Optimisation of micro W-bending process parameters using I-optimal design-based response surface methodology

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Abstract. There is an increasingly recognised requirement for high dimensional accuracy in micro-bent parts. Springback has an important influence on dimensional accuracy and it is significantly influenced by various process parameters. In order to optimise process parameters and improve dimensional accuracy, an approach to quantify the influence of these parameters is proposed in this study. Experiments were conducted on a micro W-bending process by using an I-optimal design method, breaking through the limitations of the traditional methods of design of experiment (DOE). The mathematical model was established by response surface methodology (RSM). Statistical analysis indicated that the developed model was adequate to describe the relationship between process parameters and springback. It was also revealed that the foil thickness was the most significant parameter affecting the springback. Moreover, the foil thickness and grain size not only affected the dimensional accuracy, but also had noteworthy influence on the springback behaviour in the micro W-bending process. By applying the proposed model, the optimum process parameters to minimize springback and improve the dimensional accuracy were obtained. It is evident from this study that the I-optimal design-based RSM is a promising method for parameter optimisation and dimensional accuracy improvement in the micro-bending process.

Keywords: Micro-forming / micro-bending / springback / response surface methodology / I-optimal design / optimisation

1 Introduction

The rapid development of micro-forming processes, including the micro-bending process, has focused attention on the requirements for fabricating micro parts with high dimensional accuracy and good forming quality [1,2]. With respect to the micro-bending process, springback, caused by the elastic recovery after releasing the load, is usually adopted to evaluate the dimensional accuracy and forming quality of micro-bent parts. In general, the springback of micro-bent parts is closely associated with the process parameters selected [3,4]. Therefore, establishing a mathematical model to investigate the relationship between process parameters and springback and to explore the optimum parameter combination, is of utmost importance to improve the dimensional accuracy and maintain good forming quality of micro-bent parts.

In recent years, a number of studies have attempted to explore the influences of various parameters on springback. Chikalthankar et al. presented a review on the influences of several parameters, such as punch angle, punch radius, material thickness and rolling direction on the springback of micro-bent parts [5]. Le et al. conducted experiments in a U-bending process to study the influences of different punch radii and the gap between punch and die on springback [6]. Micro U-bending experiments were also carried out by Wang et al. to examine the influence of size effects on the springback behavior [7]. It was found that the springback angle increased with a decrease of sheet thickness. Xu et al. studied the influences of punch angle, material thickness and grain size on springback in the micro V-bending process. Experimental results showed that the amount of springback decreased with decreasing grain size and punch angle [8]. Choudhury et al. employed the orthogonal experimental method to investigate the influences of 11 parameters in the micro V-bending process. It was suggested that the punch holding time, material type

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Table 1. Grain sizes under corresponding thicknesses and annealing conditions (μm).

Annealing condition	25 μm	50 μm	75 μm	100 μm
Cond. 1 (450 °C, 1 h)	26.0	28.2	30.1	28.8
Cond. 2 (550 °C, 1 h)	33.0	46.3	56.6	62.8
Cond. 3 (650 °C, 1 h)	37.3	69.5	82.8	98.2
Cond. 4 (650 °C, 3 h)	41.2	75.0	98.5	105.7

and lubrication condition were the three key factors affecting springback [9]. Gau et al. carried out three-point bending experiments to assess the effects of grain size and brass-sheet thickness on springback [10].

Considering that the relationship between the process parameters and springback is nonlinear, some researchers have committed to conducting research by using statistical methods [11–13]. Liu et al. utilized the artificial neural network (ANN) method combined with a genetic algorithm to establish a springback model to study the relationship between material thickness, bending radius and springback [14]. In addition, other ANN methods, such as back-propagation neural network (BPNN) and counter propagation neural network (CPNN), were used by Teimouri et al. to develop models to investigate the influences of punch tip radius, material thickness and rolling direction on springback of CK67 steel sheet in the V-bending process [15]. Dib et al. selected and compared several methods including multilayer perceptron (MLP), decision tree (DT), random forest (RF), support vector machine (SVM) and K-nearest neighbours (KNN) to explore the influences of sheet thickness, material properties and blank holder force on springback in the U-bending process [16]. Khamneh et al. established a mathematical model using D-optimal design-based response surface methodology (RSM) to optimise the parameters of springback in a creep age forming process, providing a novel approach to solve the parameter optimisation problem [17].

