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Air Bending of Sheet Metal Based on the Grey Prediction Model

Jing Tao[1], Zhengwei Fu[2,*] and Han Gao[3]

[1] School of Mechanical and Electrical Engineering, Hubei Polytechnic University, Huangshi 435003, China
[2] School of Machinery and Automation, Wuhan University of Science and Technology, Wuhan 430081, China
[3] Lyle School of Engineering, Southern Methodist University, Dallas,Texas 75206, United States

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Abstract

Owing to the intercoupling of multiple factors, strong nonlinearity exists during the bending of sheet metals, enabling the inevitable springback of sheet metal parts after bending unloading. Consequently, the bending forming angle becomes difficult to control, thereby seriously affecting the accuracy of the bending forming parts. A prediction model for the press amount of the upper mold and the bending forming angle was proposed in this study to address the shortage of bending accuracy and reveal the relationship between the bending forming angle and the press amount of the upper bending mold. First, elliptic fitting was used to improve the insufficient fitting of the background value of the original grey prediction GM (1,1) model and reduce the intermediate fitting error of the grey prediction model. Second, the modeling method was adopted at the head and the tail to reduce the long-term fitting error of the model and establish the mathematical model of the press amount of the upper mold and the forming angle in segmented bending based on the experimental bending data and in accordance with the actual working conditions. Finally, the feasibility of the model was verified through field experiment and ABAQUS simulation. Results show that the maximum fitting error of the prediction model for the bending angle obtained through the aforementioned method is only 0.7%, proving the model's capacity in accurately predicting the bending springback angle. The study provides a new method for controlling the bending springback of sheet metals.

Keywords: Bending forming, Bending springback, Grey system, GM (1,1) model, Prediction model

1 Introduction

Bending is widely applied in the modern manufacturing industry because of its many advantages, including low cost, high efficiency, and simple operation. However, bending is often accompanied by the springback problem, which affects the bending forming accuracy [1–2]. In the past, the control of the bending springback angle was mostly based on empirical knowledge, which could easily cause the waste of resources and manpower. Therefore, an increasing number of enterprises and teams are committed to developing a more accurate bending machinery, and the most common method is bending compensation. Two aspects are mainly considered for bending compensation, namely, mechanical and overbending compensation. Currently, the measures for mechanical compensation are mostly adopted. That is, compensation is investigated for a certain type of bending machine, and a mechanical compensation device is added to improve the bending accuracy. The accuracy requirements of bending products increase with the rapid development of the global manufacturing industry. Traditional empirical knowledge lags the trend of times, whereas mechanical compensation exhibits great limitations due to high cost, with most of research and designs focusing on a certain type of machine.

For this purpose, scholars have conducted numerous studies on the forming process of bending parts [3–4] to determine the bending forming law from the material and geometry perspectives. However, many factors influence bending and couple with one another and exhibit a high degree of nonlinearity, making the study of bending forming from a single aspect difficult [5]. Therefore, understanding the bending forming law and improving the bending forming accuracy are urgent concerns in the bending industry.

Thus, this study establishes a mathematical model of the press amount of the upper bending mold and the bending angle by introducing the grey prediction GM (1,1) model to predict the relationship between the press amount of the upper bending mold and the bending angle and provide a theoretical basis for the accurate prediction and control of the bending springback angle.

2 State of the art

Scholars have devoted themselves to the research of the bending springback to comprehend the bending springback law. M. R. Jamli et al. [6] added an artificial neural network (ANN), which was developed on the basis of a constitutive model into the finite element software as a script to simulate the bending and springback of sheet metal parts to improve the bending accuracy. However, they did not consider the errors caused by material anisotropy during the actual production. Mohammadi SV et al. [7] proposed an analytical formula for the springback prediction of composite plates to inspect the influences of the radius of the upper mold, the opening of the lower mold, and the stroke of the upper mold

