Springback trends with different process parameters and with the mechanical properties of three selected metals.

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Abstract

Products or components manufactured by the sheet metal process are indispensable in this contemporary era, from daily-used metal jars to high-tech air vehicles. Nonetheless, there are a variety of sheet metal manufacturing processes for fabricating these goods; the air-bending sheet metal process is one of the most commonly conducted methods among those. After air bending, commonly used metals — Mild Steel, Aluminum, and Stainless Steel — tend to demonstrate an unwanted characteristic called springback, which requires being controlled to produce extremely precise parts. Therefore, this study aimed to develop an empirical model that would improve springback prediction which would ultimately assist in minimizing the springback effect in bending operations. Moreover, exploring springback trends with process-related parameters and metal's mechanical properties was also the goal of this work. To achieve objectives thoroughly, several methodological approaches were incorporated sequentially: Box-Behnken experimental design, experimental data collection, conducting an ANOVA test, empirical model selection, model development, and model validation. For pursuing these approaches, the Design Expert® software, Universal Testing Machine, and Bevel Protector were utilized. Finally. in the validation phase, it was found that the developed linear models were able to prognosis springback with acceptable errors. From that mathematical model, springback trends with process-related parameters were explored. Moreover, that mathematical model was also useful revealing springback trends with proven mechanical properties of selected metals. Overall, this study provides a wider view for observing springback trends with different factors.

Keywords: Air bending; Springback; Springback trends.

1. Introduction

Products or components manufactured by sheet metal are indispensable in this contemporary era, from daily-used metal jars to high-tech air vehicles, including automobile panels, airplane skins, cans for beverages, and frames for electronic devices [1]. As a result, the sheet metal process is incorporated in many industries — especially in aircraft, automotive, food, and home appliances [2]. These industries favor sheet metal fabrication, particularly the air-bending process, for its many significance [3]. Firstly, air-bending is extremely inexpensive and versatile as it permits the fabrication of a vast range of bend angle configurations to be formed with the same set of instruments [4] [5]. Secondly, the air-bending method gives the flexibility required for manufacturing numbers. For instance, it may gratify the need to create decent parts even with a batch size of just one [5]. Thirdly, it is appropriate for sheet components with complicated, curved faces [6]. Fourthly, it requires a lower bending force than other bending modes, such as coining and bottoming [7]. Therefore, there are several significant air-bending sheet metal processes in manufacturing industries.

After understanding the significance of the air-bending sheet metal process from the aforementioned paragraph, the readers of this article may be curious to know what air-bending exactly means. Air-bending is a major conventional sheet-metal bending technique [8] [9], which involves using a punch tip to press a piece of metal — both thin and thick [10] — into a die, while leaving air between the metal and the die. This process is also known as the three-point bending process

[4], because the die touches the two points of the specimen and the punch tip touches the specimen in the middle with one more point. Like other bending processes, the air-bending technique has one crucial undesired feature which is springback [11] — defined as an elastically driven shift in the shape of a component after forming [12]. In other words, springback happens, generally speaking, in metal forming due to the primarily elastic recovery of material following the removal of the punch force [13] [14]. Since the bottoming is nonexistent in air-bending, the amount of springback is high [4]. This springback may produce substantial shape deformities in the following natural shaping stage. It is therefore vital to understand lucidly which elements affect the springback, in order to be capable of estimating the amount of the springback [15] and prevent defects. From the many previous scientific studies, it is already known that springback characteristic is impacted by several parameters such as strain hardening exponent, coating thickness, die opening, die radius, punch radius, punch travel, punch velocity [16], sheet thickness, tooling shape, lubrication conditions, material qualities, elastic modulus, and so on [17]. Among all, elastic modulus is a significant factor. Because higher elastic modulus materials are denser and stiffer, they can withstand large loads without deforming. In contrast, rubber and other materials having a lower elastic modulus distort quickly but regain their shape almost as quickly. Thus, the lower the elastic modulus, the higher the springback.

There were many springback research works were carried out by several scholars for the air-bending process. One background work on air-bending in DP600 sheet material by Ozdemir showed that as the punch tip radius rose, the springback value increased; on the other hand, when the sheet thickness increased, the springback value reduced [18]. In addition to that, it was discovered by Gupta et al. during air-bending of electro-galvanized CR4 steel that springback increased with the increase in the width of the die for every punch journey — where the flexible die width was varied but die radius, punch radius, and punch speed were maintained the same [19]. One more study by Thipprakmas et al. explored the influence of process parameters on springback in V-bending processes, by utilizing the finite element method. The findings demonstrated that material thickness had a large impact on springback and experimental validation revealed excellent agreement between finite element simulation and real findings [20]. Another finite element method based research along experimental test was done by Xie, where it was demonstrated that springback in the air bending process rose with the punch displacement, punch radius, and die spread increased [21]. Further, Garcia-Romeu et al. depicted that springback was related to bending angle and sheet thickness. It was also noted that the bigger the yielding stress was, the bigger the springback amount was [22]. Furthermore, Buang et al. found that higher yield stress, it caused a larger springback; the springback decreasing with Young's modulus increased; and thicker materials had less springback [23].

From the literature, it is clear that springback depends on materials' elastic modulus, sheet thickness, die width, and bending angle. However, most of the parameters influence on springback was not found in single research work. Put differently, none of the work attempted to incorporate all of these matrices together to see the outcomes from a different view, such as the sequence of the springback sensitivity order from highest to lowest. Moreover, hardly any paper was found where a mathematical equation was developed for all of these matrices. It can be assumed that the reason behind this could be the difficulty of blending the mechanical properties with the process parameters. Nonetheless, conventional springback theory might not help to blend these, the curve-fitting technique may be helpful to combine the mechanical properties of the specimen and process parameters to engender a mathematical equation. Therefore, in this work, one objective of this research was to develop an empirical mathematical model for prognosis springback in light of a curve-fitting equation where mechanical and process parameters exist. The second goal of this work is to order the springback sensitivity from highest to lowest for different matrices. The third purpose of this study is to seek trends of springback with process parameters and metal's mechanical properties.

The rest of this paper is organized as follows: ***Section 2*** shows methods; ***Section 3*** depicts analyses and findings; ***Section 4*** illustrates discussion; and finally, ***Section 5*** presents a conclusion.

2. Methods

This study required to conduct many things to follow sequentially and all of them are visually illustrated by a flowchart in ***Fig. 1***. Hopefully, this flowchart makes the study's methods demystify for potential readers.