To date, most of these studies have predominantly concentrated on the qualitative analysis of the influence of process parameters on springback. Few studies however have provided a quantitative analysis of process parameters. Although ANN has become the most popular method to analyse the influence of process parameters, the equation of a mathematical model could not be obtained. Moreover, previous studies have mainly dealt with conventional bending processes, such as V-bending, U-bending and three-point bending, complex bending processes have received little attention. This study therefore set out to develop a method to achieve the parameter optimisation and improve the dimensional accuracy in a micro W-bending process. In this study, a computer-generated design of experiment (DOE), an I-optimal DOE, was employed to solve the problem of an irregular experiment matrix during the design of experiment. Subsequently, a mathematical model based on the I-optimal design-based RSM was established, and its adequacy was evaluated and validated. The parameter optimisation was further performed and the optimum combination of parameters in the micro W-bending process was obtained.

2 Experimentation

2.1 Material preparation

Brass is widely used in micro-forming due to its good mechanical properties and excellent forming performance. In this study CuZn37 brass foils from cold rolling were adopted as the experimental material, with the thickness ranging from 25 to 100 μm . With a view to eliminating the effects of rolling texture and obtaining various grain sizes annealing treatments were conducted under temperatures ranging from 450 to 650 °C with 1–3 h' holding time. All the annealing treatment were carried out in the protection condition to prevent the formation of the oxidation layer on the material. The average grain sizes under corresponding thicknesses and annealing conditions are listed in Table 1.

2.2 Micro W-bending process

The W-shaped micro-bent parts have been employed in the fields of fiber-optic communication, fiber-optic sensing systems and some electronics products. To fabricate this kind of micro-bent part, a micro W-bending process was proposed. The micro W-bending experiments were carried out on a bench-top micro-forming machine, equipped with the W-shaped punch and die, as shown in Figure 1. It is shown that a bending angle of 80° was to be achieved for this micro part. The punch stroke is measured by a positional encoder with the vertical-position-resolution of 0.1 μm .

2.3 Response surface methodology

Response surface methodology is a comprehensive analysis method integrating modelling, optimisation and prediction, which is developed on the basis of mathematical statistics theory [18–21]. It is well suited when a response is influenced by several variables. The objective of applying RSM is to simultaneously optimise the levels of these variables to obtain the best response. To achieve this objective a linear or quadratic polynomial function is usually employed to establish the mathematical models between the response and the variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon \quad (1)$$

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j + \varepsilon \quad (2)$$

where y is the estimated response, x_i is the variable, k represents the number of variables, β_0 is the constant, β_i , β_{ii} and β_{ij} represent the coefficients of the linear, quadratic and the interaction parameters, respectively. ε describes the residual related to the experiments.

2.4 I-optimal design of experiments

Before applying the response surface methodology, it is first necessary to select the process parameters and their corresponding levels in the micro W-bending process. According to our preliminary pilot investigations, foil thickness, punch stroke, punching frequency and grain size do have significant influences on the springback of the W-shaped micro parts [22,23]. Regarding this there should be at least three levels for each parameter when applying

RSM, 3–4 levels were selected for each parameter, as listed in Table 2.

With the consideration that the selected parameters had different levels of contributions to an irregular experimental matrix, and the grain sizes of different foil thicknesses varied considerably under the same conditions, the I-optimal design of experiment was adopted in this study with only 56 runs at 3–4 factor levels. It is also known as IV-optimal DOE, which is a novel computer-generated optimal design method recommended to accomplish response surface designs with the aim to optimising the factor settings and achieving a better accuracy in the estimation of the response [24–26]. Compared to the Taguchi method and full factorial method which may be used for regular designs (e.g. each factor may have a same number of the level), the I-optimal DOE is more appropriate for the irregular experimental matrix. By applying the I-optimal DOE, 44 runs of four process parameters at different levels were designed. Replicates and extra model points were additionally added to reduce the standard error and estimate lack of fit, thus, improving the accuracy of the mathematical model established. The I-optimal designed matrix is presented in Table 3.

3 Results, analysis and discussion

According to the I-optimal DOE, 56 tests were carried out to investigate the influence of the parameters on springback. The experimental results are shown in Table 3. It was demonstrated that both positive and negative springback behaviour occurred in the experiments. A vision-measuring microscope, Mitutoyo Quick Scope, was used to measure the final bent angle. Thus, the springback was calculated based on the measured final bent angle minus 80°. With a view to ensuring the accuracy of measurement each W-shaped micro part was measured three times and the results were then averaged.