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on the springback but did not present a quantitative model; the model was only used to analyze the influencing factors of bending. Thipprakmas S. et al. [8] discussed the bending springback problem of asymmetric U-shaped parts through the finite element simulation method, which only focused on the bending forming process through simulation method and ignored practical situations. A. Behrouzi et al. [9] adopted the reverse compensation method to compensate for bending molds under the condition that the precise springback quantity was known and discovered that obtaining the exact solution of the springback quantity in the actual process is difficult. Vitalii Vorkov et al. [10] investigated various kinds of springback of high-strength steel sheets using the simulation method and established the parameters and models of high-strength steel sheet materials but did not intensively study the angle of bending springback. Satoshi Kitayama et al. [11] performed a sequential approximate optimization of the variable support force trajectories through the radial basis function network and found that optimal variable blank clamping force trajectories could reduce the springback. However, dynamically calculating the bending force in the present bending process is difficult. Panthi S. K. et al. [12] predicted the bending springback through the finite element method and found that bending springback was inversely proportional to the elastic modulus and directly proportional to the yield stress of materials. They presented the relationship between springback and materials but could not clearly provide a relevant bending springback model. Recep Kazan et al. [13] established a bending springback model based on a neural network model using finite element simulation data and observed that certain errors existed between the fitting data of this model and the actual values. Moreover, the error accumulation in the modeling process resulted in a large deviation. Daw-Kwei Leu et al. [14] worked out a simplified prediction method for V-shaped bending springback based on basic bending theory and by considering the thickness ratio of materials, normal anisotropy, and the strain hardening index. However, basic bending theory simplifies the model and, in most cases, exhibits a gap with reality. Fu Zemin et al. [15] established the model of bending springback radius using dimensional analysis and orthogonal experiment to design the upper mold of the bending machine. However, the model parameters must meet certain conditions and limit the application of the model. Guo Zhefeng et al. [16] combined back propagation neural network (BPNN) and spline to establish the prediction model of bending angle by applying highly accurate finite element simulation results, but the application of the model was limited by the mold opening. Liang Jicai et al. [17] reduced the bending springback by adjusting and optimizing the bending force and trajectory. However, this method is characterized by high cost and small profit. Song Y. et al. [18] worked out the springback prediction model of the T-shaped beam bending process in an artificial neural network (ANN) method and investigated the influences of materials on springback through numerical simulation. However, this method ignores the influences of secondary factors, thereby leading to low prediction accuracy. Wang Ru et al. [19] simulated springback using a software for the springback problem of automobile covering parts. They also proposed a springback compensation design method based on smooth displacement adjustment theory according to the springback compensation design of the stamping mold of reverse modeling to reduce springback. However, this method uses a software to simulate springback, which is difficult to accurately realize in the current technology. Zhang Qingfang et al. [20] established a hyperbolic panel springback compensation and correction algorithm by combining numerical simulation with experiment to improve the error in mold shape. The mold surface compensated by this method was established through interpolation, but the accuracy requirement could not be satisfied. Li Feifan et al. [21] interpolated the mold contour using a uniform B-spline curve to improve the fitting accuracy of the model to mold and determined the relationship between the changes in bending moment and curvature. However, this model does not consider the complex relationship among a large number of mutually coupling factors that influence bending.

In the aforementioned studies on bending accuracy improvement, the mold is enhanced mainly through simulation using the finite element software, but only a few studies on predicting the bending angle in actual production have been performed, and even fewer studies on the quantitative prediction model of bending angles have been investigated to solve the springback compensation problem rapidly and efficiently. This study establishes the prediction model of the bending angle using the grey prediction GM (1,1) model to compensate for these shortcomings due to its perfect predictability for grey systems and based on experimental site data; improves the background value of the original model through ellipse fitting to improve the prediction accuracy; and synthesizes the experimental data in modeling mode at the head and the tail, considering the actual situation of poor fit of the single prediction model at the latter stage to obtain the segment-based prediction models of the press amount of the upper mold and the bending angle and provide a theoretical basis for bending springback control.

The remainder of this study is organized as follows. Section 3 describes the process of grey prediction modeling and the improvement methods, presents a bending prediction model based on the experimental data, and verifies the prediction model. Section 4 verifies the bending prediction model through field experiment and ABAQUS simulation. Section 5 presents the summary and relevant conclusions.

3 Methodology

3.1 GM (1,1) modeling process

The grey prediction GM (1,1) model exhibits good predictability for grey systems with “limited samples and poor information.” Meanwhile, bending springback is influenced by many factors, in which the information is in a mess, that is, it has many uncertainties and exhibit an obvious grayscale, thereby satisfying the modeling requirement. The original known sequence is expressed by Formula (1):

$$X^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3)\cdots x^{(0)}(n)\right\} \tag{1}$$

where $x^{(0)}(1)$ is original data.

