A prediction model of drilling force in CFRP internal chip removal hole drilling based on support vector regression

Chengyang Xu 1 · Songyang Yao 1 · Gongdong Wang 1 · Yiwen Wang 2 · Jiazhong Xu 3

Received: 13 January 2021 / Accepted: 21 July 2021 / Published online: 8 August 2021
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Abstract
Drilling force is the main factor affecting the quality of carbon fiber-reinforced polymer (CFRP) holes and tool wear. Choosing appropriate process parameters can effectively control the drilling force and improve the quality of hole making and tool life. This study aimed to accurately predict and effectively control the drilling force during the chip removal hole drilling process in CFRP. First, a CFRP internal chip removal machining drilling force prediction model was derived based on the support vector regression (SVR) theory, and a suitable kernel function and loss function were introduced into the model to improve the prediction accuracy of the model. Second, a drilling experiment of the given type of CFRP material with internal chip removal was designed, and sequential minimal optimization was applied to solve the unknown parameters in the prediction model. The drilling force and tool parameters, suction parameters, and cutting parameter prediction models were constructed for processing a given type of CFRP material. Finally, using the constructed prediction model, the relationship between cutting parameters (speed and feed), tool parameters (drill diameter, peak angle, and relief angle), and suction parameters (negative pressure) and axial force during CFRP internal chip removal hole drilling was predicted and studied. The relationship between the aforementioned parameters and the axial force was in line with the research results of existing studies, and the selection range of tool parameters, cutting parameters, and suction parameters when processing a given CFRP material using an internal chip removal process was also given.

Keywords CFRP · Drilling force · Internal chip removal hole drilling · Prediction model · Support vector regression

1 Introduction
Drilling force is the main factor affecting the quality of carbon fiber-reinforced polymer (CFRP) holes and tool wear. The size of the hole is closely related to tool parameters and cutting parameters. If the parameter selection is not appropriate, it may cause excessive drilling force, and consequently, the defects such as delamination and tearing are produced [1]. Accurate prediction and effective control of the drilling force in CFRP machining are the necessary conditions to ensure the quality of CFRP drilling and reduce tool wear [2]. Therefore, studying the relationship between drilling force and various influencing factors and establishing a prediction model for CFRP drilling force are urgently needed to improve the quality of hole making and the life of cutting tools.

Scholars at home and abroad conducted extensive and in-depth research on the drilling force generated during CFRP drilling. For example, in 1990, Hocheng et al. [3] pointed out that the critical axial force was related to the cutting depth and the material properties of the machined object. In 1995, Chandrasekharan et al. [4] established the prediction model for the axial force and torque for drilling CFRP materials. In 2005, Sun et al. [5] adopted the method of CFRP drilling experiment. The influence of cutting tool material (high-speed steel and cemented carbide), cutting parameters, drilling number, and material thickness on drilling force was analyzed. In 2008, Tsao et al. [6] studied the relationship between bit diameter, feed rate, and drilling force when using candle core drill to process CFRP. In 2013, Ren et al. [7] established the relationship model between cutting edge and cutting parameters based on the cutting model of multilayer composite materials. In 2016, Hu et al. [8] introduced a drilling force model...
when processing CFRP using the pecking drilling method and conducted an in-depth study on the relationship between the drilling force, tool wear, and chip shape. In 2017, Liu et al. [9] established a full-cycle prediction model for the axial force in different drilling stages. In 2018, Meng et al. [10] established a full-period prediction model for the drilling force of CFRP for hole making and examined the relationship between the damage around the hole and the drilling force using this model based on the experimental data obtained by drilling and machining unidirectional CFRP plates.

The aforementioned analysis showed that in the CFRP hole drilling process, a nonlinear relationship existed between the drilling force and the tool parameters and cutting parameters. A suitable algorithm was needed to accurately describe this nonlinear relationship [11–13]. As an algorithm for solving nonlinear problems, support vector regression (SVR) can also maintain excellent solution performance in small-sample situations. Traditional statistical learning methods, such as neural network learning methods, can obtain only the optimal solution when the sample tends to infinity [14, 15]. When constructing the SVR parameterized model, the solution process is determined only by a small number of support vectors, not all sample data. The complexity of its calculation depends on the number of support vectors, not the dimensionality of the input sample space. Since the complexity of its calculation does not depend on the dimensionality of the sample space, it helps solving problems caused by the “curse of dimensionality” [16–18]. The internal chip removal hole drilling process is a new type of CFRP green hole drilling process. It can effectively discharge the chips generated in the cutting process through the inside of the tool in real time and effectively during the drilling process. The data on the drilling force prediction model are still rare. Therefore, this study was performed to build a drilling force prediction model during the internal chip removal hole drilling process based on the SVR theory. It provided a reference for optimizing the internal chip removal hole drilling process parameters to realize the effective control of the drilling force in the internal chip removal hole drilling process [19].

