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Prediction of Springback Behavior of Vee Bending Process of AA5052 Aluminum Alloy Sheets Using Machine Learning

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Abstract

This study explores the effect of Vee bending process parameter on the springback (SB) behavior of aluminum (AA5052) alloy at sheet thickness of (2 and 3mm) with die-opening (22, 35, and 50 mm) and punch-holding time (0, 5 and 10 second) which were experimentally examined. Furthermore, to see the relative effect of process parameter on SB behavior, a qualitative approach of analysis of variance (ANOVA) was used, whereas multi linear regression (MLR) and artificial neural network (ANN) were applied to optimize the SB behavior on specified process parameters. The experimental results revealed that as punch holding time and sheet thickness increase, SB behavior reduced, whereas in case of die opening, opposite phenomena observed. ANOVA results revealed that punch-holding time had the greatest effect on SB, followed by die opening and sheet thickness. Two-way parametric interactional effects between punch-holding time and dieopening had a significant effect on SB behavior. By contrast, the interactional effects of sheet thickness were insignificant. The comparative study of MLR and ANN shows that The ANN has better (99% SB predictability) as compared to MLR (73% SB Predictability). Furthermore, the predicted results of both models were compared with actual experimental results. It was observed that the predicted results were approximately near with actual measurements, whereas the performance of MLR and ANN model were measured from sum of absolute error and the sum of the absolute error of ANN was about 12% of that of MLR model. Therefore, ANN produced a superior SB prediction performance compared with MLR. This work demonstrates the formability of AA5052 aluminum alloy in cold work where Vee bending was performed with a punch radius of 0.8 mm.The bend specimens showed no cracks, checking, and surface roughness.

Keywords: Aluminum sheet;Vee bending;Springback; ANOVA;Multiple linear regression;Artificial neural network.

1. Introduction

Aluminum is the most abundant metallic element in the Earth's crust.Over the past five decades, it has been second only to iron in terms of industrial applications. The material properties of aluminum and its alloys, such as density, high strength-to-weight ratio, electrical conductivity, corrosion resistance, high workability, cast ability, weldability, aesthetic appeal, and high recyclability,allow numerous applications in various sectors of any national economy[1]. The utilization of aluminum alloys in the transportation industry (aviation, aerospace, and automobile industries) offers better fuel economy, reduction in CO2 emissions, and better material efficiency[2, 3].The usage of transportation industry is expected to increase as a result of environmental, regulatory, and competitive pressures[4, 5]. Lightweight material such as aluminum has a long history in designing, assembling, fabricating and metal forming [6, 7]. Sheet metal-forming operations constitute the array of manufacturing processes, chiefly cutting, drawing, and bending, performed on relatively thin metal sheets ranging from 0.4 mm to 6 mm in thickness using a stamping press, which involves a machine tool called punch and die of the various sheet metal-forming operations, bending has the most applications in the automotive and aviation industries and in the production of other metal sheet products [8].

Some of the material constitutive models used in FEA forming software programs are the kinematic hardening model, isotropic hardening models, yield functions (von Mises, Gotoh's biquadratic yield function, and Barlat Yld2000-2d, Hill'48), and their hybrids. Sheet metal-forming operations using FEA software programs consist of accurate modeling of the forming operation in the FEA simulation environment (i.e., accurate tool configuration and specifications of the forming process, e.g., die and punch radii, die and punch clearance, blank holding force, speed of deformation, and friction effects) and the selection of appropriate constitutive material models that adequately account for material behavior during the forming operation. Uemori et al.[9], validated an accurate kinematic hardening model coupled with suitable anisotropic yield function in an FEA simulation software to improve overall SB prediction reliability by using LS-DYNA (ver.971) in U and Hat bending of A5052-O and

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AA6016-T4. They ranked the following four yield functions that describe material anisotropy from most to least with respect to their SB predictability: von Mises, Gotoh's biquadratic yield function, Barlat Yld2000-2d, and Hill'48[9]. Toros[10], sought to improve SB predictability via optimization of the Yoshida–Uemori model parameters by using LS-DYNA in Vee and Ubending of 5754-H22, 5083-O and, 5005-O Al-alloys[10]. Lee et al. [11], proposed and validated a yield criterion by using data of AA5182-O, AA6022-T43, MP980, and 718AT.The yield criterion describes anisotropy hardening through the combination of quadratic and nonquadratic yield functions by following a non-associative flow rule. The proposed model accounts for better material anisotropic hardening than the Barlat Yld2000-2d and Hasford 1972 models[11].

Lee et al. [12], proposed an improvement to the kinematic hardening model that simultaneously accounts for anisotropic hardening and asymmetric plastic behavior of sheet metals unlike previous kinematic models. The proposed kinematic hardening model was obtained by coupling the Chaboche kinematic hardening model (Chaboche 1986) with the condition function, which replaces the material constants of the kinematic hardening model using data of AA5182-O, 719B, and 780R AHSS materials.The coupling enabled the accounting of mechanical properties in different rolling directions[12].Chen et al. [13]demonstrated that FEA simulation models using ABAQUS with 6016-T4 aluminum alloy in Vee bending according to a material constitutive model with varying elastic modules results in better SB prediction than models with a constant elastic modulus. However, these models showed limitations in reliable prediction of radius and included bend angle compared with the other models[13-15].Several computing tools,such as genetic algorithms, fuzzy logic, and artificial neural networks (ANN), are used in metal forming in the fields of optimization, design, and prediction.However,these computing tools must be aided by sufficient reliable data about the forming process, proper tool selection, and appropriate utilization of computational models[16, 17].

Baseriet al.[18]proposed a fuzzy learning back propagation (FLBP) algorithm for SB prediction where the focal process parameters are material thickness, sheet grain orientation, and punch tip radius in a Veebending operation of CK67 steel sheets with a punch and die angle of 60°. Their FLBP obtained the least mean absolute error compared with constant learning rate back propagation and variable learning rate back propagation in terms of training and testing and was thus the most capable ANN in SB prediction. Amdar et al. [19]demonstrated that aback propagation ANN is more capable of SB prediction with an error margin of ±2° for a 90° bend angle in an air Vee bending.They stated that better predictabilitycanbe obtained with substantially large training data.Dezelak et al. [20]developed a hybrid methodology for improving FEM SB predictability that involves coupling existing FEM models with machine learning algorithm tools (linear regression, isotonic regression, least medium square, SMO, Gaussian processes, and multilayer perceptron) for a draw bending-forming process with restraint force, friction, and tool radius as the main process variables. A modeling software called Pam-Stamp was used to create the model of the forming operation, the materials and their respective parameters of which were adopted by some researcher [20, 21].

It is worth mentioning that the main reason of using ANN based models rather than analytical based techniques is that analytical methods are mainly quite clumsy (which means sometime nonlinear partial differential equation is required for solving problem) and require many simplifying assumptions whereas ANN based methods proved to be more useful tool to model various engineering systems under real word conditions without involving complicated mathematical models. In recent decades, ANN based modeling has gained increasing importance in the materials joining field. ANN is a powerful modeling tool that mimics the natural behavior of human brain and is used to model complex problems of a non-linear nature in various engineering applications[22]. ANNs are able to learn nonlinear relationship between the process inputs and outputs with excellent generalization capabilities without involving in solving complex mathematical models using numerical and analytical approaches [23]. ANNs have the generalization capability as they can handle unseen data faster and simpler than other classical methods after a learning process using few measured data sets. Therefore, ANN-based methods have attracted the attention of scientists and researchers in different engineering and industrial disciplines, for instance, for modeling and identification of mechanical properties [24].Miranda et al. [25]applied ANN to provide a quick and reliable evaluation of punch displacement required to obtain a desired bend angle for a defined sheet metal considering two geometric parameters, namely, punch radius and die opening. The bending process was simulated for two different materials, namely, the structural steel HC220 and the dual-phase steel DP590 by using ABAQUS coupled with Python script to generate the array of results necessary for training (67.56%), testing (16.22%), and validation (16.22%).Many of the studies in the literature focused on understanding the influence of various operational parameters on SB behavior. Studies showed that increasing the values of die gap and the die gap to sheet metal thickness ratio (w/t) results in an increase in SB in air Veebending and Vee bending[26-28]. Decreasing the values of die and die corner radius and of punch–die clearance and punch radii leads to a decrease in SB in both L and Vee bending[29-36], also Metals with a low elastic modulus results in a high SB[37].SB decreases as the warm forming temperatures increase for the same combination of forming parameters [32, 33, 36, 38-41]. Many researches showed that a realistic account of frictional effects during forming simulations results in a goodforming and SB predictability of FEA software, whereasa high frictional coefficient results in a low SB[21, 34, 42-44].