To improve the regularity of the original sequence, accumulation processing must be performed on the original data to obtain the accumulative sequence (Formula (2)):

$$X^{(1)}=\left\{\sum_{i=1}^{k}x^{0}(i)\right\}=\left\{x^{1}(1),x^{1}(2)\cdots x^{1}(n)\right\} \tag{2}$$

The GM (1,1) model is established according to Accumulative Sequence (2); and the whitening differential equation is shown in Formula (3) [22]:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{3}$$

where a is the development coefficient, and b is the grey action.

The grey differential equation that correspond to the whitening differential equation is shown in Formula (4):

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{4}$$

B and Y matrices are established to determine the values of a and b in the grey differential equation, respectively (Formula (5)):

$$B=\begin{bmatrix}-z^1(2) & 1\\ -z^1(3) & 1\\ \vdots & \vdots\\ -z^1(n) & 1\end{bmatrix} \qquad Y=\begin{bmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(n)\end{bmatrix} \tag{5}$$

in which the background value is shown in Formula (6):

$$z^{(1)}(k)=\frac{1}{2}\left[x^{(1)}(k)+x^{(1)}(k-1)\right] \tag{6}$$

In accordance with Formula (7), the values of a and b are estimated by using the least square method.

$$\hat{\Phi}=\begin{bmatrix}\hat{a}\\ \hat{b}\end{bmatrix}=\left[B^TB\right]^{-1}B^TY \tag{7}$$

From the initial conditions, $\hat{x}^{(1)}(1)=x^{(1)}(1)=x^{(0)}(1)$, the accumulative response sequence of the prediction model is obtained (Formula (8)).

$$\begin{aligned}\hat{x}^{(0)}(k+1)&=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)\\ &=(1-e^a)(x^{(0)}(1)-\frac{\hat{b}}{\hat{a}})e^{-ak}\end{aligned} \tag{8}$$

To restore the original positive sequence response model of bending, Formula (8) is substituted into Formula (9) to progressively decrease the accumulative response sequence of the prediction model to obtain the prediction model.

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=(1-e^a)(x^{(0)}(1)-\frac{\hat{b}}{\hat{a}})e^{-ak} \tag{9}$$

3.2 GM (1,1) modeling optimization

Given that the original sequence ($x^{(0)}(t)$) is non-negative and $x^{(1)}(t)$ exponentially increases, approaching the background value of the original classical model with formula (6) to $\int_{k-1}^{k}x^{(1)}(t)dt$ will inevitably produce an error, as shown by the shaded area in Fig. 1.

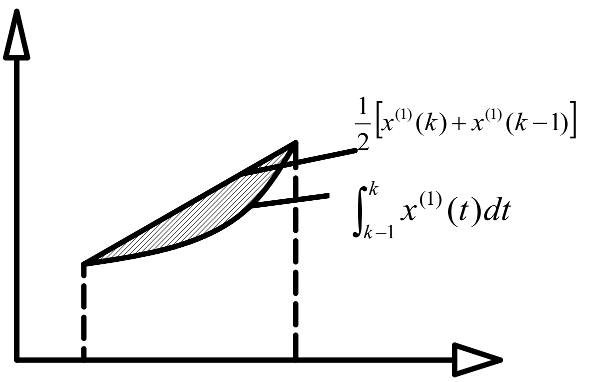


Fig. 1. Fitting error of the original background value

Now, the arc segment of $\int_{k-1}^{k}x^{(1)}(t)dt$ is fitted through an ellipse whose semi-major axis and semi-minor axis are $\left|x_k^{(1)}-x_{k-1}^{(1)}\right|$ and $k-(k-1)$,respectively (Fig. 2).