2 Construction of drilling force prediction model

The composition and working principle of the suction-type internal chip removal hole drilling system for CFRP internal chip removal processing were proposed first to construct an internal chip removal hole drilling force prediction model. Then, the construction theory of the SVR-based CFRP internal chip removal hole drilling force prediction model was proposed.

2.1 Composition and working principle of an internal chip removal hole drilling system

The suction-type internal chip removal hole drilling system (Figure 1) is composed of a machine tool, CFRP, an internal chip removal drilling bit, an external-rotation-internal-chip-removal tool handle, a chip pipe, a chip-collecting device, and so on. The internal chip removal drilling bit and the external-rotation-internal-chip-removal tool handle had chip removal holes. The function of the system was to discharge the chips generated during the drilling process of CFRP in real time through the chip removal channel, reduce the cost of manpower and material resources, improve the efficiency and quality of drilling, and realize the green processing of CFRP. The working principle of the system was that, when the machine tool was working, the spindle drove the suction-type internal chip removal drilling bit installed on the external and external-rotation-internal-chip-removal tool handle to drill. At the same time, the fan in the chip-collecting device provided the power to absorb chips (negative pressure). The system used the negative pressure to suck chips out through the chip suction channel of the drill bit and the external-rotation-internal-chip-removal tool handle with the chip removal channel into the chip-collecting device, thus completing the process of aspiration-type internal chip removal hole drilling.

2.2 Drilling force prediction model construction theory

Based on the data set $S = \{(x^1, y^1), \cdots (x^n, y^n)\}, S = X \times Y$ obtained from the experiments, SVR was used to establish the drilling force prediction model for CFRP internal chip removal hole drilling process, that is, to find the optimal function $f(x) = \langle \omega, x \rangle + b$ to make $f(x)$ as close to $y'$ as possible. At this point, the optimal curve $f(x)$ was the desired drilling force
model. The tool parameters (drill diameter, peak angle, and relief angle), cutting parameters (speed and feed rate), and aspirating parameters (negative pressure) were defined as the data set that affected the magnitude of drilling force, denoted as the set \( X, x' = x_1', x_2', \ldots, x_n' \in X \) was the vector that affected the size of the drilling force, where \( x' \) is the tool parameter, cutting parameter, and suction parameter data corresponding to each component. The data set of the predicted drilling force was defined as set \( Y \). The \( y' \in Y \) set was the value of the predicted drilling force, \( y' \) included axial force \( F \) and torque \( M \).

The data set of the relationship between the drilling force and each parameter obtained by the experiment was defined as set \( S = (s^1, s^2, \ldots, s^m) \), in which \( s^j \) followed a certain distribution and the data were independent, \( s' = (x', y') \), \( x' \in X, y' \in Y \), and this data set was a training set made up of known sample information. \( \omega \) was a vector consisting of the drilling force and the coefficients of the variables of tool parameters, cutting parameters, and aspirating parameters of the CFRP internal chip removal hole drilling process.

To ensure the prediction accuracy of the model, the \( \varepsilon \)-insensitive loss function was introduced, and the degree of loss between \( y \) and \( f(x) \) were expressed as \( c(x, y, f(x)) = |y - f(x)|_\varepsilon = \max \{0, |y - f(x)| - \varepsilon \} \). Under this loss function, the value of \( \omega \) was obtained by the minimum \( 1/2 \|\omega\|^2 + C\sum_{i=1}^{m} (\xi^i + \xi_i^*) \).

With the introduction of the slack variable, the function \( f(x) \) was determined by solving the minimum regularization problem of Eq. (1).

\[
\begin{align*}
\min \left\{ \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{n} (\xi^i + \xi_i^*) \right\} \\
\text{s.t.} \quad \langle \omega, x' \rangle + b - y' \leq \varepsilon + \xi_i \quad & \text{i} = 1, 2, \ldots, n \\
y' - \langle \omega, x' \rangle + b - \varepsilon + \xi_i^* \leq 0 \quad & \text{i} = 1, 2, \ldots, n \\
\xi_i \geq 0, \xi_i^* \geq 0 \quad & \text{i} = 1, 2, \ldots, n
\end{align*}
\]

where \( \xi = (\xi_1, \xi_2, \ldots, \xi_n)^T \), \( \xi^* = (\xi_1^*, \xi_2^*, \ldots, \xi_n^*)^T \) are the slack variables, and \( C \) is a penalty function used to adjust the errors.