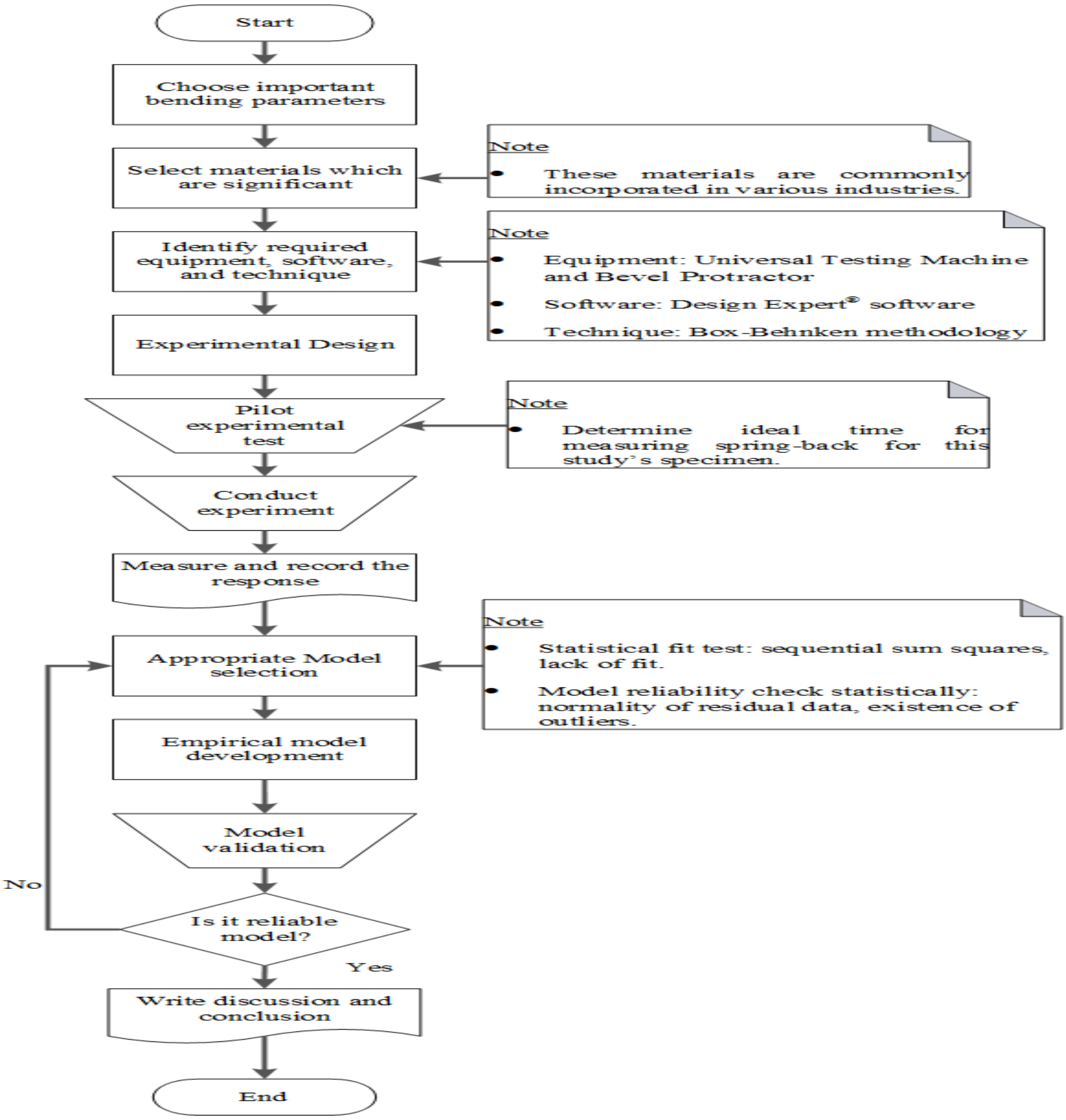

Fig. 1: *Sequences of this study.*

2.1 Study's factors specifying

There are tremendous parameters that can influence springback [16]. Thus, first and foremost, the study's parameters needed to be selected which were going to be investigated. In this study, those parameters were materials, initial bend angles, punch radius to sheet thickness ratio (P.R/S.T), and die gaps.

2.2 Materials

Appropriate materials section is a critical criterion for pursuing research pertinent to springback characteristics. The first thing that should be mentioned is that Mild Steel S355 grade is one of the commonly used materials for rod, beam, and other important structural applications [24]. Another vital material that could be considered for this research was Stainless Steel 304 — a widely used Stainless Steel in different kinds of industries for several purposes [25]. One more useful material is Aluminum 7050 alloy, particularly in the aerospace industry [26], was also the point of concern of this study. Therefore, those three materials widely utilized in industrial applications were chosen in this research: Mild Steel (S355 grade with 0.20% carbon), Stainless Steel 304 (comprising 18% chromium and 0.11% carbon), and Aluminum 7050 alloy (containing 89% aluminum). Furthermore, it should be mentioned that sheets of these materials were examined at three distinct thicknesses — 1 millimeter, 1.5 millimeters, and 2 millimeters. Because materials of varying compositions and thicknesses were incorporated in this comprehensive study in order to ensure a robust exploration of the impact of diverse material properties on springback. Moreover, to ensure precision in extracting the desired size from the bulk material, each sheet was carefully prepared to the exact dimensions of 150 millimeter in length and 30 millimeter in width, by using a hydraulic cutter.

2.3 Necessary tools: Universal Testing Machine and Design Expert® software

After choosing the desired materials, proper equipment selection is another immediate indispensable step for any experimental research. In this experiment, a Universal Testing Machine —is a very popular and versatile option for testing materials and components [27] — was used. It is commonly used in both research and quality control to provide engineering property data on a wide range of materials [28]. The Universal Testing Machine was incorporated into this study to make the bend of aforementioned three metals. ***Fig. 2*** delineates the Universal Testing Machine, which supported the experiment. In addition to this, ***Fig. 3*** depicts the photographic view of the experimental setup for air bending of specimens. Another hardware equipment was the Bevel Protector — it is a tool for measuring angles [29].

Fig. 2: *A real view of experimental setup under a Universal Testing Machine for air-bending.*

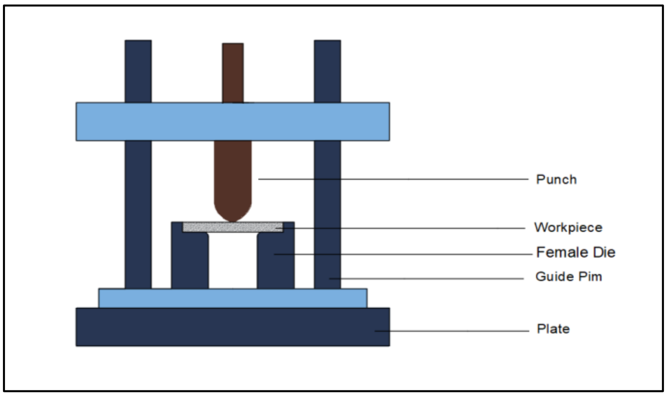

Fig. 3: *A photographic view of the experimental setup for air-bending.*

Apart from the Universal Testing Machine and Bevel Protector, another vital tool for this study was the Design Expert® software — developed by State Ease [30]. It is one of the most extensively used programs [31]. This software provided the least number of Runs — the number of experiments that must be carried out according to the selected experimental design — required in light of given factors [30]. In this investigation, there were several variable factors, delineated in ***Table 1***, as well as constant factors, illustrated in ***Table 2***, which were inserted into Design Expert® software (version 13).

Table 1 *Experimental variables and their corresponding numeric codes.*

Process factors	***Levels of each factor***		
	1	***2***	***3***
Die gap	65	70	75
P.R/S.T	5	10	15
Set angle	120	135	150
Material	Mild Steel S355 grade	Aluminum7050 alloy	Stainless Steel 304

Table 2 *Four constant factors for one response factor springback.*

Constant factor	***Corresponding value***
Die radius	5 millimeters
Initial punching force	500 Newton
Punch velocity	0.8
Sheet dimension	150 millimeters × 30 millimeters

2.4 Response surface methodology

Response Surface Methodology is a collection of statistical design and numerical optimization techniques used to optimize processes [32]. To put it another way, it is a general strategy for combining designed experiments and regression analysis to explore the relationship between one or more response variables and a set of factors that are thought to affect the responses [33] [34]. In this rummage, by using the Box-Behnken methodology — one sort of Response Surface Methodology — as a design matrix, Design Expert® software demonstrated that fifty-one individual Runs were necessary based on ***Table 1*** and ***Table 2***. In that design matrix, both the actual and coded levels for numerical and categorical factors were specified. At this moment, it needs to be clarified that if all four factors were numerical, a total of twenty-nine Runs would be required according to Box-Behnken Design; however, one categorical factor — materials — exists in this study which elevated total Runs from twenty-nine to fifty-one.

