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Multi-objective Prediction Method for Hole-drilling Quality of Multilayer PCB Based on MSVR

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Abstract. In the high-speed drilling process of multilayer printed circuit boards, various drilling parameters and drill wear directly affect the quality of the hole-drillings, which ultimately affects the performance and yield of multilayer printed circuit boards. The hole quality of multi-layer printed circuit boards mainly includes multiple indicators such as hole wall roughness, hole position accuracy and nail head thickness. This study adopts a multi-output support vector regression model to establish a correlation model between drilling parameters, drill wear and the hole quality of multilayer printed circuit boards, so as to realize the prediction of the hole-drilling quality under the conditions of variable drilling parameters and different drill wear, and the differential evolution algorithm is used to optimize the model parameters. The experimental data of drilling multilayer printed circuit boards with variable drilling parameters show that: the adopted multi-output support vector regression model has higher prediction accuracy and stronger robustness compared with other commonly used multi-output regression models, which lays the foundation for the hole-drilling quality control of multilayer printed circuit boards.

Keywords: multilayer printed circuit boards drilling, drill wear, various drilling parameters, multi-output support vector regression, hole quality prediction

1. Introduction

Drilling is an important processing procedure in the manufacturing process of multilayer printed circuit boards (PCB), and the hole-drilling quality will directly affect the final performance of the PCB [1]. There are many indicators for evaluating the hole quality of PCB, among which the main ones are hole position accuracy, hole wall roughness, nail head thickness, hole diameter tolerance and burr height, etc. [2]. Because the PCB is a fiber-reinforced layered composite material containing copper foil and resin, and the drill has a small diameter, low rigidity, small chip holding space, and poor cutting stability, the drill wear continues to accumulate with the drilling process, which affects the hole-drilling quality [3]. Moreover, in the high-speed drilling of multilayer PCB, the changes of drilling parameters will also have an important influence on the quality of hole-drillings [4,5]. Therefore, there is a complicated non-linear relationship between drill wear, drilling parameters and hole-drilling quality indicators. Through the establishment of PCB hole-drilling quality prediction and control model, the processing quality and processing efficiency can be effectively improved.

In recent years, a lot of research works have been conducted on the prediction of machining quality. Yeganefar et al. [6] used the support vector machine and neural network to predict and optimize the surface roughness with variable milling parameters. Pimenov et al. [7] took tool wear, processing time and cutting power as input, and adopted random forest model to predict the milling machined surface roughness. Jitesh et al. [8] collected multi-sensor signals during drilling and developed an adaptive neuro fuzzy inference system model using different time domains and wavelet packet features to predict the hole roundness error. The above research used machine learning methods to effectively predict the processing quality. However, these methods are single-objective prediction models. In the high-speed drilling of multilayer PCB, there is more than one hole-drilling quality evaluation index, and they have a coupling relationship, so it is necessary

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to construct a nonlinear multi-objective prediction model. The artificial neural network (ANN), which is one of the typical machine learning algorithm, simulates the input-output relationship through multi-layer neuron connections with reference to the neural network structure of the human brain. It has obvious advantages in processing nonlinear data [9], but model construction requires a large amount of data, and the generalization ability is poor. Support vector machine (SVM) is a commonly used non-linear data classification and regression machine learning algorithm, especially dealing with small sample data and high-dimensional problems, and has stronger generalization ability than other algorithms [10]. However, the traditional support vector machine algorithm is only suitable for regression model of single output system. For multi-output nonlinear data, the common method is establishing a regression model for each dimension, and then simply synthesize it without considering the coupling relationship between the output variables, the accuracy of which is not high [11].

To solve the above problems, this paper studies a multi-output support vector regression (MSVR) model by using experimental data, and adopts the differential evolution algorithm (DE) to optimize the model parameters, and finally establish a multi-objective prediction model for the hole-drilling quality of multilayer PCB. The prediction results are compared with other multi-output regression models to verify its effectiveness.