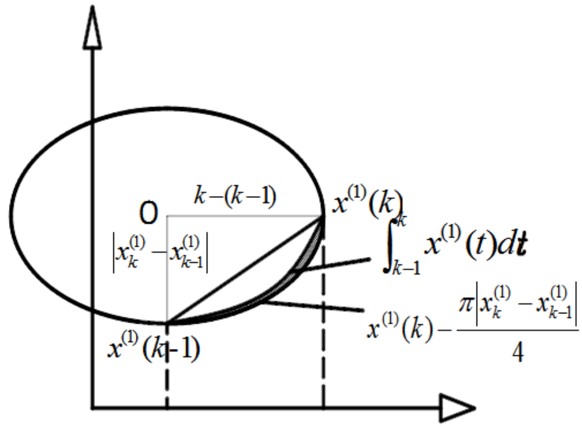


Fig. 2. Fitting of background error by ellipse

Figs. 1 and 2 indicate that the error in the improved background value decreases, and the improved background value is shown in Formula (10):

$$z^{(1)}(k)=\begin{cases}x^{(1)}(k)-\dfrac{\pi\left|x_k^{(1)}-x_{k-1}^{(1)}\right|}{4} & (x^{(1)}(k)\text{ is concave increase index})\\ x^{(1)}(k\text{-}1)+\dfrac{\pi\left|x_k^{(1)}-x_{k-1}^{(1)}\right|}{4} & (x^{(1)}(k)\text{ is convex increase index})\end{cases} \tag{10}$$

GM (1,1) modeling calculation is performed by substituting original Formula (6) into Formula (10) to remarkably improve the degree of fitting of the original background value and reduce the intermediate prediction error of the prediction model.

3.3 Data acquisition

A Dyna-Press12/8 air bending machine is used in the experiment. A V-shaped opening is adopted as the opening of the lower mold with a width of $V=20\,mm$ and an angle of $\alpha = 78^{\circ}$, and the fillet of the lower mold is $r = 0.8\,mm$. Q235 steel, with $40mm \times 20mm \times 1.5mm$ dimensions, is adopted as the bending sheet metal part. The V-shaped air bending machine model for the acquisition of experimental data is shown in Fig. 3.

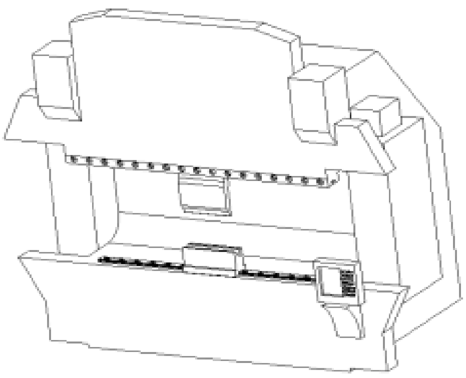


Fig. 3. Model of the V-shaped air bending machine

The descent velocity of the upper mold of the bending machine is designated and set at benchmark 0 when the upper mold touches the sheet metal part. When the upper mold descends to $1mm$, bending unloading is performed, and the bending angle of the sheet metal part is measured and recorded in Table 1. Then, the sheet metal part is replaced with the same bending sheet metal part, unloading is performed after the upper mold descends to $2mm$, and the bending angle is measured and recorded in Table 1. The press amount of the bending upper mold is increased by $1mm$ each time. The experiment cycle is repeated until the bending angle is near 78°.

3.4 GM (1,1) bending modeling

According to the bending experimental data shown in Table 1 and based on the improved GM (1,1) modeling process in Section 3.2, a prediction model is established with the bending press amount as the independent variable and the bending angle as the predicted value. First, the experimental data in Table 1 in Section 3.3 are preprocessed. Given that the press amount of the upper mold is small at the beginning of bending and the elastic deformation is large, which result in significant springback, the first end bending data are not of research significance. In this paper, the original sequence is constructed from the bending angle formed when the press amount of the upper mold is 3 mm (Formula (11)):

$$X^{(0)} = \{158, 135.6, 118.7, 103.6, 90.8, 83.7, 79.5, 78.2\} \tag{11}$$

To reduce the redundancy of calculation, the first five terms are substituted into Formula (1) to obtain the positive original sequence of the bending prediction model (Formula (12)):

$$X_1^{(0)} = \{158, 135.6, 118.7, 103.6, 90.8\} \tag{12}$$

Table 1. Bending experimental data

Upper die pressing (mm)	1	2	3	4	5	6	7	8	9	10
Bending angle (°)	176.8	165.2	158.0	135.6	118.7	103.6	90.8	83.7	79.5	78.2

GM (1,1) modeling with the improved background value is performed for Formula (12), that is, Formula (6) is substituted into Formula (10) to obtain the bending prediction model of positive sequence (Formula (13)):

$$\begin{aligned} \hat{x}_0^{(0)}(k+1) &= \hat{x}_0^{(1)}(k+1) - \hat{x}_0^{(1)}(k) \\ &= -1081.623(1 - e^{0.1390986})e^{-0.1390986\,(k-3)} \end{aligned} \tag{13}$$

The degree of fitting of the positive sequence prediction model in Formula (13) to Formula (11) of the original data is shown in Fig. 4.

