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The optimal design of micro-punching die by using abductive and SA methods

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ABSTRACT

Purpose: Punching process currently plays an important role in industrial mass production. The current study focuses on increasing accuracy, performance and extending service life of punches and dies. Optimizing the design of the punch and die has been a common topic for scholars.

Design/methodology/approach: The input parameters (punching times, clearance) and output results (wear) were used to construct a training database. The abductive network formulation established a relationship between input parameters and output results. By using the abductive modeling technique, the complicated and uncertain relationships between the input and output variables can be formulated into a useful mathematical model. Once the abductive network model was constructed, the relationships between input and output parameters variables became available. A simulated annealing algorithm (SA) with a performance index was established to optimize this process and find the best result as compared with the actual experiment values.

Findings: This study aims to establish the relationship between punching times, clearance and wear of micro punches using the abductive network, and to find relational model involving input parameters and output result of punching die in composite blanking processes. This model can be used to estimate wear between punch and die for industrial applications.

Research limitations/implications: Setting up the relational expression of punching times, clearance and wear requires a well-established database covering sufficient relevant parameters and data. In training the database, it is helpful to establish a good relational model among punching parameters. Incorrect data will cause abnormal wear. As a result, the mathematics model is difficult to converge and the neural network will inaccurately predict wear. In addition, the punching die may be changed prematurely, which increases production costs. Delay in replacing a worn punching die can result in poor quality of products.

Originality/value: As electronic production becomes increasingly smaller, the opportunity to use micro punches and dies will expand accordingly. This study established the relational expression of input and output, which can be used to correctly estimate any wear condition. This result is based on an abductive network and SA method.

Keywords: Optimal design; Composite; Experimental design; Abductive network; SA method

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MANUFACTURING AND PROCESSING OF ENGINEERING MATERIALS

1. Introduction

Industrial progress has meant thet punching dies used in mechanical applicetions is also used for mass production in the electronic/electric industry. The cross-applicability of punching dies arises because they conform with the product demand for 3C. With the development of Integreted Circuit (IC) processing technology, passive components are being increasingly minieturized, ranging from early middle-chips to existing macro-chips. The increasing minieturizetion of passive components leads to a requirement for smaller aperture of composite paper bags for various ICs. The accuracy of aperture for packaging bags, however, depends on the design of the punching dies. Good die design for punching can reduce the burr of the packaging bags. Hence, the punch and die can reach the accuracy required.

This study aims to identify the reletionship between clearance and service life of micro punches using the Neural Network, and to find reletional deta involving the service life of punches and punching parameters in non-metal punching processes. The result can be used to estimete optimal clearance between punch and die for industrial applicetions.

In the past, the clearance between punch and die was generally set up for drawing process. [1,2,3,4,5,6] ettempted to obtain the reletionship between punch profile and die clearance via the optimizetion principle. Lieu and Sowerby [7], studied the best ways to obtain the parameters of optimal clearance and profile of punch and die during square drawing. Tai and Lin [8] also tried to obtain the optimal clearance value of punch and die during drawing process using the Neural Network and Simuleted Annealing Method.

Luo [2] conducted experiments to obtain the optimal punching angle by using punches of different sizes during punching of round holes. Joo et al. [9] studied the micro-hole fabricetion by mechanical punching process. Li et al. [10] studied the plastic stetus parameter and instantaneous clearance of a punching without burr. Cheung et al. [11], studied the reletionship between IC packaged dam-bar and service life of punches. The clearance of punches and dies becomes smaller as a result of micro punching. This will adversely affect the accuracy of workpieces and reduce the service life of both punch and die components.

2. Experimental design

The experimental analysis used punches and dies made from high-speed steel subjected to surface grinding and heet treetment with hardness up to HRC 64. The punching machine was a 15t stand-up puncher, with a punching speed of 15 m/mim. In conjunction with IC chips packaging, punch and die must be rectangular and right-angled ($R \leq 0.03^R$mm). They have a short side AO and long side BO as shown in Fig. 1. The shearing angle of the punch's cutting edge was 12°.

In order to explore the reletionship between clearance and service life of the punch, eight groups of experimental deta of side AO and side BO were established. The experimental deta is listed in Table 1. Tables 2 through 5 show experimental values in millions of units punched for punch and die. This was training deta allowing for an abductive network to set up the reletionship between input deta (clearance and punching times) and output result (wear).