Further analysis showed that solving Eq. (1) was equivalent to solving the duality. The function Lagrange was introduced to obtain Eq. (2).

\[
L(\omega, b, \xi, \xi^*, \alpha, \beta, \eta, \eta^*) = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{n} (\xi^i + \xi_i^*) - \sum_{i=1}^{n} (\eta_i \xi_i + \eta_i^* \xi_i^*) - \sum_{i=1}^{n} \alpha_i (\varepsilon + \xi_i + y' - \langle \omega, x' \rangle - b) - \sum_{i=1}^{n} \beta_i (\varepsilon + \xi_i^* - y' + \langle \omega, x' \rangle + b)
\]

where \( \alpha_i \geq 0, \beta_i \geq 0, \eta_i \geq 0, \eta_i^* \geq 0, i = 1, 2, \ldots, n \). Then, Eqs. (3)–(6) were given by the function extreme value condition:

\[
\begin{align*}
\nabla_b L &= \sum_{i=1}^{n} (\alpha_i - \beta_i) = 0 \\
\nabla_{x'} L &= w - \sum_{i=1}^{n} (\alpha_i - \beta_i) x' = 0 \\
\nabla_{\xi'} L &= C - \alpha_i \eta_i = 0 \\
\nabla_{\xi_i^*} L &= C - \beta_i \eta_i^* = 0
\end{align*}
\]

Equations (3)–(6) were substituted into Eq. (2), and the extreme maximum value with regard to \( \alpha_i, \beta_i, i = 1, 2, \ldots, n \) was sought for the formulas. The duality obtained was Eq. (7).

\[
\begin{align*}
\min \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_j)(\beta_j - \alpha_j) \langle x', x' \rangle \\
+ \varepsilon \sum_{i=1}^{n} (\beta_i + \alpha_i) - \sum_{i=1}^{n} y' \langle \beta_i - \alpha_i \rangle \\
\text{s.t.} \quad \sum_{i=1}^{n} (\alpha_i - \beta_i), 0 \leq \alpha_i, \beta_i \leq C, \quad i = 1, 2, \ldots, n
\end{align*}
\]

If \( \alpha^*_i, \beta^*_i \) were the optimal solutions to the aforementioned duality, the regression function \( f(x) \) was expressed as Eq. (8).

\[
f(x) = \sum_{i=1}^{n} (\beta^*_i - \alpha^*_i) \langle x', x \rangle + b
\]

where \( b \) can be calculated according to Eq. (9).

\[
b = \frac{1}{n} \sum_{j=1}^{n} \left( y' - \frac{1}{n} \sum_{i=1}^{n} (\beta^*_i - \alpha^*_i) \langle x', x \rangle \right)
\]

If \( \beta^*_i - \alpha^*_i \neq 0 \), then \( x' \) was known as a support vector.

For this nonlinear problem, the kernel function \( K(x', x') \) needed to be introduced. Then, the nonlinear function \( f(x) = \langle \omega, \Theta(x) \rangle + b \) was found, where \( \omega, \Theta(x) \in \kappa \). The principle of this nonlinear SVR problem is shown in Figures 2 and 3 [20]. As shown in Figure 2, if the linear regression model was adopted directly, it did not give good fitting results. For this
Through further analysis, the corresponding data in Figure 2 was converted into a linear model in a high-dimensional space by appropriately selecting the kernel function, as shown in Figure 3. A linear regression model of the high-dimensional space (corresponding to the nonlinear model of the original space) was given through further analysis. Figure 3 shows the linear regression model corresponding to the regression problem as shown in Eq. (10).

![Diagram of linear regression in high-dimensional characteristic space](image)

**Fig. 3** Linear regression of data in high-dimensional characteristic space \( \kappa \) obtained by special mapping \( \phi \)

At this point, the original optimization problem corresponding to the regression problem was as shown in Eq. (10).

\[
\min \left\{ \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \right\}
\]

\[s.t. \quad f(x_i) - y_i \leq \varepsilon + \xi_i, \quad (i = 1, 2, \cdots, n)\]

\[y_i - f(x_i) \leq \varepsilon + \xi_i^*, \quad (i = 1, 2, \cdots, n)\]

\[\xi_i \geq 0, \xi_i^* \geq 0, \quad (i = 1, 2, \cdots, n)\]

As discussed earlier, the duality was obtained, that is, Eq. (11).

\[
\min_{\alpha_i, \beta_i} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\beta_i - \alpha_i) (\beta_j - \alpha_j) K(x_i, x_j)
\]

\[+ \varepsilon \sum_{i=1}^{n} (\beta_i + \alpha_i) - \sum_{i=1}^{n} y_i (\beta_i - \alpha_i)\]

\[s.t. \quad \sum_{i=1}^{n} (\alpha_i - \beta_i) = 0, 0 \leq \alpha_i, \quad \beta_i \leq C, (i = 1, 2, \cdots, n)\]

\[\alpha_i^*, \beta_i^* \] were denoted as the optimal solutions of the aforementioned duality, and the regression function was expressed as Eq. (12).

\[
f(x) = \sum_{i=1}^{n} (\beta_i^* - \alpha_i^*) K(x, x) + b
\]

Hence, the theory regarding the construction of the SVR-based CFRP internal chip removal hole drilling force prediction model was proposed. The analysis showed that in this theory, \( f(x) \) was the drilling force (i.e., output variable), \( x \) was the parameter that affects the drilling force (i.e., input variable), \( (\beta_i^* - \alpha_i^*) \) and \( b \) were the unknown parameters (i.e., unknowns) required to be solved by the prediction model. Through further analysis of this theory, it was known that it is necessary to select an appropriate kernel function and loss function to optimize the model so as to obtain a more accurate and reasonable internal chip removal hole drilling force prediction model. Therefore, the following text introduced the selection basis of the kernel function and damage function used in this study to further complete the optimization of the construction theory of the internal chip removal machining drilling force prediction model.