It should also be mentioned that among all the Response Surface Methodology methods for a higher number of variables, Box-Behnken Design and Central Composite Design are the most appropriate design methodologies. Between those two methods, the Box-Behnken Design algorithm was implemented in this research, a component of Response Surface Methodology [35] [36], as it required fewer Runs than Central Composite Design which was fifty-seven. Box-Behnken Design algorithm can generate higher-order response surfaces using fewer required Runs than a normal factorial technique [37]. Therefore, Box-Behnken Design was not only a time-effective but also a cost-efficient technique for this research.

2.5 Experimental testing procedures via a Universal Testing Machine

Since materials and necessary equipment were chosen, thus those experimental fifty-one Runs could be performed in the lab. Basically, in this rummage, a Universal Testing Machine bents sheet metal by using two adjustable dies of the same diameter but different punches which is depictured in previous ***Fig 2***. The desired die gap between two adjustable dies was achieved by T-slot manipulation — fastened with nuts and bolts. Throughout the experiment, the punch traveled and set angle both were governed by an equation ***(i)***, which helped monitor punching force and velocity. In equation ***(i)***, ***h*** stands for punch travel distance, ***d*** represents die gap, and the symbol $\boldsymbol{\theta_i}$ indicates the initial angle.

$$\boldsymbol{h = \frac{d}{2\,tan\left(\frac{\theta i}{2}\right)}} \qquad \textbf{(i)}$$

Punch travel varied with die gap and set angle, for obtaining several data — all of those fifty-one distinct Runs' experiments were conducted indiscriminately to diminish any systematic inaccuracies or noise within the experiment. Each time, the punch travel was verified by using a laser light. Moreover, sheet specimens were bent at three predetermined angles — 120, 135, and 150 degrees — throughout the experiments. During the process, upon the release of the punching force, the specimen experienced elastic recovery. Thus, the initial given predetermined set angle did not remain anymore and a new angle of that specimen was formed — it is called the 'final bend angle' in this study. Three deformed specimens of each three materials namely Stainless Steel 304, Mild Steel S355 grade, and Aluminum 7050 alloy are depicted in ***Fig. 4*** after 32 hours of punch force removal.

Fig. 4: *deformed specimens of Stainless Steel 304, Mild Steel S355 grade, and Aluminum 7050 alloy.*

Afterward, it was time to measure that final bend angle. But the question was: how could that angle measurement be conducted? Two possible ways: excluded angle or included angle measurement, depicted in ***Fig. 5a*** — both are complementary angles to each other. The excluded angle is the measurement between the outside part surface after bending and its idle straight surface prior to bend [38], demonstrated in ***Fig. 5b***. The included angle, on the contrary, is the measurement between the inside surfaces of a part [39], illustrated in ***Fig. 5c***. Since one approach needed to be chosen for determining angles, included angle measurement approach was chosen for this study. Here, equation ***(ii),*** represents the angular springback formula [39] [18], where θ_i is the initial bending set angle before load removal and θ_f is the final bend angle after load removal, and $\Delta\theta$ stands for angular springback.

$$\Delta\theta = \theta_f - \theta_i \qquad \text{(ii)}$$
$$\theta_f > \theta_i$$

The final bend angle (θ_f) was measured carefully with a bevel protractor. Therefore, subtracting the set angle from that measured final bend angle which eventually gave the angular magnitude of springback — shown in ***Fig 5d***.

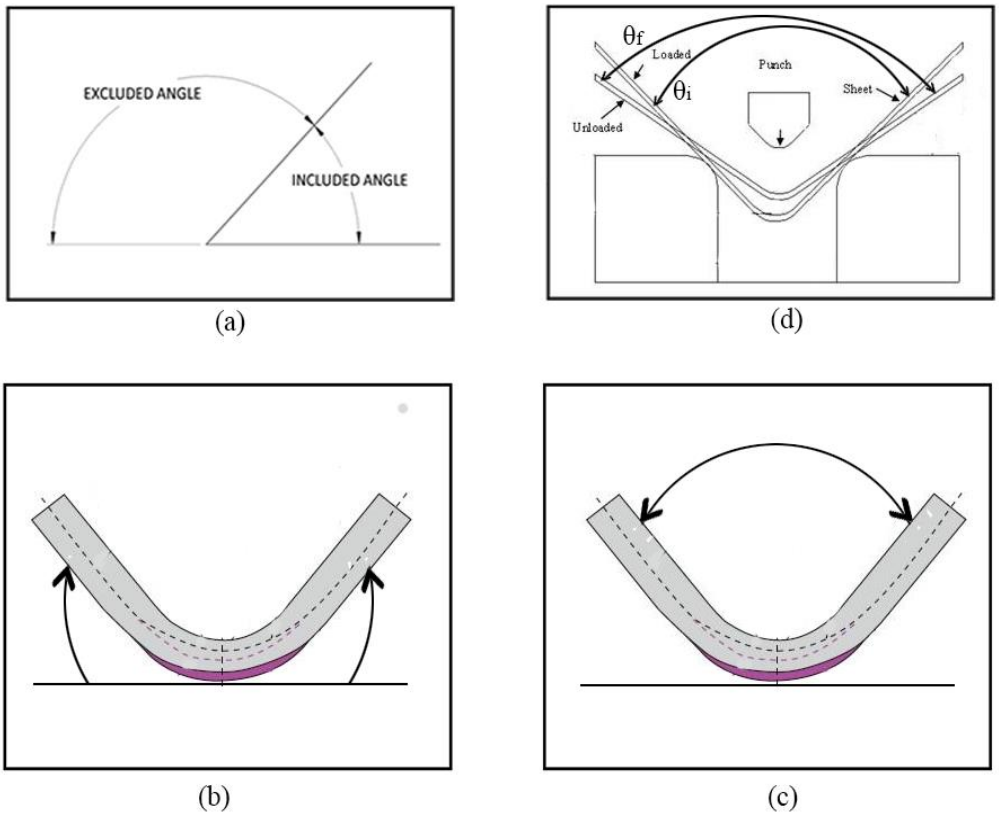

Fig. 5: *demonstration of initial bend angle and final bend angle by line art.*

Additionally, it needs to be mentioned that lubrication during the air-bending process significantly affects both punch force, die, and springback compared to the dry conditions [40]. Hence, lubrication was excluded from the experiment in order to acquire an actual scenario of those factors without affecting the outcomes, therefore, a rational conclusion could be made from this experiment.

2.6 Pilot test

In the pilot run, experiments were conducted using all parameters, including die gap, punch radius to sheet thickness ratio, material, and set angle. The result from the pilot run was thoroughly analyzed to detect any anomaly or effect of noises. Thus, from the pilot run, it was decided to conduct three trials for each experimental setup to mitigate noise and errors effectively. Additionally, measures were taken such as introducing a laser at a proper height to ensure correct punch travel and set angle alignment, thereby optimizing experimental conditions for accurate springback measurements. Apart from this, it needs to be addressed that final bend angles were subsequently measured at 8, 16, 24, 32, and 40 hours of post bending, in order to observe what the right time interval was for measuring the final spring-back angle of the parts. Since there was no further springback angle increment after 32 hours; therefore, a decision was made that all springback would be measured after 32 hours during the experimental data collection phase of this study.

