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PROBABILISTIC DESIGN OF UNCERTAINTY FOR ALUMINUM ALLOY SHEET IN RUBBER FLUID FORMING PROCESS

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Abstract. The exclusion of variations in the deterministic design method can lead to very unreliable result and instability quality. This paper proposes a probabilistic design approach for the uncertainties of rubber fluid forming process. The uncertainties consist of the inherent variations of incoming material properties, the process parameters variations and other random variations. This paper presents the probabilistic model and related models to analyze the effect of controllable factors and noise factors to rubber fluid forming process. In order to obtain the probabilistic distribution of noise factors, this paper investigates different coil-to-coil specimens of 2B06-O aluminum alloy in tensile test. The controllable factors and noise factors can be screened by Plackett-Burman method when the noise factors are too many. By the proposed probabilistic design approach, deeper understanding about the relationship between uncertainties with the part quality is achieved. This paper reduces the sensitivity of inputs variations to quality evaluation index through response surface method and the multi-objective optimization methods. Ultimately, in order to verify the probabilistic design approach into practical usage, a typical curved flanging part of 2B06-O aluminum alloy sheet is applied by the experiment, which shows the proposed method can be used to improved quality and processing optimization.

1. INTRODUCTION

Currently with the increasingly competition in the aviation industry, how to manufacture aviation products with high quality and high robustness become the key of advanced aircraft sheet metal manufacturing technology. Rubber fluid forming (RFF) process of aluminum alloy sheet is an important process method in aircraft manufacturing; the advantages of RFF are low cost tools, small to medium batch sizes, high productivity, and short cycles of products. The quality of RFF reflects the level of aviation manufacture to some extent. To keep the abreast of demands of new-style aircrafts performance, to ensure a robust and reliable product design, manufacturers must maintain advancements in quality control and quality improvement by new techniques. Many organizations [1,2] have implemented quality improvement tools and techniques such as Six-Sigma to help them in achieving this result.

The conventional process design of RFF is based upon experiences available by incorporating with a trial and error procedure. As a result, the development of a new die often requires numerous prototype tests, leading to a long design cycle and high cost. In recent years, with the development of advanced computational technology, finite element method (FEM) has been changing such philosophy, which enables us to precisely predict a forming process and detect many defects by software of FEM, thereby reducing design and prototyping costs to a considerable extent. Panthi et al. [3] utilized FEM to analyze springback in sheet metal bending process. The surrogate and meta-model techniques

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as an effective alternative have been exhaustively adopted in sheet metal forming optimization. Kayabasi and Ekici [4] integrated finite element method (FEM), response surface method (RSM) and genetic algorithm together to find the most appropriate values of forming process parameters.

However, conventional FEM simulation is a certain deterministic prediction method, and all the input parameters such as material properties and process parameters are fixed numbers, rarely considering the variations in an actual production process. Traditional deterministic methods encapsulate variability by the use of a safety factor; however, such approaches can lead to a design with both inconsistent and poor reliabilities, or over design. Practically, the sheet metal forming process is indeed nondeterministic, which needs to be considered some variations of uncertainties such as material properties, die geometries, process parameters, manufacturing precision, etc... In order to take into account various uncertainties in sheet metal forming process, Li et al. [5-7] integrated probability optimization, six sigma criterion and robust design concept to present a CAE-based six sigma robust optimization procedure. Demir et al. [8] proposed an effective design strategy, which integrated FEM, approximate model, numerical optimization algorithm and probabilistic design method to reduce stress and increase fatigue life of sheet metal die. Recent advances in combining FEM-based packages and statistical tools have made some progress in assessing the sensitivity of a process and parts design to scatter in input variables. However, these algorithms involve only single-objective function. RFF is typically characterized by a number of quality and performance, such as fracture and springback; both of them conflict with each other. Therefore, the development of multi-objective robust optimization methods for RFF process is significant and practical.

This thesis proposed a probabilistic design approach of RFF process of 2B06-O aluminum alloy sheet, considering the inherent variations of material properties and uncertainties of RFF process. The approach integrates FEM simulation, design of experiments technique, process uncertainties modeling and response surface method. This paper aims to reduce the sensitivity of subtle variations to quality evaluation index. Ultimately, the sensitivity of inputs variations to quality evaluation index could be reduced, defect rates could be minimized and product quality would be improved.

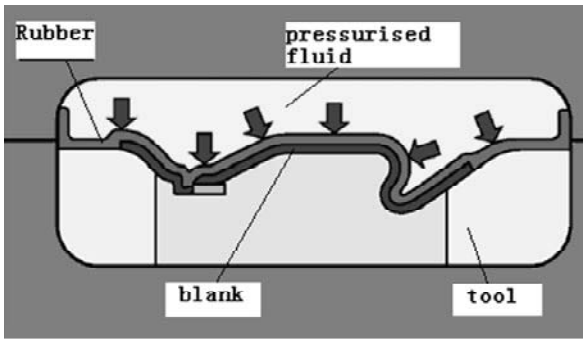

Fig. 1. Forming principle of rubber fluid forming process.

