Improve springback prediction through the development of empirical models and optimize springback for the air-bending sheet metal process for Mild Steel, Aluminum, and Stainless Steel

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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. 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. That pragmatic model was supposed to be derived from four independent parameters, such as die gap, punch radius to sheet thickness ratio, set angle, and material. In addition to this, rigorous optimization of the input variables — springback was vehemently affected by those — was also a goal of this research. To achieve both objectives thoroughly, several approaches were incorporated sequentially: Box-Behnken experimental design, experimental data collection, conducting an ANOVA test, empirical model selection, model development, confidence interval check, model validation, and finally numerical optimization. For pursuing this study's methodology, the Design Expert® software, Universal Testing Machine, and Bevel Protector were utilized. Thenceforth, the linear model was chosen in light of statistical analysis. In the validation phase, it was found that the developed linear models were able to prognosis springback with acceptable errors. Moreover, the highest sensibility of springback for one process parameter — punch radius to sheet thickness ratio — was also revealed from the developed linear models. Another feature of this study's analysis was to optimize the given factors for four different circumstances. It illustrated that different kinds of optimization were possible in light of boundary constraints. Overall, this study has some significant insights for sheet metal industries; cost, process, and design optimization; and a bright path for forthcoming research.

Keywords: Air bending; Springback; Sheet metal; Model optimization; Box–Behnken.

1. Introduction

Products or components, manufactured by sheet metal process, are indispensable in this contemporary era from daily-used metal jars to high-tech air vehicles including automobile panels, airplane skins, cans for food and beverages, and frames for electronic devices [1]. It implies that sheet metal fabrication is a vital manufacturing process [2]. It is a method of forming thin sheets of metal by applying force via core or cavity dies or both [3] as well as execution of numerous operations such as bending, blanking, stretch forming, and deep drawing [4]. It is incorporated in many industries — especially in aircraft, automotive, food, and home appliances [5]. Thus, it serves as the backbone of modern society, meeting its escalating demands effectively.

A plethora of industries rely on sheet metal forming processes, notably on bending technologies, among which air-bending stands out [6] — a three-point bending process [7]. Because this technology is extremely inexpensive as it permits the fabrication of a vast range of bend angles with only a single instrument. Another amazing characteristic of this air-bending method is that it gives the flexibility required for manufacturing, for instance, it may satisfy the need to create decent parts even with a batch size of just one [8]. Moreover, it is appropriate for sheet components with complicated, curved faces [9]. Furthermore, it is versatile, allowing a variety of bend configurations to be formed with the same set of instruments [7]. However, one crucial undesired feature of air-bending is springback — defined as an elastically driven shift in the shape of a component after forming [10]. In other words, springback happens in metal forming due to the primarily elastic recovery of material following the removal of the punch force [11] [12]. Since the bottoming is nonexistent in air-bending, so springback is high [7]. This springback following the shaping stage may produce substantial shape deformities. It is therefore vital to understand which elements affect the springback and to be capable of estimating the amount of the springback [13]. Springback characteristic is impacted by several parameters such as strain hardening exponent, coating thickness, die opening, die radius, punch radius, punch travel, punch velocity [14], sheet thickness, tooling shape, lubrication conditions, material qualities, and so on [15]. Hence, several previous research were published pertinent to these factors.

1.1 Brief background study

One background work on air-bending by Yilamu et al. which was investigated for bending and springback phenomena of Stainless Steel and Aluminum clad sheets in V-shaped. Experiments with V-bending were conducted for both scenarios. In one case, the aluminum layer was positioned within the bent clad, and the stainless steel was located outside. In another situation, the Stainless-Steel layer was positioned within the bent clad, and the Aluminum layer was located in outside. According to the data, the sheet-set state has a significant impact on the bending phenomenon [16].

In addition to that, another study effort was published by Ozdemir to explore springback behavior by employing the air V-bending technique in DP600 sheet material. The influence of varied thickness and punch tip radii on springback values were also examined. Experimental data were evaluated by the Response Surface Method (RSM). It was established that as the punch tip radius rose, the springback value increased; on the other hand, when the sheet thickness increased, the springback value reduced [17].

Another research work was carried out by Gupta et al. to examine the influence on springback due to variations in the die width during air-bending of electro-galvanized CR4 steel. A Universal Testing Machine, permitting recording of bending load and regulating of punch travel, was utilized for performing the trials. A flexible die set was employed whose die width might be modified by merely altering a distance block. But die radius, punch radius and punch speed were maintained the same. A strategy to modify one component at a time was adopted. Angles were determined by utilizing an optical profile projector and graphics. The Graphical technique was utilized for assessing the springback. It was discovered that springback increased with the increase in the width of the die for every punch journey and for non-galvanized as well as galvanized steels of varying galvanizing thicknesses. Moreover, an increase in springback was seen when the galvanizing thickness was increased [18].

Another article published by Garcia-Romeu et al. focused on springback estimation for sheet metals in an air-bending method based on an experimental study. In that study, springback values for various bending angles of Aluminum and Stainless-Steel specimens were acquired and turned into visuals for the air-bending process. Findings expanded the data that a sheet metal designer might use either to achieve the final geometry values of an air-bending item or to design bending dies [19].

Research undertaken by Yang et al. aimed to build an analytical model to forecast the springback in air-bending of Advanced High-Strength Steels, emphasizing the specific features of these materials. A computer code was constructed based on classical bending theory, and the finite element simulation was applied. The comparison between the experimental findings and forecasts suggested that the careful study of the attributes of Advanced High-Strength Steels influenced the correctness of the springback prognosis using the analytical technique [20].

The research by Thipprakmas et al. explores the influence of process parameters on springback and spring-go in V-bending processes utilizing the finite element method, Taguchi, and ANOVA approaches. The findings demonstrated that material thickness had a large impact on springback, whereas bending angle had a significant role in spring-go. The ANOVA analysis aided in evaluating the relevance of each process parameter. Experimental validation revealed excellent agreement between finite element simulation and real findings. The research gave insights into adjusting process parameters for getting desirable bending results [21].

1.2 Justification from the background study

From the literature review, it can be said that there are numerous factors affecting springback behavior in the air-bending sheet metal process. To analyze this characteristic, many tools and techniques may be utilized: Universal Testing Machine, Graphical technique, Response Surface Method, finite element simulation, Taguchi, ANOVA, and a computer code based on classical bending theory.

1.3 Conspicuous research gaps from background study

Hardly previous papers can be found where categorical variable like material was included alongside numerical factors for the development of empirical models. A few past works might be conducted to optimize factors affecting springback. But none of those considered optimizing those factors for different independent cases: comprehensive, fixed part design, cost-efficient, and performance-driven optimization.

1.4 Objective of this study

The objective of this research was to develop and investigate an empirical model whose role would predict springback, so that it could be minimized for the air-bending sheet metal manufacturing process. That pragmatic model was supposed to be derived from four critical independent parameters such as die gap, punch radius to sheet thickness ratio (abbreviated as P.R/S.T in this work), set angle, and material types. Another goal of this study was to rigorously optimize the input variables on whose springback was vehemently affected.

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.