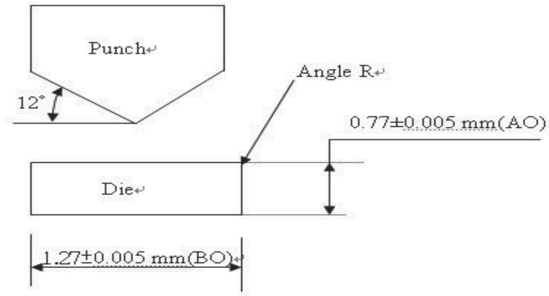


Fig. 1. Punch and die shap

The PET+PE+HMT composites were used for experiment. Where PET is Polyetylene Terephthalete, PE is Polyetylene, and HMT is one of Thermoset Dyed Polymer. The composition of experimental meterial is shown in Fig. 2. Fig. 3 and Fig. 4 show the wear condition of the punch and die after 3 x 10^6 punching operetion et a clearance of 0.015 mm.

Table 1.
The experimental deta

Parameters	Level 1	Level 2	Level 3	Level 4
Punch/die AO-clearance	0.015mm	0.018mm	0.021mm	0.024mm
Punch/die BO-clearance	0.008mm	0.011mm	0.014mm	0.017mm

Table 2.
Punch AO-Side Wear Condition (mm)

Parameters / Punching times	Clearance 0.015	Clearance 0.018	Clearance 0.021	Clearance 0.024
$1.458X10^6$	0.007	0.012	0.013	0.0132
$1.73X10^6$	0.008	0.0125	0.014	0.02
$3.2X10^6$	0.0175	0.0205	0.0220	0.025
$4.13X10^6$	0.0235	0.028	0.031	0.034
$5.2X10^6$	0.030	0.032	0.035	0.040
$6.27X10^6$	0.0365	0.0375	0.040	0.047
$7.61X10^6$	0.040	0.042	0.048	0.0525
$8.27X10^6$	0.049	0.050	0.052	0.060

Table 3.
Punch BO-Side Wear Condition (mm)

Parameters / Punching times	Clearance 0.015	Clearance 0.018	Clearance 0.021	Clearance 0.024
$1.458X10^6$	0.0095	0.001	0.008	0.010
$1.73X10^6$	0.0195	0.015	0.0195	0.020
$3.2X10^6$	0.0295	0.018	0.026	0.028
$4.13X10^6$	0.031	0.021	0.029	0.031
$5.2X10^6$	0.035	0.027	0.032	0.04
$6.27X10^6$	0.0375	0.034	0.0395	0.0425
$7.61X10^6$	0.044	0.035	0.041	0.0455
$8.27X10^6$	0.045	0.0365	0.0470	0.0490

Table 4.
Die AO-Side Wear Condition

Parameters / Punching times	Clearance 0.015	Clearance 0.018	Clearance 0.021	Clearance 0.024
$1.458X10^6$	0.7955	0.8015	0.8020	0.8070
$1.73X10^6$	0.80	0.8075	0.8060	0.8075
$3.2X10^6$	0.802	0.8080	0.8065	0.8082
$4.13X10^6$	0.8075	0.8095	0.8070	0.8085
$5.2X10^6$	0.8095	0.8096	0.8071	0.8086

Table 5.
Die BO-Side Wear Condition

Parameters / Punching times	Clearance 0.015	Clearance 0.018	Clearance 0.021	Clearance 0.024
$1.458X10^6$	1.260	1.265	1.2550	1.2835
$1.73X10^6$	1.2885	1.2900	1.2880	1.2910
$3.2X10^6$	1.2910	1.2950	1.29	1.2945
$4.13X10^6$	1.2910	1.305	1.2945	1.2950
$5.2X10^6$	1.300	1.310	1.2950	1.3000