2. Multi-objective prediction model for drilling hole quality of multilayer PCB

Multi-layer PCB hole-drilling quality control is mainly divided into two parts: one part is the monitoring of drill wear, including signal acquisition, feature extraction and selection, and monitoring model establishment; the second part is the establishment of prediction model for hole-drilling quality based on the value of drill wear obtained by monitoring and drilling parameters. Online hole-drilling quality control through threshold judgment is finally achieve, the diagram of which is shown in Fig. 1. This article mainly focuses on the second part of drilling quality monitoring of multilayer PCB. The hole-drilling quality indicators used are hole position accuracy, hole wall roughness and nail head thickness. The feasibility of the proposed method is explored. The values of drill wear are obtained from off-line observations in an orthogonal experiment.

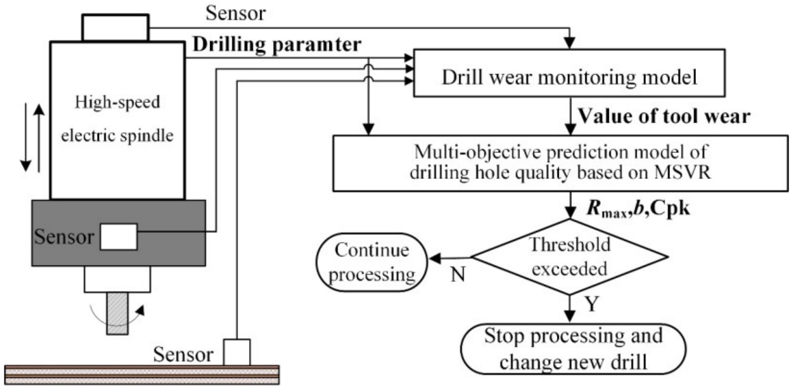


Fig. 1: Diagram of hole quality control for multilayer PCB.

2.1. Multi-objective prediction method for drilling hole quality

This study proposes a method for predicting the hole-drilling quality of multilayer PCB based on MSVR. The method uses tool wear and drilling parameters (spindle rotation speed and feed rate) as inputs and multi-output support vector regression algorithm for data-driven intelligent prediction modeling, and also uses DE algorithm to find the optimal parameters of MSVR. The specific steps are as follows: Firstly, the drilling parameters and test plan are designed for multilayer PCB drilling experiments. Secondly, the drill wear VB(X_1), drilling parameters including spindle rotation speed n(X_2) and feed rate f (X_3) are collected, and drilling state parameter set X={X_1, X_2, X_3} is achieved. In addition, drilling quality including hole accuracy Cpk (Y_1) and hole wall roughness R_{max} (Y_2), nail head thickness b (Y_3) are observed and recorded, and drilling quality parameter set Y={Y_1, Y_2, Y_3} is achieved. The prediction model dataset {X, Y} is obtained. Thirdly, the normalization process is performed to normalize the data to within the interval [0,1] to obtain the normalized dataset {X', Y}. The cross-validation method is used to divide the training set {X_{train}, Y_{train}} and the test set {X_{test}, Y_{test}}. Finally, the training set data are modeled by MSVR, while the DE algorithm is used to optimize the model parameters to obtain the trained prediction model. And the test data {X_{test}, Y_{test}} are input into the trained prediction model to verify the validity of the model.

2.2. Multi-output support vector regression model

Multi-output support vector regression model is established as follows. The modeling sample set (training set) is {X_{train}, Y_{train}}={($\mathbf{X}_i$, $\mathbf{Y}_i$)| $\mathbf{X}_i \in R^m$, $\mathbf{Y}_i \in R^n$, i=1,2,⋯,l}, where m and n denote the dimensionality of the input and output vectors respectively, and l is the sample size. The regression function between the input data and the output data is established as:

$$\mathbf{Y}_i = f\left(\mathbf{X}_i\right) = \boldsymbol{W}\boldsymbol{\phi}\left(\mathbf{X}_i\right) + \boldsymbol{B} \tag{1}$$

where $\boldsymbol{W}$ = [$\boldsymbol{W}_1$ $\boldsymbol{W}_2$ … $\boldsymbol{W}_n$]$^{\mathrm{T}}$ is the output weight, $\boldsymbol{B}$ =[b_1 b_2 … b_n]$^{\mathrm{T}}$ is the vector of bias coefficients. The typical SVR defines an insensitive zone around the estimate, while the MSVR defines a hyper-spherical insensitive zone [12]. The cost function is defined as follows:

$$L\left(u\right) = \begin{cases} 0 & u < \varepsilon \\ u^2 - 2u\varepsilon + \varepsilon^2 & u \geq \varepsilon \end{cases} \tag{2}$$