2.7 Appropriate model selection

In this phase of the research, an appropriate response model for the response factor was essential for the collected data from the experiment. There are several models, for instance, linear, first-order interaction (2FI), quadratic, and cubic [41]. Selecting the best model among those models involves comparing how well each model fits the data — it is known as the Fit Test from the statistical point of view. Analysis of variance (ANOVA) is a widely used set of statistical models aimed at comparing variation between data. ANOVA models include the partitioning of the sum of squares, lack-of-fit tests [42], and R-square test [43]. Statistical tools namely Sequential Model Sum of Squares, Lack of Fit Test, and performance of different regression models play crucial roles in this selection process.

There are three types of Sum of Squares: Type I, Type II, and Type III. The analysis of variance employs these sums. The Type I sum of squares is calculated sequentially, whereas the Type II and III Sum of Squares are computed partially. In Type I, the elements are evaluated sequentially according to their order in the model [44]. In this study, the Type I Sum of Squares was considered. Because the Sequential Model Sum of Squares assists in figuring out the gradual contribution of each term (linear, interaction, quadratic, cubic) when they are introduced to the model in a specified order [45].

The lack of Fit Test is useful for finding model inadequacies [42] [46]. The lack-of-fit test compares the unbiased estimate of variance to the estimated variance from noise within data. Potentially a lack-of-fit test could be utilized to decide which part (model or data) ought to be prioritized for refinement. A model passing the lack-of-fit test implies that the noise in the experimental data is restricting the precision of the measured values [42]. Therefore, a model requires to unable to pass the lack of fit test to have significance of the model based on acquired data correctness. For this, the P-value of the lack of fit test for the model must be more than 0.05 — the accepted criterion. On the contrary, if the P-value of the lack of fit test for the model is less than 0.05, the model is insignificant — the rejected criterion [42].

There are two metrics used to assess the effectiveness of linear regression models: adjusted R-squared and R-squared. R-squared is a metric that quantifies the proximity of the data points to the regression line that has been fitted [47]. The value ranges from 0 to 1, or from 0% to 100%. An R-squared value of 1 or 100% indicates that all variations in the dependent variable can be entirely accounted for by variations in the independent variable(s). It is vital to emphasize that a small R^2 value does not indicate a weak association, nor does a big R^2 value ensure a strong relationship [47]. An R-squared value of 0 or 0% indicates that the independent variable(s) do not account for any of the variability seen in the response variable. Conversely, the concept behind adjusted R-squared is to consider the inclusion of factors that do not substantially enhance the model. As more predictor factors are included in the model, the R-squared value will often enhance, even if those variables have only a weak association with the response variable. This might provide a deceptive perception of enhancing the accuracy of the model. The adjusted R-squared value is always lower than or equal to the R-squared value.

Furthermore, in order to provide statistical reliability for the recherche model, several plots would be considered: the normality plot, scatter diagram, and Box-Cox graph. First, the normal probability plot of residuals is used to assess the normality of the data. If the plotted points align closely with a straight line, the dataset can be considered to be normally distributed [48]. Second, a scatterplot is an effective tool for investigating connections among parameters, discerning relationships beyond facile correlations, and routing more accurate data science practices [49]. Third, the Box-Cox transformation technique is used to enhance the compression of spatial data by promoting normalcy, efficiently lowering spectral dimensions, and eliminating mistakes in spatial values [50] [51]. Thus, if the data need to be transformed from non-normality to normality, the Box-Cox could be utilized. Apart from that, if the data are already normally distributed, the Box-Cox plot will indicate that no transformation is needed. So, it can be a cross-checking technique for reinforcement that the collected data has normality. A question might be raised about how it could be understood that there is no metamorphosis needed. Well, lambda (λ) — a transformation parameter in Box-Cox [52]— values help with this. There are different standard transformations for different lambda values: lambda values of -3, -2, -1, -0.5, 0, 0.5, 1, 2, and 3 represent inverse cubic, inverse square, inverse, inverse root square, logarithmic, root square, no transformation, square, and cubic, respectively [53] [54]. So, a lambda value of one indicates that no conversion is required since the data are already normally distributed.

2.8 Empirical model development

After the selection of a model, it might be the time for development of an empirical model — this kind of model is only supported by experimental data [55]. So, those are not based on any specific theory [56]. To put it another way, empirical models are based on correlations obtained from the analysis of experimental data [57]. Empirical models that have been used for curve fitting processes to generalize the results of experiments [58] [59]. The curve fitting may be achieved by suitable methods to fit polynomials or other functions [58]. It is mandatory to mention that an empirical model can provide trustworthy results when it is based on a substantial amount of test data [60]. In this study, a particular response model was chosen in an earlier phase, and in light of that model, the final empirical model was developed with the help of Design Expert® software.

2.9 Model validation

In experimental validation, the response factor — angular springback — was forecasted in light of process parameters by using the developed empirical model for all three picked distinguished materials. Subsequently, actual angular springback was measured for the same magnitude of those four independent factors. Eventually, errors were calculated by following equation ***(iii)***.

$$\textbf{Error}\ (\%) = \frac{\textbf{Actual value} - \textbf{Predicted value}}{\textbf{Actual value}} \times \mathbf{100} \qquad \textbf{(iii)}$$

3. Analyses and findings

All the phrases of this study's analysis have been sequentially described: experimental data collection, model selection, model development, 95% confidence interval, model validation, and finally model optimization.

3.1 Experimental data collected via using a Universal Testing Machine

All of those recorded specific combinations derived from these experimental fifty-one Runs are detailed in ***Table 3***, where the magnitude of four independent variables and the corresponding value of one dependent variable for each run are shown. These experimental data were imported into Design Expert® (version 13) so that an appropriate response model could be chosen in light of necessary statistical tests.

Table 3 *Experimental design matrix of four actual independent process variables with the experimental response of springback.*

Std	***Run***	***Factor A: Die gap (millimeters)***	***Factor B: P.R/S.T***	***Factor C: Set Angle (Degree)***	***Factor D: Material***	***Response Springback (degree)***
2	1	75	5	135	Mild Steel	3
40	2	75	10	120	Stainless Steel	10
48	3	70	10	135	Stainless Steel	8
31	4	70	10	135	Aluminum	10
30	5	70	10	135	Aluminum	11
37	6	65	15	135	Stainless Steel	13
32	7	70	10	135	Aluminum	8
29	8	70	15	150	Aluminum	6
10	9	70	15	120	Mild Steel	11
47	10	70	10	135	Stainless Steel	5
36	11	75	5	135	Stainless Steel	6
3	12	65	15	135	Mild Steel	6
46	13	70	15	150	Stainless Steel	7
38	14	75	15	135	Stainless Steel	14
7	15	65	10	150	Mild Steel	5
43	16	70	5	120	Stainless Steel	8
21	17	75	15	135	Aluminum	12
35	18	65	5	135	Stainless Steel	4
45	19	70	5	150	Stainless Steel	5
24	20	65	10	150	Aluminum	9
41	21	65	10	150	Stainless Steel	5
39	22	65	10	120	Stainless Steel	9
44	23	70	15	120	Stainless Steel	10
34	24	70	10	135	Aluminum	9
23	25	75	10	120	Aluminum	11
17	26	70	10	135	Mild Steel	11
50	27	70	10	135	Stainless Steel	5
19	28	75	5	135	Aluminum	7
6	29	75	10	120	Mild Steel	13
11	30	70	5	150	Mild Steel	2
13	31	70	10	135	Mild Steel	7
49	32	70	10	135	Stainless Steel	10
33	33	70	10	135	Aluminum	12
4	34	75	15	135	Mild Steel	6
1	35	65	5	135	Mild Steel	4
12	36	70	15	150	Mild Steel	12
27	37	70	15	120	Aluminum	16
9	38	70	5	120	Mild Steel	5
28	39	70	5	150	Aluminum	3
42	40	75	10	150	Stainless Steel	5
20	41	65	15	135	Aluminum	10
16	42	70	10	135	Mild Steel	9
5	43	65	10	120	Mild Steel	13
25	44	75	10	150	Aluminum	7
8	45	75	10	150	Mild Steel	11