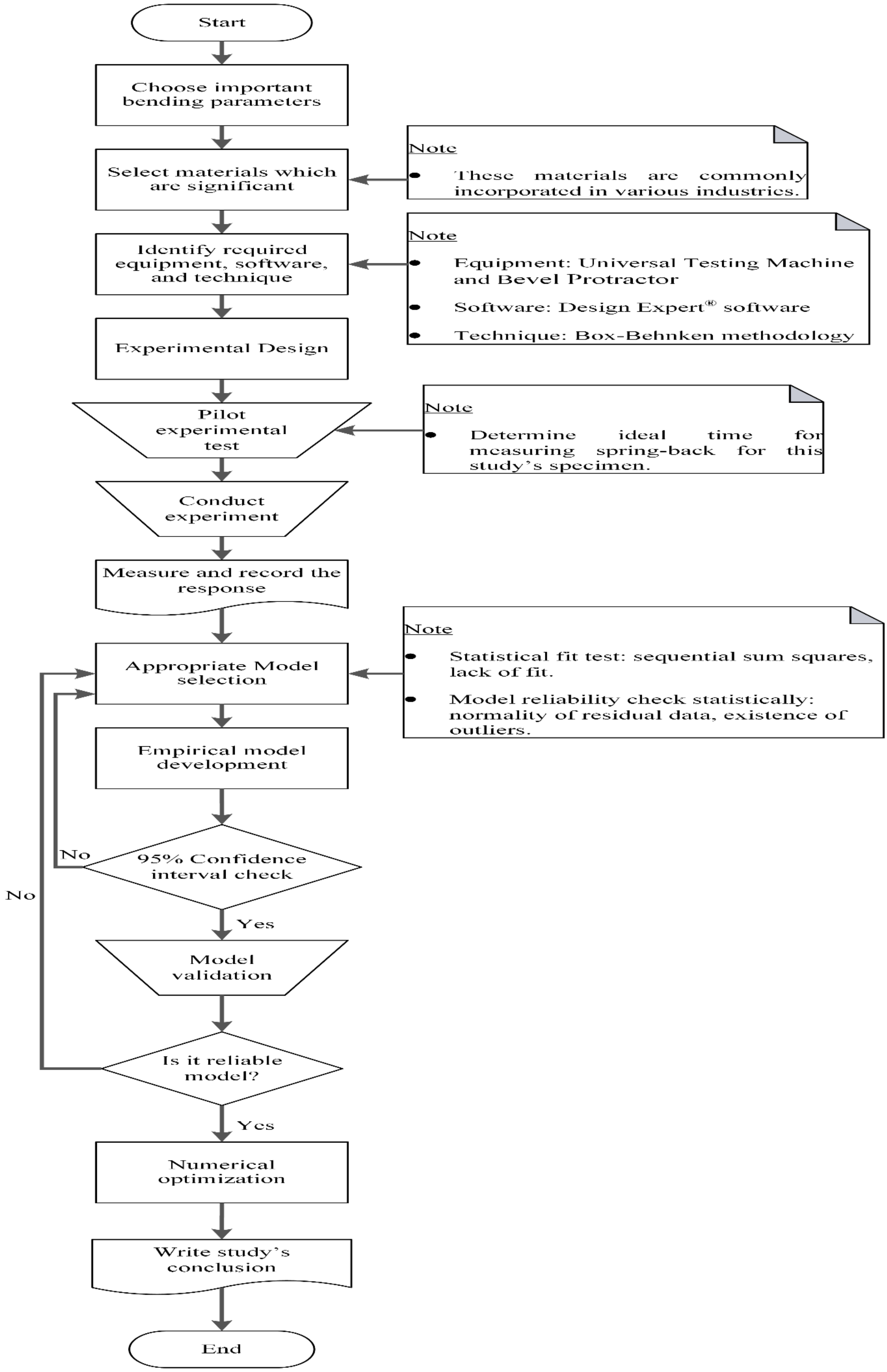

Fig. 1: Sequences of this study.

2.1 Study's factors specifying

There are numerous parameters that can influence springback [14]. 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 [22]. 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 [23]. Another useful material is Aluminum 7050 alloy, particularly in the aerospace industry [24], was also the point of concern of this study. Therefore, those three materials widely utilized in industrial applications were chosen in this study: 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 150mm in length and 30mm 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 study, a Universal Testing Machine —is a very popular and versatile option for testing materials and components [25] — was used. It is commonly used in both research and quality control to provide engineering property data on a wide range of materials [26]. The Universal Testing Machine was incorporated into this study to make the bend of aforementioned three metals. Fig. 2 shows 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 [27].

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

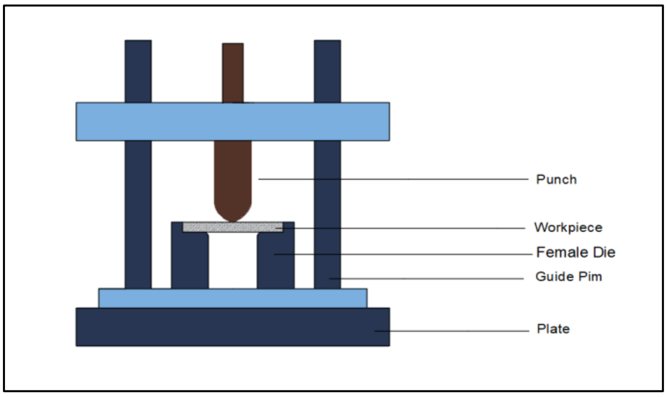

Fig. 3: A photographic view of the experimental setup for air-bending.

Apart from the Universal Testing Machine and Bevel Protector, another vital tool for this study was the Design Expert® software — developed by State Ease [28]. It is one of the most extensively used programs [29]. It was first released in 1996 to help carry out experimental designs such as determining the optimum formula for a preparation. Apart from optimization, this software could also interpret the factors in the experiment. 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 or information for optimization [28]. In this study, there were several variable factors, shown 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	***Units***	***Symbol***	***Levels of each factor***		
			1	***2***	***3***
Die gap	mm	DG	65	70	75
Punch Radius / Sheet Thickness	-	PR/ST	5	10	15
Initial bend angle	Degree	SA	120	135	150
Material	-	Material	Mild Steel S355 grade	Aluminum 7050 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 X 30 millimeters

2.4 Response surface methodology

Response Surface Methodology is a collection of statistical design and numerical optimization techniques used to optimize processes [30]. 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 [31] [32]. It is widely used in research and development and industrial applications [31]. In this study, 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 study, a component of Response Surface Methodology [33] [34], 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 [35]. 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 study, a Universal Testing Machine bents sheet metal by using two adjustable dies of the same diameter but different punches which is shown 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)***, $\boldsymbol{h}$ stands for punch travel distance, $\boldsymbol{d}$ represents die gap, and the symbol $\boldsymbol{\theta_i}$ indicates the initial angle.

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

Punch travel varied with die gap and set angle, for obtaining several data — all of those fifty-one distinct Runs' experiments were conducted randomly to minimize 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 [36], demonstrated in Fig. 5b. The included angle, on the contrary, is the measurement between the inside surfaces of a part [37], 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 [37] [17], where $\boldsymbol{\theta_i}$ is the initial bending set angle before load removal and $\boldsymbol{\theta_f}$ is the final bend angle after load removal, and $\Delta\boldsymbol{\theta}$ stands for angular springback.

$$\boldsymbol{\Delta\theta = \theta_f - \theta_i} \qquad \textbf{(ii)}$$

$$\boldsymbol{\theta_f > \theta_i}$$

The final bend angle ($\boldsymbol{\theta_f}$) 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. To improve repeatability, each experiment was replicated three times and the average result was recorded.