where ε is the hyper-spherical insensitive zone. The objective function and of the multi-output support vector regression model are:

$$\min \ \frac{1}{2}\sum_{j=1}^{n}\left\|\boldsymbol{W}_j\right\|^2 + C\sum_{i=1}^{l}L\left(u_i\right) \tag{3}$$

where $u_i = \left\|\boldsymbol{e}_i\right\| = \sqrt{\boldsymbol{e}_i^{\mathrm{T}}\boldsymbol{e}_i}$, $\boldsymbol{e}_i = y_i - \boldsymbol{W}\boldsymbol{\phi}\left(\mathbf{X}_i\right) - \boldsymbol{B}$, C is a hyperparameter which determines the trade-off between the regularization and the error reduction term. Then, Lagrange multipliers α_i are introduced and the Lagrange function is achieved:

$$\begin{aligned} L\left(\boldsymbol{W},\boldsymbol{B}\right) = {} & \frac{1}{2}\sum_{j=1}^{n}\left\|\boldsymbol{W}_j\right\|^2 + C\sum_{i=1}^{l}L\left(u_i\right) \\ & -\sum_{i=1}^{l}\alpha_i\left(u_i^2 - \left\|y_i - \boldsymbol{W}\boldsymbol{\phi}\left(\mathbf{X}_i\right) - \boldsymbol{B}\right\|^2\right) \end{aligned} \tag{4}$$

According to Karush-Kuhn-Tuker Theorem (KKT conditions), partial derivatives of $L(\boldsymbol{W}, \boldsymbol{B})$ with respect to $\boldsymbol{W}_j$, b_j, u_i, and α_i are equal to 0, the equation is obtained:

$$\begin{bmatrix} \boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{D}_{\alpha}\boldsymbol{\phi} + \boldsymbol{I} & \boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{\alpha} \\ \boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{\phi} & \boldsymbol{I}^{\mathrm{T}}\boldsymbol{\alpha} \end{bmatrix}\begin{bmatrix} W_j \\ b_j \end{bmatrix} = \begin{bmatrix} \boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{D}_{\alpha}y_j \\ \boldsymbol{\alpha}^{\mathrm{T}}y_j \end{bmatrix} \tag{5}$$

where $\boldsymbol{\phi} = \left[\boldsymbol{\phi}(\mathbf{X}_1), \boldsymbol{\phi}(\mathbf{X}_2), \cdots \boldsymbol{\phi} \quad \right]^{\mathrm{T}}$, $\boldsymbol{D}_{\alpha}$=diag{α_1 α_2 … α_l}, α= [α_1 α_2 … α_l]$^{\mathrm{T}}$, $\boldsymbol{I}$=[1 1 … 1]$^{\mathrm{T}}$. $\boldsymbol{W}_j$ is denoted as a linear combination of the feature space:

$$\boldsymbol{W}_j = \sum_{i=1}^{l}\boldsymbol{\phi}\left(X_i\right)\beta_i^j = \boldsymbol{\phi}^{\mathrm{T}}\beta^j \tag{6}$$

The above equation can be expressed as:

$$\begin{bmatrix} \boldsymbol{K} + \boldsymbol{D}_{\alpha}^{-1} & \boldsymbol{I} \\ \boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{K} & \boldsymbol{I}^{\mathrm{T}}\boldsymbol{\alpha} \end{bmatrix}\begin{bmatrix} \beta_j \\ b_j \end{bmatrix} = \begin{bmatrix} y_j \\ \boldsymbol{\alpha}^{\mathrm{T}}y_j \end{bmatrix} \tag{7}$$

where $K_{i,j} = \kappa\left(\mathbf{X}_i, \mathbf{X}_j\right) = \boldsymbol{\phi}^{\mathrm{T}}(\mathbf{X}_i)\boldsymbol{\phi}(\mathbf{X}_j)$. The output can be expressed as:

$$f\left(\mathbf{X}_i\right) = \sum_{i=1}^{l}\boldsymbol{K}_j\left(\mathbf{X}, \mathbf{X}_i\right)\beta_j + b_j \tag{8}$$

The target of MSVR is transformed into finding the best β and b. Then the iterative method is adopted to solve the problem.