Several studies investigated the effects of increasing yield strength on the same material subjected to different degrees of heat treatments of aluminum sheets ,such as AA 2014 (O, T4, and T6) and AA3003 (O, H22, and H24).They reported the highest SB in the T6 and H24 tempers and the least SB in the conditions yield strength is increased [45, 46].A large punch-holding time or bottoming minimizes SB [32, 36, 38].SB and bending load decreases with increasing frequency, RMS, and peak current density because of the electroplastic effects of electric pulse during electricity-assisted forming.Electric pulse-assisted forming is less energy intensive compared with traditional warm forming processes[47-51]. Highly precise dimensions of the product in sheet metal-forming process are required to obtain a precise work piece. The same requirement is needed for Vee bending process. Applying mathematical modeling in SB prediction eliminates the need for simplifying assumptions as is the case inFEA simulation models. However, modeling requires sufficient experimental data to ensure accuracy[52].

The purpose of this study is to investigate the effect of process parameters on Vee bending SB behavior of aluminum AA5052 sheet metal. The results of this study will help the researchers and industry to understand the behavior of AA 5052 aluminum sheet on specified process parameters and the effect of mentioned factors such as punch-holding time, sheet thickness, and open die on springback behavior. Furthermore, multiple linear regression MLR, ANOVA, and ANN tools were utilized for SB prediction. The effect of punch-holding time, sheet thickness, and die opening size effect on SB behavior were considered in prediction. The prediction performance of these models were evaluated on the basis of sum of absolute % error. The detail discussion on MLR, ANOVA and ANN will be discussed further in their sections.

2. Methodology

In this study commercial AA5052-H36 alloys sheets were used. The dimensions of all Veebending specimens were 70 mm × 30 mm × 2/3 mm. The cutting of all specimens were done in rolling direction as-received sheet. Bending operation performed perpendicular to the rolling direction. The standard chemical compositions of the as-received AA5052-H36 alloys sheets are presented in Table 1.Their mechanical properties are listed in Table 2.The Vee bending sheet-forming operation was conducted on AA5052-H36 alloy sheet metals to investigate the effects of sheet metal thickness (2and 3 mm), die opening (22, 35, and 50 mm),and punch-holding time (0, 5, and 10 s) on SB behavior via multilevel factorial design of experiments (Table 3).The parameters punch and die angle (85°), punch speed (15 mm/sec), and punch radius (0.8 mm) were constant. The die used was an industrial multi-angle Vee die made of carbon steel.The working parts and ground were induction hardened to 55–60 HRC.The die had different die openings (50, 35, 22, and 16 mm) and a fixed angle of 85°. The punch had the same angle as the die (85°) with a punch radius of 0.8 mm (Figure 1).

Table 1. Chemical compositions of AA5052-H36 (Almg2.5) alloy sheets (wt%)

Si	Fe	Cu	Mn	Mg	Cr	Zn	Others		Al
							Each	Total	
0.25	0.40	0.10	0.10	2.2–2.8	0.15–0.35	0.10	0.05	0.15	95.75–96.65

Table 2. Mechanical properties of AA5052-H36 (Almg2.5) alloy sheets

Density	2680 kg/m^3
Hardness (Brinell/Vickers)	73 / 83
Tensile strength (ultimate)	275 MPa
Tensile strength (yield)	240 MPa
Elastic modulus (tension/shear/compression)	69.3 / 25.9 / 70.7 GPa
Poisson's ratio	0.33
Shear strength	160 MPa
Fatigue strength	130 MPa

Table 3. L_{18} - $2^1 \times 3^2$mixed-level factorial design (repeatability × 5)

Run Order	Part Type	Blocks	Process Parameters		
			Die width (mm)	Sheet thickness (mm)	Punch holding time (s)
1	1	1	22	2	0
2	1	1	22	2	5
3	1	1	22	2	10
4	1	1	22	3	0
5	1	1	22	3	5
6	1	1	22	3	10
7	1	1	35	2	0
8	1	1	35	2	5
9	1	1	35	2	10
10	1	1	35	3	0
11	1	1	35	3	5
12	1	1	35	3	10
13	1	1	50	2	0
14	1	1	50	2	5
15	1	1	50	2	10
16	1	1	50	3	0
17	1	1	50	3	5
18	1	1	50	3	10

Others experimental details:
Punch radius: 0.8 mm (constant); punch and die angle: 85°
Punch speed: 15 mm / sec

2.1. Experimental Procedure

The experimental work consisted of adapting the Veebending punch and die assembly into a hydraulic press (Figure 2). All Vee bendswere performed with a constant punch velocity of 15 mm/sand a repeatability factor of 5 in accordance with the parameters defined in Table 3. Prior to the start of each bending operation, the surfaces of the sheet metals, punch, and die were thoroughly cleaned until free of debris or dirt.

Bending suffers the drawback of SB behavior. The phenomenon of SB is the partial elastic recovery experienced by the sheet metal upon removal of the applied load on conclusion of the forming operation as shown in Figure 3c. SB can be expressed as the difference between the final included angle of the formed part (α') and the included angle of the forming tool or punch (α'_b) (Eqn: 1.1a or 1.1b) [53]. It is usually a cause for unsatisfactory bending since it results in loss of dimensional control in the formed part and it leads to problems that impacts cost and quality in downstream manufacturing processes following bending. This work seeks to evaluate the SB behavior of AA5052-H36 aluminium alloy undergoing vee bending.

$$SB = \alpha' - \alpha'_b \tag{1.1a}$$

$$SB = \frac{(\alpha' - \alpha'_b)}{\alpha'_b} \tag{1.1b}$$

The Vee-bending experiment involved loading the test specimen onto the die surface and operating a control lever that depressed the punch into the die cavity to bend the sheet metals into a Vee shape Figure 3 (a, b) and according to the punch displacements specified in Table 4. Immediately after forming, the punch was retracted. The acceptability of the bends was based on the absence of evident surface cracking, excessive surface roughness, checking, and edge cracking as viewed under a 30×magnification camera. The samples met the acceptability criteria (Figure 4). At the end of each experimental run, the bent test specimens were properly labeled and subjected to SB angle measurements by using an optical angle-measuring device.

At the end of each experimental run, the bent test specimens are properly labelled, after which they are observed for forming defects and their SB angle measured using an optical angle measuring device as shown in Figure 5a. Validation SB angle measurement was done through digitizing the specimen and measuring the SB using an online angle / bevel protractor as shown in Figure 5b.

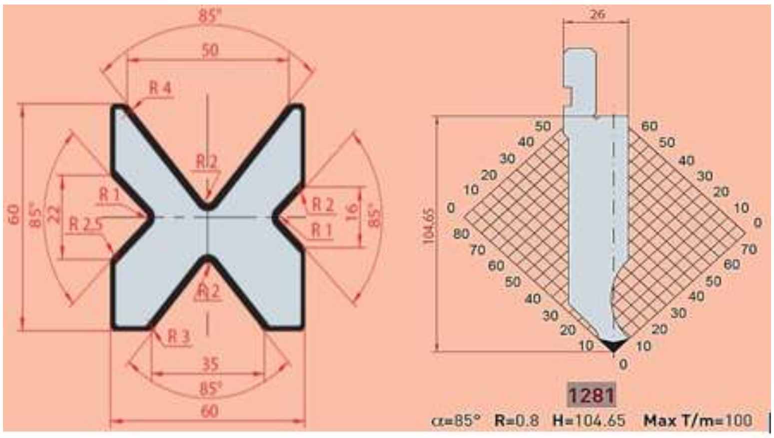
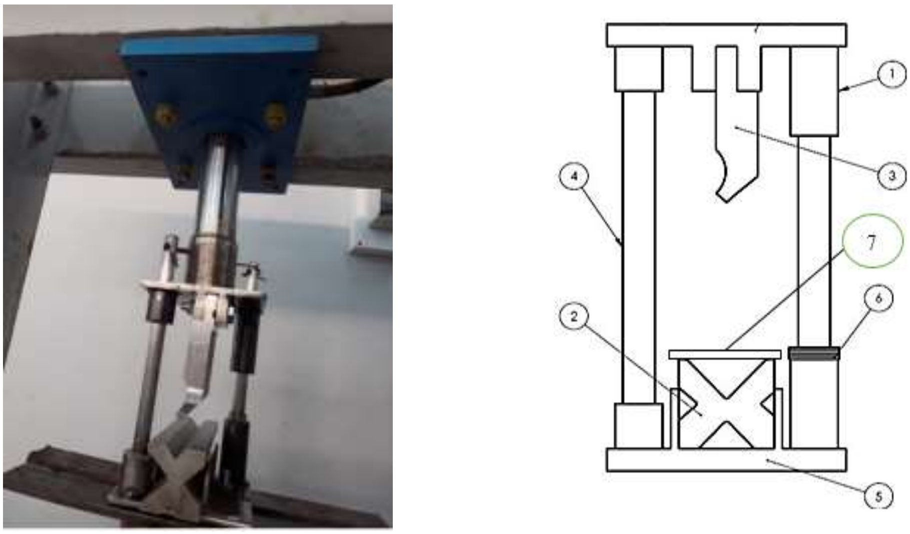