26	46	70	5	120	Aluminum	7
18	47	65	5	135	Aluminum	4
14	48	70	10	135	Mild Steel	11
51	49	70	10	135	Stainless Steel	4
15	50	70	10	135	Mild Steel	10
22	51	65	10	120	Aluminum	12

3.2 Appropriate model selection

To determine the best model based on inserted experimental data, a statistical Fit Test was necessitated to perform. Albeit there were many models — linear, first-order interaction (2FI), quadratic, and cubic — in the Design Expert® program, the linear model was suggested by the software after incorporating a test namely the Sequential Model of Sum of Squares. Because the linear model was not only significant (Sequential p-value less than 0.05) but also had the least sequential p-value among all models in that test. The outcomes of the Sequential Model of the Sum of Squares test are depicted in ***Table 4***.

Table 4 *Sequential Model Sum of Squares*

Source	*Sum of Squares*	*Degree of freedom*	*Mean Square*	*F-value*	*p-value*	*Comment*
Mean vs Total	3475.31	1	3475.31			
Linear vs Mean	**297.12**	**5**	**59.42**	**10.50**	**< 0.0001**	**Suggested**
2FI vs Linear	7.92	9	0.8796	0.1284	0.9986	
Quadratic vs 2FI	25.10	3	8.37	1.25	0.3087	
Cubic vs Quadratic	109.98	15	7.33	1.18	0.3630	Aliased
Residual	111.57	18	6.20			
Total	4027.00	51	78.96			

Another test as a complete part of the statistical Fit Test is Lack of Fit. It was also conducted in this study's experimental data to cross-check whether the linear model was appropriate or not. The selected linear model had an insignificant Lack-of-Fit with a p-value of 0.184, illustrated in ***Table 5***, which was above the 0.05 threshold, indicating that the model fitted the data well without significant inconsistency. This criterion was crucial as it ensured the model's robustness and reliability in capturing the underlying data structure.

Table 5 *Lack of Fit Tests*

Source	*Sum of Squares*	*Degree of freedom*	*Mean Square*	*F-value*	*p-value*	*Comment*
Linear	**208.16**	**33**	**6.31**	**1.63**	**0.1843**	**Suggested**
2FI	200.25	24	8.34	2.16	0.0831	
Quadratic	175.14	21	8.34	2.16	0.0856	
Cubic	65.17	6	10.86	2.81	0.0604	Aliased
Pure Error	46.40	12	3.87			

The performance of different regression models was also evaluated and displayed in ***Table 6*** taking into account some metrics: standard deviation (Std. Dev.), coefficient of determination (R^2), adjusted R^2, predicted R^2, and the predicted residual error sum of squares (PRESS). These values helped in comparing the models and selecting the most appropriate one. After comparing those models, a linear model was suggested due to its balanced performance across various metrics. It had a relatively low standard deviation (2.38), indicating good precision. Moreover, the R^2 value of 0.5386 betokened a reasonable amount of variation explained by the model. The adjusted R^2 (0.4873) and predicted R^2 (0.4010) were both positive and higher than those of the more complex models. Besides, The Predicted

R^2 of 0.4010 was in reasonable agreement with the Adjusted R^2 of 0.4873; i.e. the difference was less than 0.2, indicating better predictive power and generalizability for the minimum variety between them. Furthermore, the PRESS value (330.44) was the lowest among all models, suggesting that the linear model had the best predictive accuracy. These factors made the linear model the most suitable choice, balancing simplicity and effectiveness.

Table 6 *Performance of different regression models*

Source	*Std. Dev.*	*R^2*	*Adjusted R^2*	*Predicted R^2*	*PRESS*	*Comment*
Linear	2.38	0.5386	0.4873	0.4010	330.44	Suggested
2FI	2.62	0.5529	0.3791	-0.0175	561.33	
Quadratic	2.59	0.5984	0.3916	-0.1066	610.49	
Cubic	2.49	0.7978	0.4383	-3.3838	2418.50	Aliased

This statistical Fit Test is summarized in ***Table 7*** where the linear model had a Sequential p-value well below the required 0.05 threshold, indicating that the model terms significantly contribute to the fit. Additionally, the model was not aliased, making it faithful. Another aforementioned criterion was an insignificant p-value — greater than 0.05 — for the Lack of Fit test and the linear model also belonged to that condition. Furthermore, the linear model also demonstrated the close values between Adjusted R^2 and Predicted R^2, with scores of 0.4873 and 0.4010, respectively. These values indicate the best balance of fit and predictive performance by the linear model for this study's experimental data. In comparison, the first-order interaction (2FI), quadratic, and cubic models exhibited poor closeness between Adjusted R^2 and Predicted R^2 values, suggesting overfitting and impecunious predictive performance.

Table 7 *Fit test summary*

Source	*Sequential p-value*	*Lack of Fit p-value*	*Adjusted R^2*	*Predicted R^2*	*Comment*
Linear	**< 0.0001**	**0.1843**	**0.4873**	**0.4010**	**Suggested**
2FI	0.9986	0.0831	0.3791	-0.0175	
Quadratic	0.3087	0.0856	0.3916	-0.1066	
Cubic	0.3630	0.0604	0.4383	-3.3838	**Aliased**

Apart from that statistical Fit Test, the Normal Plot of the residuals graph — depicted in ***Fig 6*** — for the elected linear model conspicuously showed that the residuals closely follow a straight line, indicating they were approximately normally distributed. The points are symmetrically distributed around the line without significant outliers, suggesting fortuitous errors and reliable model predictions. The consistency of residuals across the range of predicted values indicates homoscedasticity, confirming that the variance of residuals was constant. This observation validated the use of the linear model, confirming its appropriateness for the data and indicating that no transformation of the response variable was necessary.