3. Multilayer PCB drilling experiments

3.1. Experimental design

The PCB boards used in the experiments are NP140 with thickness of 1.60 mm. The drill is double-edged carbide drill with diameter of 0.3 mm. The experiments were conducted on a six-axis high-speed drilling machine (HITACHI, maximum speed 160,000r/min), as shown in Figure 2. In order to observe the quality of the machined hole internal surface, the slices of the machined hole were first made, then ground and polished, and observed using a metallographic microscope (LEICA DM 2500M). An automatic optical hole position inspection machine was used to measure the hole position accuracy which is indicated by Cpk. The smaller the Cpk, the lower the hole position accuracy. A microscope (Nikon L-IM 0643613) was used to observe the wear on the back face of the drill (maximum width of wear band VB).

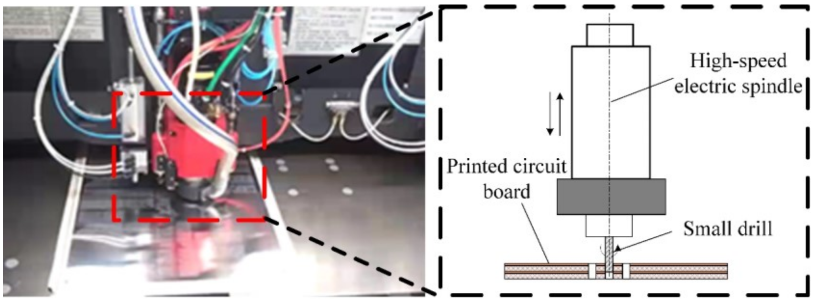


Fig. 2: High-speed drilling experiment setup.

Drilling parameters used in the experiment are shown in TABLE I. For each set of experiments with various drilling parameters, a full life machining test of the drill was performed, and values of VB were measured every 1000 holes and recorded. In addition, for every 1000 holes drilled in the experiment, five holes were drilled to measure the hole wall roughness R_{max}, nail head thickness b and hole position accuracy Cpk, and the average of the measurements was calculated as the final value.

Table 1: Drilling parameters used in the experiment

Test number	Spindle rotation speed, n / (krpm)	Feed rate, f / (mm/s)
1	100	20
2	100	30
3	100	40
4	125	20
5	125	30
6	125	40
7	150	20
8	150	30
9	150	40

3.2. Experimental Results

Due to the hard and brittle glass fiber and resin composite in the PCB, the flank and the cutting edge of the drill are subjected to friction and impact during the drilling process of the PCB, resulting in progressive drill wear. When drill wear reaches a certain value, the drill should be changed to ensure the hole-drilling quality. The drill wear on the chisel edge and main cutting edge has a triangular shape, and is increased with hole-drilling number increasing, which is shown in Fig. 3. The observed hole wall roughness R_{max} and nail head thickness b and hole position accuracy Cpk are shown in Fig. 4(a), (b) and (c).

The effects of the hole number, feed rate and spindle rotation speed on the hole-drilling quality are shown in Fig. 6(a), (b) and (c). From Fig. 4 and Fig. 5(a), it can be seen that the hole wall roughness (Rmax) increases with the hole-drilling number (drill wear) and feed rate increasing, and the unevenness of hole sidewall occurs mainly at the junction of glass fiber and resin. This is due to the fact that the cutting edge of the drill becomes less capable of cutting the glass fiber, and the glass fiber is pushed to break and fall off, which increases the hole wall roughness. The increase of feed rate causes the increase of cutting force, and the glass fiber breaks after the force exceeds the elastic limit, which also leads to the increase of hole wall roughness. The effect of spindle rotation speed on hole wall roughness has no obvious pattern. From Fig. 4

and Fig. 5(b), it can be seen that the nail head thickness (b) increases with the increase of drill wear, which is due to the extrusion of copper foil to the top and bottom after the drill is dulled. When the spindle rotation speed is constant, the thickness of nail head decreases with the increase of feed speed, which is because the cutting speed becomes faster and the cutting temperature is lower, and the copper foil is not easily extruded. There is also no obvious rule for the spindle rotation speed on the nail head thickness. From Fig. 5(c), it can be seen that the hole position accuracy (Cpk) decreases with the increase of drill wear, which is because and the location of entering drilling becomes difficult. When the spindle rotation speed is constant, the hole position accuracy increases with the increase of feed rate, which is because the drill becomes easier to enter drilling. There is also no obvious law on the effect of spindle rotation speed on the hole position accuracy.

