Int J Interact Des Manuf (2009) 3:25–33
DOI 10.1007/s12008-009-0059-7

ORIGINAL PAPER

Modeling of springback on air bending process of interstitial free steel sheet using multiple regression analysis

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Received: 20 October 2008 / Accepted: 12 January 2009 / Published online: 11 February 2009

Abstract This paper describes the development of regression based mathematical models for the prediction of springback in air bending process of interstitial free (IF) steel sheet. Punch travel (d), strain hardening exponent (n), punch radius (r_p), punch velocity (v_p) and width of the sheet (w) have been considered as input parameters and springback as output parameter to develop the model. Based on experimental results, various regression models namely, linear, linear-square, linear-interaction and quadratic terms for the springback prediction were developed for IF steel sheets. It is found that, the results obtained from the quadratic model are accurate in prediction of springback than others.

Keywords Process modeling · IF steel · Air bending · Springback

List of symbols

Y_{Dry}	Springback for dry conditions in degrees
r_p	Punch radius in mm
d	Punch travel in mm
n	Strain hardening exponent
v_p	Punch velocity in mm/s
w	Width of the sheet in mm
θ_s	Springback angle ($\theta_1 - \theta_2$) in degrees
θ_1	Bending angle before springback in degrees
θ_2	Desired bending angle after springback in degrees
$\hat{Y}$	Estimated value
β_i	Regression coefficient of ith independent variable
β_{ij}	Regression coefficient of interaction of ith independent variable
x_i	ith independent variable
ε	An error component

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1 Introduction

Automobile industries depend largely on sheet metal forming processes for manufacturing components. The popularity of sheet metal products is attributable to their lightweight, great interchangeability, good surface finish and low cost. Numerous fundamental studies have been conducted over the years in an attempt to obtain a basic understanding of sheet metal bending. Sheet-metal forming processes, including bending, stretching and drawing are extensively applied in industry. Sheet metal bending is an important process in sheet metal forming process and manufacture. Springback prediction is a major issue for the sheet metal manufacture to evaluate the desired shape of a product. Springback refers to the shape discrepancy between the fully loaded and unloaded configurations.

The process chosen for analysis is air bending because of its excellent flexibility and reduction in bend force. In air bending, the required angle is produced on the workpiece by adjusting the depth of the punch entering the die opening. Changing the size of the die opening also changes the amount of force needed to bend. As the die opening increases, the force required for bending decreases and vice versa. The sheet material used in this investigation is interstitial free (IF) steel owing excellent formability.

Regression analysis is used to investigate and model the relationship between a response variable and predictors. It is a common tool for experimental analysis of data, when the response variable is continuous. Multiple linear regression analysis (MRA) is widely used for various types of statistical analysis. It is also very helpful to present the results of many experiments in terms of an empirical model, that is, an equation derived from the data that expresses the relationship between the response and important design factors [1]. Stepwise regression removes and adds variables to the regression model for the purpose of identifying a useful subset of the predictors. Best subsets regression identifies the best fitting regression models that can be constructed with the predictor variables. For modeling, MRA is simple, economical and relatively easy for use. The other competing modeling approaches are response surface methodology (RSM) and artificial neural network (ANN). For prediction, the response surface methodology requires slightly more number of experimentations. In the case of ANN prediction, it requires larger number of training patterns for achieving better results [2].