2. PROCESS ROBUSTNESS AND METHOD

2.1. Process robustness of rubber fluid forming process

Rubber fluid forming process is one of the most important processes in the aviation manufacturing. The forming principle of RFF as shown in Fig. 1, the tools produce the forming force expansion through the filled high-pressure liquid in rubber cell, and relative movement occurs between die and sheet metal, until the formed parts keep close to the mold surface, and the pressure of the high-pressure liquid will stop. During the forming process of RFF, rubber keeps close to forming parts and makes the material plastic flow sufficient. High precision formed parts can be used for aircraft assembly without trimming or rework.

A major obstacle to quality improvement in any system is the variability of the inputs and the changing process conditions over time. The RFF process is influenced by many sources of scatter. Col, A. [9] identified the following parameters as most significant: material variability, tooling variability, process variability, lubrication, and random variability.

For rubber fluid forming process of aluminum alloy sheet, the controllable input factors are fluid forming forces and lubrication condition, the noise factors such as strain hardening coefficient "*n*", strength coefficient "*K*", Young's modulus "*E*" et al., and the output objectives are fracture and springback, which are the significant quality evaluation index. Because another output objective wrinkles could be prevented by elimination wrinkles belts in the experiments. In this work a quantitative relation between robustness and a limited number of factors is obtained using the typical flanging parts of 2B06-O aluminum alloy

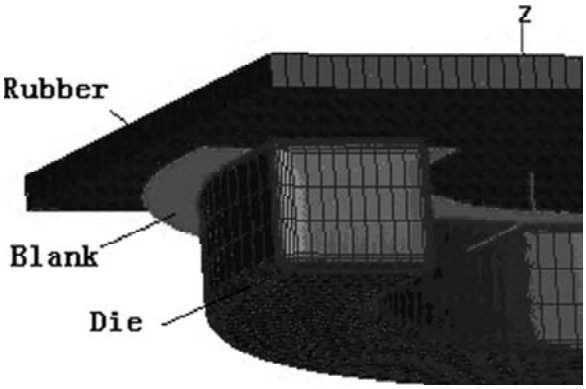

Fig. 2. Analytical simulation model.

sheet in RFF procedure. The criterion for robust performance is the achievement of the maximum thinning below a specified amount, the springback is smaller-the-better-type, and they are both insensitive to noise factors. An investigation into which scattering input parameters are most influential on fracture and springback is also performed.

2.2. Response surface method

Response surface method (RSM) is a useful statistical tool for modeling and analysis where the response is affected by several input factors. In general, the response model can be written using matrix notation

$$y(x,z) = \beta_0 + x'\beta + x'Bx + z'y + x'\Delta z + \varepsilon, \qquad (1)$$

where $\boldsymbol{y}(\boldsymbol{x},\boldsymbol{z})$ denotes the quality characteristic, $\boldsymbol{x}$ denotes the vector of control factors, $\boldsymbol{z}$ denotes the vector of noise factors. β_0 is the intercept, **b** is the vector of coefficients for the linear effects in control variables, $\boldsymbol{B}$ is the matrix whose main diagonals are the regression coefficients associated with the pure quadratic effects of the control factors and whose off-diagonals are one-half of the mixed quadratic (interaction) effects of the control factors, γ is the vector of coefficients for the linear effects in the noise variables, and Δ is the matrix of the control-factor by noise-factor interaction effects. Finally, ε is a random error. Let us assume that ε is IID $N(0, \sigma_\varepsilon^2)$. We simplify results by assuming all noise random variables are continuous and, in accordance with design level centering and scaling, $E(z)$=0 and Var ($\boldsymbol{z}$)= $\sigma_\varepsilon^2 I$. Using expectation and variance operations taken over z and ε on Eq. (1) we obtain estimates of the mean and variance response surfaces as

$$\hat{\mu}(\hat{y}) = \hat{\beta}_0 + \boldsymbol{x}'\hat{\boldsymbol{\beta}} + \boldsymbol{x}'\hat{\boldsymbol{B}}\boldsymbol{x} \qquad (2)$$

$$\hat{\sigma}_z^2\left[\hat{y}(x)\right] = \sigma_z^2\left(\hat{y}' + \boldsymbol{x}'\hat{\boldsymbol{\Delta}}\right)\left(\hat{y}' + \boldsymbol{x}'\hat{\boldsymbol{\Delta}}\right)' + \hat{\sigma}_\varepsilon^2 \qquad (3)$$

where $\hat{\beta}_0$, $\hat{\boldsymbol{\beta}}$, $\hat{\boldsymbol{B}}$, $\hat{\gamma}$, $\hat{\boldsymbol{\Delta}}$ are regression coefficients from the fitted model of Eq. (1).