3.1 Establishment of the mathematical model

In this study, Design-Expert 8 (Stat-Ease Inc.) software was employed to perform the regression and graphical analysis, and the analysis of variance (ANOVA). In order to choose the best model which could fit the experimental data well, linear, two-factor interaction (2FI), quadratic and cubic models were analysed and compared. The statistical analysis results of the models are listed in Table 4.

Fig. 1. (a) Micro-forming machine; (b) schematic illustrations of bending punch and die; (c) W-shaped micro-bent part.

Table 2. Process parameters and their corresponding levels.

Symbols	Parameters	Level 1	Level 2	Level 3	Level 4
A	Foil thickness, t (μm)	25	50	75	100
B	Punch stroke, s (mm)	9.582	9.635	9.688	
C	Punching frequency, f (Hz)	0.15	0.20	0.25	
D	Grain size, d (μm)	Cond. 1	Cond. 2	Cond. 3	Cond. 4

Table 3. I-optimal DOE and corresponding response.

Run	Parameters				Response
	A (μm)	B (mm)	C (Hz)	D (μm)	Springback ($^{\circ}$)
1	75	9.688	0.15	Level 3	-4.062
2	25	9.582	0.25	Level 3	14.383
3	75	9.688	0.15	Level 3	-5.837
4	50	9.688	0.25	Level 3	1.952
5	100	9.582	0.15	Level 3	-4.912
6	100	9.635	0.15	Level 4	-5.114
7	100	9.582	0.15	Level 1	-3.313
8	25	9.635	0.2	Level 3	7.428
9	25	9.582	0.25	Level 2	17.787
10	75	9.635	0.2	Level 2	-3.158
11	100	9.582	0.25	Level 1	2.514
12	50	9.635	0.2	Level 1	3.458
13	25	9.688	0.25	Level 2	8.407
14	25	9.688	0.25	Level 1	10.988
15	25	9.582	0.15	Level 2	7.283
16	100	9.688	0.15	Level 2	-4.988
17	25	9.635	0.25	Level 4	2.410
18	25	9.582	0.25	Level 1	22.107
19	100	9.582	0.25	Level 2	-3.854
20	75	9.635	0.2	Level 1	-0.283
21	50	9.582	0.2	Level 3	2.193
22	100	9.582	0.15	Level 2	-4.391
23	75	9.582	0.25	Level 4	-2.380
24	100	9.582	0.25	Level 2	-0.403
25	50	9.688	0.25	Level 3	1.923
26	50	9.635	0.2	Level 1	5.619
27	100	9.688	0.25	Level 1	-1.437
28	75	9.635	0.15	Level 4	-5.565
29	50	9.582	0.15	Level 3	-1.673
30	25	9.688	0.15	Level 2	-0.446
31	100	9.688	0.2	Level 2	-4.514
32	100	9.582	0.2	Level 4	-4.679
33	100	9.688	0.25	Level 4	-5.067
34	50	9.635	0.2	Level 2	0.405
35	50	9.582	0.2	Level 4	2.058
36	75	9.635	0.2	Level 1	0.603
37	75	9.688	0.2	Level 4	-4.638
38	25	9.635	0.25	Level 4	5.269
39	75	9.688	0.25	Level 2	-3.455
40	75	9.582	0.25	Level 3	-0.321
41	100	9.635	0.15	Level 4	-5.114
42	25	9.688	0.2	Level 3	4.318
43	50	9.635	0.2	Level 2	1.273
44	25	9.635	0.15	Level 3	-1.016
45	100	9.635	0.2	Level 3	-4.237
46	100	9.635	0.25	Level 3	-3.884
47	100	9.688	0.15	Level 1	-4.927

Table 3. (continued).

Run	Parameters				Response
	A (μm)	B (mm)	C (Hz)	D (μm)	Springback ($^\circ$)
48	75	9.635	0.15	Level 2	-3.901
49	25	9.688	0.15	Level 1	-1.772
50	25	9.688	0.2	Level 4	3.190
51	25	9.582	0.15	Level 4	3.679
52	100	9.688	0.2	Level 3	-5.017
53	50	9.635	0.2	Level 1	3.854
54	50	9.688	0.15	Level 4	-6.424
55	25	9.582	0.15	Level 1	8.058
56	50	9.635	0.25	Level 4	-0.357

Table 4. Comparisons of several RSM models for springback.