Modeling of the springback for quality product and selection of appropriate bending angle is an important issue in sheet bending technology. Reviewing the literature, it is found that researchers have been studying the phenomenon of bending for nearly four decades. Wang et al. [3] described a mathematical model for plane strain sheet bending to predict springback and the maximum bending force on the punch and the die. Hang et al. [4] conducted an experimental study for steel sheets and described effects of process variables like punch radius, die radius, punch speed, friction coefficient, strain hardening exponent, normal anisotropy and etc., on V-die bending process. Gary [5] described statistical variability in material properties on springback. An analytical model was proposed by Kim et al. [6] to predict springback and bend allowance simultaneously in air bending process. Song et al. [7] discussed springback prediction approaches such as analytical model, numerical simulation using finite element methods and the mesh free method. Garcia Romeu et al. [8] presented new springback graphics for air vee bent sheet metal parts based on an experimental work. Ihab Ragai et al. [9] discussed the effect of sheet anisotropy on the springback of stainless steel 410 draw bend specimens through experimentally and finite element analysis. Bruni et al. [10] investigated the effect of process parameters namely temperature, punch speed and punch radius on springback of AZ31 magnesium alloy. Dongye Fei et al. [11] investigated the springback behaviour of cold rolled transformation induced plasticity (TRIP) steels in air v-bending process. Peng Chen et al. [12] analyzed the springback for advanced high strength steel (AHSS) by finite element approach. Strano et al. [13] proposed the logistic regression for the empirical determination of forming limit diagram. Tiernan et al. [14] described the application of the surface response method to model the extrusion force. Senthilvelan et al. [15] developed mathematical models for P/M working process using regression analysis and the models could be used to predict the strength coefficient and strain hardening exponent of P/M copper performs. Qamar et al. [16] proposed linear and quadratic models for determination of fracture toughness. Cheng et al. [17] used neural networks and regression models to predict bending angle of sheet metal formed by laser. Paulo Daviam et al. [18] presented a study to evaluate the effect of the processing parameters under the geometric form of clad in laser cladding by powder using multiple regression analysis. Naceur et al. [19] focused on a response surface method for optimization problems in sheet metal forming.

Due to the complexity of sheet bending processes, the development of theoretical models for these processes is difficult and cumbersome. Consequently, empirical models attained by means of experimental research are used to replace the theoretical models. Furthermore, conventional prediction of springback is by trial and error method and it is expensive and laborious. These are the motivations to develop a mathematical model using multiple regression analysis for the prediction of springback in IF steel sheet air bending process from the experimental data. For this analysis, four structures of regression models are considered namely, linear, linear-square, linear-interaction and quadratic models. Analysis of variance (ANOVA) was performed to check the validity of the proposed model. The paper is organized as follows, an identification of parameters is presented for conducting the experiments, which is then followed by an outline of regression models. The best sub set, proposed models, ANOVA, correlation, comparison, error analysis regression statistics for springback are presented. The paper concludes with a discussion on current modeling capabilities and limitations.

2 Mathematical modeling using multiple regression analysis

A variety of mathematical models may be used to analyze springback in the bending process. One of these methods is multiple regression analysis and the formulation is simple. Process model relates the input variables to the response variable of the process and thereby it is possible to predict the overall response of the process. The relationship between input and response variables could be found out by developing a regression based mathematical model using statistical techniques. Once the model is formed, the values of the actual process variable are substituted in the equation to predict the response of the process.

2.1 Regression design and procedure

Various models were compared to find the best fit and an appropriate model was chosen since it has higher adjusted R^2. The individual mathematical models were also tested for their accuracy with F test and R^2 values. The higher F value and adjusted R^2 squared value suggest that the mathematical models developed are accurate and have satisfactory goodness of fit.

Assumptions

- The errors are normally distributed
- The mean of the errors is zero
- Errors have constant variance
- The model errors are independent

2.2 Design structures

With multiple linear regression analysis [1], the basic relationship is written as

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{1}$$

where

Y is the dependent variable (predicted springback)
β_0 is the estimator of intercept,
$\beta_1, \beta_2, \ldots, \beta_k$ are linear terms,
k is the number of factors
x_i is the ith independent Variable
ε is the random error

The various linear models of Eq. 1 in terms of the estimated response can be written as:

$$\hat{Y} = (Y - \varepsilon). \tag{2}$$

Linear terms can be expressed as

$$\hat{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i. \tag{3}$$

Linear-square terms is presented as

$$\hat{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2. \tag{4}$$

Linear-interaction terms is represented as

$$\hat{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i,j}^{k} \beta_{ij} x_i x_j. \tag{5}$$

Quadratic terms have the form

$$\hat{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i,j}^{k} \beta_{ij} x_i x_j \tag{6}$$

where $\beta_{11}, \beta_{22} \ldots \beta_{kk}$ are the square terms, and $\beta_{12}, \beta_{13} \ldots \beta_{k-1,k}$ are the second order interaction terms.

