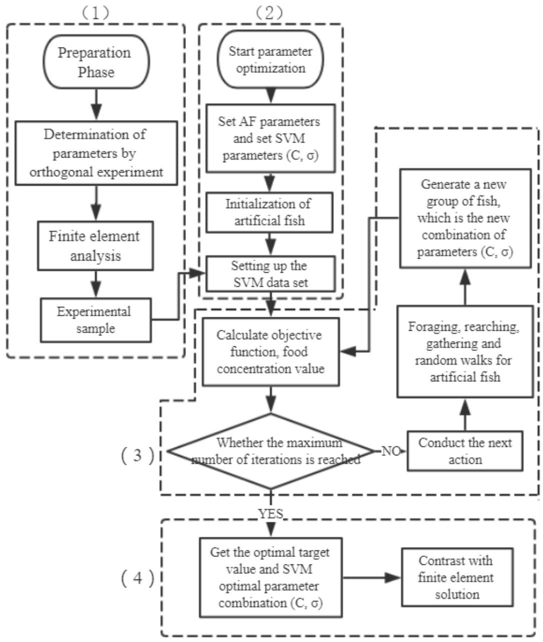

Figure 1: A flow chart of the approximate model established by AF-SVM.

4.1 Experimental Data

In this paper, the approximate model of the maximum deformation displacement of the bed is developed based on the design dimension of a grinder bed structure. According to the design and practical experience, the thickness of the bed wall and fascia as design variables, see table 1.

Table 1:Design variables and symbols.

Parameter	Design variables	Size (mm)
X_1	Load-bearing Wall Thickness	60
X_2	Ordinary wall thickness	50
X_3	Thickness of ordinary rib plate	20
X_4	Thickened rib thickness	40

The selected design variables are shown in Figure 2.

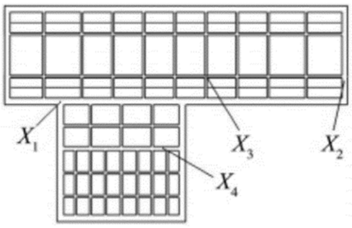

Figure2:schematic diagram of design variable of grinder bed body.

In order to establish an approximate model, sample collection is the first step. Orthogonal test method has the characteristics of neat comparability and balanced dispersion. It can use a sample number as small as possible to obtain more comprehensive sample points and improve modeling efficiency.4 variable parameters can be taken 4 values in their respective feasible fields. Use the orthogonal table to design the sample table 2,select the variables as 4 factors, select the orthogonal table $L_{25}(4^5)$,a total of 25 groups of training.

In order to improve the efficiency of the analysis and reduce the calculation time, the model is simplified without affecting the calculation precision of the model, ignoring the load-hole, the line hole, the threaded hole, the keyway, the retract groove and so on, and the partial transition arc is reduced to the right angle. At the same time, set aside 5mm distance between the joint surface, establish the small convex platform, conveniently in the ANSYS, on the bolt, the Guide slider and so on the joint part to add the parameter, simulates the combination parameter the stiffness and the damping unit. The use of Pro/E software to create a simplified bed solid model shown in Figure 3.

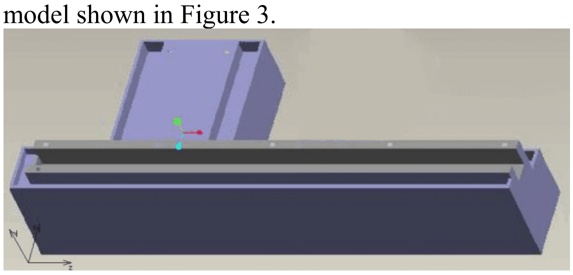

Figure 3:simplified rinder bed solid model.

The grinder bed material is set to HT200,elastic modulus E=120gpa,Poisson's ratio v=0.28,density ρ=7000kg/m3,strength limit σ≥300mpa.The contact surface between the bottom of the bed and the foundation is added with the displacement full restraint to realize the fixing of the bed. The contact surface of the slider is divided in the guide plane, and the load pressure is applied 0.689MPa.The pressure between the bed and the column is 0.12MPa.Through the ANSYS mesh division formed 19,742 nodes, 9,358 units. The meshed model is shown in Figure 4.