Model	Sequential P-value	Lack of fit P-value	R^2	R^2_{Adj}	R^2_{Pred}	PRESS	Remarks
Linear	< 0.0001	0.0028	0.7687	0.7505	0.7190	565.82	
2FI	< 0.0001	0.0557	0.9107	0.8908	0.8697	262.38	
Quadratic	0.0018	0.1449	0.9406	0.9204	0.8921	217.30	Suggested
Cubic	0.0050	0.6427	0.9830	0.9593	0.7584	486.35	Aliased

In Table 4, there are six indices to evaluate the adequacy of the above-listed four models. If the P-value is smaller than 0.05, it indicates the factors or their interaction effects significantly influence the response. The second index is R^2 , which interprets how well the model fits. The closer the R^2 to one, the better the model fits the data. The adjusted R^2 (R^2_{Adj}) is the third index used to calculate the amount of variation around the mean of the model. The predicted R^2 (R^2_{Pred}) is then adopted to estimate how accurately the model predicts a response value. PRESS is the predicted residual error sum of squares. The smaller the PRESS is, the more accurate the model will be. Moreover, it is expected to be a good fit, if the lack-of-fit P-value is not significant.

It is evident from the results obtain that R^2 of the quadratic model is higher than that of the linear and 2FI models. R^2_{Adj} is also in good agreement with R^2_{Pred} . Furthermore, in the quadratic model, the P-value is significant and the PRESS is the smallest with an insignificant lack-of-fit compared to the other models. Consequently, the quadratic model was selected since it could shed light on the relationship between several process parameters and the response more accurately. Although R^2 and R^2_{Adj} of the cubic model were higher than those of the quadratic model, it was still not chosen to develop the mathematical model since it was aliased.

After selecting the quadratic model as the regression method, the mathematical relationship was established between the process parameters and springback, which could be expressed in equation (3). The established mathematical model is subject to some constraints: $25 \mu\text{m} \leq A$ (foil thickness) $\leq 100 \mu\text{m}$, $9.582 \text{ mm} \leq B$ (punch stroke) $\leq 9.688 \text{ mm}$, $0.15 \text{ Hz} \leq C$ (punching

frequency) $\leq 0.25 \text{ Hz}$, $26 \mu\text{m} \leq D$ (grain size) $\leq 105.7 \mu\text{m}$.

$$\begin{aligned} \text{Springback} = & 77961.50939 - 5.67159A - 16098.73858B \\ & + 1232.30690C - 5.44468D \\ & + 0.59368AB - 0.79681AC + 2.09518 \\ & \times 10^{-3}AD - 103.08753BC \\ & + 0.54138BD - 0.67250CD - 7.19789 \\ & \times 10^{-4}A^2 + 830.84592B^2 \\ & - 245.19301C^2 + 9.66634 \times 10^{-4}D^2 \end{aligned} \quad (3)$$

3.2 Adequacy evaluation of the mathematical model

The adequacy of the established quadratic model was evaluated by employing the ANOVA and the results are presented in Table 5.

It is shown in the table that P-value of the developed model for springback is smaller than 0.05, suggesting the model is significant at a 95% confidence interval. Meanwhile, the ANOVA results reveal that the foil thickness, punch stroke, punching frequency and grain size have significant influence on the response. In addition, the lack-of-fit P-value 0.1449 is more than 0.05, which is not significant compared with pure error, demonstrating that the experimental error is mainly caused by random error. This model could be further used to analyse and predict the response quantitatively. Furthermore, there are other indices used to evaluate the adequacy of the developed model. R^2 of the model is 0.9406, which is very close to one, indicating the model has a good fit performance between

Table 5. ANOVA results of RSM model for springback.

Source	Sum of squares	df	Mean square	F-value	P-value	Remarks
Model	1893.920	14	135.280	46.400	<0.0001	Significant
A-foil thickness	34.910	1	34.910	11.970	0.0013	Significant
B-punch stroke	119.870	1	119.870	41.120	<0.0001	Significant
C-punching frequency	184.980	1	184.980	63.450	<0.0001	Significant
D-grain size	88.690	1	88.690	30.420	<0.0001	Significant
AB	27.140	1	27.140	9.310	0.0040	Significant
AC	42.120	1	42.120	14.450	0.0005	Significant
AD	29.600	1	29.600	10.150	0.0028	Significant
BC	2.130	1	2.130	0.730	0.3976	Not significant
BD	15.590	1	15.590	5.350	0.0259	Significant
CD	21.870	1	21.870	7.500	0.0091	Significant
A ²	4.100	1	4.100	1.410	0.2426	Not significant
B ²	51.750	1	51.750	17.750	0.0001	Significant
C ²	3.650	1	3.650	1.250	0.2698	Not significant
D ²	9.750	1	9.750	3.340	0.0748	Not significant
Residual	119.530	41	2.920			
Lack of Fit	104.490	32	3.270	1.950	0.1449	Not significant
Pure Error	15.040	9	1.670			
Cor Total	2013.450	55				
Std. Dev.	1.710		R ²		0.9406	
Mean	0.540		Adj R ²		0.9204	
C.V. %	318.480		Pred R ²		0.8921	
PRESS	217.300		Adeq Precision		29.0290	