3 Scheme of investigation

The experimental investigations were planned in the following sequence:

- Choosing the parameters and their levels
- Design and conducting experiments
- Best subset regression analysis
- Multiple regression models
- Testing the model adequacy
- Comparison of measured and predicted response values
- Regression statistics

3.1 Choosing of parameters and their levels

Based on the literature and the previous work done on this field by authors [3,4,11], five independent controllable predominant bending parameters that are having greater influences on the springback is chosen. They are punch travel, strain hardening exponent, punch radius, punch velocity and width of the sheet. In the air bending process, the bend angle is determined by the punch travel. Strain hardening exponent has not yet been addressed much in bending analysis. But the strain hardening exponent effects the springback. The punch radius also influenced the springback significantly in the bending process. During the bending process, while one side of the sheet metal is subjected to intensive forcing of compressive stress on one surface, the other surface is subjected to tensile stress. The stress value depends on the bend region; thereby, the width of the sheet affects the springback. Furthermore, the plain strain relative to the sectional end portions. Table 1 shows values of independent parameters and symbols used in the experiments with five levels for each. The key factor in developing a mathematical model is to obtain sufficient experimental data simulating the working environment in the laboratory.

3.2 Developing and conducting experiments

In this work, the regression analysis is designed to formulate the process models to predict the springback, so that the springback compensation can be calculated. In order to find out the determinant of response variables, the five input variables are regressed. Classical experimentation using

Table 1 Levels and values of parameters

Si no	Parameter/notations/units	Parameter levels				
		1	2	3	4	5
1	Punch travel (d) in mm	5	10	15	20	25
2	Strain hardening exponent (n)	0.307	0.310	0.311	0.317	0.325
3	Punch radius (r_p) in mm	6	8	10	12	14
4	Punch velocity (v_p) in mm/s	0.3577	0.5	0.606	0.67	0.802
5	Width of the sheet (w) in mm	30	40	50	60	70

one-factor-at-a-time strategy is too complex and is not easy to use. A large number of experiments to be carried out when the number of process parameters increases. In the case of factorial design for five levels five parameters implicate large number of tests. To solve this problem, the Taguchi technique uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments. Taguchi approach is commonly employed for optimizing the parameter levels. In this work, the Taguchi orthogonal array coupled with regression analysis is adapted for predicting the response within the range of experimentation. Furthermore, the equation constructed from MRA gives more precise estimate and is fairly simple to handle computationally. As the regression analysis technique uses the experimental data based on the orthogonal arrays, 25 experiments were carried out for IF steel material with five input variables. Five factors five level design of experiment matrix is employed to carryout the experimental investigation and is presented in Table 2. The design is balanced so that the factor levels are weighed equally and to analysis many factors with a few runs. Statistical analysis is used to study the effects of bending parameters on springback. In order to verify the feasibility of the proposed models, validation experiments were conducted. MINITAB Statistical Software (Version13) was employed for multiple regression analysis.

Conducting experiments

The IF steel sheets used for the bending were cut into (120×1.2) dimensions with a width of 30, 40, 50, 60 and 70 mm. All samples were cut from rolled steel sheet and used in the as-received condition. Five types of sample orientations were prepared from the rolled sheet. The orientation properties are measured in terms of strain hardening exponent values in five directions, namely, 0°, 22.5°, 45°, 67.5° and 90° to the rolling direction of the sheet, thereby incorporate different strain hardening exponent, that are obtained through the tensile test. The stock from which blanks were cut must be flat enough for the blanks to be properly inserted into tooling and to remain in position during forming. The samples were cleaned thoroughly to remove the dust and rust by wiping. The chemical composition of the IF steel sheet used in the present investigation are given in the Table 3.This steel consists of low amount of carbon and nitrogen. They have excellent workability and mechanical properties due to the presence of alloying elements such as Mn and Si.