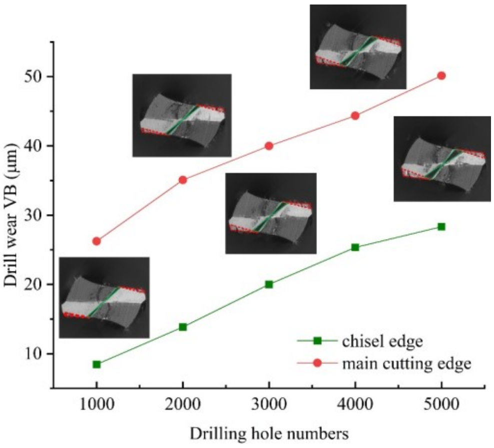
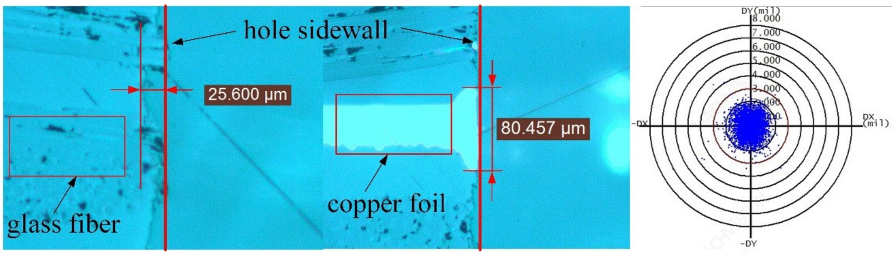


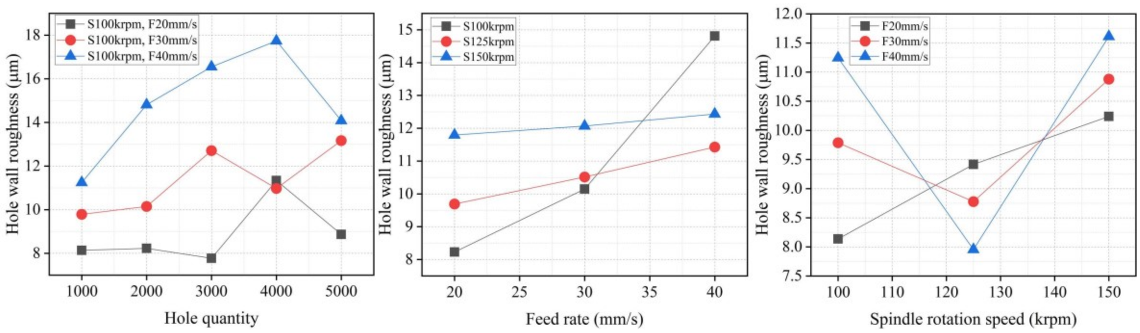
Fig. 3: The relationship between the hole-drilling number and drill wear.



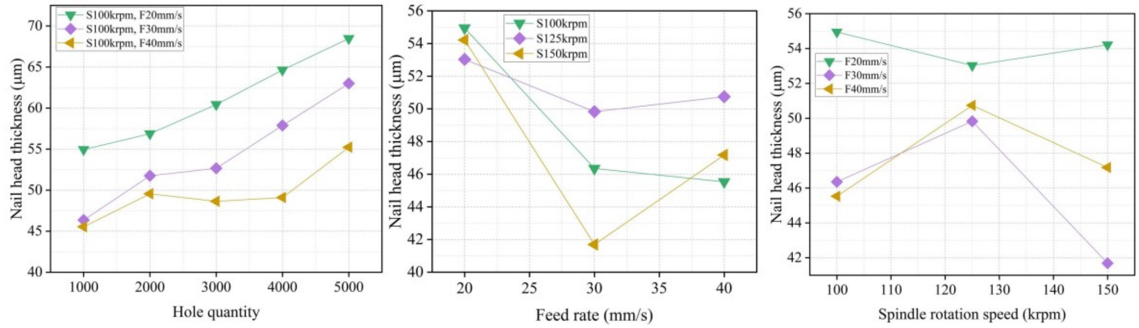
（a）R_{max} （b）b （c）Cpk

Fig. 4: The hole-drilling quality.