Figure 1. Cross section of the multi-angle Vee die and punch

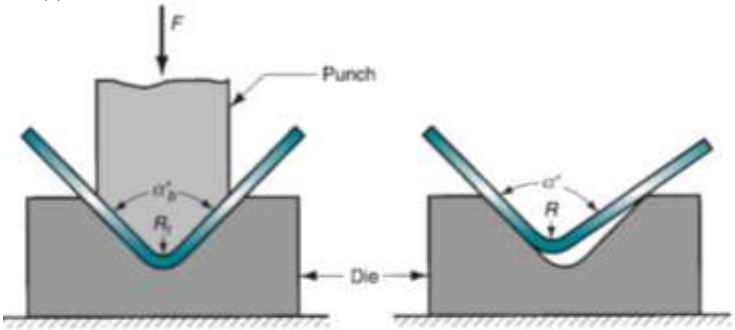


1- Punch guide sleeve, 2- Die, 3- Punch, 4- Guide shaft, 5- Base support, 6- Displacement control shims, 7- Sheet metal

Figure 2. Vee bending punch and die assembly adapted to hydraulic press

(a)

(b)



(c)

Figure 3. Punch displacement in the die cavity: (a) bending operation with 22 mm die openingfor a 2 mm AA5052-H36 sheet thickness; (b) bending operation35 mm die opening for a 2 mm AA5052-H36 sheet thickness (c) SB phenomenon[53].

Table 4. Punch Displacement in the die cavities

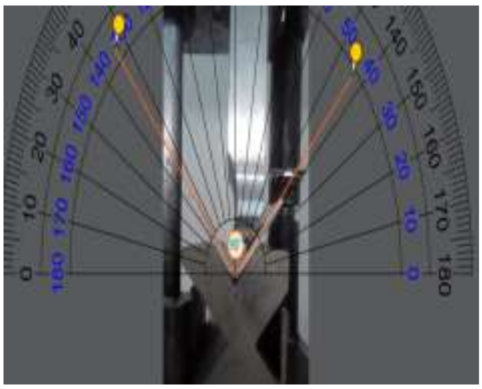
Sheet thickness	22 mm die width	35 mm die width	50 mm die width
2 mm	7.5 mm	14 mm	20.5 mm
3 mm	6.5 mm	13 mm	19.5 mm

(a)

(b)

Figure 4. A bentspecimen viewed under 30×magnification: (a) exterior; (b) Interior

(a)



(b)

Figure 5. Measurement tool used to measure SB (a) Angle profile projector (b) Angle measurement with online angle / bevel protractor

3. Results and Discussion

The specimens after bending are shown in Figure 6.The SB results are presented in Figures 7, 8, and 9 with different die openings, SB decreased as punch-holding time increased (Figures7 and 8). Moreover, SB clearly decreased as punch-holding time increased with the same die opening and sheet thickness. SB also increased as die opening increased. However, this trend was not observed at 5 spunch-holding time during which SB decreased between die opening of 22 and 35mmlikely because of noise or disturbances during the experimentation. Table 5 shows the output results of experiments.

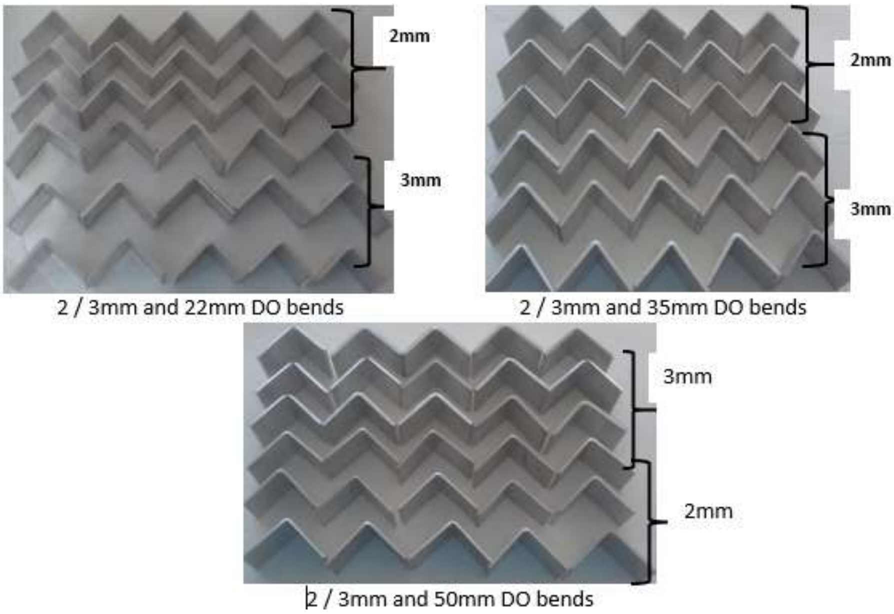


Figure 6. Specimens with different die openings after bending

Table 5. Final included angles after bending and their respective SB

Exptal Runs	Designation	Experimental runs results (°)						Experimental SB results (°)					
		1	2	3	4	5	Av.	1	2	3	4	5	Av.
1	DO22-2mm-0sec	92.5	89.5	92.0	89.5	91.0	**90.9**	7.5	4.5	7	4.5	6	5.9
2	DO22-2mm-5sec	89.8	90.0	90.5	90.6	91.1	90.4	4.8	5	5.5	5.6	6.1	5.4
3	DO22-2mm-10sec	88.0	88.5	87.5	87.0	87.0	87.6	3	3.5	2.5	2	2	2.6
4	DO22-3mm-0sec	91.5	89.5	90.0	88.0	90.0	**89.8**	6.5	4.5	5	3	5	4.8
5	DO22-3mm-5sec	88.0	90.0	88.0	89.5	90.0	89.1	3	5	3	4.5	5	4.1
6	DO22-3mm-10sec	87.0	86.5	87.5	88.0	87.0	87.2	2	1.5	2.5	3	2	2.2
7	DO35-2mm-0sec	93.0	92.0	89.0	90.0	91.5	**91.1**	8	7	4	5	6.5	6.1
8	DO35-2mm-5sec	89.7	90.0	89.5	87.0	91.0	89.4	4.7	5	4.5	2	6	4.44
9	DO35-2mm-10sec	89.0	89.5	90.5	88.5	87.0	88.9	4	4.5	5.5	3.5	2	3.9
10	DO35-3mm-0sec	88.5	91.5	89.5	90.8	89.0	**89.9**	3.5	6.5	4.5	5.8	4	4.86
11	DO35-3mm-5sec	87.0	88.5	89.0	87.0	87.5	87.8	2	3.5	4	2	2.5	2.8
12	DO35-3mm-10sec	86.0	85.7	88.5	88.0	87.0	87.0	1	0.7	3.5	3	2	2.04
13	DO50-2mm-0sec	92.0	91.0	91.5	92.0	91.0	**91.5**	7	6	6.5	7	6	6.5
14	DO50-2mm-5sec	90.5	92.3	92.0	90.0	91.5	91.3	5.5	7.3	7	5	6.5	6.26
15	DO50-2mm-10sec	91.0	91.0	91.5	90.2	91.7	91.1	6	6	6.5	5.2	6.7	6.08
16	DO50-3mm-0sec	91.5	90.0	91.0	91.7	92.0	**91.2**	6.5	5	6	6.7	7	6.24
17	DO50-3mm-5sec	90.5	90.0	88.5	92.5	90.0	90.3	5.5	5	3.5	7.5	5	5.3
18	DO50-3mm-10sec	89.0	88.5	90.4	89.5	91.0	89.7	4	3.5	5.4	4.5	6	4.68