The experiments were performed in a Universal Testing Machine (UTM). The die and punch were made of hardened steel. The die was mounted on the fixed platform provided on the UTM. The punch was mounted above the die in the movable head of the UTM. The center axis of the punch coincides with die. The sample was located in proper position over the die with extreme care. The width of the punch is 90 mm. The experiments were conducted under dry conditions. The load was applied gradually and proper depth was given to deform the sheet. Figure 1 shows schematic diagram of the experimental setup with sheet.

The punch displacement was recorded from digital meter of UTM respectively. The difference between bend angles $(\theta_1 - \theta_2)$, when the sample was subjected to load (θ_1) and after removal of load (θ_2) gives the springback angle (θ_s). The above steps were repeated with different levels. There are two sets of experiments, one for fitting (Table 2) and other (Table 7) for validation to verify the effectiveness of the models. In order to formulate regression models for the prediction of springback, five process variables, namely, punch travel, strain hardening exponent, punch radius, punch velocity and width of the sheet are considered and to verify the developed model, several experiments were conducted.

4 Statistical analysis

The first set of experimental values is used for building the model. On the basis of mathematical model and statistical analysis, the following discussions were performed.

4.1 Best subsets regression analysis

Best subsets regression analysis is carried out for finding the significance of the five control parameters. All possible subsets of the parameters are evaluated with one parameter, two parameters and so on.

Table 2 Design matrix of independent parameters

Test number	Values of parameters					Measured springback (degrees)
	d	n	r_p	v_p	w	
1	5	0.307	6	0.3577	30	6.01
2	5	0.311	8	0.5	40	5.23
3	5	0.325	10	0.606	50	4.41
4	5	0.317	12	0.67	60	3.52
5	5	0.310	14	0.802	70	1.72
6	10	0.307	8	0.606	60	4.32
7	10	0.311	10	0.67	70	3.65
8	10	0.325	12	0.802	30	5.31
9	10	0.317	14	0.3577	40	3.10
10	10	0.310	6	0.5	50	5.48
11	15	0.307	10	0.802	40	5.11
12	15	0.311	12	0.3577	50	2.89
13	15	0.325	14	0.5	60	2.10
14	15	0.317	6	0.606	70	4.55
15	15	0.310	8	0.67	30	6.41
16	20	0.307	12	0.5	70	2.41
17	20	0.311	14	0.606	30	3.57
18	20	0.325	6	0.67	40	7.30
19	20	0.317	8	0.802	50	5.41
20	20	0.310	10	0.3577	60	3.29
21	25	0.307	14	0.67	50	2.92
22	25	0.311	6	0.802	60	6.21
23	25	0.325	8	0.3577	70	3.58
24	25	0.317	10	0.5	30	5.26
25	25	0.310	12	0.606	40	4.19

All the response values appear as average of three measurements

Table 3 Chemical composition of IF steel (in wt%)

C	0.0035
Mn	0.4
Si	0.008
S	0.007
P	0.044
Al	0.045
N (ppm)	35
Ti	0.04
B	0.0008
Nb	0.001
Fe	Rest