The mean-squared error model proposed by Lin and Tu [10] are usually used for robust optimization as demonstrated [11, 12]. Based on Eq. (2) and Eq. (3), three different types of MSE functions can be defined as follows:

Case 1. Target is best

$$mse = \left\{\hat{\mu}_z\left[\hat{y}(\boldsymbol{x})\right] - \tau\right\}^2 + \hat{\sigma}_z^2\left[\hat{y}(\boldsymbol{x})\right]. \qquad (4)$$

Case 2. The smaller the better

$$mse = \left\{\hat{\mu}_z\left[\hat{y}(\boldsymbol{x})\right]\right\}^2 + \hat{\sigma}_z^2\left[\hat{y}(\boldsymbol{x})\right]. \qquad (5)$$

Case 3. The larger the better

$$mse = -\left\{\hat{\mu}_z\left[\hat{y}(\boldsymbol{x})\right]\right\}^2 + \hat{\sigma}_z^2\left[\hat{y}(\boldsymbol{x})\right]. \qquad (6)$$

2.3. Proposed probabilistic design approach for uncertainty

The proposed probabilistic design approach is capable of reducing RFF process performance variation and improving process quality. The approach fully integrates FEM, Central Composite Designs (CCD), RSM, multi-objective optimization to achieve the robust optimization results. For some really complex situations in which the number of noise factors is too much, Plackett-Burman (P-B) design of screening experiments is performed firstly, and then important noise factors which have significant effects on objective functions are chosen.. Though numerical methods have been in practical use for process design and control, the proposed approach will have great utility in the design and evaluation of production processes.

3. PROBABILISTIC MODELING AND NUMERICAL SIMULATION CALCALATION

Numerical techniques identify the cause and effect of variation on the RFF process is appealing. In this paper, firstly, a typical model of flanging parts in RFF procedure was presented, 2B06-O aluminum alloy sheet, including geometry model, material model, and springback model. Secondly, factors measure experiment in tension test was carried out, which could measure the variation of material properties such as strain hardening coefficient "n",

material strength "*K*", Young's modulus "*E*", etc.. Thirdly, important noise factors were observed through P-B design of screening experiments. Finally, robust optimization was realized by RSM and multi-objective optimization methods. In addition, experiment verification is necessary to prove the practicability and validity of the proposed method.

3.1. Geometry model

An analytical model should be chosen for its representative and simplicity for efficiency. This paper approaches a kind of curved flanging part to analyze the effect of variations, because the curved flanging part is a representative part of aviation manufacturing. It has a gently curved and dimensionally accurate surface. The analytical simulation model is shown in Fig. 2. The analytical model parameters are listed in Table 1, concluding stretch radius R_1 and radius R_2, central angle of bending, flanging height and thickness of blank. The FEM simulation is calculated on PAM-STAMP 2G software.

3.2. Material model

The selected sheet material is 2B06-O aluminum alloy sheet, and the thickness of blank is 2mm, which is typical for RFF process in aviation filed. The effective stress–strain curve obeys the relation, and the material properties are listed in Table 2.

3.2.1. Yield criterion of aluminum alloy sheet

In 1948, Hill introduced sheet anisotropic yield equation first time, and proposed yield criterion for orthotropic materials and the principal stress space, which can be expressed as

$$2f(\sigma_{ij}) = F\left(\sigma_2 - \sigma_3\right)^2 + G\left(\sigma_3 - \sigma_1\right)^2 + H\left(\sigma_1 - \sigma_2\right)^2, \tag{7}$$

Table 1. Analytical model parameters.

Geometrical parameter	Value
Stretch flanging radius of R_1/mm	100
Flanging radius of R_2/mm	150
Central angle of bending θ /°	90
Flanging height *h* /mm	15
Thickness of blank t_c/mm	2

where *F*, *G*, and *H* are independent of the anisotropy parameter, depending on the material from the experiments, which can be formulated as follows

$$\begin{cases} F = \dfrac{2R_0}{\left(1+R_0\right)R_{90}} \\ G = \dfrac{2}{1+R_0} \\ H = \dfrac{2R_0}{1+R_0} \\ N = \dfrac{\left(R_0+R_{90}\right)\left(1+2R_{45}\right)}{\left(1+R_0\right)R_{90}} \end{cases}, \tag{8}$$

where R_0, R_{45}, and R_{90} represents that anisotropy index difference direction with the rolling direction as 0°, 45°, and 90°.

3.2.2. Hardening model of aluminum alloy sheet

Experiment curve maybe not suitable for direct application on numerical simulation, so it is necessary to simplify and fitting data points. Hollomon law is a representative model that be used for modeling of aluminum alloy, which can be represented as

$$\text{Hollomon law: } \sigma = K \cdot \varepsilon^n, \tag{9}$$

where σ is stress, *K* is strength coefficient, ε is strain, and *n* is strain hardening coefficient.

Table 2. Probabilistic distribution of material properties.