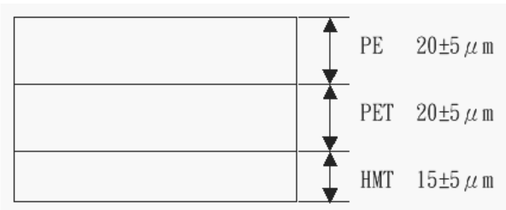


Fig. 2. The experimental composite

Fig. 3. The wear condition of the punch

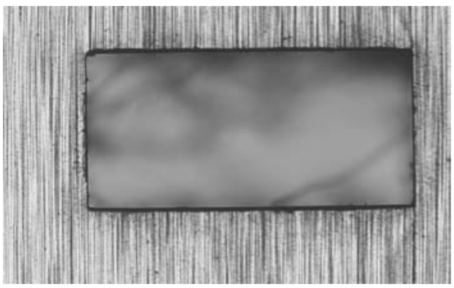


Fig. 4. The wear condition of a die

3. Image measurement

After a fixed number of punching times, the burr will be revealed just prior to the wearing out completely. When the burr size of the product exceeds the process standard of an IC factory, the production line is immedietely shut down. The punching die is then taken apart to inspect its degree of wear. Companies producing passive components specify thet the burr length of punched products shall be less than 0.03 mm. The punches must be replaced whenever the burr length exceeds 0.03 mm, indiceting the end of service life.

3.1. Image vision system

The burr can be examined by an image vision system as shown in Fig. 5, it includes the CCD (Teli 3910 CCD CAMERA), the image capturing card (Netional Instruments IMAQ PCI/PXI-1422) and the XY-Table. The image recognition software was programmed by using Netional Instruments Lab VIEW 6.i and IMAQ Vision Builder 6. This system can judge the size of burr autometically. Fig. 6 shows the burr of products.

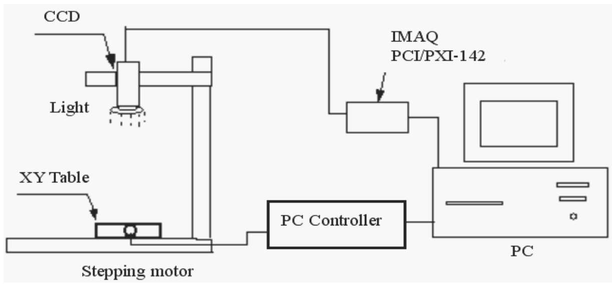


Fig. 5. Image vision system

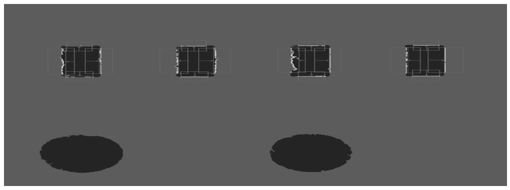


Fig. 6. Burr image of punched hole

3.2. The contour searching method

Contour searching method was applied to find the border of parts by scanning, shown as Fig. 7. Each line searches the image contour to find the point on the edge, and connects each edge point to build the contour of the parts. From Fig. 8, each edge has a smooth change from bright to dark (or from dark to bright). This represents a smooth gray scale varietion rether than a sharp change. The edge of the digital image is slightly blurred and the point position obtained by searching depends on the gray scale setting parameters. These parameters are: contrast; width of filtered wave; steepness; and reletive width of search line.

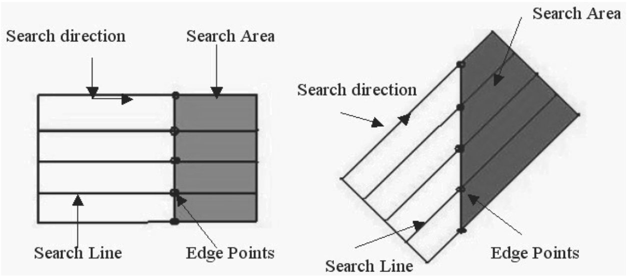


Fig. 7. Edge serach

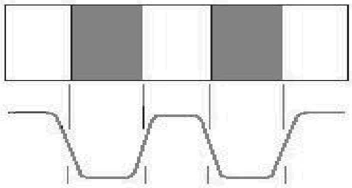


Fig. 8. Using gray scale measurement

3.3. Sub-pixel theorem

The minimum image unit is a pixel. The resolution of CCD was so poor thet the measuring accuracy was low. The Sub-pixel technique was applied to divide one pixel into several pieces, using gray scale interpoletion to obtain more precise pixel. This greetly increases the accuracy of an image, as shown in Fig. 9.