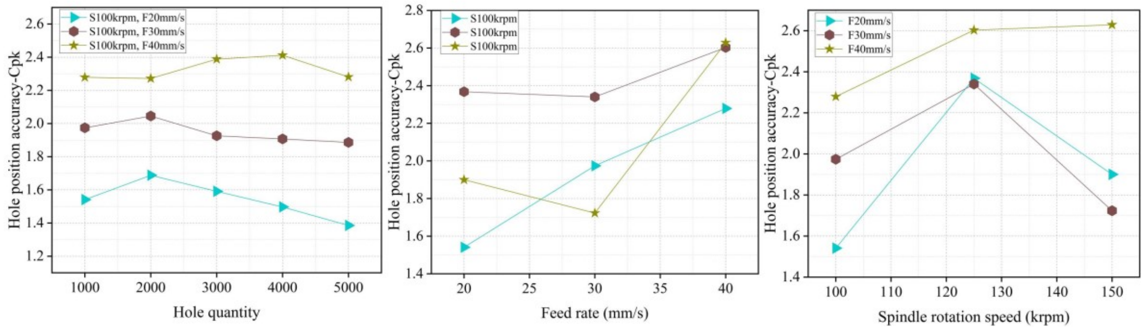
In conclusion, the influence of drill wear and feed rate on hole-drilling quality is regular and linear, yet the influence of spindle speed on drilling quality is unknown. Furthermore, the influence between different indicators is coupled, so there is a non-linear mapping relationship between drilling parameters, drill wear and hole-drilling quality. Therefore, the accurate description of the mapping relationship is the key to construction of the prediction method for hole-drilling quality. In order to realize the multi-objective hole-drilling quality control of multilayer PCB, MSVR is used for the establishment of the multi-objective prediction method.



(a) Effect of hole quantity, feed rate and spindle rotation speed on hole wall roughness



(b) Effect of hole quantity, feed rate and spindle rotation speed on nail head thickness



(c) Effect of hole quantity, feed rate and spindle rotation speed on hole position accuracy

Fig. 6 Drilling hole quality influencing factors

3.3. Method Validation

Since there is a nonlinear mapping relationship between drilling parameters, drill wear and hole-drilling quality, and the drilling quality index is multidimensional, a multi-output support vector regression model is used for regression modeling. Since the drilling parameters (feed rate and spindle rotation speed) and drill wear have different magnitudes, the data are first normalized to the interval [0,1] for all input data, thus ensuring a higher accuracy output.

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

where x_i' is the normalized value of the i-th sample; x_i is the original value of the sample; $x_{\max}$ is the maximum value of sample; $x_{\min}$ is the minimum value of sample.

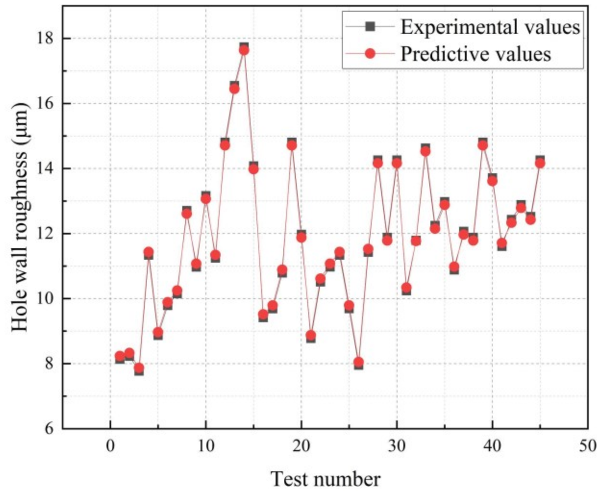
In this paper, the linear kernel function, polynomial kernel function and radial basis kernel function are commonly used in support vector machines for model building. The support vector machine realizes the mapping of the input space to the high-dimensional Hilbert space through the kernel function, so the choice of the kernel function type is particularly critical. This article used the linear kernel function, polynomial kernel function and radial basis function (RBF) kernel to build the model. It was found that the final training results of the model established by the linear kernel function and the polynomial kernel function could not converge, so the radial basis function kernel was finally selected as the kernel function of the multi-output support vector regression model:

$$K_j\left(\mathrm{X},\mathrm{X}_i\right) = \exp\left(-\frac{\left\|\mathrm{X}-\mathrm{X}_i\right\|^2}{2\sigma^2}\right) \tag{10}$$