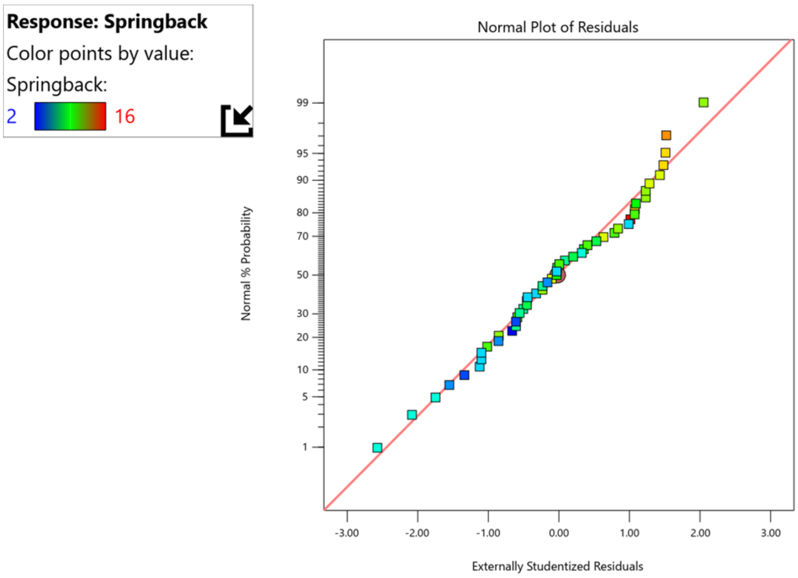

Fig. 6: *Statistical check for normality of residual data for selected linear model.*

Another thing is that the Residuals vs. Predicted graph — demonstrated in ***Fig 7*** — for the selected linear model delineates that the residuals were haphazardly scattered around the horizontal axis, indicating no systematic pattern. This randomness suggested that the model's predictions were unbiased and that the linear relationship was appropriate. Additionally, the spread of the residuals is consistent across all levels of predicted values, indicating homoscedasticity, meaning the variance of the residuals remains constant. There are no noticeable outliers, — arise due to mechanical faults, human error, or instrument error [61] — confirming that the model assumptions are met, and no transformation of the response variable was needed.

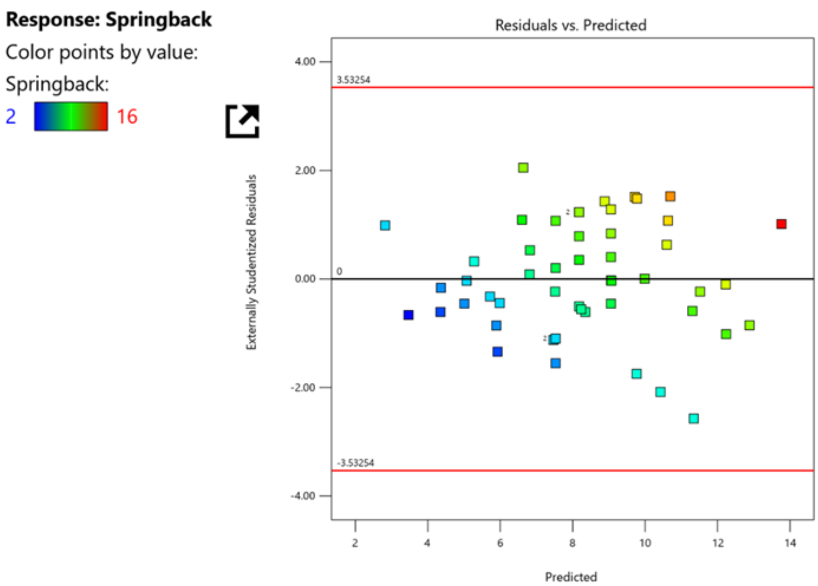

Fig. 7: *Scattered plot of Residuals vs Predicted data for selected linear model.*

The Box-Cox graph, delimitated in ***Fig 8***, for the recherche linear model, indicates that a Lambda value of 1 is appropriate, suggesting that no transformation of the response variable was necessary. The graph delimitates that the confidence interval for the optimal Lambda includes 1, confirming that the linear model without conversion was felicitous. This bolsters the assumption that the response variable assuaged the requirements for normality and homoscedasticity without any change of state. Consequently, the linear model with a Lambda value of 1 is validated as the best choice, ensuring accurate and verisimilar results.

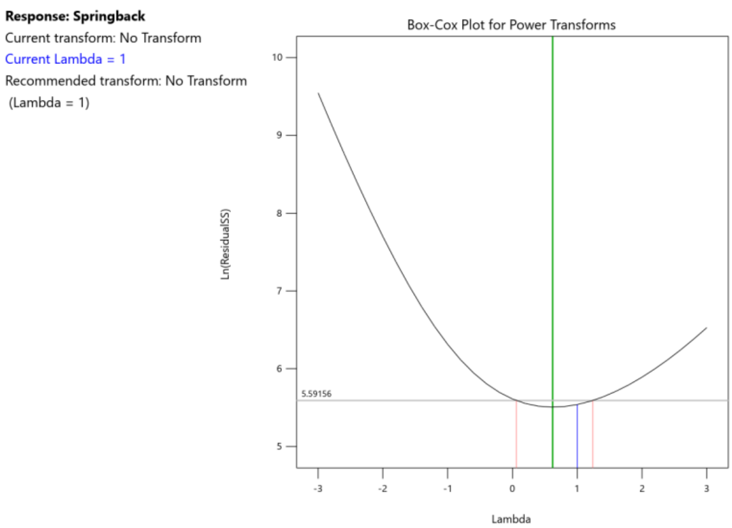

Fig. 8: The Box-Cox graph for the selected linear model.

3.3 Empirical model development

A relationship between the input parameters and the output parameter was developed in light of that selected linear model. Initially the relationship as a coded equation — expressed in equation ***(iv)*** — was developed by the Design Expert® program for divination springback based on several input factors.

$$\boldsymbol{Springback = 8.25 + 0.4583 \times A + 2.71 \times B - 2.00 \times C - 0.0784 \times D_1 + 0.8039 \times D_2} \quad \textbf{(iv)}$$

In equation ***(i)***, the intercept of 8.25 provides the baseline when all factors are at their reference levels. Die gap (A) and PR/ST (B) positively influence springback with a coefficient of 0.4583 and 2.71, respectively, while set angle (C) negatively affects springback having a coefficient of -2.00. For material types, -0.0784 signifies the effect of material being Mild Steel (coded as 1 for D_1 and 0 for D2), and 0.8039 signifies the effect of material being Aluminum (coded as 0 for D1 and 1 for D_2). When using Stainless Steel (SS), both dummy variables D_1 and D_2 were coded as -1, reflecting how springback differed compared to Mild Steel and Aluminum. It is luminous from this coded equation ***(iv)*** that springback has the most sensitivity for PR/ST (B) independent factor since it has the maximum coefficient among all.

In addition to that coded equation, actual equations could also be revealed from the Design Expert® program for each material. Actual equations of Mild Steel, Aluminum, and Stainless Steel are ***(v)***, ***(vi)***, and ***(vii)***, respectively.

The actual equation for Mild Steel:

$$\boldsymbol{Springback_{MS} = 14.34314 + 0.091667 \times Die\ Gap + 0.541667 \times P.R/S.T - 0.133333 \times Set\ Angle} \quad \textbf{(v)}$$

The actual equation for Aluminum:

$$\boldsymbol{Springback_{AL} = 15.22549 + 0.091667 \times Die\ Gap + 0.541667 \times P.R/S.T - 0.133333 \times Set\ Angle} \quad \textbf{(vi)}$$

The actual equation for Stainless Steel:

$$Springback_{SS} = 13.69608 + 0.091667 \times Die\ Gap + 0.541667 \times P.R/S.T - 0.133333 \times Set\ Angle \quad \textbf{(vii)}$$

3.4 Experimental validation of the developed models

In this phase of this study, experimental validation was executed for each material with the help of their corresponding actual equations. To clarify it for Mild Steel, 71.5 millimeters die gap, 8 ratios of P.R/S.T, and 135 degrees set angle were given during experimental validation; as a result, the Mild Steel specimen witnessed a 7-degree springback in the lab. Predicted springback, on the contrary, of that Mild Steel part was 7.23 degree by using actual springback equation ***(v)*** for the same process parameters. Therefore, the error was, technically speaking, -3.286% which was calculated by equation ***(iii)***. The first row of ***Table 8*** represents this scenario. Analogously, the second and third rows depicts the summary of the experimental validation settings for Aluminum and Stainless Steel. The results of the experiments also showed that the established model was credible, as the percentages of errors were excellently tinny.