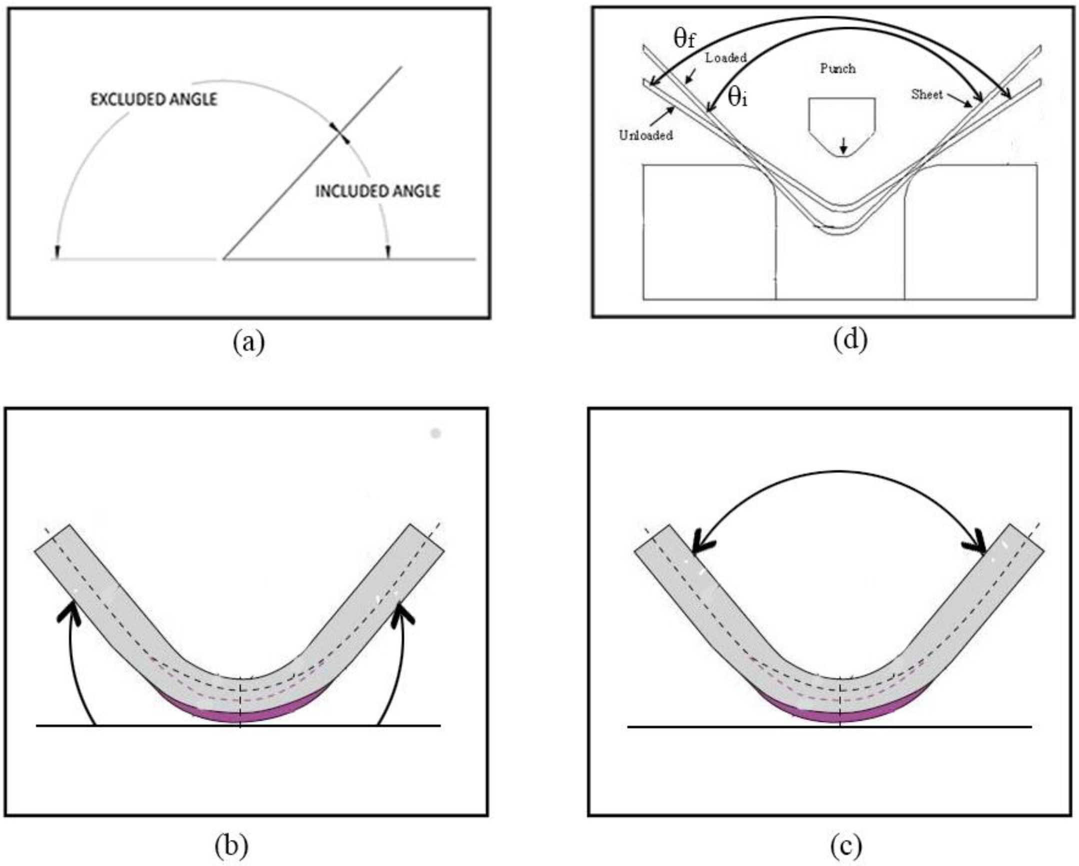

Fig. 5: demonstration of initial bend angle and final bend angle by line art.

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 [38]. 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 response models, for instance, linear, first-order interaction (2FI), quadratic, and cubic [39]. 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 [40], and R-square test [41]. 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 [42]. 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 [43].

The lack of Fit Test is useful for finding model inadequacies [40] [44]. 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 [40]. 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 [40].

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 [45]. 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 [45]. 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 improve, 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 selected 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 [46]. Second, a scatterplot is an effective tool for investigating connections among parameters, discerning relationships beyond facile correlations, and routing more accurate data science practices [47]. 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 [48] [49]. 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 transformation needed. Well, lambda (λ) — a transformation parameter in Box-Cox [50]— 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 [51] [52]. So, a lambda value of one indicates that no transformation 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 [53]. So, those are not based on any specific theory [54]. To put it another way, empirical models are based on correlations obtained from the analysis of experimental data [55]. Empirical models that have been used for curve fitting processes to generalize the results of experiments [56] [57]. The curve fitting may be achieved by suitable methods to fit polynomials or other functions [56]. It is mandatory to mention that an empirical model can provide reliable results when it is based on a substantial amount of test data [58]. 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 Confidence interval

In this stage, the chosen developed model requires to demonstrate how much error it may tolerate. It can be inferred that researchers gather information from samples and anticipate that it discloses reality about the population of interest. However, sample statistics are not guaranteed to properly represent what is true of the population. This is where confidence intervals are important. A confidence interval (CI) — also known as error tolerance level or margin of error [59] — is a spectrum of scores inside which you are certain the genuine population value resides. Said another way, a confidence interval reveals how much sampling mistakes could influence the outcomes of research [60]. Basically, the confidence interval is the probability of the assertion, which by convention is set at 95%, although it is also rather usual to see values of 99%, 99.9%, and even 90%. The trade-off for a higher level of confidence is greater [61]. The 95% confidence interval is one of the most regularly stated confidence intervals [62]. Hence, in this study, a 95% confidence interval was considered. The main difference is that the bigger the percentage utilized, the surer one is that the genuine population estimate fits within the range [62]. Actually, it illustrates how data transformations may be used to convert anomalous information to a normal distribution. It is to be addressed that data necessary to calculate a confidence interval for the mean should be at least substantially regularly distributed [63]. In this study, as a 95%

confidence interval was right for the developed empirical model, the next phase was model validation experimentally.

2.10 Model validation

In experimental validation, the response factor — angular springback — was forecasted in light of process parameters via using the developed empirical model for all three selected 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)***.

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

2.11 Optimization techniques

After validating the constructed chosen model experimentally, it was time to apply optimization techniques. In this study, the numerical technique was employed using the Design Expert® software to minimize springback for four different cases. The initial step was defining the boundary constraints, after which the software identified the optimal factor settings that meet these criteria. In that numerical optimization, a function exists in that software namely Desirability — it is an established method for assessing optimal combinations among all variables [64]. It employs an established scale to assess the extent to which a process metric fulfills its prerequisites, and it also helps discern among alternatives in order to select an optimal process design [65]. To make this concept clearer, it can be written that Desirability is an objective function whose values lie from 0 to 1 [64]. Zero indicates undesired output whereas one implies a very desired outcome [64]. Therefore, the value of the Desirability function is useful to pick the best conditions among alternatives. During the numerical optimization throughout Design Expert® software, it is capable of determining the optimal point by itself that offers the greatest value for the desirability function.