### 2.3 Kernel function and loss function

It is necessary to introduce appropriate kernel function and loss function when modeling to obtain an accurate prediction model of drilling force for chip removal in CFRP. Therefore, the loss function and kernel function used in this study were selected to establish a high-precision prediction model between the parameters and drilling force, and the drilling force prediction model with loss function was given.

1. **Kernel function**

   A nonlinear relationship exists between drilling force and various parameters in CFRP internal chip removal hole drilling. It is necessary to select a suitable kernel function for constructing the input space to represent the nonlinear relationship between drilling force and tool parameters, cutting parameters, and suction parameters, so as to make it more in line with the accuracy requirements of the prediction model. Available data showed that the definition of the kernel function given by different published studies was slightly different. According to the solution needs, this study used a previously described method [14] to define the kernel function. Some commonly used kernel functions are shown in Table 1.

| Kernel Function                     | Characteristics                                                                 |
|-------------------------------------|---------------------------------------------------------------------------------|
| Gaussian radial basis kernel function | a scalar function that is symmetric along the radial direction. |

The Gaussian radial basis kernel function was chosen when modeling in this study according to the role of the kernel function in the drilling force prediction model and the characteristics of the Gaussian radial basis kernel function (a scalar function that is symmetric along the radial direction).

2. **Loss function**

   The analysis showed that under normal circumstances, the prediction model could not provide the fitting function between the drilling force and various parameters very closely.
The loss function related to the error was introduced to obtain a drilling force prediction model that took into account the fitting error and accuracy, so as to reduce the fitting error as much as possible and obtain a better fitting result. Table 2 lists some commonly used loss functions.

When using the loss functions in Table 2 and the support vector machine to model the drilling force of the internal chip removal hole drilling process, it was necessary to introduce the slack variables $\xi = (\xi_1, \xi_2, \cdots, \xi_n)^T$, $\xi^* = (\xi_1^*, \cdots, \xi_n^*)^T$ and the constraint $f(x^*) - y^\leq \xi_i$, $i = 1, 2, \cdots, n$. Then, the loss of the sample point $(x^*, y^*)$ was expressed as $c_i = c(\xi_i) + c(\xi_i^*)$, where $c$ was the selected loss function.

When the other loss functions in Table 2 were used instead of the $\varepsilon$-insensitive loss function, the original problem of the support vector machine regression machine became Eq. (13).

$$\min \frac{1}{2} \sum_{i=1}^{n} \left(c_i(\xi_i) + c(\xi_i^*)\right)$$

s.t. $f(x^*) - y^* \leq \xi_i, i = 1, 2, \cdots, n$

$y^* - f(x^*) \leq \xi_i^* i = 1, 2, \cdots, n$

$\xi_i, \xi_i^* \geq 0 i = 1, 2, \cdots, n$

Similarly, the duality was obtained as Eq. (14).

$$\min \frac{1}{2} \sum_{i,j=1}^{n} (\beta_i - \alpha_i)(\beta_j - \alpha_j)K(x^*, x^j)$$

$$- \sum_{i=1}^{n} y_i^*(\beta_i - \alpha_i) - C \sum_{i=1}^{n} (T(\xi_i^*) + T(\xi_i))$$

s.t. $\sum_{i=1}^{n} (\alpha_i - \beta_i) = 0,$

$$\beta_i \leq C \frac{d^2 c(\xi_i^*)}{d(\xi_i^*)} = 0, \ldots i = 1, 2, \cdots, n$$

$$\xi_i^{(*)} = \inf \left\{ \xi_i^* \bigg| C \frac{d^2 c(\xi_i^*)}{d(\xi_i^*)} \geq \alpha_i^{(*)} \right\}$$

$$\alpha_i^{(*)}, \xi_i^{(*)} \geq 0$$

where $T(\xi_i^{(*)}) = c(\xi_i^{(*)}) - \xi_i^{(*)} \frac{d^2 c(\xi_i^*)}{d(\xi_i^*)}.$

As the Huber loss function was highly robust and insensitive to outliers, the Huber loss function was used for modeling analysis in this study. The optimization model of the regression problem is shown in Eq. (15).

$$\min \frac{1}{2} \sum_{i,j=1}^{n} (\beta_i - \alpha_i)(\beta_j - \alpha_j)K(x^*, x^j)$$

$$- \sum_{i=1}^{n} (\beta_i - \alpha_i)y_i^j + \frac{\varepsilon}{2C} \sum_{i=1}^{n} (\beta_i - \alpha_i)^2$$

$$s.t. \sum_{i=1}^{n} (\alpha_i - \beta_i), 0 \leq \beta_i, \alpha_i \leq C, i = 1, 2, \cdots, n$$

where $\beta_i, \alpha_i$ are denoted as the optimal solutions of the aforementioned duality. The regression function $f(x)$ was still Eq. (12).