Table 8 *Confirmation Experiment*

No. of Experiment	***Process Parameters***				***Response factor: Springback (degree)***		
	Die gap (mm)	***P.R/ S.T***	***Set Angle (degree)***	***Materials***	***Predicted***	***Actual***	***Error (%)***
1	71.5	8	135	Mild Steel	7.23	7	-3.286
2	74.5	12	125	Aluminum	11.89	12	0.917
3	68.5	6	145	Stainless Steel	3.89	4	2.750

4. Discussion

The aforementioned three equations ***(v), (vi),*** and ***(vii)*** have numerous insights. First, process-related insights are upheld below:

- From the equations, it can be inferred that if the die gap and punch radius to sheet thickness are constant, by then the bigger the initial set angle results the lower the springback. Although previously Garcia-Romeu et al. wrote that springback had a relation with bending angle [22], this study clearly shows how this relationship is connected. It reinforces Garcia-Romeu et al.'s work [22].

$$\boldsymbol{Springback \propto -Set\ Angle}$$

where the Die gap and P.R/S.T are held constant.

- In addition to this, if the initial bending angle and the punch radius to sheet thickness are considered constant, then another relation can be drawn between springback and die gap — a higher die gap leads to a larger springback. This outcome perfectly supports the findings of Gupta et al.'s [19] and Xie's [21] works — springback increased with the increase in the width of the die.

$$\boldsymbol{Springback \propto Die\ Gap}$$

where the Set angle and P.R/S.T are held constant.

- Further, similarly, the increment of punch radius to sheet thickness means raising the springback — if the die gap and the initial bending angle are stable. It has two implications.

Firstly, if the sheet thickness is considered constant, then it can be said that the rise of the punch tip radius results in greater springback. It supports findings of Xie's work [21]. Secondly, if the tip of the punch radius is considered constant, by then springback is supposed to be decreased with respect to the increment of sheet thickness. Both Thipprakmas et al. [20], and Garcia-Romeu et al. [22] wrote that sheet thickness had an impact on springback, but this study articulates how the relation is. These two implications from this study reinforce the outcomes of Ozdemir's study [18].

$$\boldsymbol{Springback \propto Tip\ of\ Punch\ Radius}$$

where the Set angle, die gap, and sheet thickness are held constant.

$$\boldsymbol{Springback \propto \frac{1}{Sheet\ thcikness}}$$

where the Set angle, die gap, and the tip of the punch radius are held constant.

- These equations are also helpful in understanding the sensitivity of the process factors on springback. While P.R/S.T is most sensitive process parameter pertinent to springback, die gap is less influential process factor.

Second, apart from these process parameters, these three equations together also have significance for unearthing insights pertinent to metal's mechanical properties. For this reason, at the beginning of this study, one categorical variable material was taken as one factor. Readers of this article may ask two questions: why was categorical material variable considered? why were the materials' properties — elastic modulus, yield strength, shear modulus, and tensile strength — not considered directly during data collection? Well, the mechanical properties of three selected metals are known and values are specific, for instance, the elastic modulus of Mild Steel S355, Stainless Steel, and Aluminum 7050 alloy are 210×10^3 MPa, 190×10^3 MPa, and 72×10^3 MPa, respectively. Therefore, if elastic modulus were considered as a factor, then these same elastic modulus values would input each of the corresponding materials for different Runs or Records in the data set. So, different mechanical properties — such as yield strength, shear modulus, and tensile strength — required more factors, resulting in an increase in the total number of factors but having the same corresponding values for each metal. Thus, without increment total factors but still having the ability to scrutinize mechanical characteristics, one categorical factor — material — could deal with this, because mechanical properties change when materials are different and so does springback.

Now, to show the mechanical properties' influence on springback, process parameter values need to be kept or inputted the same for three selected metals, so that the impact of process parameters does not exist while comparing the mechanical behaviors. In this case, values of the die gap, P.R/S.T, and set angle can be given as 70 millimeters, 10 ratios, 135 degrees, in sequence, for equations ***(v), (vi),*** and ***(vii).*** As a result, the corresponding springback for Mild Steel S355, Aluminum 7050 alloy, and Stainless Steel are 8.176545 degrees, 9.058895 degrees, and 7.529485 degrees obtained from equations ***(v), (vi),*** and ***(vii),*** in order. Actually, when the same inputs were given in three equations for process parameters, then the difference maker is the variable-free term — constant. The variable-free term for equations ***(v), (vi),*** and ***(vii)*** are 14.34314, 15.22549, and 13.69608, sequencially for Mild Steel S355, Aluminum 7050 alloy, and Stainless Steel 304. It can be inferred that these variable-free terms are different due to the different metal's mechanical properties.

- So, like above mentioned example, if values of the die gap, P.R/S.T, and set angle can be given as 70 millimeters, 10 ratios, 135 degrees, in sequence, for equations ***(v), (vi),*** and ***(vii).*** As a result, the corresponding springback for Mild Steel S355, Aluminum 7050 alloy, and Stainless

Steel are 8.176545 degrees, 9.058895 degrees, and 7.529485 degrees obtained from equations ***(v), (vi),*** and ***(vii),*** in order. Additionally, the yield strength of these metals has been taken from Solidworks material library which are 495 MPa, 275 MPa, and 206 MPa for Aluminum 7050 alloy, Mild Steel S355, and Stainless Steel 304, orderly. Therefore, although process parameters are identical for the three materials, the higher the metal's yield strength is, the greater the springback can happen. It supports Garcia-Romeu et al.'s study's outcomes [22] and Buang et al.'s findings [23]. ***Table 9*** depicts this relation. Apart from keeping calculated springback for the above example, variable-free term values are also written in this table to show that this relation will continue for any given value for process parameters but have to be identical for all materials to be logically compared.

Table 9 *relation between springback and yield strength when process parameters are held constant.*

	Aluminum 7050 alloy	***Mild Steel S355***	***Stainless Steel 304***
Calculated Springback (degree) from equations when die gap, P.R/S.T, and set angle are given as 70 millimeters, 10 ratios, 135 degrees, in sequence.	9.058895	8.176545	7.529485
Variable-free term from springback equations (v), (vi), and (vii)	15.22549	14.34314	13.69608
Yield Strenght (MPa)	495	275	206

- Similarly, the shear modulus of Aluminum 7050 alloy, Mild Steel S355, and Stainless Steel 304 are 26.9×10^3 MPa, 79×10^3 MPa, and 75×10^3 MPa, respectively — taken from Solidworks material library. Again, for above mentioned process parameters, for instance, springback for Mild Steel S355, Aluminum 7050 alloy, and Stainless Steel are 8.176545 degrees, 9.058895 degrees, and 7.529485 degrees. Aluminum had a far lower shear modulus than Mild Steel and Stainless Steel, but aluminum had a higher springback. It indicates that a lower shear modulus of metals means more springback. But this trend is not demonstrated for Mild Steel and Stainless Steel, because their shear modulus is very closed, and perhaps the influence of shear modulus on springback is surpassed by other mechanical properties of Mild Steel and Stainless Steel. ***Table 10*** illustrates it.