3. Analysis 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.

Run	***Factor A: Die gap (millimeters)***	***Factor B: P.R/S.T***	***Factor C: Set Angle (Degree)***	***Factor D: Material***	***Response springback (degree)***
1	75	5	135	Mild Steel	3
2	75	10	120	Stainless Steel	10
3	70	10	135	Stainless Steel	8
4	70	10	135	Aluminum	10
5	70	10	135	Aluminum	11
6	65	15	135	Stainless Steel	13
7	70	10	135	Aluminum	8
8	70	15	150	Aluminum	6

9	70	15	120	Mild Steel	11
10	70	10	135	Stainless Steel	5
11	75	5	135	Stainless Steel	6
12	65	15	135	Mild Steel	6
13	70	15	150	Stainless Steel	7
14	75	15	135	Stainless Steel	14
15	65	10	150	Mild Steel	5
16	70	5	120	Stainless Steel	8
17	75	15	135	Aluminum	12
18	65	5	135	Stainless Steel	4
19	70	5	150	Stainless Steel	5
20	65	10	150	Aluminum	9
21	65	10	150	Stainless Steel	5
22	65	10	120	Stainless Steel	9
23	70	15	120	Stainless Steel	10
24	70	10	135	Aluminum	9
25	75	10	120	Aluminum	11
26	70	10	135	Mild Steel	11
27	70	10	135	Stainless Steel	5
28	75	5	135	Aluminum	7
29	75	10	120	Mild Steel	13
30	70	5	150	Mild Steel	2
31	70	10	135	Mild Steel	7
32	70	10	135	Stainless Steel	10
33	70	10	135	Aluminum	12
34	75	15	135	Mild Steel	6
35	65	5	135	Mild Steel	4
36	70	15	150	Mild Steel	12
37	70	15	120	Aluminum	16
38	70	5	120	Mild Steel	5
39	70	5	150	Aluminum	3
40	75	10	150	Stainless Steel	5
41	65	15	135	Aluminum	10
42	70	10	135	Mild Steel	9
43	65	10	120	Mild Steel	13
44	75	10	150	Aluminum	7
45	75	10	150	Mild Steel	11
46	70	5	120	Aluminum	7
47	65	5	135	Aluminum	4
48	70	10	135	Mild Steel	11
49	70	10	135	Stainless Steel	4
50	70	10	135	Mild Steel	10
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 reliable. 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 selected 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 random 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.

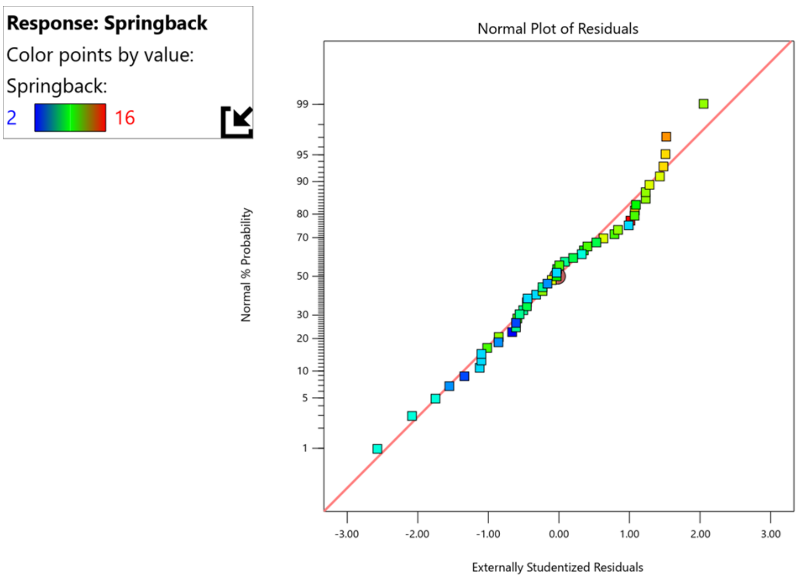

Fig. 6: Statistical check for normality of residual data for selected linear model.

Another thing is that the Residuals vs. Predicted graph — demonstrated in Fig 7 — for the selected linear model shows that the residuals were randomly 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 [66] — confirming that the model assumptions are met, and no transformation of the response variable was needed.

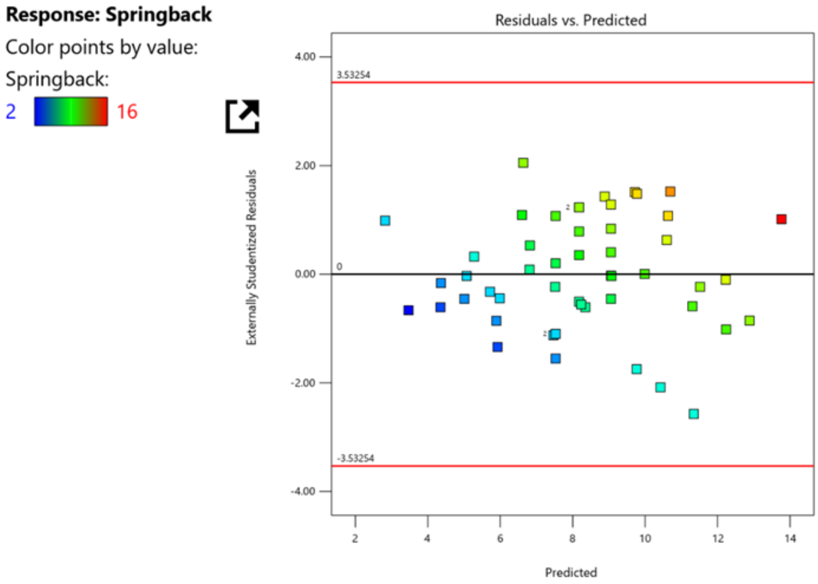

Fig. 7: Scattered plot of Residuals vs Predicted data for selected linear model.

The Box-Cox graph, shown in Fig 8, for the selected linear model, indicates that a Lambda value of 1 is appropriate, suggesting that no transformation of the response variable was necessary. The graph shows that the confidence interval for the optimal Lambda includes 1, confirming that the linear model without transformation was suitable. This supports the assumption that the response variable satisfied the requirements for normality and homoscedasticity without any transformation. Consequently, the linear model with a Lambda value of 1 is validated as the best choice, ensuring accurate and reliable results.

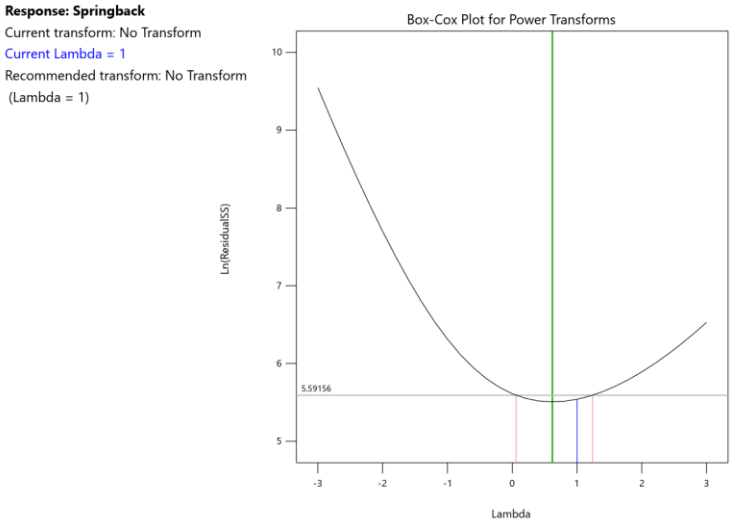

Fig. 8: The Box-Cox graph for the selected linear model.