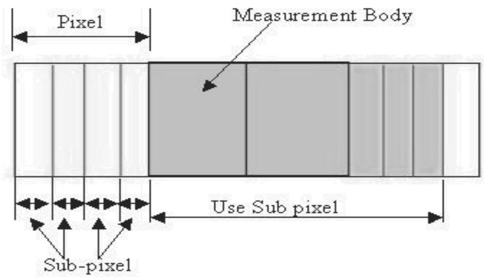


Fig. 9. Sub-pixel measurement

4. Abductive network synthesis and evaluation

Abductive network is a specific neural network. In an abductive network, a complex system can be decomposed into smaller, simpler subsystems grouped into several layers using polynomial function nodes. The polynomial network proposed by Ivakhnenko [12] is a group of methods of deta handling (GMDH) techniques. These nodes evaluete the limited number of inputs by a polynomial function and generete an output to serve as an input to subsequent nodes of the next layer. The general polynomial function in a polynomial functional node can be expressed as follows:

$$y_0 = B_0 + \sum_{i=1}^{n} B_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} B_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} B_{ijk} x_i x_j x_k + ... \quad (1)$$

where x_i, x_j, x_k are the inputs, y_0 is the output, and B_0, B_i, B_{ij}, B_{ijk} are the coefficients of the polynomial functional nodes.

In this paper, several specific types of polynomial functional nodes are used in polynomial network to predict the residual blank length in some different kind of deep-drawing parameters. These polynomial functional nodes are named as normalizer (N), unitizer (U), white (W), singles (S), double (D) and triples (T) node. These are explained as follows:

4.1. Normalizer

A normalizer transforms the original input variables into a relatively common region.

$$a_1=q_0+q_1x_1 \quad (2)$$

Where a_1 is the normalized input, q_0 and q1 are the coefficients of the normalizer, and x_1 is the original input.

4.2. White node

A white node consists of the linear weight sums of all the outputs of the previous layer.

$$b_1=r_0+r_1y_1+r_2y_2+r_3y_3+...+r_ny_n \quad (3)$$

where y_1, y_2, y_3, y_n are the inputs of the node, b_1 is the output of the node, and the r_0, r_1, r_2, r_3, ... r_n are the coefficients of the triple node.

4.3. Singles, double, and triples node

These are named according to the numbers of the input variables. The algebraic form of each of these nodes is shown in the following equation:

$$\text{single: } c_1= s_0+ s_1z_1+s_2z_1^2+s_3z_1^3 \quad (4)$$

$$\text{double: } d_1=t_0+(t_1n_1+t_2n_1^2+t_3n_1^3)+ (t_4n_2+t_5n_2^2+t_6n_2^3) + (t_7n_1n_2) \quad (5)$$

$$\text{triple: } e_1= u_0+(u_1o_1+u_2o_1^2+u_3o_1^3)+ (u_4o_2+u_5o_2^2+u_6o_2^3)+(u_7o_3+u_8o_3^2+u_9o_3^3) +u_{10}o_1o_2+u_{11}o_2o_3+u_{12}o_1o_3+u_{13}o_1o_2o_3 \quad (6)$$

where: z_1, z_2, z_3,..., z_n, n_1, n_2, n_3,..., n_n, o_1, o_2, o_3,...., o_n are the inputs of the node, c_1 ,d_1 and e_1 are the outputs of the node, and the s_0, s_1, s_2, s_3,..., s_n , t_0, s_1, t_2, t_3, ..., t_n , u_0, u_1, u_2, u_3,..., u_n are the coefficients of the single, double, and triple nodes.

These nodes are third-degree polynomial equations. The doubles node and triples node have cross-terms, allowing interaction among the node input variables.

4.4. Unitizer

On the other hand, a unitize coverts the output to a real output.

$$f_1=v_0+v_1i_1 \quad (7)$$

Where i_1 is the output of the network, f_1 is the real output, and v_0, v_1 are the coefficients of the unitize.

To build a complete adductive network, the first requirement is to train the database. The information given by the input and output parameters must be sufficient. A predicted square error (PSE) criterion is then used to automatically determine an optimal structure. The principle of the PSE criterion is to select the least complex yet still accurate network as possible. The PSE is composed of two terms; that is:

$$PSE=FSE+K_P \quad (8)$$

Where FSE is the average square error of the network for fitting the training data and K_P is the complex penalty of the network, shown as the following equation:

$$K_P = CPM\,\frac{2\,\sigma_p^2\,K}{N} \quad (9)$$

Where CPM is the complex penalty multiplier, K is the number of coefficient in the network; N is the number of training data to be used and σ_p^2 is a prior estimate of the model error variance.