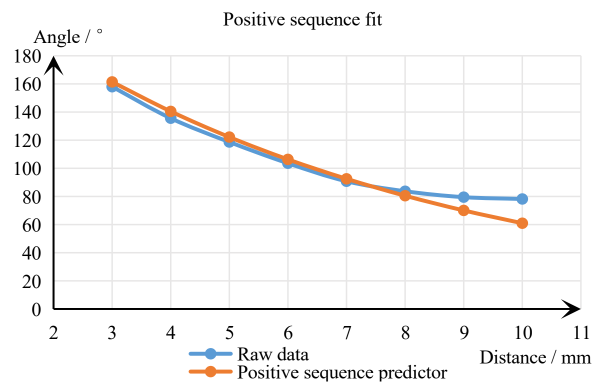


Fig. 4. Degree of fitting of positive prediction model to the actual value

Fig. 4 shows that the positive sequence grey prediction model of bending deviates from the original data after the press amount of the upper mold reaches $7mm$, and although the improved background value enhances the intermediate degree of fitting of the GM (1,1) model, the maximum error in the long-term prediction of the model cannot be completely eliminated. Thus, the springback angle cannot reach the required control accuracy. To avoid the large error that exists in the prediction model, this study establishes a reverse sequence prediction model for the experimental data in Formula (11), and the original data of the reverse sequence is shown in Formula (14):

$$X_1^{(0)} = \{78.2, 79.5, 83.7, 90.8, 103.6\} \tag{14}$$

Similarly, the improved GM (1,1) model is used to establish the inverse sequence prediction model for Formula (14) (Formula (15)):

$$\begin{aligned} \hat{x}_1^{(0)}(k+1) &= \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k+1) \\ &= 952.14(1 - e^{-0.079196})e^{0.079196k} \end{aligned} \tag{15}$$

Formula (15) is a reverse sequence bending prediction model, which should be changed into the positive sequence prediction model, to obtain the prediction model of the press amount of the bending upper mold and bending angle, as processed in Formula (16):

$$\hat{x}_2^{(0)}(k+1) = 952.14(1-e^{-0.079196})e^{0.079196\ (10\text{-}k)} \tag{16}$$

The degree of fitting between the reverse sequence prediction model (16) and the original sequence (11) is shown in Fig. 5.

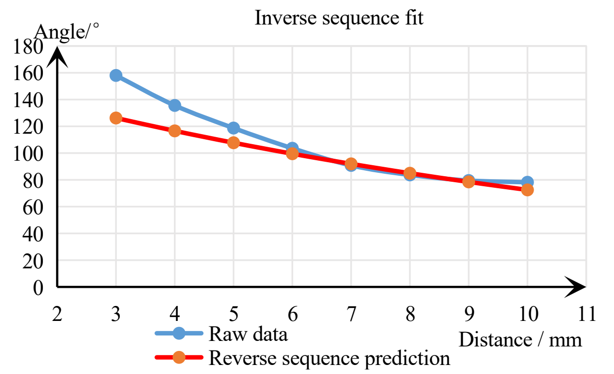


Fig. 5. Degree of fitting between the reverse sequence prediction model and the actual value

Fig. 5 indicates that the reverse sequence prediction model deviates from the original data before the press amount of the upper mold reaches $7mm$. To improve the accuracy of the bending prediction model, the positive sequence prediction model (13) and the reverse sequence model (16) are integrated to obtain the segmented function of the bending prediction model (Formula (17)). The knee point is press value 7, at which the positive sequence error is greater than the reverse sequence error.

$$\hat{x}^{(0)} = \begin{cases} -1081.623(1-e^{0.1390986})e^{-0.1390986(k-3)} \\ \qquad\qquad\qquad (3<k\le 7) \\ 952.14(1-e^{-0.079196})e^{0.079196(10-k)} \\ \qquad\qquad\qquad (7<k<10) \end{cases} \tag{17}$$

where $\hat{x}^{(0)}$ is the prediction bending angle (°), and k is the press amount of the upper mold (mm).