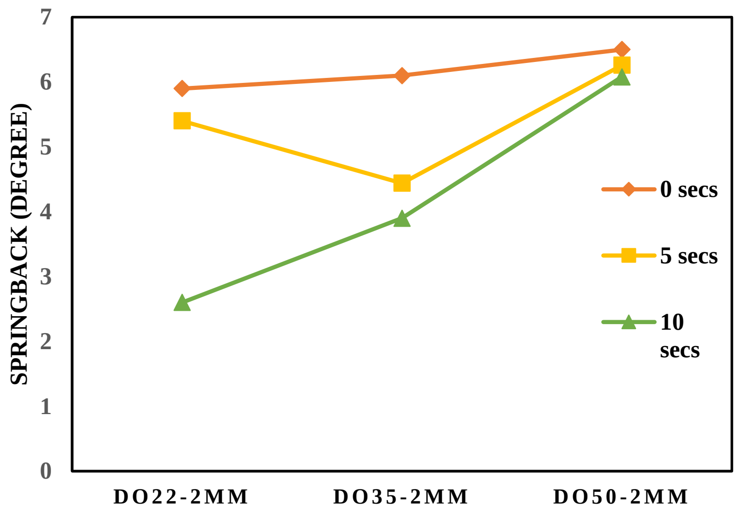


Figure 7. SB across die openings of 22, 35, and 50 mm for a sheet with a thickness of 2 mm

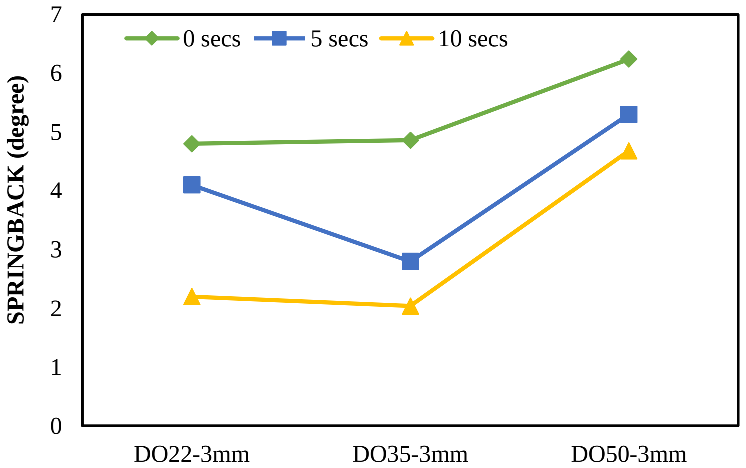


Figure 8. SB across die openings of 22, 35, and 50 mm for a sheet with a thickness of 3 mm

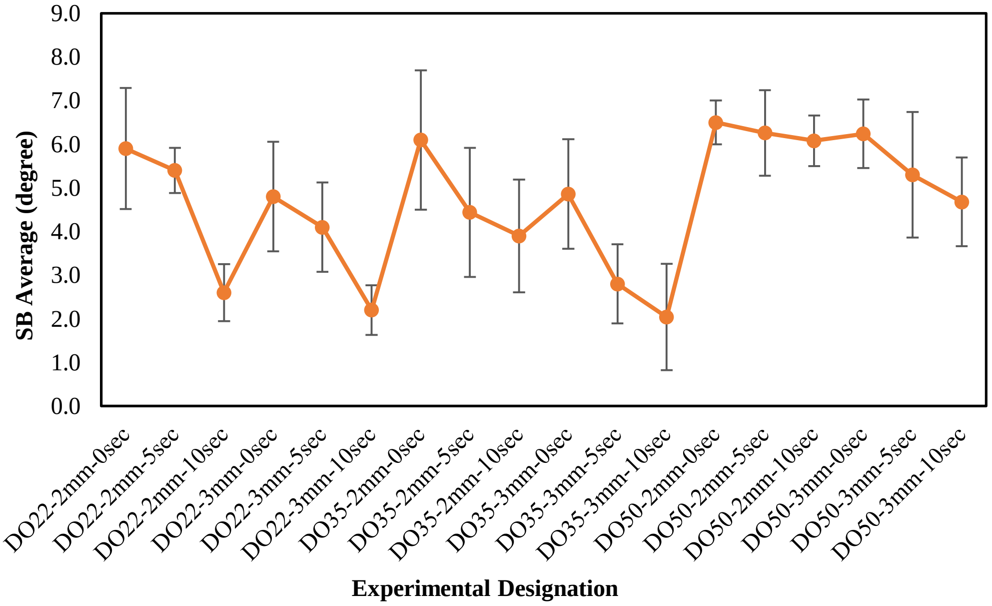


Figure 9. SB averages and standard deviations for different experimental runs.

3.1. ANOVA

The results of ANOVA are summarized in Table 6.The effects of sheet thickness, die opening, and punch-holding time on SB behavior was statistically significant (i.e., P-value ≈ 0 < 0.05). The Pareto chart (Figure10) and the F-values (Table 7) show that punch-holding time had the greatest effect on SB behavior (47.46%), followed by die opening (30.44%). By contrast, sheet metal thickness had the least effect (19.63%).

The parametric interaction effects between die opening and punch-holding time were statistically significant (Table 6). Interactions involving sheet thickness were not statistically significant (P-value: 0.371, 0.707 > 0.05), which shows that the interaction effect of sheet thickness is minimal on SB behavior. The Pareto chart (Figure 11) and the F-values (Table 6) follow the same hierarchal order as that of ANOVA results (Table 5) and Pareto chart (Figure 11). However, the interactional effects between die opening and punch-holding time, occupying a fourth position after sheet thickness in terms of their combined impact on SB.

Table 6. ANOVA without considering parametric interaction effects

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	142.49	47.496	32.61	0.000
Sheet thickness	1	28.67	28.674	19.69	0.000
Die opening	1	44.48	44.477	30.53	0.000
Punch-holding time	1	69.34	69.337	47.60	0.000
Error	86	125.27	1.457		
Lack-of-Fit	14	40.71	2.908	2.48	0.006
Pure Error	72	84.56	1.174		
Total	89	267.76			

Table 7. ANOVA considering parametricinteraction effects

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	13	180.734	13.9026	12.14	0.000
Linear	5	159.521	31.9042	27.86	0.000
Sheet thickness	1	28.674	28.6738	25.04	0.000
Die opening	2	61.442	30.7208	26.83	0.000
Punch holding time	2	69.406	34.7028	30.31	0.000
2-Way Interactions	8	21.213	2.6516	2.32	0.028
Sheet thickness × Die opening	2	2.303	1.1514	1.01	0.371
Sheet thickness × Punch-holding time	2	0.798	0.3988	0.35	0.707
Die opening × Punch-holding time	4	18.112	4.5281	3.95	0.006
Error	76	87.022	1.1450		
Lack-of-Fit	4	2.466	0.6164	0.52	0.718
Pure Error	72	84.556	1.1744		
Total	89	267.756			

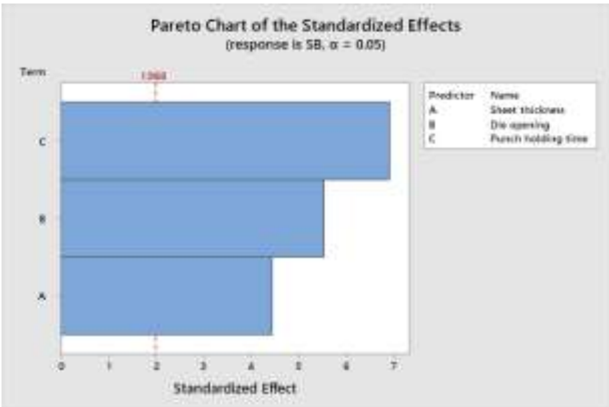


Figure 10. Pareto chart of parametric influence on SB behavior

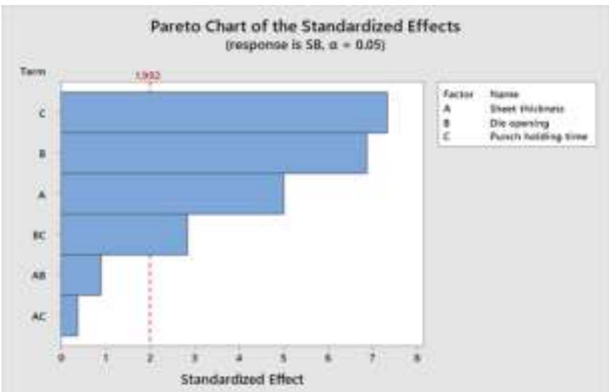


Figure 11. Pareto chart of parametric influence on SB behavior with parametric interactional effects

The effects of individual parameters on SB behavior (Figure 12) shows that increasing punch-holding time and sheet metal thickness decreased SB. The present results were consistent with earlier findings[28, 29, 32, 35, 36, 38, 45].The effects of punch-holding time on SB was largely due to its effect on the other factors, such as friction, bending moment, residual stresses arising from the bending operation, differences between tensile stress on the outer bend region and compressive stress on the inner bend region, and alteration of the geometric rigidity of the material. During the punch-holding time, the shape of the formed part was constrained, ensuring increased friction between the punch, sheet metal, and die. Hence, the sheet metal conformed well to the forming angles of the punch and die. The internal stresses from bending were relieved, thereby decreasing the elastic strains in the bending zone and increasing the permanent (plastic) strains. Moreover, the bending moment due to compressive load acting normally to the sheet decreased [54, 55].