3.3 Development Empirical Model

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 can be said 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:

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

Moreover, from these three equations ***(v), (vi),*** and ***(vii)***, it can be inferred that when die gap, P.R/S.T, and set angle have the same value for all three equations, by then only distinguished maker will be the constant of each equation. Because it makes the difference. To make this proposition more sense, a visual graph can be created with the help of MS Excel software where the die gap, P.R/S.T, and set angle have the value of 70 millimeters, 10 ratios, 135 degrees, in sequence for the equations and eventually corresponding springback of each material has been illustrated in Fig. 9. From this graph, it can be written that, Aluminum has the supreme characteristic for spring-back whereas Stainless Steel exhibits least spring-back properties among three selected materials.

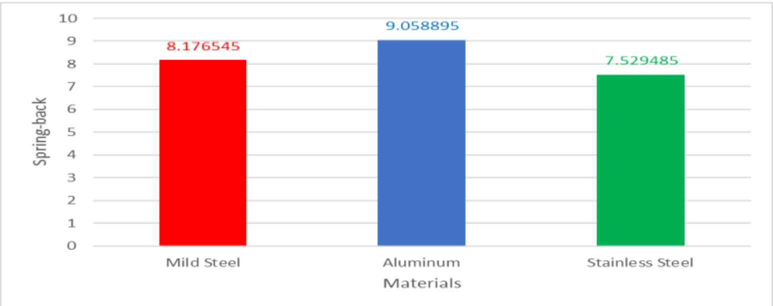

Fig. 9: Column graph for comparison springback behavior.

3.4 Confidence interval for the developed linear model

The 95% Confidence Limit Bands graphs, visualized in Fig 10, for the three numerical factors display the relationship between each factor and the response variable. Each graph shows the predicted response along with upper and lower confidence limits, providing a visual representation of the prediction accuracy and variability. These bands help in understanding the range within which the true response is expected to lie with 95% confidence, highlighting the reliability of the model predictions for each numerical factor. It consists of four subplots.

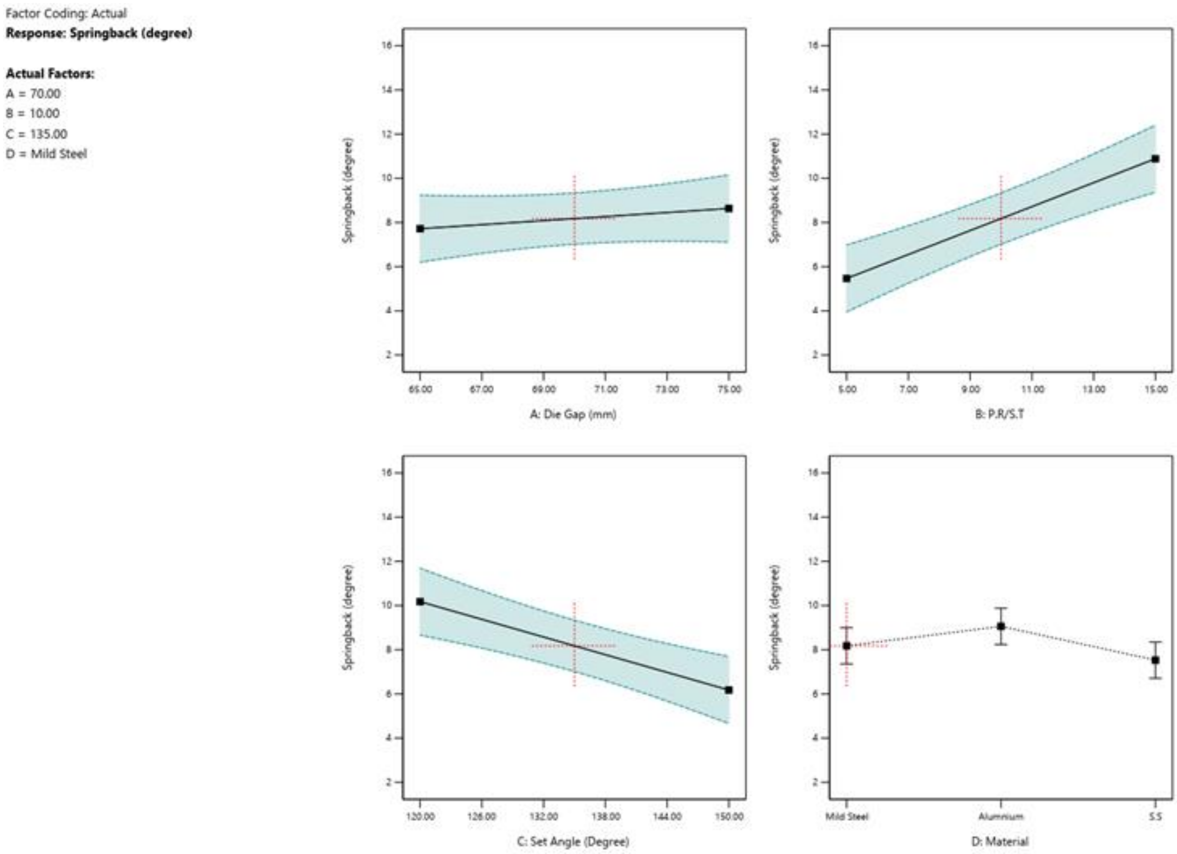

Fig. 10: Ninety-five percent confidence interval graph.

Firstly, the plot for the die gap shows a positive linear relationship between the die gap (mm) and springback. The 95% confidence bands (shaded area) indicate the prediction interval, which is relatively narrow, suggesting reliable predictions. As the die gap increases, the springback slightly increases. Secondly, the punch radius to sheet thickness ratio graph also illustrates a positive linear relationship between PR/ST and springback. The 95% confidence bands are shown, indicating the range within which the true response is expected to lie with 95% confidence. An increase in PR/ST results in a notable increase in springback. Thirdly, in the next graph, a negative linear relationship between set angle (degrees) and springback is depicted. The 95% confidence bands are present, showing the reliability of predictions. As the set angle increases, the springback decreases. Eventually, the fourth subplot shows the influence of the categorical factor namely material on springback. The graph highlights the mean springback for each material, with error bars representing the 95% confidence intervals.

3.5 Experimental validation of the developed model

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 spring-back, 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 -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: Spring-back (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

3.6 Numerical optimization

There was total of four optimization cases according to the needs: comprehensive, fixed part design, cost-efficient, and performance-driven optimization.

3.6.1 Comprehensive optimization of springback

Strive for maximum optimization of springback by simultaneously optimizing all key parameters. In other words, the Design Expert® program was permitted to pursue optimization of whatever it needed for four independent factors to minimize the dependent factor springback. To conduct this comprehensive optimization, the software required some boundary conditions which are shown in Table 9.

Table 9 Boundary conditions for comprehensive optimization.