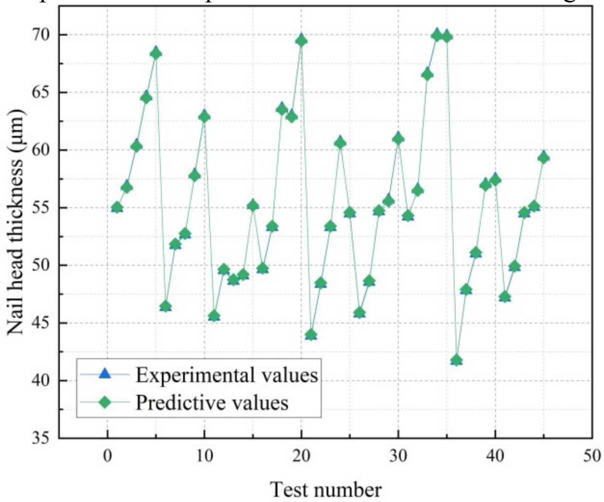
where σ is the hyperparameter of the RBF kernel, which defines the feature length scale for learning the similarity between samples.

The parameters have a great influence on the generalization performance of the model. When the penalty factor C is too large, the generalization performance of MSVR will be reduced. In contrast, a too small value of C will increase the training error. Additionally, the larger the hyperparameter σ, the larger the training error. Nevertheless, a too small value of σ will lead to the model overfitting. In this paper, a DE algorithm is used to find the optimal model parameters, and the optimal penalty factor C=100 and the optimal hyperparameter σ=0.1. The regression results obtained and actual experimental results are shown in Fig.

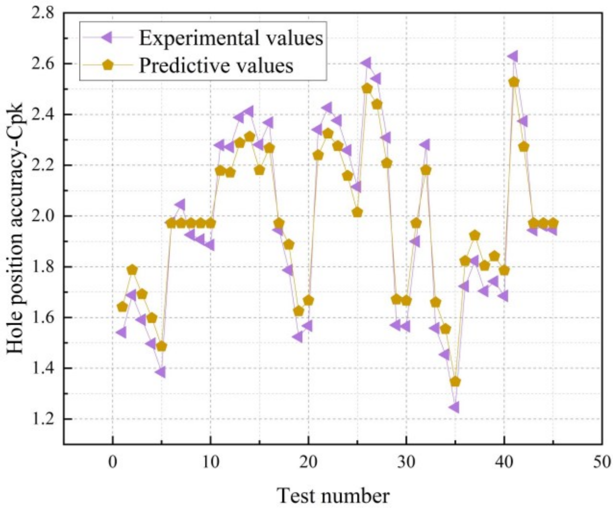
6(a)-(c). It can be seen that the errors between the predicted and experimental values of hole wall roughness and nail head thickness are small, while the errors of hole position accuracy Cpk are slightly larger. Additionally, more stable and accurate predictive results are achieved compared with results of establishing a regression model for each dimension because the coupling relationship between the outputs is considered.



(a) Experimental and predictive values of hole wall roughness



(b) Experimental and predictive values of Nail head thickness



（c）Effect of hole quantity, feed rate and spindle rotation speed on hole position accuracy

Fig. 6 Drilling hole quality influencing factors

3.4. Comparative analysis

To further analyze the advantages of the MSVR model, the MSVR model is compared with other multi-output machine learning regression algorithms like Linear Regression (LR), K-Nearest Neighbours Regression (KNNR), Classification and Regression Tree (CART), and Random Forest Regression (RFR). In this paper, the root mean square error (RMSE) and mean absolute percentage error (MAPE) are used as model evaluation indexes to compare the results of different models. A smaller RMSE means a better model prediction performance, and a smaller MAPE means a better model prediction performance.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{11}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\frac{Y_i - \hat{Y}_i}{Y_i} \tag{12}$$

where n denotes sample size; Y_i is the i-th sample value; $\hat{Y}_i$ is the predictive value of the model.