The effects of process parameters were found prominent in this study such as when punch-holding time increases, a reduction in SB behavior was found. Similarly, the effect of sheet thickness on SB behavior is also vital, and it is observed that SB increases as sheet thickness decreases. This phenomena applies on at least a thickness of 3mm attributed to the reduction in elastic sheet recovery due to the increase in bulk deformation of the sheet metals, as sheet thickness decreases the rigidity of material which minimizes the effect of elastic recovery stated by Leu et al[29]. According to Cruz et al [56] the die opening is significant factor in bending operation. Typically, the selection of die opening is dependent on sheet thickness. According to the author, the recommended industrial ratio of die-opeing/sheet-thickness ratio between 6 and 10. As for the effects of die opening on SB behavior, the main effect is plotted in Figure 12, which shows that SB behavior slightly decreased when die opening was increased from 22 mm to 35 mm. In current study, it has been observed that SB behavior significantly increased when die opening increased from 35 mm to 50 mm whereas an increase in sheet thickness results as reduction in SB behavior as discussed by [57, 58]. Overall, an increase in die opening increased SB behavior whereas the combine effect of sheet thickness and die opening on the SB behavior is nominal as shown in figure 11.

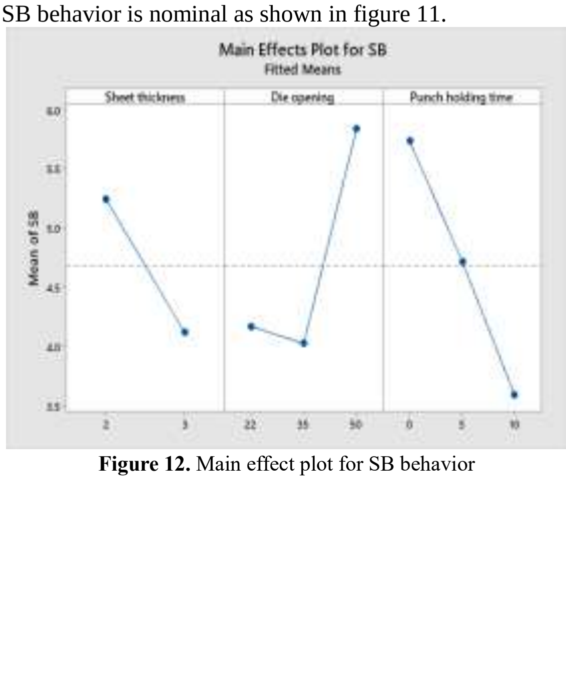


Figure 12. Main effect plot for SB behavior

3.2. Springback Predictability: Multiple Linear Regression and Artificial Neural Network

3.2.1. Multiple Linear Regression Analysis

Regression analysis is useful in designed experiments to build a quantitative model relating the important factors to the response. Regression model is mostly used to investigate and model the relationship between the response variable and predictors. It is a common tool used for data analysis in experimental studies, when the response variable is continuous. MLR is widely used in different types of statistical analysis. Regression analysis is one of the frequently utilized technique in conventional prediction to show the relation between dependent and independent variables. Relation between dependent variable and predictor variable is represented by linear equation (5). The basic relationship of multi linear regression Equation (2) is driven from Montgomery [59]. Regression model shows the relationship between the output values and one or more input values. Multiple regression model is a parametric model. There are many statistic and machine learning methods to predict the results such as linear, generalized and nonlinear regression model[60]. Multi linear regression (MLR) is a classic method that has many advantages like interpretability, simplicity, easy accommodation during variable transformation, supposing the hypothesis of normality and many more[61]. In present study MLR model was driven by Matlab software tool. Regression analysis considered the averages of SB outputs of the experimental runs are presented in Table 8 and 9.The overall regression model was as follows:

$$C = a + b_1x_1 + b_2x_2 + \dots + 1b_nx_n + \varepsilon \quad (2)$$

C is a predicted response, a is constant and ε is the random error. Whereas, x_1, x_2, x_3, ...$x_n$are the variable that effect the springback. b_1, b_2, b_3, ... b_n are regression co-efficient that determine the contribution of the variables to the springback.

$$B = (C - \varepsilon) \quad (3)$$

So we can rewrite the equation 2

$$B = a + b_1x_1 + b_2x_2 + b_3x_3 \quad (4)$$

$$SB = 6.3834 - 1.1289\ ST + 0.061446\ DO - 0.2150\ PHT \quad (5)$$

The P-values of the constant and independent variables, as well as the overall regression model (i.e., P-values << 0.05), revealed significant correlation between SB behavior and the independent variables. The results indicated the reliability of the regression model in predicting SB. The overall SB prediction capability obtained using the regression model was 73.02% of the target SB value, demonstrating that the model was reasonably reliable.

3.2.2. Artificial Neural Network (ANN)

Neural network (NN) is branch of statistical machine learning and has been utilized in prediction of various kind of tasks. ANN is inspired by natural neutron[60]. ANN consists of a number of processing elements or units called neurons. ANN is buildup of interconnecting artificial programmed neurons that imitate the properties of biological neurons[62].ANN for SB prediction, which was conducted with MATLAB,consideredtheaverages of SB in each experimental run as the target output. There are many various types of algorithms and architectures are available to us in ANN. In this present workaback propagation algorithm, namely, feed-forward back propagation network (nftool) were used to train the model, which is the most common network structure developed to predict the SB. In this technique neurons are organized into layers and have only forward connection. The first layer is input layer and consist of number of neuron which are usually equal to the number of input. The last layer is called output layer and contain number of computational neurons. All layers between the input and output are called hidden layers, which contains many computational neurons and transfer functions[63].In recent years many researcher [64-68] are applying ANN in prediction of spring back results. Furthermore, there is no specified methods to select the number of hidden neurons. Thus, mostly the selection of hidden neurons depend on minimum mean square error (MSE). There are many various types of algorithms that are available for training the model input data. The selection of algorithm was based on the performance and learning speed which can provide the best fit to the data. Therefore, Levenberg-Marquard (LM) backpropagation algorithm was selected to train the model. LM was especially constructed for quicker convergence in back propagation algorithms. The presented technique is the quickest technique, and it supports the numerical solution to obtain mean square error [69].

In this study a Levenberg–Marquardt optimization training algorithm, was applied in modeling the neural network. The gradient descent with momentum weight and bias learning function was chosen as the adaption-learning function. The structure of the neural network consisted of two layers, a hidden layer and an output layer, together with the three inputs (i.e., sheet thickness, die opening, and punch-holding time) and the output from the network (the corresponding average SB output) (Figure 13).In developing the neural network, 70% of the data was used for training the network, 15% for validation, and 15% for testing. ANN model with two input and one output with hidden layer which include eight nodes, beginning with one node to fabricate and evaluate by using Levenberg-Marquard procedure. The unseen nodes employ the sigmoid transfer function and the outcome node employed the linear transfer function. The model trained multiple time to obtain optimal predicted results. The overall SB predicted results of AA 5052 show that correlation coefficient of training data is 0.99647. Also, the coefficient correlation value of R-square for validation and testing are 0.99979 and 1 respectively. The closeness of correlation training data and validation data indicates that the prediction efficiency of the model is acceptable. The overall correlation coefficient value of R-square of the model was found to be 0.99637. Figure 14 shows that the prediction capabilities of the model are good because its correlation coefficient is relatively close to 1.