Name	***Goal***	***Lower Limit***	***Upper Limit***	***Lower Weight***	***Upper Weight***	***Importance***
Die Gap	in range	65	75	1	1	5
P.R/S.T	in range	5	15	1	1	5
Set Angle	in range	120	150	1	1	5
Material	in range	Mild Steel	Stainless Steel	1	1	5
Spring-back	minimize	2	16	1	1	5

After incorporating the optimization operation in light of these boundary conditions, the Design Expert® program did many iterations, which is depicted in Fig. 11, and finally gave an optimized senecio picked by the *"red dotted plus symbol"*. Therefore, optimized values of die gap, P.R/S.T, set angle, and material were 65.00 millimeters, 5.00 ratios, 150.00 degrees, and Stainless Steel. For these values, the optimized springback magnitude was 2.363 degrees. In addition to that, the value of the desirability function was 0.974 (rounded off to thousandths) which was very near to one — indicating that the linear model was nicely optimized under given boundary conditions.

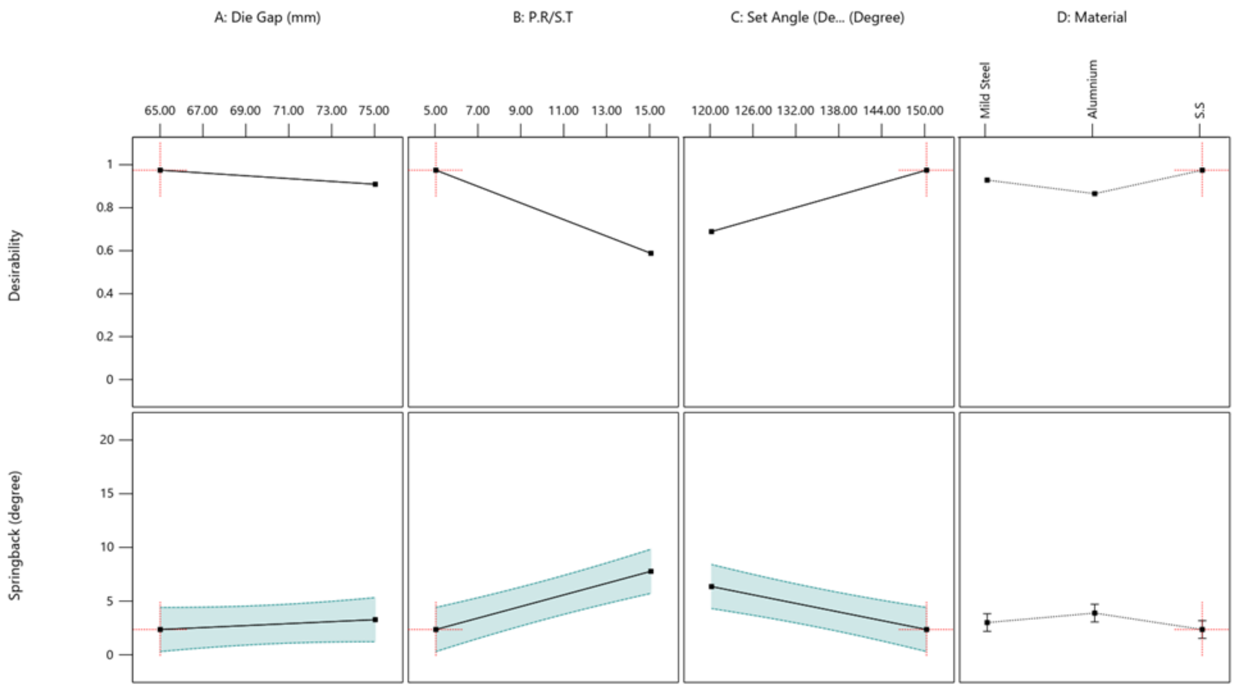

Fig. 11: Optimized senecio of comprehensive case among many iterations by the Design Expert® program.

3.6.2 Fixed part design optimization

It can be easily understandable that most of the real cases, a set angle and material may be mandatory to be kept fixed for fabricating a specific desirable component. Therefore, fixed-part design optimization was also assimilated in this study. To perform such optimization analysis, it was assumed that a part was required to be manufactured via an air-bending sheet metal process whose bending set angle needed to be 135 degrees and it must be made of Mild Steel. However, the other two independent factors such as die gap and P.R/S.T could be altered to achieve minimize springback. Thus, software was allowed following constraints, shown in Table 10, under confined limits. At this moment, readers may be confused after noticing ranges of those two fixed valued factors — set angle and material. To eliminate this confusion, it is necessary to clarify that the software's desirability function enforced those ranges; however, the goals of those two fixed factors were specific. Another software feature was *Importance* whose values were five for die gap, P.R/S.T, and springback because those variables got the maximum priority.

Table 10 Boundary conditions for fixed part design optimization.

Name	***Goal***	***Lower Limit***	***Upper Limit***	***Lower Weight***	***Upper Weight***	***Importance***
Die Gap	in range	65	75	1	1	5
P.R/S.T	in range	5	15	1	1	5
Set Angle	135.00	120	150	1	1	1
Material	Mild Steel	Mild Steel	Stainless Steel	1	1	1
Springback	minimize	2	16	1	1	5

After conducting the optimization operation based on the aforementioned constraints, the Design Expert® program did numerous iterations, which is demonstrated in Fig. 12, and eventually an optimized senecio was found by the software, which was picked by the *"red dotted plus symbol"* in the graph. Optimized values of die gap and P.R/S.T were 65.00 millimeters and 5.00 ratios, accordingly. In this circumstance, the fixed part was supposed to witness a springback of 5.010 degrees. Furthermore, the score of the desirability function was 0.785 (rounded to thousandths), which was considerably close to 1, exhibiting that the linear model was well optimized beneath the stated limit conditions. Moreover, the *"red dotted plus symbol"* in Fig. 12 is located at 135 degrees for set angle and Mile Steel for material as specified in Table 10 according to analysis goals. Thus, the upper and lower limits of set angle had null values in the desirability scale in this figure. Likewise, Aluminum and Stainless Steel had zero desirability values.