Setting $x_i = \alpha_i - \beta_i$, Eq. (15) was expressed as Eq. (16)

$$\min \frac{1}{2} x^T Qx - y^T x$$

$$e^T x = 0, s.t. - Ce \leq x \leq Ce$$

where $x = (x_1, x_2, \cdots, x_n)^T, y = (y_1, y_2, \cdots, y_n)^T, e = (1, 1, \cdots, 1)^T \in \mathbb{R}^n, Q = K + \sigma I/n$, $K = (K(x_i, x_j))_{i,j=1}^n$.

The component $x_1$ that was not equal to 0 in the optimal solution $(x = (x_1^*, x_2^*, \cdots, x_n^*))$ of this model was called as support vector.

Hence, the theory underlying the construction of the CFRP internal chip removal machining drilling force prediction model was proposed, but the unknown parameters in the model were not solved. Therefore, the following text introduced a solution process of the drilling force prediction model for chip removal processing in a given type of CFRP material.

### 3 CFRP drilling experiment

The preceding text described the CFRP drilling force modeling theory based on SVR. However, unknown parameters in the model needed to be solved to get the drilling force

### Table 2: Commonly used loss functions

| Loss functions          | Formula                                  |
|------------------------|------------------------------------------|
| $\varepsilon$-insensitivity | $|\xi_i|_c$                           |
| Laplace                | $|\xi_i|$                                |
| Gauss                  | $\frac{1}{2} |\xi_i|$                           |
| Robust loss function   | $\frac{1}{2} \sum (\xi_i^2)_j, |\xi_i|_c \leq \sigma$ |
|                        |                                          | $|\xi_i|_c - \sigma, other$ |
| Huber                  | $\frac{1}{2} \sum (\xi_i^2)_j, |\xi_i|_c \leq \epsilon$ |
|                        |                                          | $\epsilon |\xi_i|_c - \frac{\epsilon}{2}, other$ |
prediction model for a given type of CFRP material with internal chip removal. The previous analysis showed that it was necessary to carry out internal chip drilling experiments to obtain the corresponding solution test data $S$ so as to solve the unknown parameters. Therefore, the following text introduced the CFRP internal chip removal machining drilling force experiment and discussed the construction of the internal chip removal drilling force prediction model for processing a given type of CFRP material based on the experimental data set.

### 3.1 Experimental condition

This study used experimental methods to obtain the experimental data needed to establish a drilling force prediction model. The CFRP used in the study was provided by Hafei Industry Co., Ltd. Its density was 1760 kg/m$^3$, the longitudinal elastic modulus was 235 GPa, the transverse elastic modulus was 14 GPa, Poisson’s ratio was 0.2, the shear modulus was 28 GPa, the tensile strength limit was 3.59 GPa, and the compressive strength limit was 2.7 GPa. Its structure was orthogonal ply with a thickness of 4.5 mm. The processing equipment used in the study was a suction-type internal chip removal system. The testing equipment used was a Kistler 9171A rotary dynamometer, and the cutting force was transmitted to the computer through the data acquisition system and signal conditioner. The experimental configuration is shown in Figure 4.

The aspirating internal chip drill bit used in the study was designed independently [19]. This drill bit was manufactured by Guohong Tool System (Wuxi). The actual object is shown in Figure 5. The blade structure is shown in Figure 6.

The PCD blade for the aspirating internal chip removal drill bit, as shown in Figure 6, adopted a double-edged structure, in which the function of the major cutting edge was to cut, function of the major and minor cutting edges was to ream and smoothen, and the function of the minor cutting edge was to smoothen. The blade parameters shown in the figure were as follows: $D$, blade diameter; $a_1$, point angle; $a_2$, small point angle; $r$, chisel edge slope; $L_1$, major cutting-edge vertical length; $L_2$, major and minor cutting-edge vertical length; $h$, chisel edge length; and $\lambda$, relief angle. The specific parameter values are shown in Table 4.

The analysis of existing research results showed that the main factors affecting CFRP drilling force were tool parameters and cutting parameters. Further analysis of the CFRP internal chip removal processing showed that the factors that affected the size of the drilling force included the suction parameters in addition to the tool parameters and the chip parameters. Therefore, this study selected tool parameters, cutting parameters, and suction parameters, as shown in Table 3, as the experimental parameters to ensure the accuracy of the prediction model. During the study, each group of parameters was subjected to three repeated experiments, and the average value was taken as the result. Note: The small cutting-edge angle $a_2$ of the drill bit was 45°, the chisel edge inclination $r$ was 48°, and the PCD thickness $h$ was 1.5 mm. The length ratio of the main cutting edge and the minor cutting edge was $L_1:L_2 = 1:1$.