Performance index	Noise factors of material properties							
	E/GPa	r_0	r_{45}	r_{90}	σ_s/MPa	*K*/MPa	*n*	μ
Mean	66	0.625	0.748	0.694	79	355.5	0.241	0.1
Tolerance	5	0.0396	0.0744	0.034	4.029	15.4	0.011	0.05
CV /%	7.58	6.34	9.95	4.90	5.1	4.33	4.56	50

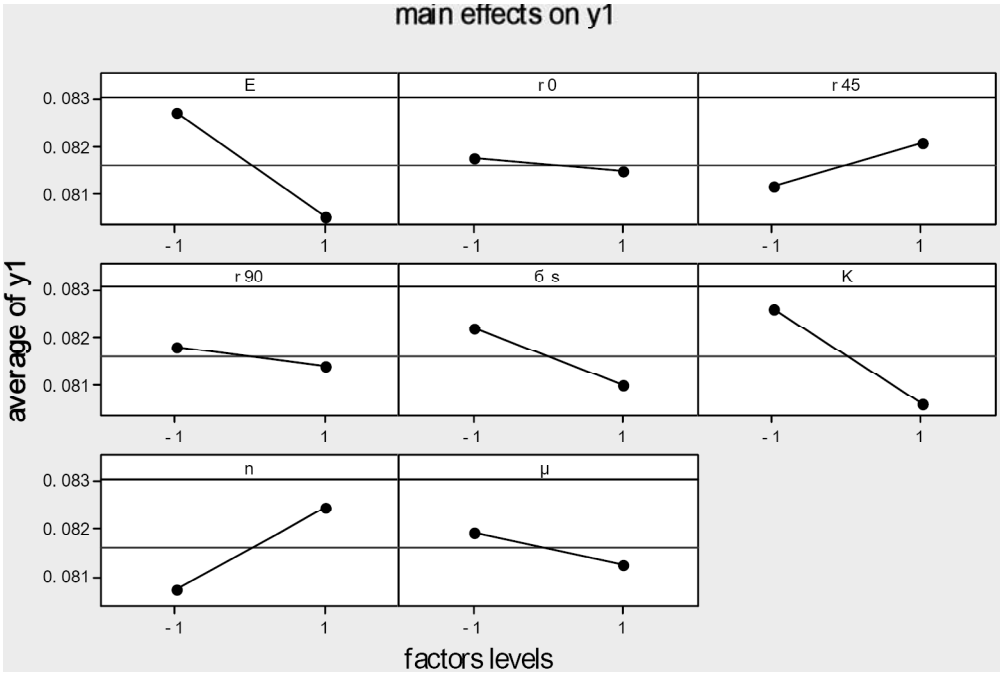

Fig. 3. Plots of noise factor effects on y_1.

3.2.3. Rubber material model

In the RFF numerical simulation, Mooney-Rivlin model can guarantee relatively accurate prediction of springback value, which can be represented as

Mooney-Rivilin model:

$$W = C_{10}\left(\bar{I}_1 - 3\right) + C_{01}\left(\bar{I}_2 - 3\right), \tag{10}$$

where C_{01} and $C_{10}$are rubber material constants respectively.

This research investigates the polyurethane rubber material properties tests with Shore hardness 70, 80, and 90.The specimens are designed according to national standard. Tensile speed is 500±50mm/min, and compression speed is 10±2mm/min. By calculating and fitting curves, the polyurethane rubber material Shore hardness is selected as 80, and the rubber material constants are C_{01}= 0.680 and C_{10}=0.990.

3.3. Noise factors measure in tension test

To investigate the different variations of aluminum alloy sheet properties, a group of tensile test is proposed. Kinsey and Cao [13] have researched that many factors including material variables affect the process by experiment. According to national standards, 27 coil-to-coil samples of 2B06-O aluminum alloy for tensile test have been prepared, each 9 samples in one direction, total three directions along the rolling 0°, 45°, and 90°. The tensile test machine named TE Electronic testing machine, which is designed by the Department of Aircraft Manufacturing Engineering of Beihang University. After statistical analysis, Table 2 shows the mean and tolerance of noise factors of material properties.

3.4. Screening experiments for noise factors

In the RFF process, material properties include Young's modulus E, initial yield stress σ_s, anisotropy index r_0, r_{45}, and r_{90}, strength coefficient K, strain hardening coefficient n, which can affect the results of forming process. Friction coefficient m is closely related to lubricate condition, surface roughness, and velocity of forming pressure. Actually, these factors are uncontrollable and may be taken as noise factors. P-B screening design is widely used in industrial experiments to screen important factors from a large number of potential factors. In this study, 12 runs are performed to screen the significant noise factors according to the preliminary experiments. Table 3 and Table 4 present the factors and their levels by the P-B experimental design.

Respectively, where the effects of noise factors on y_1 and y_2 were calculated based on 12 runs of FEM numerical simulations. Fig. 3 shows the main effects of noise factor on y_1, which represents the relative thinning index

Table 3. Noise factors and their levels.