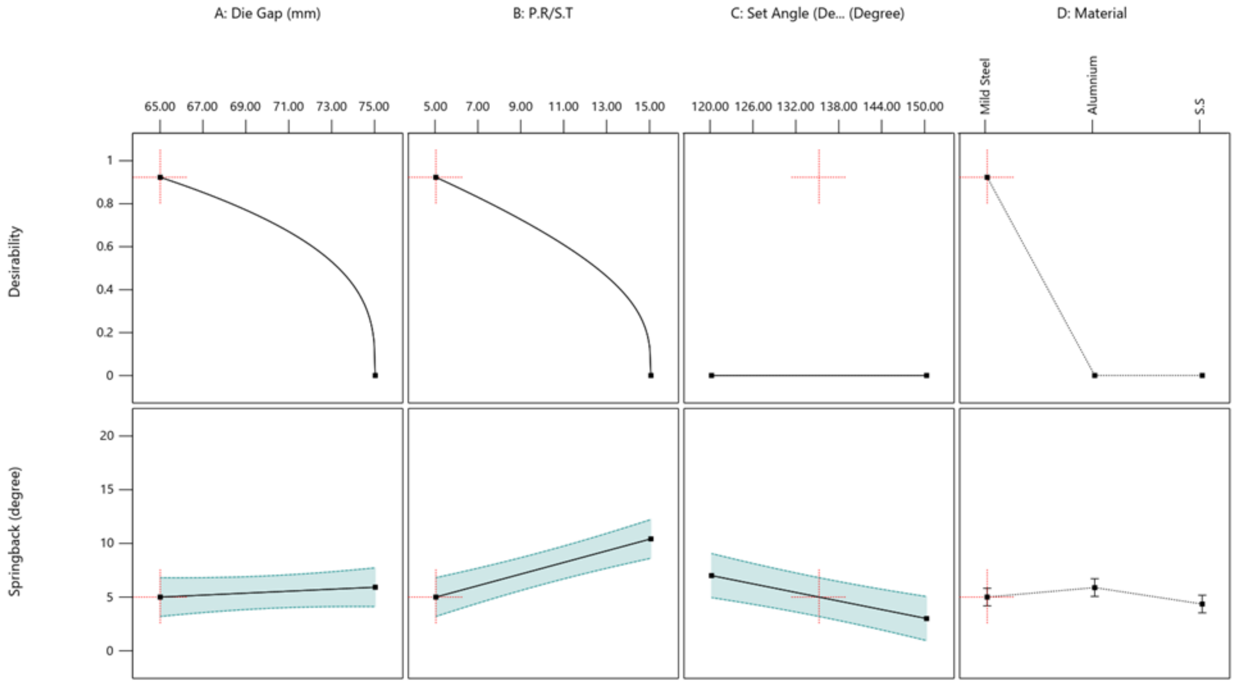

Fig. 12: Optimized senecio of fixed part design case among many iterations by the Design Expert® program.

3.6.3 Cost-efficient optimization

When considering cost efficiency, the primary focus could be the factors that have a significant impact on springback while minimizing changes to other variables. For this experiment optimizing the set angle and die gap can potentially yield substantial improvements in springback control without extensive changes in material or other design parameters. This approach is cost-effective because it targets specific variables known to influence springback significantly but there is no requirement for additional expenditure. To gain a cost-efficient optimization analysis, the following boundary constraints, exhibited in Table 11, were considered.

Table 11 Boundary conditions for cost-efficient optimization.

Name	***Goal***	***Lower Limit***	***Upper Limit***	***Lower Weight***	***Upper Weight***	***Importance***
Die Gap	minimize	65	75	1	1	5
P.R/S.T	in range	5	15	1	1	1
Set Angle	maximize	120	150	1	1	5
Material	in range	Mild Steel	Stainless Steel	1	1	1
Springback	minimize	2	16	1	1	5

The Design Expert® software detected that the optimal springback was 2.363 degrees where the die gap, P.R/S.T, set angle, and material were 65.00 millimeters, 5.00 ratios, 150 degrees, and Stainless Steel, respectively, illustrated in Fig 13. Besides, the magnitude of the desirability function was 0.991 (rounded to thousandths), which was remarkably around one, implying that the linear model was adequately optimized according to the given border conditions.

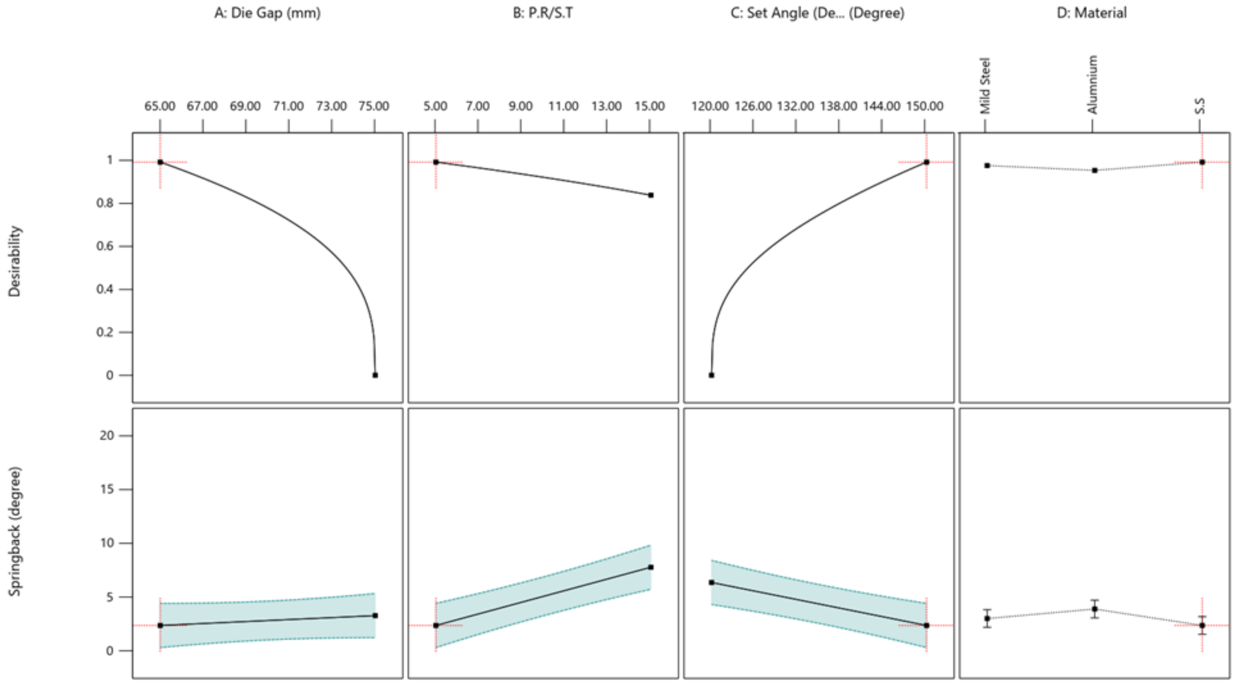

Fig. 13: Optimized senecio of cost-efficient case among many iterations by the Design Expert® program.

3.6.4 Performance-driven optimization

In this case, the study's deliberation was to optimize factors that highly influence the performance characteristics of the springback. To determine which factors were mostly sensitive, it was necessary to look at previously written equations ***(v), (vi),*** and ***(vii)***, from where it was apparent that the set angle and PR/ST ratio were very sensitive and significantly affect output variable springback. Hence, by optimizing the PR/ST ratio and initial set angles, springback can be alleviated in the most effective way. For this case, boundary conditions were given to the software likewise shown in Table 12.

Table 12 Boundary conditions for performance-driven optimization.

Name	***Goal***	***Lower Limit***	***Upper Limit***	***Lower Weight***	***Upper Weight***	***Importance***
Die Gap	in range	65	75	1	1	1
P.R/S.T	minimize	5	15	1	1	5
Set Angle	maximize	120	150	1	1	5
Material	in range	Mild Steel	Stainless Steel	1	1	1
Springback	minimize	2	16	1	1	5

The Design Expert® software also identified that the optimal springback was 2.363 degrees where the die gap, P.R/S.T, set angle, and material were 65.00 millimeters, 5.00 ratio, 150 degrees, and Stainless Steel, respectively. Plus, the numerical value of the desirability function was 0.991 (rounded to thousandths), which was impressively approximately one, pointing to the fact that the linear model was sufficiently optimized to satisfy the supplied border conditions. Albeit it was surprisingly same optimal outcomes that the earlier case-3 had; curves of Fig 14 clarified that it was different investigation than case-3 did.