the parameters and the response. Adj R^2 (0.9204) is in good agreement with Pred R^2 (0.8921), implying the model has a high prediction accuracy and a good consistency between the predicted values and the experimental values. The adequacy precision ratio of the model is 29.0290 (Adeq Precision > 4), which indicates the model has excellent discrimination. The reliability of the developed model is additionally checked by drawing the normal probability plot of residuals. As illustrated in Figure 2, the experimental errors distribute normally, indicating a high degree of fit between the model and the experimental results.

3.3 Response surface analysis

It is suggested from the evaluation of the adequacy of the established model that the quadratic model of springback has good fitting performance, small experimental error and high prediction accuracy. Accordingly, it could be used to investigate the influence of the main effects and the interaction effects of the process parameters on springback of the W-shaped micro-bent parts.

3.3.1 Influence of the main effects of parameters on springback

The main effects of parameters on springback were plotted by Minitab17 software. As shown in Figure 3, when the foil thickness increases from 25 to 50 μm , the amount of

Fig. 2. Normal probability plot of residuals for percentage change in springback.

springback decreases sharply, denoting the dimensional accuracy increases. When the thickness increases from 50 to 75 μm , the springback behaviour of the micro parts changes from positive springback to negative springback with the amount of negative springback increasing significantly. As the thickness continues to increase to 100 μm , the amount of negative springback only shows a

Fig. 3. Main effects plot for springback.

small increase, indicating that the dimensional accuracy of the micro-bent parts has a slight decline. In addition, punch stroke also presents a similar influence to that from the foil thickness on springback. With the increase of punch stroke, the dimensional accuracy of micro-bent parts increases first and then decreases. However, punching frequency displays an opposite influence trend compared to the above two parameters. As the frequency increases, the amount of negative springback decreases gradually. When the frequency is equal to 0.2 Hz, the springback of the micro part is close to zero, exhibiting high dimensional accuracy. Then as the punching frequency continues to increase, the amount of positive springback increases, demonstrating that the dimensional accuracy decreases gradually. It can also be seen from Figure 3 that the grain size of the material also has a significant effect on the dimensional accuracy. The amount of positive springback decreases with the increase of grain size. When the grain size increases to Level 3, a slight negative springback behaviour is observed. The amount of negative springback then increases significantly with the increase of grain size. Consequently, it could be noticed in Figure 3 that the foil thickness is the most critical parameter affecting the springback behaviour and the dimensional accuracy of micro-bent parts.

3.3.2 Influence of the interaction effects of parameters on springback

It can be observed in Table 5 that the interactions between foil thickness and punch stroke, foil thickness and punching frequency, foil thickness and grain size, punch stroke and grain size, punching frequency and grain size, do have significant influences on the response. Meanwhile, it also can be seen in the main effects plot for springback that the foil thickness influences the springback most. Therefore, the 3D response surface graphs between foil thickness and the other three parameters were plotted in Figure 4, and these are utilized to explore the influence of interaction effects of parameters on springback.

Figure 4a shows the 3D response surface plot of the interaction effect of foil thickness and punch stroke when the punching frequency is 0.2 Hz and grain size remains

constant at Level 3. It can be observed that if the punch stroke remains at 9.582 mm, the springback amount varies by 13.339° (from 9.592° to -3.747°) when the foil thickness increases from 25 to 100 μm . If the foil thickness remains at 25 μm , the springback amount varies by 5.351° (from 9.592° to 4.241°) when the punch stroke increases from 9.582 to 9.688 mm. Hence, it can be noted that the influence of the punch stroke is less than that of the foil thickness.

The surface plot of the interaction effect between the foil thickness and punching frequency is illustrated in Figure 4b. It reveals that when the foil thickness is constant at 25 μm , the amount of positive springback increases significantly (from 0.039° to 9.748°) with the increase of punching frequency, whereas the amount of negative springback decreases slightly (from -6.225° to -4.655°) with an increasing punching frequency when the foil thickness is constant at 100 μm . Additionally, when the foil thickness is 25 μm and the punching frequency is 0.15 Hz, the springback is 0.039° , presenting good dimensional accuracy of the micro-bent parts.