Table 8. Coefficients of regression analysis (Multiple R: −0.8819; R-sq: −0.7778; R-sq(adj): −0.7302; R-sq(pred): −0.6424; SE: −0.762624)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	6.3834	1.0966	5.821	4.4376e-05	
Sheet thickness	−1.1289	0.3595	−3.1401	0.0072322	1.00
Die opening	0.061446	0.015712	3.9108	0.0015679	1.00
Punch-holding time	−0.2150	0.04403	−4.883	0.00024185	1.00

Table 9. ANOVA considering average SB values

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	28.498	9.4992	16.33	7.55e-05
Residual	14	8.142	0.5816		
Total	17	36.640			

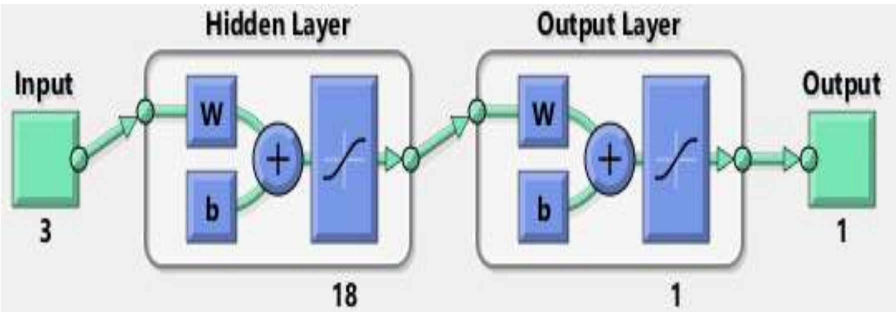


Figure 13. Structure of the neural network

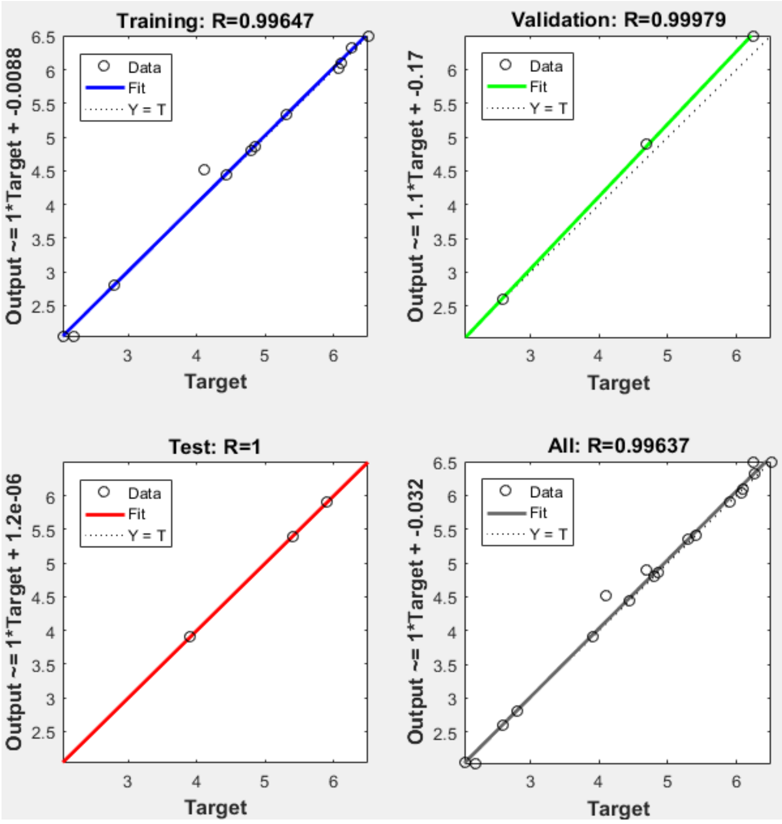


Figure 14. SB prediction capability of the network

3.2.3. Comparison amongexperimental, MLR, and ANN on SB prediction

The performance of MLR and ANN in predicting SB was compared. The SB prediction capability of the ANN was superior to that of MLR(Table 10). The superiority of ANN results prediction compared to multi linear regression model were found [70]. Multi linear regression (MLR) model is a simple model, therefore to evaluate the results more, complex statistical modeling technique ANN were applied to get better results[71].In recent years some researchers[70, 72-74] applied MLR for similar datasets, however, in this study we used MLR to compare the performance of ANN, and as it evident from our analysis that ANN (99% SB predictability) produced superior SB prediction performance compared with MLR (73% SB Predictability). Furthermore, some author [60, 70, 75] has applied the MLR and ANN to predict the performance of the model and mostly they found that the ANN has better prediction result compare to regression model. To evaluate the performance of models some authors like Narayanasamy et al[70], Liu et al [59] and Asmael et al [18] has used the absolute % error as performance evaluation criteria to check the prediction capability of trained models. Therefore, in this study we also choose absolute % error as performance evaluator.As can be observed from Table 9. The prediction error of ANN model is much less than the MLR model. In this study the sum of the absolute error of ANN with respect to deviations from the experimental SB values was about 12% of that of MLR. Optimizing the MLR regression model, wherein the objective function was the minimization of the sum of its absolute error, resulted in approximately 5% overall improvement of its SB prediction capabilities. The MLR model is expressed below:

Regression model: SB = 5.4948 – 0.8462 ST + 0.0658 DO– 0.2201 PHT,

Where the constant and coefficients of the original MLR model were subjected to the following constraints: $4 \leq$ Co-eff. C ≤ 10; $-2 \leq$ Co-eff. ST ≤ -0.8; $0.02 \leq$ Co-eff. DO ≤ 0.1; $-0.4 \leq -$Co-eff. PHT ≤ -0.1

Table 10. Comparison of SB prediction performance of MLR and ANN

#	Exp. SB Av.	MLR Predicted SB Av.	MLR Predicted Error	Optimized MLR Predicted SB Av.	Optimized MLR Predicted Error	ANN Predicted SB Av.	ANN Prediction Error
1	5.9000	5.4775	0.4225	5.2473	0.6527	5.8573	0.0427
2	5.4000	4.4025	0.9975	4.1467	1.2533	5.3077	0.0923
3	2.6000	3.3275	−0.7275	3.0462	−0.4462	2.6016	−0.0016
4	4.8000	4.3486	0.4514	4.4011	0.3989	4.8157	−0.0157
5	4.1000	3.2736	0.8264	3.3006	0.7994	4.1036	−0.0036
6	2.2000	2.1986	0.0014	2.2001	−0.0001	2.6712	−0.4712
7	6.1000	6.2763	−0.1763	6.1010	−0.0010	6.4418	−0.3418
8	4.4400	5.2013	−0.7613	5.0005	−0.5605	4.4338	0.0062
9	3.9000	4.1263	−0.2263	3.9000	0.0000	3.9012	−0.0012
10	4.8600	5.1474	−0.2874	5.2549	−0.3949	4.8441	0.0159
11	2.8000	4.0724	−1.2724	4.1544	−1.3544	3.0411	−0.2411
12	2.0400	2.9974	−0.9574	3.0538	−1.0138	2.0401	−0.0001
13	6.5000	7.1979	−0.6979	7.0862	−0.5862	6.4999	0.0001
14	6.2600	6.1229	0.1371	5.9856	0.2744	6.2391	0.0209
15	6.0800	5.0479	1.0321	4.8851	1.1949	6.1128	−0.0328
16	6.2400	6.0691	0.1709	6.2400	0.0000	6.2404	−0.0004
17	5.3000	4.9941	0.3059	5.1395	0.1605	5.3015	−0.0015
18	4.6800	3.9191	0.7609	4.0389	0.6411	4.6041	0.0759
	Sum of absolute error		10.2126		9.7322		1.3649

4. Conclusion

This work demonstrated the cold formability of AA 5052-H36 aluminum alloy. The Vee bends were performed with a punch radius of 0.8 mm. The bent specimens showed no evident cracks, checking, and surface roughness. The effects of sheet thickness, die opening, and punch-holding time on the SB behavior of AA5052-H36 aluminum alloy undergoing Veebending were experimentally investigated. MLR and ANN tools were utilized for SB prediction. We arrived at the following conclusions:

The effect of process parameters were investigated in current study, which leads to conclude that the punch-holding time had the greatest effect on SB behavior, followed by die opening and sheet thickness. Furthermore, the increment of punch-holding time and sheet thickness led to the reduction SB behavior, whereas extension in die opening size brings improvement in SB behavior.

Parametric interactional effects between punch-holding time and dieopening showed significant effects on SB behavior. SB was minimized further by optimizing the values of both parameters, i.e., increasing punch-holding time and reducing die opening within the limits imposed by the capabilities of the manufacturing system. Interactional effects of sheet thickness with either die opening or punch-holding time had no significant effects on SB behavior.

MLR and ANN model were applied to predict the SB behavior and predicted results were compared with experimental results of SB behavior. MLR and ANN were proved to be reliable tools for SB prediction. ANN (99% SB predictability) produced superior SB prediction performance compared with MLR (73% SB predictability).The sum of the absolute error of ANN in SB prediction was about 12% of that of MLR. The overall predicted results of MLR and ANN are reasonably near to actual SB measurement results. Clearly, it is found that the ANN model correlates the SB with the aforesaid parameters with a good degree of estimation.