5. Relationship between punch/die clearance and wear

Establishing the relationship of clearance, punching times and wear requires a well-established database covering sufficient relevant parameters and data. This database needs training to establish a good wearing model. Incorrect data and improper parameters, however, make it difficult to collect the wear information, while associated estimation leads to inaccuracy beyond control. These databases are listed in Tables 2 through 5. The punching times and wear condition of punch AO-side and BO-side are listed in Tables 2 through 3, and those of die AO-side and BO-side listed in Tables 4 through 5.

An adductive network synthesizes a three-layer network automatically. It is comprised of design factors (punching times and clearance size) and output factor (wear value). The polynomial equations used in this network are listed in Fig. 10 and Fig. 11. In the adductive network (Fig. 10), each layer of output had three sub-layers of input (e.g., T_5 (Triple5) had W_6 (White6), S_7 (Single7), and N_1 (Normalizer1) three layers, T4 had T_5 (Triple5), D_8 (Double8) and W_6 (White6) three layers. Input parameters include clearance of the punch/die and punching times. Output parameter includes the wear value of the punch's AO-side and BO-side. The others (die's AO-side and die's BO-side) individually have similar polynomial equations.

To verify the accuracy of the neural network, this study utilized another set of new dies for a wear test (see Table 6). The wear of punch AO side with clearance 0.015 mm et 3 x 10^6 th punching times is 0.016 mm by actual experiment, while the neural prediction is 0.015 mm, with an error value of 6.3 %. The maximum error of the wear was on the die BO side with clearance 0.013 mm et 5 x 10^6 th punching times, the wear prediction of the neural network is 1.2972 mm, and actual experiment value is 1.412 mm, with an error value of 8.1 %.

Table 6.
Comparison between the neural network prediction and experimental data

Method \ Punching times	The punch AO side wear with clearance		The punch BO side wear with clearance	
	$3x10^6$th	$8x10^6$th	$3x10^6$th	$8x10^6$th
Neutral prediction	0.015 mm	0.044 mm	0.026 mm	0.042 mm
Experimental data	0.016 mm	0.046mm	0.028mm	0.045 mm
Error	6.3%	4.3%	7.1%	6.7%
Method \ Punching times	**The die AO side wear with clearance**		**The die BO side wear with clearance**	
	$3x10^6$th	$5x10^6$th	$3x10^6$th	$5x10^6$th
Neutral prediction	0.796mm	0.810mm	1.290mm	1.297mm
Experimental data	0.821mm	0.842mm	1.402mm	1.412mm
Error	3.0%	3.8%	8.0%	8.1%

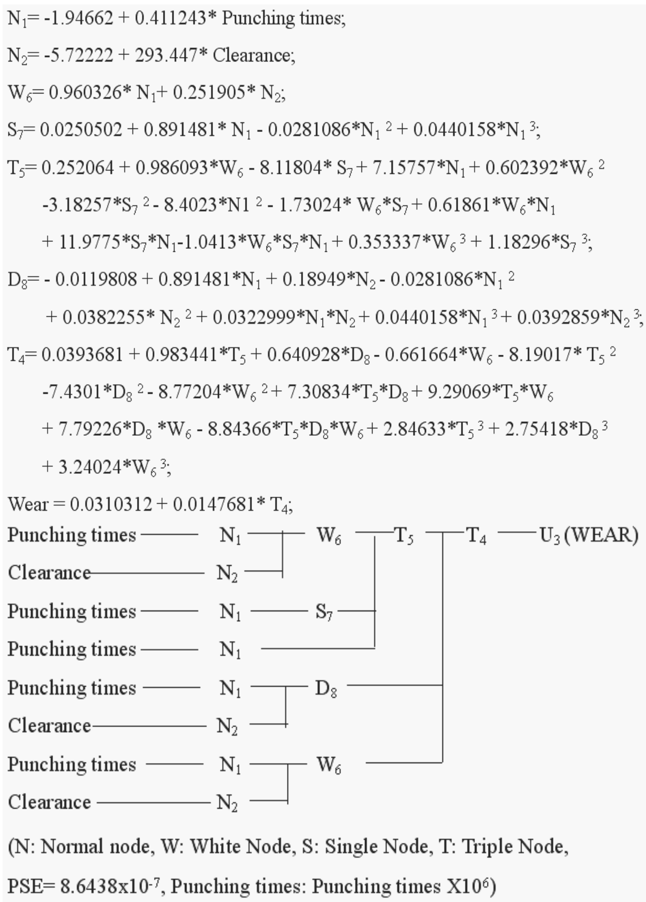
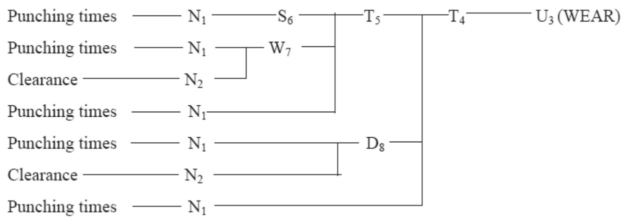