Table 10 *relation between springback and shear modulus when process parameters are held constant.*

	Aluminum 7050 alloy	***Mild Steel S355***	***Stainless Steel 304***
Calculated Springback (degree) from equations when die gap, P.R/S.T, and set angle are given as 70 millimeters, 10 ratios, 135 degrees, in sequence.	9.058895	8.176545	7.529485
Variable-free term from springback equations (v), (vi), and (vii)	15.22549	14.34314	13.69608
Shear Modulus (MPa)	26.9×10^3	79×10^3	75×10^3

- Similarly, the elastic modulus of Aluminum 7050 alloy, Mild Steel S355, and Stainless Steel 304 are 72×10^3 MPa, 210×10^3 MPa, and 190×10^3 MPa, respectively — taken from Solidworks material library. In this case, both Mild Steel S355 and Stainless Steel have closedly greater elastic modulus; Aluminum 7050 alloy, however, has a far lower elastic modulus. ***Table 11*** shows that the less the elastic modulus, the more the springback. Buang et al. [23] wrote the same speculation. But this relation may be valid if the difference between two elastic moduli is huge — for example, the difference between the elastic modulus of Aluminum 7050 alloy and Mild Steel S355 is huge. But if the elastic modulus difference between two metals is closed, then this relation may not be valid due to the influence of other mechanical properties. More generally, this trend is not applicable between Mild Steel S355, and Stainless Steel 304, because of their closeness of elastic modulus values. Therefore, other materials, properties may impact more than that of their elastic modulus.

Table 11 *relation between springback and elastic modulus when process parameters are held constant.*

	Aluminum 7050 alloy	***Mild Steel S355***	***Stainless Steel 304***
Calculated Springback (degree) from equations when die gap, P.R/S.T, and set angle are given as 70 millimeters, 10 ratios, 135 degrees, in sequence.	9.058895	8.176545	7.529485
Variable-free term from springback equations (v), (vi), and (vii)	15.22549	14.34314	13.69608
Elastic Modulus (MPa)	72×10^3	210×10^3	190×10^3

- Another similiter situation is demonstrated by Poisson ration. The Poisson ratio of Aluminum 7050 alloy, Mild Steel S355, and Stainless Steel 304 are 0.33. 0.28, and 0.29, respectively. Mild Steel S355 and Stainless Steel have far lower poisson ration than that of Aluminum 7050 alloy. It means higher poisson ratio resulting more springback. However, if the poisson ratio of two metals are very near, by then this relation may not valid due to the influence of other materials properties. ***Table 12*** displays this relation.

Table 12 *relation between springback and poisson ratio when process parameters are held constant.*

	Aluminum 7050 alloy	***Mild Steel S355***	***Stainless Steel 304***
Calculated Springback (degree) from equations when die gap, P.R/S.T, and set angle are given as 70 millimeters, 10 ratios, 135 degrees, in sequence.	9.058895	8.176545	7.529485
Variable-free term from springback equations (v), (vi), and (vii)	15.22549	14.34314	13.69608
Poisson Ratio	0.33	0.28	0.29

5. Conclusion

The research presented in this study showcases significant advancements in the prediction of springback in air-bending operations for sheet metal, specifically focusing on Mild Steel, Aluminum, and Stainless Steel. Applying the Box–Behnken experimental design, this research demonstrates a means to optimize experimental Runs, thereby reducing both experiment time and cost. By developing an empirical model that incorporates critical parameters such as die gap, punch radius to sheet thickness ratio (P.R/S.T), set angle, and material, this study addresses the inherent challenges associated with springback. Moreover, using a categorical factor, called material, for developing empirical models will be a significant reference for similar imminent works. Moreover, the developed models have practical applications that can significantly benefit the manufacturing industry. For instance, it can rectify the precision of manufacturing setups and part designs by providing authentic springback foresight, especially in scenarios where conducting tests is prohibitively expensive. The model also serves as a valuable tool for guiding product development to achieve high precision, which is crucial for producing quality components. This research upheld some springback trends pertinent to process-related parameters and metal's mechanical properties.

This study reveals some trends between process parameters and springback. For instance, the larger the initial set angle, the less springback there will be if the die gap and punch radius to sheet thickness remain constant. Another trend that is a higher die gap results in a larger springback, according to another relationship between springback and die gap if the initial bending angle and the punch radius to sheet thickness are taken to be constant. Moreover, in a similar vein, assuming the die gap and the initial bending angle remain constant, increasing the punch radius to sheet thickness ratio results in an increase in springback. Indirectly it tells another two trends: first, the increase in punch tip radius leads to more springback if the thickness of the sheet is kept constant; second, in contrast, springback might be reduced in relation to the increase in sheet thickness if the punch radius tip is thought to be constant. In addition to these process-related trends with springback, it is also found which process parameter has supreme sensitivity and which one has inferior sensitivity on springback. While P.R/S.T is the most sensitive process parameter pertinent to springback, the die gap is a less influential process factor. Die gap is a less significant process factor, although P.R./S.T. is the most sensitive process parameter relevant to springback.

This work also indicates some trends between material mechanical properties and springback. For example, the amount of springback that can occur increases with the yield strength of the metal. If two metals have shear modulus values such as one is very high and another one is very low, then lower shear modulus is the cause of higher springback. But if two metals have shear modulus closed, then this trend may not be valid, due to the influence of other mechanical properties. Thus, it can be said that springback is not solely dependent on the shear modulus and the trend is not linear at all. Similarly, a lower elastic modulus means greater springback. But this trend is also non-linear, indicating if two metals have nearly elastic modulus values, then other mechanical properties of metals may bypass this trend. Furthermore, more springback is the outcome of a higher Poisson ratio. It is also a nonlinear trend.

4.1 Limitations of the study

There were, howbeit, some limitations in this research. Firstly, this study was not conducted at constant room temperature; therefore, the thermal effect could slightly distort the outcomes. Secondly, though an empirical model could be developed in this study, it was not able to foretell the absolute value of springback. It means there were acceptable errors under the validation stage. Thirdly, the Bevel Protector was kept for measuring the integer angular value of all fifty-one Runs and validation. Simply put, all of the collected experimental data of springback were integers due to Bevel Protector's measuring specification.

4.2 Future work

Several aspects can be undertaken in future research to give more dimensions to this current study. To start with, limitations of the current study may be transcended such as by maintaining a constant room temperature and using a highly precise Bevel Protector. Furthermore, the Finite Element Method, a sort of simulation, can be incorporated to analyze springback in forthcoming research work when numerous experimental trials will be a white elephant. Moreover, a lot of experimental data can be collected to use as a training data set for developing an artificially intelligent model for predicting springback including both process parameters and mechanical properties. It will be a supercalifragilisticexpialidocious prospective research work for springback prognostication, won't it?

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Credit authorship contribution statement

Sharif Muktadir Hossain Chowdhury: manuscript writing, research method development, experimental data collection, software, visual representation, and performed formal analysis. ***Md Nazmul Hasan Dipu:*** manuscript writing, software, visual representation, performed formal analysis, and revised the whole manuscript. ***Mohammad Muhshin Aziz Khan:*** supervision, idea generation, research method development, tool selection, and critically revised the whole work.

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