Level	Noise factors							
	E	r_0	r_{45}	r_{90}	σ_s	K	n	μ
1	61	0.586	0.673	0.66	74.971	340.1	0.23	0.05
2	71	0.665	0.822	0.728	83.029	370.9	0.252	0.15

Table 4. Experimental design using P-B screening design and results.

Run	Noise factors								Responses	
	E	r_0	r_{45}	r_{90}	σ_s	K	n	μ	y_1	y_2
1	-1	1	-1	1	1	1	-1	-1	0.0797	0.3926
2	-1	-1	1	-1	-1	1	-1	1	0.0818	0.3908
3	1	-1	-1	1	-1	1	1	1	0.0801	0.3879
4	1	1	1	1	1	1	1	1	0.0796	0.3945
5	-1	1	1	1	-1	-1	-1	1	0.0833	0.3717
6	1	1	-1	-1	-1	1	-1	-1	0.0793	0.3791
7	-1	-1	1	-1	1	1	1	-1	0.0832	0.4149
8	1	-1	-1	-1	1	-1	-1	1	0.0796	0.3725
9	-1	-1	-1	1	-1	-1	1	-1	0.0850	0.3923
10	1	-1	1	1	1	-1	-1	-1	0.0807	0.3798
11	-1	1	-1	-1	1	-1	1	1	0.0832	0.3916
12	1	1	1	-1	-1	-1	1	-1	0.0838	0.3853

$$\min y = \left|\ln\left(t_{\min} / t_0\right)\right|, \tag{11}$$

where $t_{\min}$ represents the minimum thickness of forming parts, and t_0 is initial thickness of blank. Fig. 4 shows the main effects of noise factor on y_2, which represents the maximum springback value, a separation of the part from the die. As a result, the order of noise factors effects on y_1 is: $E>K>n>\sigma_s>r_{45}>\mu>r_{90}>r_0$; and the order of noise factors effects on y_2 is: $n>K>E>\sigma_s>\mu>r_0>r_{45}>r_{90}$. On the basis of the above mentioned analysis, it is observed that the objective functions y_1 and y_2 are more sensitive to the variations of noise factors E, K, and n.

3.5. Response surface method and multi-objective optimization

Response surface method is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. For RFF process of aluminum alloy sheet, the controllable factors are forming forces F and lubrication condition μ, which can be represented as x_1 and x_2 respectively. After screening experiments by P-B design for noise factors, it is easy to observe that the noise factors n, E, and K are relatively more important, which are represented as z_1, z_2, and z_3, respectively. Moreover, the responses y_1 and y_2 represent relative thinning index and maximum springback value, which are the significant quality evaluation index of RFF process to predict fracture and springback. Controllable factors with relevant levels are listed in Table 5, and noise factors and their levels are listed in Table 6. By 28 runs of FEM numerical simulations, Table 7 shows the experimental design results.

RSM can be used to build an explicit function to connect process inputs to process performance outputs, giving each response a fitted response model as

When $x_2 = 0.05$

$$\begin{aligned} y_1 &= 0.085 - \left(2.753E-5\right)x_1 - 0.003z_1 \\ &-\left(1.792E-5\right)z_2 - \left(4.329E-6\right)z_3 \\ &+\left(3.750E-7\right)x_1z_2, \end{aligned} \tag{12}$$

$$\begin{aligned} y_2 &= 0.9910 - 0.012x_1 - 0.513z_1 - 0.007z_2 \\ &+\left(5.437E-5\right)x_1z_2 + \left(2.910E-5\right)x_1z_3, \end{aligned} \tag{13}$$