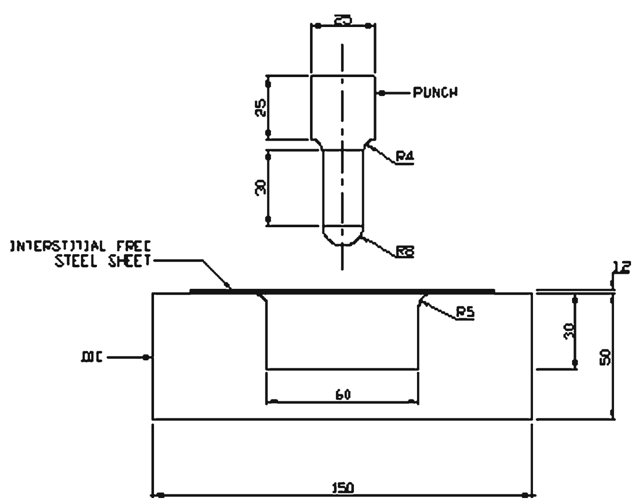

Fig. 1 Schematic diagram of the experimental set up

Table 4 reports the two best models that are constructed from each sub set. The values of R^2 and R^2 (adj) represent the regression confidence and the adjusted regression confidence respectively. They should be at least 60% and the two values should not differ much [20]. In the case of springback, for five variable subset the R^2 value of the model is as high as 97.5% and the difference between the R^2 and R^2 (adj) is 0.6%, and hence all five parameters have been selected. In the same way, for the springback five variable subset shows the highest R^2 and R^2(adj) values and the least difference. Hence all five parameters have been selected for MRA.

Table 4 Best subsets regression results for springback

Responses	Variables	R^2	R^2(adj)	C-p	**S**	d	n	r_p	v_p	w
Springback	1	60.9	59.2	276.8	0.91874			√		
	1	28.9	25.8	521.0	1.23960					√
	2	89.8	88.9	58.6	0.47958			√		√
	2	67.5	64.5	228.9	0.85704			√	√	
	3	96.4	95.8	10.7	0.29320			√	√	√
	3	90.7	89.3	54.1	0.46980		√	√		√
	4	97.2	96.7	6.2	0.26270		√	√	√	√
	4	96.7	96.0	10.5	0.28842	√		√	√	√
	5	97.5	96.9	6.0	0.25534	√	√	√	√	√

√, possible subset of the parameters

Table 5 Multi-regression models for springback

Terms/notations/units	Regression models	R^2 (%)	R^2(adj) (%)	Equation number
Linear (Y_{Dry}) (degrees)	$2.91 + 0.0106d + 20.4n - 0.389r_p + 2.39v_p - 0.0536w$	97.5	96.9	7
Linear-square (Y_{Dry}) (degrees)	$-23.49 + 0.00824d + 180.916n - 0.3327r_p + 3.3234v_p - 0.03w + 0.00008d^2 - 253.749n^2 - 0.002821r_p^2 - 0.8054v_p^2 - 0.0002357w^2$	97.6	95.9	8
Linear-interaction (Y_{Dry}) (degrees)	$-42.8925 + 0.521658d + 167.145n - 0.017696r_p + 23.0415v_p + 0.438012w - 1.64475dn - 0.0092645dr_p1 - 0.25534d\ \ v_p - 0.00114240dw - 1.42426nr_p - 73.9706nv_p - 1.40081nw + 0.200319r_pv_p + 0.00179915r_pw - 0.088321v_pw$	98.8	96.8	9
Quadratic model (Y_{Dry}) (degrees)	$134.868 - 1.76939d - 902.346n - 3.56834r_p + 40.5456v_p + 0.988406w + 0.0630572d^2 + 1691.7n^2 + 0.205291r_p^2 + 113.487v_p^2 + 0.0106328w^2 - 1.771690dn + 0.125020dr_p + 1.14855d\ \ v_p - 0.0360303dw + 0.155119nr_p - 79.3695nv_p - 1.62916nw - 6.89611r_pv_p + 0.0165057r_pw + 1.92601v_pw$	99.9	99.5	10

d punch travel in mm, n strain hardening exponent, r_p punch radius in mm, v_p punch velocity in mm/s, w width of the sheet in mm

4.2 Selection of multi-regression model

In order to choose a proper regression model, the higher value of R^2 have to be selected, by trying different models and choosing one that produces the best predictive ability. The obtained multiple linear regression equation for validation is shown in Table 5. The MRA between the parameters and response (springback) was done with a sample size of 25. Although the geometry and the material properties of the tools and sheet blanks are in the model, the variation in the method of regression modeling by user may result in a significant influence on springback simulation results.