The model in Formula (17) satisfactorily avoids the large error in the long-term prediction of the original GM (1,1), and only the highly fitting segment between the GM (1,1) model and the original data is selected, thereby greatly increasing the degree of fitting of the bending prediction model to the original data (Fig. 6). This prediction model converts time variable k in the traditional grey prediction model into the bending press amount, thereby enabling the continuity of the value of the bending press amount of the air bending grey prediction model.

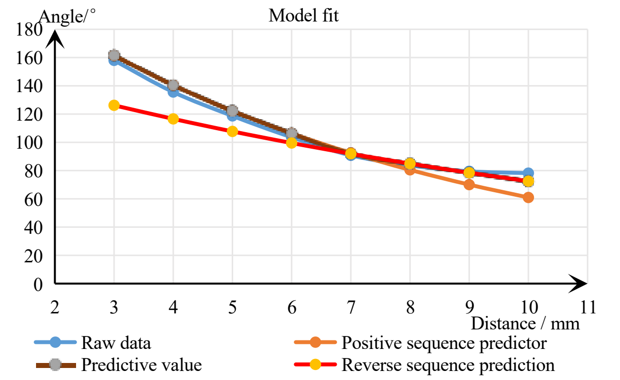


Fig. 6. Degree of fitting between the reverse sequence prediction model and the actual value

3.5 Inspection of relative error

To determine whether the relative error of the air bending prediction model conforms to the requirements or not, the predicted values obtained in Formula (17) are compared with the original data in Formula (11) point-by-point to calculate the residual and relative errors.

The residual sequence is calculated in Formula (18).

$$E = [e(1), e(2)\cdots e(n)] = X^{(0)} - \hat{X}^{(0)} \tag{18}$$

where $e(i) = x^{(0)}(i) - \hat{x}^{(0)}(i)$.

Then, relative error is obtained using Formula (19).

$$\varepsilon(i) = \left|\frac{e(i)}{x^{(0)}(i)}\right| \times 100\% \tag{19}$$

The residual and relative errors of the prediction model are shown in Table 2.

Table 2. Predictive model residual and relative error table

Pressing amount (mm)	Actual value (°)	Predictive value (°)	Residual E	Relative error ε(%)
3	158	161.4186391	−3.41863914	2.163695658
4	135.6	140.4571715	−4.857171526	3.581984901
5	118.7	122.2177138	−3.517713755	2.96353307
6	103.6	106.3467916	−2.746791645	2.651343287
7	90.8	91.93979092	−1.139790918	1.255276341
8	83.7	84.9393877	−1.239387701	1.480749942
9	79.5	78.47200337	1.027996626	1.293077517
10	78.2	72.49705325	5.702946746	7.292770775

The average relative error of the model is obtained using Formula (20):

$$\bar{\varepsilon} = \frac{1}{n}\sum_{i=1}^{n}|\varepsilon(i)| = 2.8353\% \tag{20}$$

The accuracy of the entire prediction model is shown in Formula (21):

$$\mathrm{P} = (1-\bar{\varepsilon}) \times 100\% = 97.1647\% \tag{21}$$

When $P > 90\%$, the prediction accuracy of the model is high. Therefore, the accuracy of the prediction model complies with the requirements.

3.6 Inspection of correlative degree

To compare the grey prediction model of air bending and the actual data curves better, the correlative degree is adopted for inspection, and the larger the correlative degree is, the better the degree of fitting of the prediction model to the actual curve is. Formula (22) is used to calculate the correlation coefficients between the predicted values of the model and the actual values.

$$\xi_k = \frac{\min\left|x^0(k) - \hat{x}^0(k)\right| + 0.5\max_{1\le k\le n}\left|x^0(k) - \hat{x}^0(k)\right|}{\left|x^0(k) - \hat{x}^0(k)\right| + 0.5\max_{1\le k\le n}\left|x^0(k) - \hat{x}^0(k)\right|} \tag{22}$$

The correlation coefficients of all points in the grey prediction model are calculated in order and obtained by Formula (23).

$$\xi = \begin{bmatrix} 0.843647737, 0.678114365, 0.741561603, 0.778322151, \\ 1, 0.956023474, 0.992347108, 0.44808408 \end{bmatrix} \tag{23}$$

Formula (23) is substituted into Formula (24) to calculate the grey correlative degree of the air bending prediction model.

$$\xi = \frac{1}{n}\sum_{k=1}^{n}\xi_k = 0.804762565 \tag{24}$$

The grey correlative degree of the entire model is more than the generally required grey correlative degree of 0.6. Therefore, the entire model fits the actual model well.