When $x_2 = 0.10$

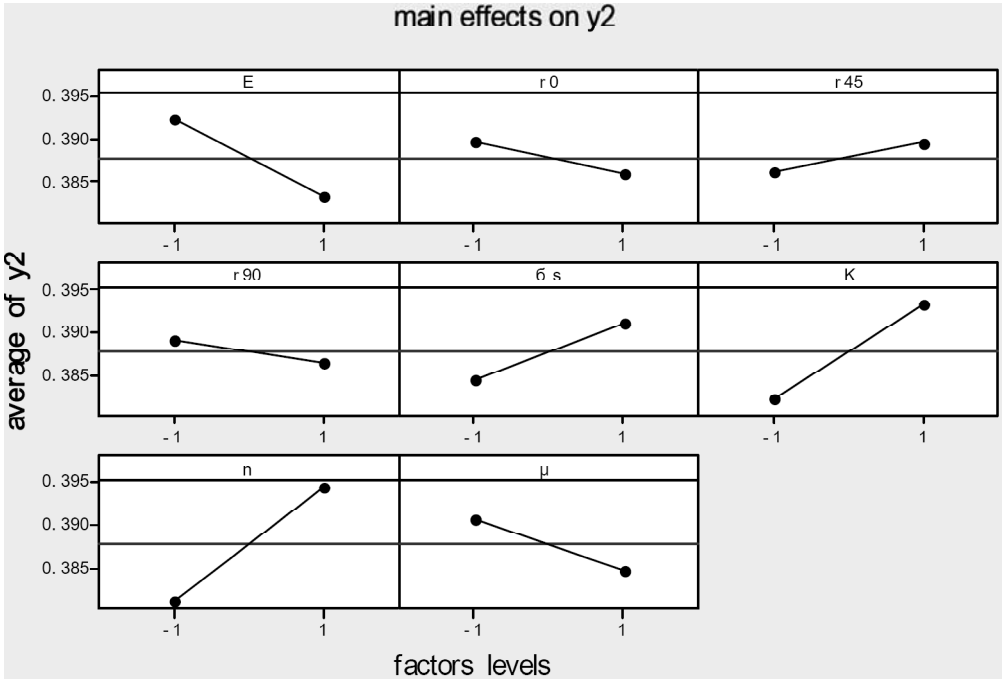

Fig. 4. Plots of noise factor effects on y_2.

Table 5. Controllable factors with relevant levels.

	Levels		
	-1	0	1
x_1 (Forming forces F /MPa)	20	30	40
x_2 (Lubrication condition μ)	0.05	0.1	0.15

$$y_1 = 0.086 - (2.753E-5)x_1 - 0.004z_1 - (1.792E-5)z_2 - (4.329E-6)z_3 + (3.750E-7)x_1z_2, \quad (14)$$

$$y_2 = 0.9270 - 0.012x_1 - 0.5960z_1 - 0.006z_2 + (5.437E-5)x_1z_2 + (2.910E-5)x_1z_3. \quad (15)$$

When $x_2 = 0.15$

$$y_1 = 0.087 - (2.753E-5)x_1 - 0.009z_1 - (1.792E-5)z_2 - (4.329E-6)z_3 + (3.750E-7)x_1z_2, \quad (16)$$

$$y_2 = 1.111 - 0.012x_1 - 0.916z_1 - 0.008z_2 + (5.437E-5)x_1z_2 + (2.910E-5)x_1z_3. \quad (17)$$

In this paper, it is assumed that $\sigma^2_{z_1} = \sigma^2_{z_2} = (0.03/3)^2$, $\sigma^2_{z_3} = (0.025/3)^2$.

Table 6. Noise factors and their levels.

Noise factors	Levels		
	-1	0	1
$z_1(n)$	0.23	0.241	0.252
z_2 (E /GPa)	61	66	71
z_3 (K /MPa)	340.1	355.5	370.9

The process means and process variations for y_1 and y_2 can be obtained based on Eqs (2) and (3). y_1 and y_2 are the smaller the better. The multi-objective robust optimization is thus formulated as:

$$\min(mse_1, mse_2)$$
$$mse_1 = (\hat{\mu}_1(y_1))^2 + \hat{\sigma}_1^2(y_1),$$
$$mse_2 = (\hat{\mu}_2(y_2))^2 + \hat{\sigma}_2^2(y_2), \quad (18)$$
$$s.t.\ y_1 \geq 0.08.$$

The optimization problem is solved by multi-objective genetic algorithm and the optimal control factors settings are obtained with x_1 = 40 and x_2 = 10. Table 8 shows the results of multi-objective optimization. Ultimately, the controllable factors settings in RFF process robust optimization of 2B06-O aluminum alloy curved flanging parts are F = 40 MPa, and μ = 0.10.

Table 7. Experimental design using CCD design and results.

Run	Factors					Responses	
	x_1	x_2	z_1	z_2	z_3	y_1	y_2
1	1	-1	-1	1	-1	0.0820	0.3272
2	0	0	0	-1	0	0.0823	0.3467
3	-1	1	-1	1	-1	0.0825	0.2491
4	-1	1	1	1	1	0.0822	0.2365
5	0	0	0	0	0	0.0823	0.3248
6	1	1	1	1	-1	0.0823	0.2700
7	-1	-1	1	1	-1	0.0820	0.2871
8	-1	0	0	0	0	0.0823	0.3056
9	-1	1	-1	-1	1	0.0825	0.3320
10	0	0	0	0	-1	0.0823	0.3166
11	0	0	0	0	1	0.0822	0.3331
12	-1	-1	1	-1	1	0.0819	0.3478
13	-1	-1	-1	1	1	0.0819	0.3059
14	0	0	0	1	0	0.0822	0.3029
15	1	-1	1	-1	-1	0.0820	0.3704
16	1	1	-1	-1	-1	0.0825	0.3424
17	0	0	0	0	0	0.0823	0.3248
18	-1	1	1	-1	-1	0.0824	0.3043
19	1	0	0	0	0	0.0823	0.3441
20	0	0	1	0	0	0.0822	0.3183
21	0	0	-1	0	0	0.0823	0.3314
22	0	-1	0	0	0	0.0819	0.3423
23	0	1	0	0	0	0.0823	0.2997
24	-1	-1	-1	-1	-1	0.0822	0.3515
25	1	1	-1	1	1	0.0824	0.3156
26	1	1	1	-1	1	0.0822	0.3477
27	1	-1	-1	-1	1	0.0819	0.4072
28	1	-1	1	1	1	0.0818	0.3414