The model development is done to move rapidly and efficiently along the path of improvement toward the vicinity of the response. This is evaluated by the R^2 value. More the R^2 value, the model is closer to the response and more accurate. When comparing the developed models, the linear model and linear-square model have exhibited lack of fit as they are not considering the interactions. Comparison between linear interaction and quadratic models show that quadratic model is relatively closer to the response as the R^2 value is higher. A Quadratic model regression model (i.e. Eq. 10 in Table 5) was selected as the only model ensuring a sufficient fit ($R^2 = 99.9\%$). It is evident

Table 6 Analysis of variance (ANOVA) results for springback

Source of variation	DF	Seq SS	Adj SS	Adj MS	F value	Probability (α)	$F_{(0.05,5,24)}$
Regression	20	49.6563	49.6563	2.48282	264.85	0.000	4.53
Linear	5	48.455	8.54455	1.70891	182.3	0.000	
Square	5	0.0574	0.55446	0.11089	11.83	0.016	
Interaction	10	1.1438	1.14385	0.11438	12.20	0.014	
Residual error	4	0.0375	0.03750	0.00937			
Total	24	49.6938					

Table 7 Comparison of measured and predicted springback values based on proposed model

Test number	Values of parameters					Springback (degrees)		Error (%)
	d	n	r_p	v_p	w	Measured values	Predicted values	
1	5	0.325	14	0.802	70	1.60	1.55	−3.42
2	10	0.307	12	0.802	30	4.5	4.60	2.26
3	15	0.325	10	0.5	70	3.9	3.82	−1.99
4	20	0.317	8	0.802	50	5.45	5.44	−0.12
5	20	0.31	6	0.606	30	8.41	8.43	0.20
6	25	0.311	6	0.802	70	1.45	1.42	−1.96

that the quadratic model has better prediction than the others.

4.3 Analysis of variance (ANOVA) of Quadratic model

The calculated total sum of squares value is used to measure the relative influence (% contribution) of the factors. The larger the value of the sum of squares, the more influential is the factor for controlling the response. The results of ANOVA for significance of regression in multiple regressions for springback are shown in Table 6.The adequacy of the model was tested using the ANOVA technique. As calculated F is greater than the critical F, the null hypothesis is rejected and concluded that there is significant difference between regressions (parameters). As per this technique, the calculated value of the F ratio of the model developed does not exceed the standard tabulated value of F Ratio for a desired level of confidence say 95 %. The springback has been mainly influenced by first order terms followed by interaction terms.

4.4 Comparison

The comparison made between another set of values obtained by experimental measurements and MRA model. The error was obtained by the following equation.

$$\text{Error (\%)} = \frac{(V_m - V_{\exp})}{V_{\exp}} \times 100 \tag{11}$$

where V_m is the value of the model and $V_{\exp}$ the experimental value measured.

A comparison of measured and predicted springback value using the prediction technique (Regression model) are presented in the Table 7. From the Fig. 2, it is clear that the quadratic model has better predictions, which are expected due to the presence of square and interaction terms (non-linear) in the analysis.

4.5 Regression statistics

The influences of process parameters on springback have been analyzed based on the proposed model. The regression statistics for springback is listed in Table 8. From statistic t test value of springback, it is known that the effects of punch radius and punch travel are more pronounced compared to the other factors. The width of the sheet, punch velocity and strain hardening exponent were other significant factors. As the t test probability values of the following parameters for springback; punch radius, punch travel, strain hardening exponent and width of the sheet were significant.