### 3.2 Experiment results

Using the aforementioned systems and tools, the CFRP internal chip removal hole drilling experiments under different cutting parameters (rotation speed and feed rate) and aspirating parameters (negative pressure) were carried out. The obtained drilling force and torque results are shown in Table 3. The experimental results showed that the quality of the holes obtained met the requirements of CFRP hole-making accuracy. This study mainly introduced the problem of drilling force modeling, and therefore the results of the experimental hole-making quality were not elaborated.

### 4 Construction of drilling force prediction model

#### 4.1 Forecast model accuracy analysis

The CFRP internal chip removal machining drilling force prediction model was constructed based on the experimental data in Table 4 using Platt’s SMO algorithm and Eqs. (8) and (9). The numerical simulation and precision analysis were carried out on the following two problems to verify that the accuracy of the established model met the requirements of drilling force prediction modeling before construction.
Model 1: The tool parameters (drill diameter, peak angle, and relief angle), aspirating parameters (negative pressure), and cutting parameters (cutting speed, feed rate) were independent variables, and the axial force was used as the dependent variable to establish the relationship model. (Note: The axial force in the prediction model was the maximum axial force generated during drilling. Because the axial force in CFRP hole drilling was the main reason that affected hole drilling defects and tool wear, effectively controlling the maximum axial force generated during machining could effectively inhibit the occurrence of defects and reduce tool wear speed.)

Model 2: The tool parameters (drill diameter, peak angle, and relief angle), aspirating parameters (negative pressure), and cutting parameters (cutting speed and feed rate) were independent variables, and the torque was used as the dependent variable to establish the relationship model.

Table 3 Parameters of experimental blade

| Name          | Value       |
|---------------|-------------|
| D (mm)        | 6, 8, 10    |
| α (°)         | 90, 120, 140|
| λ (°)         | 8, 12, 16   |
| f (mm/min)    | 50, 150, 260|
| n (r/min)     | 3000, 4000, 5000|
| P (KPa)       | 9, 12, 15   |

Fig 7 and 8 are diagrams showing the fitting effect of the relational model obtained by solving the aforementioned two problems with the sample data in Table 4.

The analysis of simulation results in Figures 7 and 8 showed that the drilling force prediction model constructed according to the theory and solution algorithm in this study had very little error with the sample data, that is, the accuracy of the built prediction model met the modeling requirements of this study. Table 5 shows the penalty function value and the fitting accuracy and optimal solution fitness value of the relationship model when using Model 1 and Model 2 based on the SVR theory. It corresponded to the mean square error of the performance indicators used in the SVR test. The definition of the goodness of fit and fitness were as follows.

Mean square error (MSE): \[ \text{MSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i-x_i^*)^2}{n}} \]

Fitness values: \[ \text{R}_{\text{New}} = \frac{\sum_{i=1}^{n}(y_i-x_i)^2}{\sum_{i=1}^{n}(y_i-y^*)^2} \]

Adaptability: \[ \text{SE} = \frac{1}{2} x^T Q x - y^T x \]

where \( x \) and \( x^* \) represent the actual value and the predicted value, respectively, and \( Q \) and \( y \) are as defined in Eq. (16). The smaller the mean square error, the closer the goodness of fit was to 1, which meant that the regression function fit the data better, and the independent variable explained the dependent variable better. The fitness function was the objective function of SVR corresponding to the original problem Eq. (16). Therefore, the smaller the fitness, the better the ability of the given algorithm to solve the SVR regression problem.

The analysis of results in Table 5 showed that the drilling force prediction model established based on the theory described in this study had high mean square error and fitting accuracy, that is, the accuracy of the constructed model met the requirements.

4.2 Predictive model of drilling force for internal chip removal processing

The prediction model for the relationship between tool parameters, suction parameters, and cutting parameters and axial force was established based on the accuracy analysis of the drilling force prediction model. The tool structure used for prediction is shown in Figure 6. The experimental data set used to solve the unknown prediction model is shown in Table 4. Combining Eqs. (8) and (9) and using the SMO solving algorithm, the coefficient values in the predictive model (Eq. (17) for the original model was Eq. (12)) were as shown in Table 6.

For the convenience of analysis, let \( x = (x_1, x_2, x_3, x_4, x_5, x_6) \) be the independent variables; \( x_1, x_2, x_3, x_4, x_5, x_6 \in R \) represent the drill bit diameter, the point angle, the length of the chisel edge, the negative pressure, the rotational speed, and the feed rate. Let \( z_1, z_2, z_3, z_4, z_5, z_6 \) be the data set to be applied when solving the regression model, that is, the values of the tool parameters, aspirating parameters, and processing parameters used in the experiments.
\[
\begin{align*}
\mathbf{f}(x) &= \sum_{i=1}^{18} \rho_i^* K_1(x_i, x) + b_1 \quad \text{Axial force} \\
\mathbf{f}(x) &= \sum_{i=1}^{18} \theta_i^* K_2(x_i, x) + b_2 \quad \text{Torque}
\end{align*}
\]

\[ (17) \]

5 Prediction study on factors influencing the axial force

The result analysis of existing research indicated that the axial force is the main cause of delamination defects and tool wear in CFRP hole drilling. Therefore, the established model could be applied to predict the relationship between the tool parameters, the aspirating parameters, the cutting parameters, and the axial force to provide a reference for the subsequent selection of the process parameters of the CFRP internal chip removal hole hole drilling process.