4 Result Analysis and Discussion

To verify the reliability of the prediction model of the air bending press amount and the bending angle established through the grey prediction GM (1,1) model, the model is verified by field test and ABAQUS simulation. When the bending angle is 90°, the value of the press amount of the bending upper mold is determined as $7.27mm$ according to the established prediction model (Formula (17)).

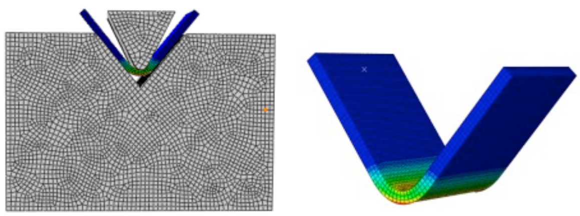
In the field experiment, a Dyna-press12/8 air bending machine is adopted for verification, and the sheet metal part is made of the same raw material as the original Q235. As the press amount of the upper mold of the bending machine for experiment is only accurate up to $0.1mm$, the upper mold of the bending machine is pressed down to $7.3mm$ for verification in this field experiment. After the press amount of the upper mold of the bending machine is preset to $7.3mm$, an angle measuring instrument is used, and the experiment field and formation of the sheet metal part are shown in Fig. 7.

Upon measurement using the angle measuring instrument, when the press amount of the upper mold is $7.3mm$, the bending angel of the sheet metal part is 89.4°, and the calculated error with the prediction model (Formula (17)) is 0.7%.

The simulation verification is performed in ABAQUS. First, the bending model is established in ABAQUS because the deformation of the upper and lower bending molds is negligible in the bending process. Thus, the upper and lower molds during modeling are designed as rigid bodies for simplicity, and the bending sheet metal part is defined as the deformed body of Q235. Unloading is performed after the press amount of displacement of the upper mold is preset to $7.27mm$. The process of ABAQUS bending simulation and the results are shown in Fig. 8.

a b

Fig. 7. (a) Field experiment and (b) formed sheet metal part



a b

Fig. 8. (a) ABAQUS simulation process and (b) forming angle

When the press amount of the sliding block of the upper mold is $7.27mm$, the forming angle of the ABAQUS simulated bending part is 89.52°, and the calculated error with the prediction model is 0.53%.

The field experiment shows a relatively larger error than the simulation because of the insufficient accuracy of the bending machine and the measuring instrument and the uneven sheet metal. The simulation error is produced by the existence of errors in the model itself and in data acquisition during the establishment of the model. However, all errors of the bending prediction model are within the required range. The model verification proves the feasibility of applying the grey prediction model in air bending.

5. Conclusions

To rapidly and accurately obtain the springback prediction model of bending angle, the relationship between the press amount of the bending upper mold and the bending angle was determined to obtain the expected bending angle by controlling the press amount of the upper mold. This study, obtained the segment-based model of the press amount of the upper mold and the bending forming angle of the air bending model and verified the feasibility of the model through experiment and ABAQUS simulation by introducing the grey prediction GM (1,1) model, improving the background value of the original model through ellipse fitting, and fitting the experimental data of air bending by modeling at the head and the tail. The following conclusions could be drawn on the basis of the aforementioned discussion:

(1) The improvement of the background value of the original GM (1,1) prediction model through ellipse fitting reduces the intermediate fitting error of the original model.

(2) The bending forming angle can be combined with the characteristics of grey prediction, and the established grey prediction bending model exhibits a high degree of fitting with the reality.

(3) The bending prediction model established on the basis of grey theory can reflect the relationship between the press amount of the bending upper mold and the bending angle, such that the ideal bending angle can be achieved by controlling the press amount of the upper mold.

This study established the bending angle prediction model by combining experiment and theory. The model can achieve the expected bending angle with high accuracy by controlling the press amount of the bending upper mold, thereby exhibiting the significance of improving the accuracy of bending parts. However, during the actual production, the prediction models must be established individually for different bending parts and machines. Therefore, in future research, a prediction model database should be built for different production conditions and situations for a more convenient and faster access of bending prediction models.

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