5 Conclusions

Mathematical model for springback has been developed to correlate the aforesaid process parameters in air bending of IF steel sheets. Based on the experiments, a regression study was conducted and the following conclusions were drawn.

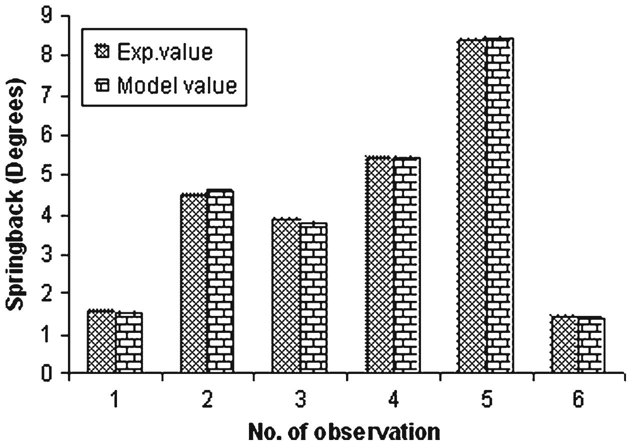

Fig. 2 Comparison of experimental and model springback values

- The mathematical models developed using regression methods has been analyzed and the most significant process parameters and their effects have been studied. This work considered five process parameters for springback such as punch travel, strain hardening exponent, punch radius, punch velocity and width of the sheet. In general, it can be considered that the MRA model correlates springback with the aforesaid parameters with a good degree of approximation. There is a capability of the model to determine the influence of parameter interactions in the process. The proposed approach would have been an excellent demonstrator of the potential of multi regression analysis.
- From the regression statistics, it is concluded that the punch radius, punch travel and width of the sheet are the most influencing factors in controlling springback, whereas width of the sheet and punch velocity have least effect on springback. The strain hardening exponent has moderate effect on springback. The interaction terms punch travel and punch velocity, punch velocity and width of the sheet are also effect springback in significant manner.
- The models could be easily implemented in the real production environment to resolve the uncertainty of springback due to variation in process parameters, thereby large volume of experimentation is reduced. This reduces the design cost of tooling. The prediction methods require short computation time and are useful to simulate the process. MRA approach is an efficient way of predicting springback and can be followed during the industrial metal working process with the same tooling and setup.
- The limitation of this model is that it is valid only within the specified range of the process parameters. Any extrapolation must be confirmed by further experiments.

Table 8 Regression statistics for springback

Factor designation	Coefficient	Sequential sum of seq	T ratio	Probability (α)
a	−5.23	2.69733	−1.939	0.125
d	−3.229	0.84795	−3.808	0.019
n	0.129	0.05044	2.552	0.063
r_p	−2.846	0.39298	−7.243	0.002
v_p	−0.213	0.15170	−1.403	0.233
w	0.894	0.47988	1.862	0.136
d^2	6.306	1.74053	3.623	0.022
n^2	0.137	0.11456	1.196	0.298
r_p^2	3.285	1.04877	3.132	0.035
v_p^2	5.601	1.60720	3.485	0.025
w^2	4.253	1.05172	4.044	0.016
dn	−0.159	0.08045	−1.982	0.119
dr_p	5.001	1.79126	2.792	0.049
dv_p	2.551	0.46854	5.446	0.006
dw	−7.206	1.70852	−4.218	0.014
nr_p	0.006	0.05874	0.095	0.929
nv_p	−0.159	0.13084	−1.213	0.292
nw	−0.293	0.10594	−2.768	0.050
r_pv_p	−6.128	2.09531	−2.925	0.043
r_pw	1.32	0.32584	4.052	0.015
v_pw	−8.557	1.93657	−4.419	0.012

a constant, d punch travel in mm, n strain hardening exponent, r_p punch radius in mm, v_p punch velocity in mm/s, w width of the sheet in mm