3.6. Experiment verification

The typical curved flanging parts of 2B06-O aluminum alloy sheet in RFF are used to verify the practicability and validity of the proposed approach. Usually, there are relatively a large number of noise factors. To obtain the effects of noise factors on responses, many tests will be needed. The levels of noise factors should be strictly controlled, which results in high cost. Taguchi's composite noise factors method integrates all the noise factors into one, including two levels or three level design of outer array, which can significantly reduce the number of tests. Therefore, the test uses $L_9(3^4)$ orthogonal design for controllable factors in the inner array, and composite noise factors method with two levels in the outer array.

After measuring the springback value and statistical analysis, it can be concluded that the quality of 2B06-O aluminum alloy flanging parts is excellent without fracture and wrinkle under F=40 MPa, and m=0.10. Fig. 5 shows the formed parts of RFF process experiments, and Fig. 6 shows the die in curved flanging RFF experiment. The central angle of bending is 90°, so we put the central angle of 45° as the benchmarks for measure location, and both sides are equal portions. Fig. 7 and Fig. 8 show that the red lines in formed parts are the measure locations.

Table 8. Robust optimization results.

	mse_1	mse_2	mse	x_1
x_2 = 0.05	0.0071	0.3982	0.2026	40
x_2 = 0.10	0.0072	0.1998	0.1035	40
x_2 = 0.15	0.0074	0.3982	0.2028	40

The paper compared the springback angle results between the simulation and experiment to verify

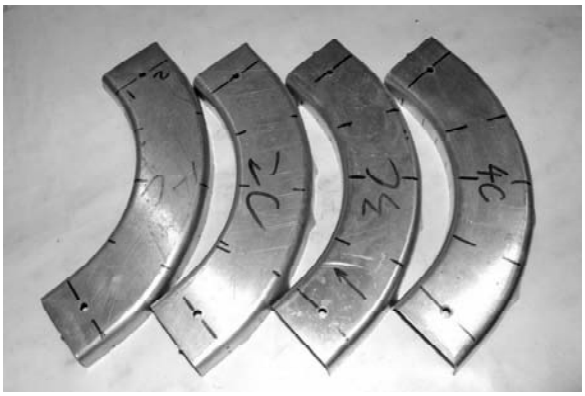

Fig. 5. Formed parts of experiment.

Fig. 6. Die of experiment.

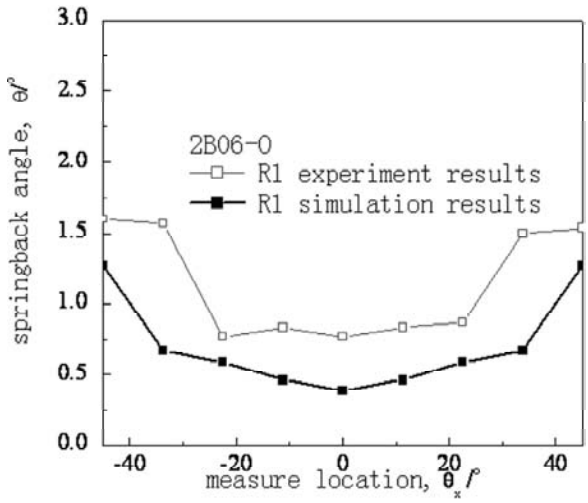

Fig. 7. Comparison results in stretch radius R_1.

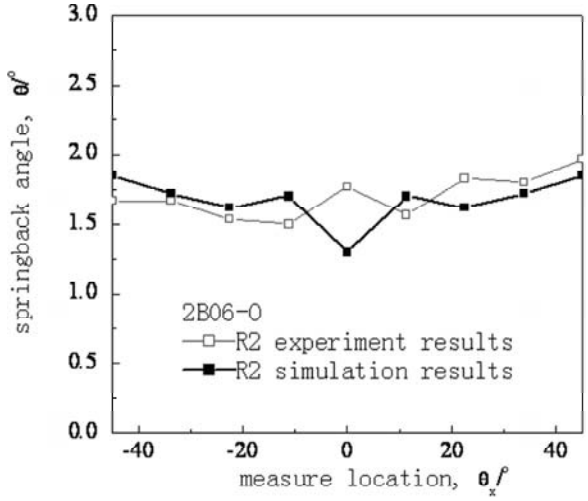

Fig. 8. Comparison results in stretch radius R_2.

the validity of probabilistic design approaches. Figs. 7 and 8 show the springback angle comparison results for simulation and experiments in stretch radius R_1 and R_2. The results show that both simulations and experiments have the same tendency and the deviation of spingback angle less than 0.5 degree proves that the results are relatively accurate and accepted.