5. Reference

[1] Lumley, R., Fundamentals of aluminium metallurgy: production, processing and applications. 2010: Elsevier.

[2] Nasir, T.; O. Kalaf; M. Asmael; Q. Zeeshan; B. Safaei; G. Hussain; A. Motallebzadeh. The experimental study of CFRP interlayer of dissimilar joint AA7075-T651/Ti-6Al-4V alloys by friction stir spot welding on mechanical and microstructural properties. Nanotechnology Reviews, 2021. 10. (1): 401-413.

[3] Maheshwari, A.S.; R.R. Gawande. Improving Surface Quality of AA 6351 by the Stiff Burnishing. JJMIE, 2016. 10. (4).

[4] NASIR, T.; O. KALAF; M. ASMAEL. Effect of rotational speed, and dwell time on the mechanical properties and microstructure of dissimilar AA5754 and AA7075-T651 aluminum sheet alloys by friction stir spot welding. MATERIALS SCIENCE-MEDZIAGOTYRA, 2021. 27. (3): 308-312.

[5] Soori, M.; M. Asmael. A review of the recent development in machining parameter optimization. Jordan Journal of Mechanical and Industrial Engineering, 2022. 16. (2): 205-223.

[6] Asmael, M.; B. Safaei; O. Kalaf; Q. Zeeshan; F. Aldakheel; T. Nasir; Z. Yang. Recent developments in tensile properties of friction welding of carbon fiber-reinforced composite: A review. Nanotechnology Reviews, 2022. 11. (1): 1408-1436.

[7] Liu, Y.; L. He; S. Yuan. Wear Properties of Aluminum Alloy 211z. 1 Drilling Tool. Jordan Journal of Mechanical and Industrial Engineering, 2021. 15. (1).

[8] Groover, M.P., Fundamentals of modern manufacturing: materials processes, and systems. 2007: John Wiley & Sons.

[9] Uemori, T.; S. Sumikawa; T. Naka; N. Ma; F. Yoshida. Influence of Bauschinger Effect and Anisotropy on

Springback of Aluminum Alloy Sheets. Materials Transactions, 2017. 58. (6): 921-926.
[10] Toros, S. Parameters determination of Yoshida Uemori model through optimization process of cyclic tension-compression test and v-bending springback. Latin American Journal of Solids and Structures, 2016. 13. (10): 1893-1911.
[11] Lee, E.-H.; T.B. Stoughton; J.W. Yoon. A yield criterion through coupling of quadratic and non-quadratic functions for anisotropic hardening with non-associated flow rule. International Journal of Plasticity, 2017. 99. 120-143.
[12] Lee, E.-H.; T.B. Stoughton; J.W. Yoon. Kinematic hardening model considering directional hardening response. International Journal of Plasticity, 2018. 110. 145-165.
[13] 13. Chen, Y.; X. Li; L. Lang. Various elastic moduli of AA6016 and their application on accurate prediction of springback. Journal of the Chinese Institute of Engineers, 2019. 42. (4): 319-326.
[14] Yoshida, F.; T. Uemori; K. Fujiwara. Elastic–plastic behavior of steel sheets under in-plane cyclic tension–compression at large strain. International journal of plasticity, 2002. 18. (5-6): 633-659.
[15] Yang, M.; Y. Akiyama; T. Sasaki. Evaluation of change in material properties due to plastic deformation. Journal of Materials Processing Technology, 2004. 151. (1-3): 232-236.
[16] Pattanaik, L. Applications of Soft computing tools in metal forming: a state-of-art review. Journal of Machining and Forming Technologies, 2013. 5. (1/2): 29.
[17] Anitha, J.; R. Dasa; M.K. Pradhan. Multi-objective optimization of electrical discharge machining processes using artificial neural network. Jordan Journal of Mechanical and Industrial Engineering, 2016. 10. (1).
[18] Baseri, H.; M. Bakhshi-Jooybari; B. Rahmani. Modeling of spring-back in V-die bending process by using fuzzy learning back-propagation algorithm. Expert Systems with Applications, 2011. 38. (7): 8894-8900.
[19] Inamdar, M.; P. Date; U. Desai. Studies on the prediction of springback in air vee bending of metallic sheets using an artificial neural network. Journal of Materials Processing Technology, 2000. 108. (1): 45-54.
[20] Dezelak, M.; I. Pahole; M. Ficko; M. Brezocnik. Machine Learning for the Improvement of Springback Modelling. Advances in Production Engineering & Management, 2012. 7. (1).
[21] Carden, W.; L. Geng; D. Matlock; R. Wagoner. Measurement of springback. International Journal of Mechanical Sciences, 2002. 44. (1): 79-101.
[22] Asmael, M.; T. Nasir; Q. Zeeshan; B. Safaei; O. Kalaf; A. Motallebzadeh; G. Hussain. Prediction of properties of friction stir spot welded joints of AA7075-T651/Ti-6Al-4V alloy using machine learning algorithms. Archives of Civil and Mechanical Engineering, 2022. 22. (2): 1-19.
[23] Babajanzade Roshan, S.; M. Behboodi Jooibari; R. Teimouri; G. Asgharzadeh-Ahmadi; M. Falahati-Naghibi; H. Sohrabpoor. Optimization of friction stir welding process of AA7075 aluminum alloy to achieve desirable mechanical properties using ANFIS models and simulated annealing algorithm. The International Journal of Advanced Manufacturing Technology, 2013. 69. (5): 1803-1818.
[24] Elsheikh, A.H.; S.W. Sharshir; M. Abd Elaziz; A.E. Kabeel; W. Guilan; Z. Haiou. Modeling of solar energy systems using artificial neural network: A comprehensive review. Solar Energy, 2019. 180. 622-639.
[25] Miranda, S.S.; M.R. Barbosa; A.D. Santos; J.B. Pacheco; R.L. Amaral. Forming and springback prediction in press brake air bending combining finite element analysis and neural networks. The Journal of Strain Analysis for Engineering Design, 2018. 53. (8): 584-601.
[26] Vasudevan, D.; R. Srinivasan; P. Padmanabhan. Effect of process parameters on springback behaviour during air bending of electrogalvanised steel sheet. Journal of Zhejiang University-SCIENCE A, 2011. 12. (3): 183-189.
[27] Inamdar, M.; P. Date; S. Sabnis. On the effects of geometric parameters on springback in sheets of five materials subjected to air vee bending. Journal of Materials Processing Technology, 2002. 123. (3): 459-463.
[28] Garcia-Romeu, M.; J. Ciurana; I. Ferrer. Springback determination of sheet metals in an air bending process based on an experimental work. Journal of Materials Processing Technology, 2007. 191. (1-3): 174-177.
[29] Leu, D.-K.; Z.-W. Zhuang. Springback prediction of the vee bending process for high-strength steel sheets. Journal of Mechanical Science and Technology, 2016. 30. (3): 1077-1084.
[30] Gassara, F.; R. Hambli; T. Bouraoui; F. El Halouani; D. Soulat. Optimization of springback in L-bending process using a coupled Abaqus/Python algorithm. The International Journal of Advanced Manufacturing Technology, 2009. 44. (1-2): 61-67.
[31] Buang, M.S.; S.A. Abdullah; J. Saedon. Effect of die and punch radius on springback of stainless steel sheet metal in the air v-die bending process. Journal of Mechanical Engineering and Sciences, 2015. 8. 1322-1331.
[32] Kim, H.W.; J.H. Yu; C.-W. Lee. Study of V-bending deformation Characteristics of Magnesium alloy sheet in Warm Forming. in Journal of Physics: Conference Series. 2018. IOP Publishing.
[33] Kuo, C.-C.; B.-T. Lin. Optimization of springback for AZ31 magnesium alloy sheets in the L-bending process based on the Taguchi method. The International Journal of Advanced Manufacturing Technology, 2012. 58. (1-4): 161-173.
[34] Jadhav, S.; M. Schoiswohl; B. Buchmayr. Applications of finite element simulation in the development of advanced sheet metal forming processes. BHM Berg-und Hüttenmännische Monatshefte, 2018. 163. (3): 109-118.
[35] ÖZDEMİR, M. Mathematical modeling of the effect of different parameters on spring back in sheet metal formability process. American Journal of Engineering Research (AJER), 2017. 6. (10): 198-205.
[36] Zong, Y.; P. Liu; B. Guo; D. Shan. Springback evaluation in hot v-bending of Ti-6Al-4V alloy sheets. The International Journal of Advanced Manufacturing Technology, 2015. 76. (1-4): 577-585.
[37] Alhammadi, A.; H. Rafique; M. Alkaabi; J.A. Qudeiri. Experimental investigation of springback in air bending process. in IOP Conference Series: Materials Science and Engineering. 2018. IOP Publishing.
[38] Choudhury, I.A.; V. Ghomi. Springback reduction of aluminum sheet in V-bending dies. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2014. 228. (8): 917-926.
[39] Ján, S.; J. Miroslav. Springback prediction in sheet metal forming processes. Journal for Technology of Plasticity, 2012. 37. (1).
[40] Soualem, A.; S. Hakimi. Experimental Study and Prediction of the Springback under Heat Treatments for Anisotropic Sheet. Experimental Techniques, 2018. 42. (3): 253-260.
[41] Verma, R., Effect of elevated temperature on mechanical behaviour and springback of aluminum alloy brazing sheets. 2016, University of Waterloo.
[42] Hou, Y.; J. Min; J. Lin; Z. Liu; J.E. Carsley; T.B. Stoughton. Springback prediction of sheet metals using improved material models. Procedia Engineering, 2017. 207. 173-178.
[43] Sigvant, M.; J. Pilthammar; J. Hol; J. Wiebenga; T. Chezan; B. Carleer; A.H. Van Den Boogaard. Friction and lubrication modeling in sheet metal forming simulations of a Volvo XC90 inner door. in International Deep Drawing Research Group Conference on Challenges in Forming High-Strength Sheets, IDDRG, Linz. 2016.