Fig. 10. The relationship between punching parameters and wear of punch's AO-Side



(N: Normal node, W: White Node, S: Single Node, T: Triple Node, PSE= $1.45\text{x}10^{-6}$,

Punching times: Punching times$\text{X}10^{6}$)

N_1= -1.94662 + 0.411243* Punching times;

S_6= 0.24844 + 0.558846*N_1 - 0.26907*N_1^2+ 0.246756*N_1^3;

N_2= -3.66809 + 293.447* Clearance;

W_7= 0.939094*N_1 + 0.0501915*N_2;

T_5= - 21.5951 + 88.2579*S_6 + 2.4158*W_7 - 51.2481*N_1 - 4.64762*S_6^2 + 41.3221* W_7^2
+ 49.5672* N_1^2 - 7.65221*S_6*W_7 + 14.9325*S_6*N_1 - 69.869*W_7*N_1
- 1.01751*S_6*W_7*N_1 + 0.374606*S_6^3 - 0.190928*W_7^3 - 20.8571*N_1^3;

D_8= 0.147595 + 0.558846*N_1 - 0.0133938*N_2 - 0.26907*N_1^2 + 0.104098*N_2^2
+ 0.0319228*N_1*N_2 + 0.246756* N_1^3 + 0.0400222* N_2^3;

T_4 = 0.112132 + 0.044546*T_5 - 0.337019*D_8 + 0.882326*N_1 + 1.76062*T_5^2
+ 0.779504*D_8^2 + 1.76557*N_1^2 + 0.325588*T_5*D_8 - 3.56402*T_5* N_1
- 1.06171*D_8*N_1 - 2.30099*T_5*D_8* N_1 + 0.962033*T_5^3 + 0.899457*D_8^3
+ 0.609214*N_1^3;

Wear = 0.0312969 + 0.0125889* T_4;

Fig. 11. The relationship between punching parameters and wear of punch's BO-Side

6. SA method and optimal clearance selection

Metropolis et al. [13] proposed a criterion to simulete the cooling of a solid to a new stete of energy balance. The basic criterion used by Metropolis is an optimizetion algorithm called "simuleted annealing".

In this paper, the simuleted annealing algorithm is conduced to search for the optimal clearance parameter. Fig. 12 shows the flow chart of the SA method. In the SA, initial tempereture T_s, final tempereture T_e, and a set of initial process parameter vectors O_x was given. The objective function obj is defined corresponding to the clearance values performance index. The objective function can be recalculeted through all the different perturbed compensetion parameters. If the new objective function becomes smaller, the perturbed process parameters are accepted as the new process parameters and the tempereture drops a little in scale. That is:

$$T_{i+1} = T_i C_T \tag{10}$$

Where i is the index for the temperature decrement and the C_T is the decaying ratio for the temperature (C_T <1).

However, if the objective function becomes larger, the probability of acceptance of the perturbed process parameters is given as:

$$P_r(\text{obj})=\exp\left[\frac{\Delta\ obj}{k_B T}\right] \tag{11}$$

Where k_B is the Boltzmann constant and Δobj is the difference in the objective function. The procedure is repeated until the temperature T approaches zero. It shows the energy dropping to the lowest state.