References

1. Montgomery, D.C.: Design and Analysis of Experiments. Wiley, Singapore (2001)
2. Inamdar, M.V., Date, P.P., Desai, U.B.: Studies on the prediction of springback in air vee bending of metallic sheets using an artificial neural network. J. Mater. Process. Technol. **108**, 45–54 (2000)
3. Altan, T., Wang, C., Kinzel, G.: Mathematical modeling of plane strain bending of sheet and plate. J. Mater. Process. Technol. **39**, 279–304 (1993)
4. Huang, Y.-M., Leu, D.-K.: Effects of process variables on V-die bending process of steel sheet. Int. J. Mech. Sci. **40**, 631–650 (1998)
5. Gary, H.D.: The effect of statistical variability in material properties on springback. Int. J. Mater. Prod. Tech. **20**(1–3), 180–192 (2004)
6. Kim, H., Nargundkar, H., Altan, T.: Prediction of bend allowance and springback in air bending. J. Manuf. Sci. Eng. **29**, 342–351 (2007)
7. Song, N., Qian, D., Cao, J., Liu, W.K., Li, S.: Effective models for prediction of springback in flanging. J. Eng. Mater. Tech. **23**, 456–461 (2001)
8. Garcia-Romeu, M.L., Ciurana, J., Ferrer, I.: Springback determination of sheet metals in air bending process based on an experimental work. J. Mater. Process. Technol. **191**, 174–177 (2007)
9. Ragai, I., Lazim, D., Nemes, J.A.: Anisotropy and springback in draw bending of stainless steel 410: experimental and numerical study. J. Mater. Process. Technol. **166**, 116–127 (2005)
10. Bruni, C., Forcellese, A., Gabrielli, F., Simoncini, M.: Air bending of AZ31 magnesium alloy in warm and hot forming conditions. J. Mater. Process. Technol. **177**, 373–376 (2006)
11. Fei, D., Hodgson, P.: Experimental and numerical studies of springback in air v-bending process for cold rolled TRIP steels. Nucl. Eng. Des. **236**, 1847–1851 (2006)
12. Chen, P., Koc, M.: Simulation of springback variation in forming of advanced high strength steels. J. Mater. Process. Technol. **190**, 189–198 (2007)
13. Strano, M., Colosimo, B.M.: Logistic regression analysis for experimental determination of forming limit diagrams. Int. J. Mach. Tools Manuf. **46**, 673–682 (2006)
14. Tiernan, P., Draganescu, B., Hillery, M.T.: Modelling of extrusion force using the surface response method. Int. J. Adv. Manuf. Technol **27**, 48–52 (2005)
15. Senthilvelan, T., Raghu Kandan, K., Venkatraman, A.: Modelling of process parameters on the working of P/M copper performs. J. Mater. Process. Technol **142**, 767–772 (2003)
16. Qamar, S.Z., Sheikh, A.K., Arif, A.F.M., Pervez, T.: Regression based CVN-K_{IC} Models for Hot Work Tool Steels. Mater. Sci. Eng. A **430**(1–2), 208–215 (2006)
17. Cheng, P.J., Lin, S.C.: Using neural networks to predict bending angle of sheet metal formed by laser. Int. J. Mach. Tools Manuf. **40**(8), 1185–1197 (2000)
18. Paulo Davim, J., Carlos, O., Cardoso, A.: Predicting the geometric form of clad in laser cladding by powder using multiple regression analysis (MRA). Mater. Des. **29**(5), 922–927 (2008)
19. Naceur, H., Ben-Elechi, S., Batoz, J.L., Knopf-Lenoir, C.: Response surface methodology for the rapid design of aluminum sheet metal forming parameters. Mater. Des. **29**(4), 781–790 (2008)
20. Jack, G.Z., Daniel, H., Calvin, C.C.: Parametric process optimization to improve the accuracy of rapid prototyped stereolithography parts. Int. J. Mach Tools Manuf. **40**, 1–17 (1999)