Figure 4c depicts the interaction plot of thickness and grain size on springback. When the punch stroke and punching frequency are kept at their intermediate levels, the parts with a thickness of 25 μm present positive springback behaviour at all the levels of grain size, and the springback amount decreases with increasing grain size, indicating increasing dimensional accuracy. Conversely, the negative springback behaviour is exhibited when the foil thickness is 100 μm , and the springback amount increases with the increase of grain size. From this figure, it can be noticed that the springback behavior with different thicknesses is not consistent, suggesting that the springback behavior and dimensional accuracy are more sensitive to the foil thickness than the grain size.

3.4 Optimisation of response

The objective of conducting this parametric investigation into the springback in the micro W-bending process is to achieve desired dimensional accuracy with optimised process parameters. Therefore, the response surface optimisation was performed to obtain the optimum combination of the process parameters, minimise the springback amount and improve the dimensional accuracy of micro-bent parts. RSM optimisation results for springback are shown in Table 6. The goal of the optimisation is to achieve the minimisation of the springback amount. The optimum process parameters are found to be a foil thickness of 75 μm , punch stroke of 9.635 mm, punching frequency of 0.2 Hz and Level 1 of the grain size. The corresponding springback after optimisation is -0.047° , as presented in Figure 5.

4 Conclusions

An I-optimal DOE-based response surface methodology was developed in this study to optimise the parameters of a micro W-bending process. This proposed method offers an efficient approach to achieve the optimisation of various process parameters at different levels, which could not be

Fig. 4. Interaction effects of parameters on springback. (a) response surface plot of interactions between thickness and stroke on springback; (b) response surface plot of interactions between thickness and frequency on springback; (c) interaction plot of thickness and grain size on springback.

Table 6. RSM optimisation result for springbak.

Response	Goal	Optimum combination				Pre. response	Desirability
		Foil thickness (μm)	Punch stroke (mm)	Punching frequency (Hz)	Grain size (μm)		
Springback (°)	0°	75	9.635	0.2	Level 1	-0.047°	0.993

Fig. 5. Contour plot of the optimised springback.

solved by traditional DOE. By applying this method, a mathematical model was established to describe the relationship between the process parameters and the springback, which was used to represent the dimensional accuracy of micro-bent parts. Afterwards, the adequacy of the developed model was evaluated and validated. The influence of the main and interaction effects of the parameters on springback were subsequently analysed. Optimisation was also performed to determine the optimum combination of process parameters. Based on the results obtained, the following conclusions can be drawn:

- The statistical analysis and comparison results of several RSM models have suggested that the quadratic model is most applicable to describe the relationship between process parameters and the response.
- A mathematical model was established based on the quadratic polynomial regression method. Statistical analysis has proved that the developed model is evidently significant at a 95% confidence interval with good fitting performance (R^2 is 0.9406), small experimental errors (PRESS is 217.3, Std. Dev. is 1.71) and high prediction accuracy (Pred R^2 is 0.8921).
- It can be drawn from the analysis of the main parameter effects of the foil thickness, punch stroke and grain size that they have demonstrated similar influences on the springback. That is the amount of positive springback decreases and the amount of negative springback increases with the increase of the corresponding parameter level, whereas the punching frequency

exhibits an opposite tendency. In addition, foil thickness is the most significant parameter affecting springback in the micro W-bending process.

- Analysis of the interactions between the foil thickness and punch stroke, foil thickness and punching frequency, foil thickness and grain size, have revealed their statistically significant influences on springback. It can also be noticed that the foil thickness and grain size not only affect the dimensional accuracy, but also have an influence on the springback behaviour in the micro W-bending process.
- RSM optimisation shows that the optimum process parameters to minimise the springback amount and achieve a better dimensional accuracy of micro-bent parts are 75 μm , 9.635 mm, 0.2 Hz and Level 1 for foil thickness, punch stroke, punching frequency and grain size, respectively.

Taken together, the research that was demonstrated experimentally and statistically in this study has verified that the I-optimal DOE-based response surface methodology is an effective and adequate method for the optimisation of micro W-bending process parameters. More broadly, the present investigation is important for conducting further in-depth research on the dimensional accuracy evaluation and quality control of the micro parts fabricated by various forming processes. In particular, further studies regarding the influences of the grain size on the dimensional accuracy of the micro parts formed by micro-forming would be worthwhile.

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