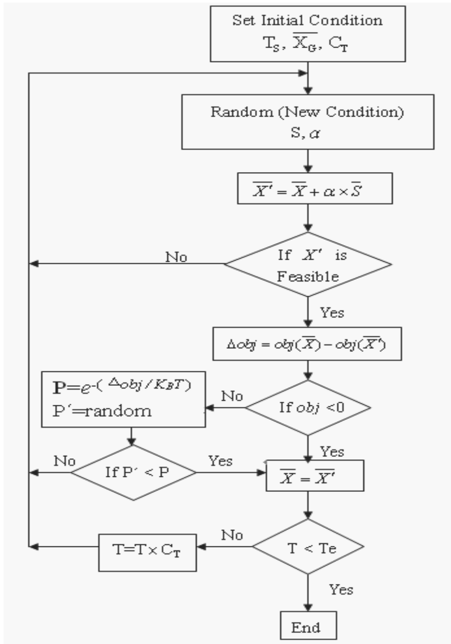


Fig. 12. The flow chart of SA method

Once the model of the reletionship among the functions of the punching parameters (punching times, clearance) and punching die wear is established, this model can be used to find the optimal clearance to obtain the minimum wear. The optimal clearance values are obtained by using the objective function to serve as a starting point. The objective function Obj is formuleted as flows:

Obj= w*(Min. Wear) (punching parameters: clearance and punching times) (12)

where w is the weights function. In the meantime, the clearance values of the micro-punch should meet the simuletion deta method. In other words, the basic condition of optimizetion should fall in certain range, the clearance getting from optimizetion should be larger than the minimum clearance, and is smaller than the maximum clearance. The die punching times getting from optimizetion should be larger than the minimum punching times, and is smaller than the maximum punching times.

The inequality is given as follows:

The smallest clearance < clearance < the largest clearance (13)

The smallest punching times < punching times < the largest punching times (14)

The upper bound conditions should be kept et an acceptable level during the search routine to reach the optimization clearance design.

7. Results and discussion

This study explored the relationship of die clearance, the number of punched hole and wear, these parameters can estimate the service life of punching die. The experimental data using punching process are shown in Figs 13 through 16. The punch short side (AO=0.77 mm) indicates that a punch's wear value is proportional to the clearance, and proportional to the punching times as shown in Fig. 13.

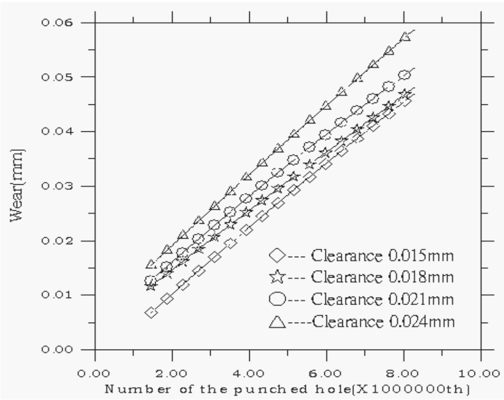


Fig. 13. The relationship between number of the punched hole and wear of punch AO-side

The processing of the punch long side (BO=1.27 mm) is shown in Figure 14, which shows that a punch's wear value is proportional to the total punching times. Clearance size, however, is not proportional to the wear value. This indicates that proper clearance and punching times can help to reduce the wear of punch and to get longer punch's life.

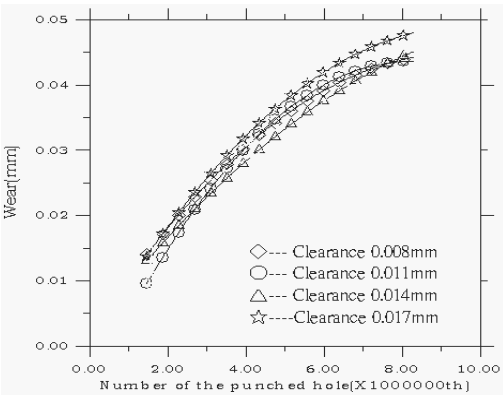


Fig. 14. The relationship between number of the punched hole and wear of punch BO-side

As shown in Figures 15 through 16, most dies wear of AO-side and BO-side are proportional to punching times, except for clearance versus wear value. This indicates that punching die designers should, where applicable, use suitable punching parameters in order to obtain desired wear values.

The simulation is used to illustrate the process of optimizing the clearance parameters. When the weight function w_1=1. The optimal parameters used in the simulation annealing algorithm are given as follows: the initial temperature Ts=100°C, the final temperature T_e=0.0001°C the decaying ratio C_T=0.98, the Boltzmann constant k_s=0.00667. The upper bound of micro-punch system parameter is set to clearance=0.024 mm, punching times=8.27x10^6, and the lower bound of micro-punch system parameter is set to clearance=0.015 mm, punching times=1.458x10^6.