5.1 Prediction of the influence of cutting parameters

(1). Prediction of the influence of feed rate on the axial force

![Sample fitting results of model 1](image_url)
The relationship between the feed rate and the axial force was predicted using the aforementioned model under the conditions of the rotation speed of 3000 r/min, the diameter of the drill bit of 8 mm, the relief angle of 12°, the point angle of 130°, and the negative pressure of 9 kPa. The obtained curve of the change in the axial force versus the feed rate is shown in Figure 9.

The analysis in Figure 9 showed that when the feed rate gradually increased, the axial force also increased. Comparing the aforementioned prediction results with the research conclusions of existing researchers, it was seen that the change in the axial force with the feed rate predicted by this model was consistent with the research conclusions of existing researchers. The reasons for the aforementioned phenomenon were analyzed. When the feed rate increased, the quality of the material removed by the drill bit in a unit time increased, and hence the axial force increased. Further analysis with reference to the aforementioned prediction results showed that the range of feed rate that could be selected was 50–200 mm/min when drilling to meet the requirements of drilling processing.

(2). Prediction of the effect of rotational speed on the axial force

The relationship between the rotational speed and the axial force was predicted using the aforementioned model under the conditions of the feed rate of 200 mm/min, the diameter of the drill bit of 8 mm, the relief angle of 12°, the point angle of 130°, and the negative pressure of 9 kPa. The curve of the change in the axial force obtained versus the rotational speed is shown in Figure 10.

The analysis of the prediction results in Figure 10 showed that the axial force followed a downward trend as the speed increased. Comparing the aforementioned prediction results with the research conclusions of existing scientific researchers, it was seen that the change in the axial force with rotational speed predicted using the model was consistent with the research conclusions of existing scientific researchers. The reasons for the aforementioned phenomenon were analyzed. When the cutting speed increased, the cutting heat generated by the cutting process increased, which caused the softening of the CFRP material matrix, leading to the reduction of the axial force in the cutting process. Further analysis with reference to the aforementioned prediction results showed that the range of feed rate could be selected from 3000 to 5000 r/min to meet the requirements of drilling.

Table 5 Simulation experiment parameter values, fitting accuracy, and fitness values

| Model  | C  | Fitting accuracy | Fitness values | MSE | RNew | Fitness values |
|--------|----|----------------|----------------|-----|------|----------------|
| Model 1 | 30 | 0.0675 0.8991 | -1.8498        |     |      |                |
| Model 2 | 45 | 0.0703 0.8975 | -2.0965        |     |      |                |

Table 6 Coefficient values in the model

| Variable | Value | Variable | Value |
|----------|-------|----------|-------|
| $\rho_1^*$ | -7.8532 | $\theta_1^*$ | -1.4364 |
| $\rho_2^*$ | -11.2680 | $\theta_2^*$ | -1.4254 |
| $\rho_3^*$ | -20.1445 | $\theta_3^*$ | -1.3655 |
| $\rho_4^*$ | -6.7848 | $\theta_4^*$ | -1.4075 |
| $\rho_5^*$ | -3.1004 | $\theta_5^*$ | -1.4454 |
| $\rho_6^*$ | 33.5738 | $\theta_6^*$ | -1.4055 |
| $\rho_7^*$ | 17.7479 | $\theta_7^*$ | -1.2757 |
| $\rho_8^*$ | -1.8722 | $\theta_8^*$ | -1.4154 |
| $\rho_9^*$ | 7.2239 | $\theta_9^*$ | -1.3655 |
| $\rho_{10}^*$ | -33.9988 | $\theta_{10}^*$ | -1.4204 |
| $\rho_{11}^*$ | 2.1916 | $\theta_{11}^*$ | -1.3955 |
| $\rho_{12}^*$ | -28.5517 | $\theta_{12}^*$ | -1.5552 |
| $\rho_{13}^*$ | -31.7368 | $\theta_{13}^*$ | -1.4005 |
| $\rho_{14}^*$ | 5.1670 | $\theta_{14}^*$ | -1.3735 |
| $\rho_{15}^*$ | 13.3546 | $\theta_{15}^*$ | -1.3955 |
| $\rho_{16}^*$ | -7.3938 | $\theta_{16}^*$ | -1.4125 |
| $\rho_{17}^*$ | -4.6680 | $\theta_{17}^*$ | -1.3855 |
| $\rho_{18}^*$ | 27.7327 | $\theta_{18}^*$ | -1.3456 |
| $b_1$ | 0.00254 | $b_2$ | 0.3359 |
Comparing and analyzing the prediction results of feed and speed on the axial force revealed that the influence of feed on the axial force was much greater than the influence of speed on the axial force when drilling holes in the CFRP material.