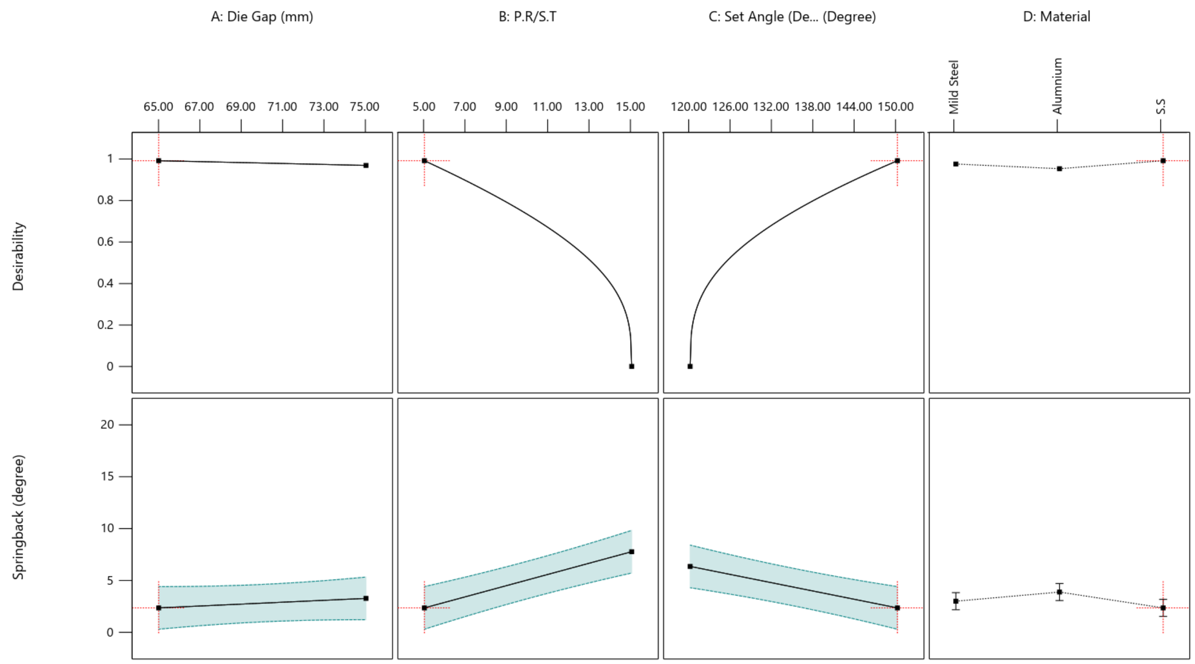

Fig. 14: Optimized senecio of performance-driven among many iterations by the Design Expert® program.

Table 13 summarizes the all-fours circumstances of optimal outcomes found from numerical analysis.

Table 13 Summary of numerical optimization for better comparison.

Case	***Die Gap***	***P.R/S.T***	***Set Angle***	***Material***	***Springback***	***Desirability***
Comprehensive	65.000	5.000	150.000	Stainless Steel	2.363	0.974
Fixed part design	65.000	5.000	135.000	Mild Steel	5.010	0.785
Cost-efficient	65.000	5.000	150.000	Stainless Steel	2.363	0.991
Performance driven	65.000	5.000	150.000	Stainless Steel	2.363	0.991

4. Conclusion

The research presented in this study showcases significant advancements in the prediction and optimization 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 method 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, set angle, and material, this study addresses the inherent challenges associated with springback. The inclusion of punch radius to sheet thickness ratio and materials as parameters is particularly notable, as it represents an unprecedented approach in the field. Besides 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 improve the precision of manufacturing setups and part designs by providing reliable springback predictions, 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.

From this rigorous study, it can be written that the empirical model may be an insightful mathematical tool for the air-bending sheet metal manufacturing process for many purposes.

- ✓ Springback can be predicted and controlled for commonly employed materials Mild Steel, Aluminium, and Stainless Steel with the help of developed pragmatic mathematical models. In other words, equations ***(v), (vi),*** and ***(vii)*** in this study will be useful to forecast the springback of abound products made of corresponding materials in various industries. Thus, the desirable exact shape of the products or components — quality for high precision and accuracy — can be achieved which will eventually lead to reduce unwanted defects.
- ✓ Another thing that the empirical model could offer is to scrutinize the independent process parameter that has the most sensibility on the springback. In this study, the punch radius to sheet thickness factor had the most influence on springback.
- ✓ One more feature of several empirical models is that they let the springback properties among different materials be comparable. For instance, equations ***(v), (vi),*** and ***(vii)*** in this study helped to infer that Aluminum has the highest Spring-back behavior whilst Stainless Steel may exhibit the least springback characteristic among all three materials.
- ✓ Furthermore, along three numerical process parameters — die gap, P.R/S.T, and set angle — in this research, one categorical factor namely material was included in the linear model to give a novel dimension.

Moreover, the study showcases various optimization criteria, such as optimizing all parameters for maximum springback reduction, which serve as useful references for both industrial and laboratory settings. These criteria can help manufacturers identify the most cost-effective and efficient methods to minimize springback, ultimately leading to better process control and product quality. Therefore, numerical optimization was also a penetrating part of this meticulous investigation for helping manufacturers. It aids in ameliorating the bending process by figuring out the optimal point for different cases. There were four different optimization circumstances investigated in this study: comprehensive, fixed part design, cost-efficient, and performance-driven. This numerical optimization analysis depicted that there were some situations when a model might not only be optimized for cost-effectiveness but also it could be optimized for performance-driven cases. The rows three and four of Summery Table 13 solidify this proposition. It is a mostly desirable optimization that modern sheet metal manufacturers may seek since it can catch two birds with one stone. In addition to this, the numerical investigation also demonstrated that a linear model could be optimized for fixed-part design cases with an acceptable desirability value. Thus, optimization could be accomplished during manufacturing of a sheet metal part, even though some design restrictions are provided from R&D department.

Overall, this research offers important insights and methodologies that can be directly applied to the sheet metal industry, facilitating cost savings, process improvements, and more precise product designs. It also lays a foundation for future research in optimizing bending operations and controlling springback, contributing to the ongoing development of advanced manufacturing techniques.

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. In other words, 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. Limitations of the current study may be eliminated 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 incorporated to analyze springback in forthcoming research work when numerous experimental trials will not be cost-effective. 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. In that AI model, numerous materials could be utilized to focus on material characteristic like strength, hardness, elasticity, and thermal conductivity in order to evaluate springback for any future novel material in advance in light of its properties. As a result, with the help of that AI model, different process parameters, such as die gap, and set angle, can be included along material characteristics — for example, strength, hardness, elasticity, thermal conductivity, and so on — in order to forecast springback. That model will be helpful not only for common industries for fabricating sheet metal-related goods but also for research and development sectors. For instance, a specialized material may require to be invented for developing a component for the space-exploring robot, in that case, the springback of the component may be predicted based on needed process parameters and deliberately made novel metal with customized material characteristics. It will diminish not only the cost of the research but also foreshorten development time of the product. Furthermore, that vigorous AI model might be useful for allowing researchers to put diverse combinations of inputs for independent variables without any trial experiment for divergent sets of input parameters for each time. There will be no need for developing empirical model for various materials or different input types at every time; only a vehement AI model could be the panacea for all kinds of springback pertinent issues. 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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