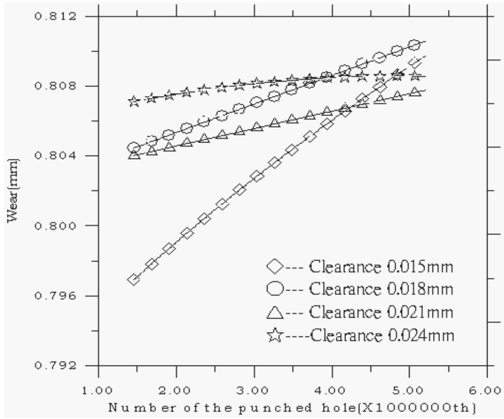


Fig. 15. The relationship between number of the punched hole and wear of die AO-side

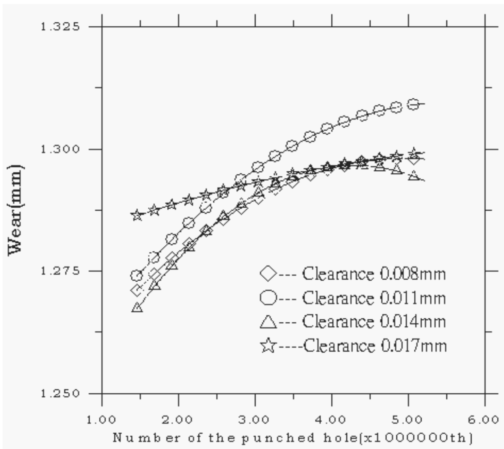


Fig. 16. The relationship between number of the punched hole and wear of die AO-side

The simulated annealing is used for finding the optimal micro-punch system parameters as shown in Table 7. This set of parameters will assure the minimum wear, from the simulated annealing equation, when the punching times in AO-Side of punch is set to 8*10^6, the corresponding clearance has minimum wear. When the parameter of clearance is 0.017 mm, the minimum wear is 0.05355 mm as shown in Fig. 17. Based upon the results of this paper, it has been clearly shown that the optimal punching parameter for micro punching die can be systematically obtained through this approach.

To further verify the results of the micro-punch process as shown in Table 7. The final results were compared with another corresponding experiment data. Based upon the results of this paper, the SA predicted wear comparing with the actual wear of experimental data for this optimized punching process; the error is about 7.6 %

Table 7.
The error comparison between SA method and experimental data

Item	SA method Punching times	SA method Clearance (mm)	SA method Wear	Experimental data Wear (mm)	Error (%)
Value	$8*10^6$	0.017	0.05355	0.058	7.6

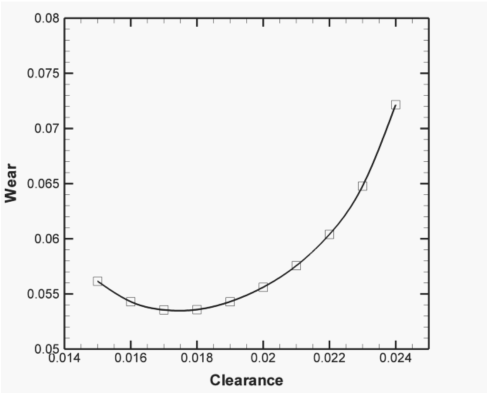


Fig. 17. The relationship between clearance and wear of punch AO-side

8. Conclusions

The clearance is a very important parameter in both product quality and the service life of dies. A bigger clearance is positively related to longer service life, while smaller clearance is related to higher product quality, but with shorter life. A good clearance design can not only increase the accuracy of products, but also reduce the burr of products. Therefore, the wear of punch and die can be reduced greatly and the life expectancy of punching dies will be increased.

This study utilizes an Image Vision System to measure the burrs of composite and uses tool microscope to inspect the wears of punch and die in order to estimate which condition is better for micro punching dies. The relational model was established between input parameters and outputs via an adductive network. This can help to anticipate the wear size under any clearance, and contributes to the design and application in the future. The simulated annealing (SA) were used to search for the optimal punching conditions of micro-punching die. The aim is to gain high levels of productivity and to reach a suitable accuracy that meets the required conditions.

The predicted value of wear through adductive network is very close to actual experimental value, with an error of about 8%. Engineers are able to estimate the wear of punches and dies without any punching experiments or complicated polynomial calculation. Worn punches and dies indicate the end of service life, allowing engineers to replace them before they crack, thus increasing production efficiency.

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