5.2 Prediction of the influence of cutting tool parameters on the axial force

(1). Prediction of the influence of the point angle on the axial force

The relationship between the point angle of the drill bit and the axial force was predicted using the aforementioned model under the conditions of the rotational speed of 3000 r/min, the feed rate of 200 mm/min, the drill bit diameter of 8 mm, the relief angle of 12°, and the negative pressure of 9 kPa. The curve of the change in the axial force obtained versus the point angle of the drill bit is shown in Figure 11.

The analysis of the prediction results in Figure 11 showed that the axial force generally increased as the front angle increased. Further analysis showed that when the front angle was in the range of 120°–135°, the axial force increase with the increase in the front angle was not obvious. Comparing the aforementioned prediction results with the experimental results obtained in this study, it was seen that the change in the axial force with the front angle predicted using this model was consistent with the experimental conclusions. The causes of the aforementioned phenomenon were analyzed. When the front angle increased, the entering angle increased. When the entering angle increased, the length of the cutting edge involved in cutting per unit time increased, resulting in an increase in the axial force. When the front angle increased, the chisel edge oblique angle decreased, that is, the chisel edge length increased, leading to an increase in the axial force. Further analysis with reference to the aforementioned prediction results showed that the angle of the front angle could be selected from 120 to 135° when designing the drill bit, to satisfy the needs of the drilling processing requirements.

(2). Prediction of the influence of the relief angle on the axial force

The relationship between the chisel edge and the axial force was predicted using the aforementioned model under the conditions of the rotation speed of 3000 r/min, the feed rate of 200 mm/min, the drill bit diameter of 8 mm, the point angle of 130°, and the negative pressure of 9 kPa. The curve of the change in the axial force obtained versus the relief angle of the drill bit is shown in Figure 12.

The analysis of the prediction results in Figure 12 showed that when the relief angle was less than 14°, the axial force tended to decrease as the relief angle increased. When the clearance angle was greater than 14°, the axial force fluctuated (the fluctuation value was small) as the clearance angle increased. The causes of the aforementioned phenomenon were analyzed. The increase in the relief angle led to a decrease in the squeeze friction between the flank face of the drill bit and the material to be cut during the hole drilling process, in turn leading to the reduction of the axial force. Further analysis with reference to the aforementioned prediction results showed that the relief angle could be selected from 12 to 14° when designing the drill bit, to meet the drilling processing requirements.
5.3 Prediction of the influence of suction parameters on the axial force

The relationship between the negative pressure and the axial force was predicted using the aforementioned model under the conditions of the rotation speed of 3000 r/min, the feed rate of 200 mm/min, the drill bit diameter of 8 mm, the point angle of 130°, and the length of the relief angle of 12°. The curve of the change in the axial force obtained versus the drilling negative pressure is shown in Figure 13.

The analyses of the prediction results in Figure 13 showed that the drilling force followed a downward trend as the negative pressure increased. The reasons for the aforementioned phenomena were analyzed as follows. When the internal chip removal hole drilling was performed, the direction of the drilling force generated by the drill bit hole machining was downward along the axis of the drill bit, and the direction of the chip aspirating force generated by the aspirating chip negative pressure was upward along the axis. The axial force measured in the study was the resultant force of the aforementioned two forces. It was thus deduced that the axial force generally decreased as the negative pressure increased.

6 Conclusions

(1). The CFRP internal chip hole drilling force prediction model based on the SVR theory was established. Also, the selection of the kernel function and loss function for the model was completed according to the requirements of model precision and accuracy.

(2). The SOM algorithm was used to solve the unknown parameters in the prediction model for internal chip removal hole drilling, and the CFRP internal chip hole drilling force prediction model was established.

(3). The investigation on the influence of cutting parameters, tool parameters, and suction parameters on the axial force was completed using internal chip removal to constructing the drilling force prediction model for a given type of CFRP material. Also, the optimal cutting parameters and tool selection range for processing a given type of CFRP material were given.

Author contribution Theoretical analysis and model construction were completed by XC and WY. The experimental design and analysis were completed by XC and WG. The thesis was written by XC and YS. The supervision and optimization of the paper were completed by WY and XJ.

Funding This study was financially supported by the Shenyang Aerospace University Expo project (120421007), the National Defense Science and Technology Innovation Special Zone Fund Project (208052020162), and the National Natural Science Fund under the Project (51475127).

Data availability All data generated or analyzed during this study are included in this published manuscript.

Declarations

Ethics approval Not applicable

Consent to participate Not applicable

Consent for publication The authors consent to publish this article

Competing interests The authors declare that they have no conflict of interest.

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