Table 2: Comparative analysis

Algorithm	$R_{\max}$		b		Cpk	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
MSVR	0.099	0.863	0.103	0.188	0.092	4.659
LR	1.722	11.16	3.898	5.878	0.253	9.919
KNNR	1.479	10.2	3.911	5.893	0.236	10.52
RFR	0.674	4.769	1.593	2.456	0.1	4.056

As can be seen from TABLE II, the RMSE values of 0.099, 0.103 and 0.092 at hole wall roughness and nail head thickness and hole accuracy of MSVR model are smaller than the results of other algorithms. The MAPE values of 0.863 and 0.188 at hole wall roughness and nail head thickness are also much smaller than other models, and the value of 4.659 at hole accuracy is only slightly larger than 4.056 of RFR. In conclusion, MSVR has better predictive performance.

4. Conclusion

In order to realize hole-drilling quality control of multilayer PCB, this paper firstly studies the influence of drilling parameters and drill wear on hole-drilling quality. Then, a multi-output support vector regression model is established, and the predictive results are compared with other multi-output machine learning algorithms. The following conclusions are drawn from this work:

(1) The effects of drill wear and feed rate on hole wall roughness, nail head thickness and hole position accuracy are linearly related, while the effects of spindle rotation speed on those have no obvious pattern. In the process of multilayer PCB drilling, there is a non-linear mapping relationship between drilling parameters, drill wear and hole-drilling quality.

(2) The RBF kernel is selected as the kernel function of MSVR and the model parameters are optimized by the DE algorithm. The MSVR prediction errors of the hole wall roughness and nail head thickness are small and the prediction error of the hole position accuracy (Cpk) is relatively larger.

(3) RMSE and MAPE are selected as the model evaluation indexes, and the predictive results are compared with linear regression model, K-nearest neighbor regression model and random forest regression model, which shows that MSVR has a better prediction performance.

5. Acknowledgements

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6. References

[1] Zheng LJ, Wang CY, Song YX, Yang LP, Qu YP, Ma P, et al. A Review on Drilling Printed Circuit Boards. *Advanced Materials Research*. 2011, 188:441–449.

[2] Watanabe H, Tsuzaka H, Masuda M. Microdrilling for printed circuit boards (PCBs)—Influence of radial run-out of microdrills on hole quality. *Precision Engineering*. 2008, 32:329-335.

[3] Zheng LJ, Wang CY, Fu LY, Yang LP, Qu YP, Song YX. Wear mechanisms of micro-drills during dry high speed drilling of PCB. *Journal of Materials Processing Technology*. 2012, 212:1989-1997.

[4] Zheng L, Wang C, Yang L, Song Y, Fu L. Characteristics of chip formation in the micro-drilling of multi-material sheets. *International Journal of Machine Tools and Manufacture*. 2012, 52:40-49.

[5] Venkatesan K, Nagendra KU, Anudeep CM, Cotton AE. Experimental Investigation and Parametric Optimization on Hole Quality Assessment During Micro-drilling of Inconel 625 Superalloy. *Arabian Journal for Science and Engineering*. 2020, 46:2283–2309

[6] Yeganefar A, Niknam SA, Asadi R. The use of support vector machine, neural network, and regression analysis to predict and optimize surface roughness and cutting forces in milling. *The International Journal of Advanced Manufacturing Technology*. 2019, 105:951-965.

[7] Pimenov DY, Bustillo A, Mikolajczyk T. Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. *Journal of Intelligent Manufacturing*. 2018, 29:1045-1061.

[8] Ranjan J, Patra K, Szalay T, Mia M, Gupta MK, Song Q, Krolczyk G, et al. Artificial Intelligence-Based Hole Quality Prediction in Micro-Drilling Using Multiple Sensors. *Sensors*. 2020, 20:885.

[9] Patra K, Jha AK, Szalay T, Ranjan J, Monostori L. Artificial neural network based tool condition monitoring in micro mechanical peck drilling using thrust force signals. *Precision Engineering*. 2017, 48:279-291.

[10] Lin, Y. Support Vector Machines and the Bayes Rule in Classification. *Data Mining and Knowledge Discovery*. 2002, 6:259–275.

[11] Xu S, An X, Qiao X, Zhu L, Li L. Multi-output least-squares support vector regression machines. *Pattern Recognition Letters*. 2013, 34:1078-1084.

[12] Bao Y, Xiong T, Hu Z. Multi-step-ahead time series prediction using multiple-output support vector regression. *Neurocomputing*. 2014, 129:482-493.