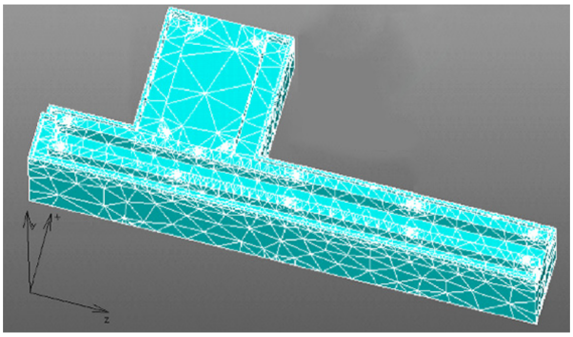

Figure 4: meshed model in ANSYS.

The maximum deformation U (μm) of the sample data is obtained by ANSYS .See Table 2.

Table 2：Orthogonal test results.

No.	Design variable				Analysis results
	X_1	X_2	X_3	X_4	U(μm)
1	54	42	16	36	1.925
2	54	44	18	38	1.854
3	54	46	20	40	1.783
4	54	48	22	42	1.745
5	54	50	24	44	1.685
6	56	42	18	44	1.789
7	56	44	20	36	1.801
8	56	46	22	38	1.738
9	56	48	24	40	1.691
10	56	50	16	42	1.863
11	58	42	20	42	1.728
12	58	44	22	44	1.683
13	58	46	24	36	1.689
14	58	48	16	38	1.848
15	58	50	18	40	1.798
16	60	42	22	40	1.675
17	60	44	24	42	1.637
18	60	46	16	44	1.789
19	60	48	18	36	1.789
20	60	50	20	38	1.734
21	62	42	24	38	1.631
22	62	44	16	40	1.775
23	62	46	18	42	1.727
24	62	48	20	44	1.675
25	62	50	22	36	1.676

4.2 Experimental Simulation

First of all, in order to avoid a certain dimension feature value being too large and influence the final result. the sample data is normalized and the convergence speed of the program is ensured.

The value range of the penalty parameter C of the radial kernel correlation parameter of support vector machine is set to (0,10),The range of σ is (0,10),Population evolutionary algebra is 50,Population size is 5,Try-number is 5,congestion factor δ is 0.618.Visual is 0.5.Step is 0.1.

Optimized SVM parameter model,C=4.6721，σ=0.0136.In order to verify the validity of the approximate model,5 output data are randomly selected as test samples, and compared with the results of finite element analysis, see table 3.

Table 3：Test samples.

No.	Design variable				Analysis results
	X_1	X_2	X_3	X_4	U(μm)
1	65	47	25	44	1.661
2	63	55	16	36	1.719
3	57	54	24	37	1.677
4	58	48	22	43	1.649
5	67	45	19	41	1.664

Compare the output value of the approximate model on the test sample with the output value of the finite element ,as shown in Figure 5,where the diamond point represents the approximate model and the triangle represents the finite element solution.

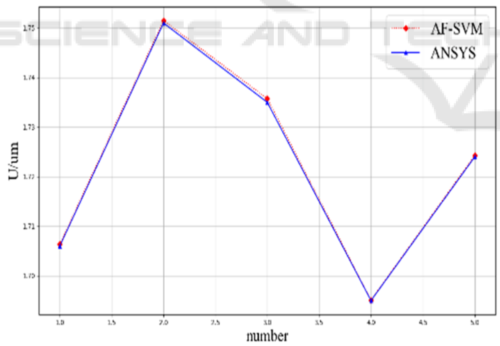

Figure 5：Compare the output value of the approximate model with the output value of the finite element

The actual relative error of the finite element solution and approximate model value is 3.605%,as shown in table 4.

Table 4 Simulation results of the test sample SVM approximation model.

No.	Finite element solution	Test solution	Relative error
1	1.661	1.706	2.709%
2	1.719	1.751	1.861%
3	1.677	1.735	3.458%
4	1.649	1.695	2.789%
5	1.664	1.724	3.605%

From Figure 5 and Table 4,we can see that compared with the exact verification value of the finite element analysis, the SVM with optimized parameters has a very high precision, and the relative error of the finite element analysis and the approximate model is less than 5%.Moreover,the running time of AF-SVM algorithm is very fast ,and the results obtained by SVM with parameter optimization have good engineering practicability.

5 CONCLUSIONS

In this paper, in order to calculate the deformation value of the grinder bed, the problem of time consuming is too long for finite element analysis. Replacing finite element analysis model with approximate model based on AF-SVM. Under the premise of guaranteeing the accuracy of calculation, fewer finite element analysis times are invoked, which significantly reduces the computational time cost. The experimental results show that the proposed method can meet the practical requirements of engineering and can be extended to approximate simulation of other mechanical structures to achieve the rapid demonstration of general scheme.

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