4. RESULTS AND DISCUSSION

4.1. Effects of main noise factors on forming quality

4.1.1. Effect of strain hardening coefficient *n*-values

Strain hardening coefficient is represented by the *n*-values in the flow stress equation, which approximates the relation between true stress and true strain during plastic deformation of a metal. The coefficient *n*-values play a crucial role in sheet metal forming. The larger the *n*-values, the more the material can elongate before necking. Thus, as the *n*-values increases, the material's resistance to necking increases, and the material can be stretched farther before necking starts.

It is well-known that increasing the *n*-values also increases the formability of the material. The effect of the *n*-values in sheet metal forming is ambiguous. In this paper, for RFF, higher *n*-values may reduce wrinkling; a high *n*-values results in higher strain hardening in the flange and higher springback, so the material does not fracture easily when the forming force is increased.

4.1.2. Effect of Young's modulus *E*

Negative influence is visible for variation in Young's modulus to forming quality. During the unloading of the sheet, the moment is assumed to be purely elastic, in which *E* is inversely proportional to the amount of springback.

4.1.3. Effect of strength coefficient *K*

In the process of metal plastic forming, the flow stress formula has always been a significant basis for analyzing plastic deformation. The material strength coefficient is significant and indispensable parameters of the stress flow formula. Therefore,

the variation of *K* directly effect the forming results of RFF process.

4.2. Effects of controllable factors to forming quality

4.2.1. Effect of forming forces *F*

Forming forces is a significant controllable factor for aluminum alloy sheet in RFF process. Under the relatively larger forming forces, sheet metal will flow smoothly; formed parts will close to die more easily. Although, the formed parts will fracture or wrinkle when the forming forces is too large or too small. Therefore, it is crucial to find out a scientific method to optimize the appropriate forming force value.

4.2.2. Effect of lubrication condition

The friction exists in the middle of sheet metal and dies, also exists between the sheet metal and rubber. The friction is distinct for different lubrication condition and different forming process. Therefore, it is significant to investigate the optimal lubrication condition for aluminum alloy sheet in RFF process. An increase in friction results in a decrease in the transmittal of tension to the die face from the sidewall. This drop in tension results in lower strains over the die face and a larger plastic modulus, hence the increase in springback.

5. CONCLUSION

1) This paper proposed a probabilistic design of uncertainties approach for 2B06-O aluminum alloy sheet in RFF process. Analytical model is presented to provide the user with a good understanding of the mechanics. It also helps the user deep understanding the effect of material and process parameters on forming quality in RFF process.

2) This paper observed that objective functions are relatively more sensitive to the variations of noise factors *E*, *K*, and *n* by P-B design methods in screening experiment. RSM can be used to build an explicit function to connect process inputs to process performance outputs, and the robust optimization results in RFF process of 2B06-O aluminum alloy curved flanging parts can be obtained by multi-objective optimization.

3) After experiment verification, the paper compared the results between the simulations and experiments to verify the proposed approach. The results show the same tendency of simulations and experiment, and the proposed approach can improve the robust and quality of aluminum alloy sheet in RFF process.

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REFERENCES

[1] D. Manual // *Filtr. Sep*. **43** (2006) 34.
[2] M.Sokovic, D. Pavletic and S. Fakin // *J. Mater. Process. Technol.* **162** (2005) 777.
[3] S. K. Panthi, N. Ramakrishnan, K. K. Pathak and J. S. Chouhan // *J. Mater. Process. Technol*. **186** (2007) 120.
[4] O. Kayabasi and B. Ekici // *Mater. Des.* **28** (2007) 2665.
[5] Y. Q. Li, Z. S. Cui, X. Y. Ruan and D. J. Zhang, In: *Proc. of NUMISHEET **2005*** **(**Detroit, USA, 2005), p. 819.
[6] Y. Q. Li, Z. S. Cui, X. Y. Ruan and D. J. Zhang // *Int. J. of Adv. Manuf. Technol.* **30** (2006) 631.
[7] Y. Q. Li, Z. S. Cui, D. J. Zhang, X. Y. Ruan and J. Chen // *Chin. J. Mech. Eng*.**19** (2006) 251.
[8] I. Demir, O. Kayabasi and B. Ekici // *Mater. Des.* **29** (2008) 721.
[9] A. Col, In: *Proc. of the 6th International ESAFORM Conference on Material Forming* (Salerno, Italy, 2003), p. 183.
[10] Kwang-Jae K. Dennis and K. J. Lin // *J. Qual. Technol.* **30** (1998) 1.
[11] O. Köksoy // *Appl. Math. Comput.* **196** (2008) 603.
[12] L. J. Shen, Y. Zhao and J. Yang // *Adv. Mater. Res*. **118–120** (2010) 881.
[13] B. Kinsey and J. Cao, In: *Proc. of Sheet Metal Stamping: Development Applications* (Detroit, USA, 1997), p. 107.