[44] Hol, J.; J. Wiebenga; B. Carleer. Friction and lubrication modelling in sheet metal forming: Influence of lubrication amount, tool roughness and sheet coating on product quality. in Journal of Physics: Conference Series. 2017. IOP Publishing.

[45] Ahmed, G.S.; H. Ahmed; M.V. Mohiuddin; S.M.S. Sajid. Experimental evaluation of springback in mild steel and its validation using LS-DYNA. Procedia materials science, 2014. 6. 1376-1385.

[46] Sarıkaya, O.T., Analysis of heat treatment effect on springback in v-bending. 2008.

[47] Lee, J.; H.J. Bong; Y.-S. Lee; D. Kim; M.-G. Lee. Pulsed Electric Current V-Bending Springback of AZ31B Magnesium Alloy Sheets. Metallurgical and Materials Transactions A, 2019. 50. (6): 2720-2731.

[48] Ao, D.; X. Chu; Y. Yang; S. Lin; J. Gao. Effect of electropulsing on springback during V-bending of Ti-6Al-4V titanium alloy sheet. The International Journal of Advanced Manufacturing Technology, 2018. 96. (9-12): 3197-3207.

[49] Chu, X.-R.; L. Wang; S.-X. Lin; Z.-M. Yue; J. Gao. Experimental Investigation on Formability of AZ31B Magnesium Alloy V-Bending Under Pulse Current. Acta Metallurgica Sinica (English Letters), 2018. 31. (12): 1249-1257.

[50] Zhao, Y.; L. Peng; X. Lai. Influence of the electric pulse on springback during stretch U-bending of Ti6Al4V titanium alloy sheets. Journal of Materials Processing Technology, 2018. 261. 12-23.

[51] Cinar, Z.; M. Asmael; Q. Zeeshan; B. Safaei. Effect of springback on A6061 sheet metal bending: a review. J Kejuruteraan, 2021. 33. (1): 13-26.

[52] Rao, V.R.; N. Ramanaiah; M. Sarcar. Optimization of volumetric wear rate of AA7075-TiC Metal Matrix Composite By Using Taguchi technique. Jordan Journal of Mechanical and Industrial Engineering, 2016. 10. (3).

[53] Groover, M.P., Fundamentals of modern manufacturing: materials, processes and systems, 4th ed. 4th ed. 2010. 1025.

[54] Karaağaç, İ. The Evaluation of Process Parameters on Springback in V-bending Using the Flexforming Process. Materials Research, 2017. 20. (5): 1291-1299.

[55] Ogawa, T.; A. Hirahara; F. Yoshida. Reduction of Springback of Sheet Metals by Bottoming. in AIP Conference Proceedings. 2010. American Institute of Physics.

[56] Cruz, D.J.; M.R. Barbosa; A.D. Santos; S.S. Miranda; R.L. Amaral. Application of Machine Learning to Bending Processes and Material Identification. Metals, 2021. 11. (9): 1418.

[57] Adnan, M.F.; A.B. Abdullah; Z. Samad. Springback behavior of AA6061 with non-uniform thickness section using Taguchi Method. The International Journal of Advanced Manufacturing Technology, 2017. 89. 2041-2052.

[58] Dev, G.P.; P.S. Livingston; M. Shunmuganathan; R. Surendar; A. Subramanian; A. Christopher; K. Ganesh. Analysis of 6061 Aluminium Alloy Sheet Metal Bending Process for Various Thickness Using Finite Element Modelling. International Journal of Theoretical and Applied Mathematics, 2016. 2. (2): 93-99.

[59] Montgomery, D.C., Design and analysis of experiments. 2017: John wiley & sons.

[60] Nasir, T.; M. Asmaela; Q. Zeeshana; D. Solyali. Applications of Machine Learning to Friction Stir Welding Process Optimization. Jurnal Kejuruteraan, 2020. 32. (1): 171-186.

[61] Chakraborty, T.; A.K. Chakraborty; S. Chattopadhyay. A novel distribution-free hybrid regression model for manufacturing process efficiency improvement. Journal of Computational and Applied Mathematics, 2019. 362. 130-142.

[62] Maind, S.B.; P. Wankar. Research paper on basic of artificial neural network. International Journal on Recent and Innovation Trends in Computing and Communication, 2014. 2. (1): 96-100.

[63] Bishop, C.M., Pattern recognition and machine learning. 2006: springer.

[64] Nasrollahi, V.; B. Arezoo. Prediction of springback in sheet metal components with holes on the bending area, using experiments, finite element and neural networks. Materials & Design, 2012. 36. 331-336.

[65] Teimouri, R.; H. Baseri; B. Rahmani; M. Bakhshi-Jooybari. Modeling and optimization of spring-back in bending process using multiple regression analysis and neural computation. International Journal of Material Forming, 2012. 7. (2): 167-178.

[66] Sathish, T. GAC-ANN Technique for Prediction of Spring Back Effect in Wipe Bending Process of Sheet Metal. Materials Today: Proceedings, 2018. 5. (6): 14448-14457.

[67] Kazan, R.; M. Fırat; A.E. Tiryaki. Prediction of springback in wipe-bending process of sheet metal using neural network. Materials & design, 2009. 30. (2): 418-423.

[68] Liu, W.; Q. Liu; F. Ruan; Z. Liang; H. Qiu. Springback prediction for sheet metal forming based on GA-ANN technology. Journal of Materials Processing Technology, 2007. 187. 227-231.

[69] Kayri, M. Predictive Abilities of Bayesian Regularization and Levenberg–Marquardt Algorithms in Artificial Neural Networks: A Comparative Empirical Study on Social Data. Mathematical and Computational Applications, 2016. 21. (2).

[70] Narayanasamy, R.; P. Padmanabhan. Comparison of regression and artificial neural network model for the prediction of springback during air bending process of interstitial free steel sheet. Journal of Intelligent Manufacturing, 2010. 23. (3): 357-364.

[71] Melo, A.P.; M. Fossati; R.S. Versage; M.J. Sorgato; V.A. Scalco; R. Lamberts. Development and analysis of a metamodel to represent the thermal behavior of naturally ventilated and artificially air-conditioned residential buildings. Energy and Buildings, 2016. 112. 209-221.

[72] Du, Z.; Y. Hu; N.A. Buttar. Analysis of mechanical properties for tea stem using grey relational analysis coupled with multiple linear regression. Scientia Horticulturae, 2020. 260. 108886.

[73] Candon, M.; M. Esposito; H. Fayek; O. Levinski; S. Koschel; N. Joseph; R. Carrese; P. Marzocca. Advanced multi-input system identification for next generation aircraft loads monitoring using linear regression, neural networks and deep learning. Mechanical Systems and Signal Processing, 2022. 171. 108809.

[74] özdemir, M. Optimization of Spring Back in Air V Bending Processing using Taguchi and RSM Method. Mechanics, 2020. 26. (1): 73-81.

[75] Muthu Krishnan, M.; J. Maniraj; R. Deepak; K. Anganan. Prediction of optimum welding parameters for FSW of aluminium alloys AA6063 and A319 using RSM and ANN. Materials Today: Proceedings, 2018. 5. (1, Part 1): 716-723.