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Prediction of the spring back of AA5052 under a variety of parameters through the use of artificial neural network and finite element analysis

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ABSTRACT

Bending is a commonly utilized method in the manufacturing of aluminum components. Spring back is a well-known problem in sheet metal forming that reduces operating efficiency and compromises dimensional precision. The predicting the part's ultimate shape after spring back and designing tooling to adjust for it remains a practical concern in the manufacturing business. Using available finite element analysis (FEA) and artificial neural network (ANN), this paper predicts the spring back of AA5052 under various variables. The results demonstrate that the spring back phenomenon is significantly influenced by the thickness of AA5052 and the angle of rolling. Following the thickness of AA5052, which accounts for 38.7% of the overall variance, angle of rolling, representing 32.3% of the total variation, is the procedure-dependent variable. The maximum spring back value was 10.5 at the thickest (2 mm) and the minimum was 3.5 at the thinnest 1 mm thickness in practice. The SB findings were analyses by comparing experimental, FEA, and ANN values. The ANN model exhibited a minimum SB of 3.488 with an error of 0.3%, whereas the FEA model demonstrated a minimum SB of 3.447 with an error of 1.56%. In this context, the ANN model is proficient in rapidly forecasting spring back, lowering analysis time, minimizing errors, lowering cost, and expediting product success.

Keywords: spring back, finite element analysis, artificial neural network, thickness of AA5052, angle of rolling.

INTRODUCTION

Sheet metal forming activities encompass many production processes, mostly including drawing and bending. These procedures are performed on relatively thin metal sheets with thicknesses between 0.4 mm and 6 mm with a machine tool including a punch and die. Defects accompany sheet metal forming procedures in the products [1]. To mitigate these faults, it is essential to implement measures, such as employing an appropriate design tool or engineering program that thoroughly analyses the production process. In this context, to tackle these difficulties, the industry required an engineering program that could lower the costs of equipment and tools. With an error rate of less than 5%, finite element analysis has proven to be excellent in forming operations [2]. Here, lower costs and time with math and Solid Works models in the wire bending machine [3]. Bending is the method of manipulating materials along a certain axis with a tool without the need to remove any chips. It is placing a metal sheet over the matrix on the press die and curving it around the punch tip as it enters the die. Bending dies employ a female die and punch to induce permanent alterations in sheet material according to the desired shape production, as shown in Figure 1a. Despite the popularity of V-bending for its ease and versatility in creating numerous components, this technique has an inherent defect known as Spring-back (SB). Figure 1b illustrates the geometric alteration a component undergoes after releasing itself from the stresses of the forming tool [4, 5].A spring-back alters the final form of a component after sheet metal is produced,

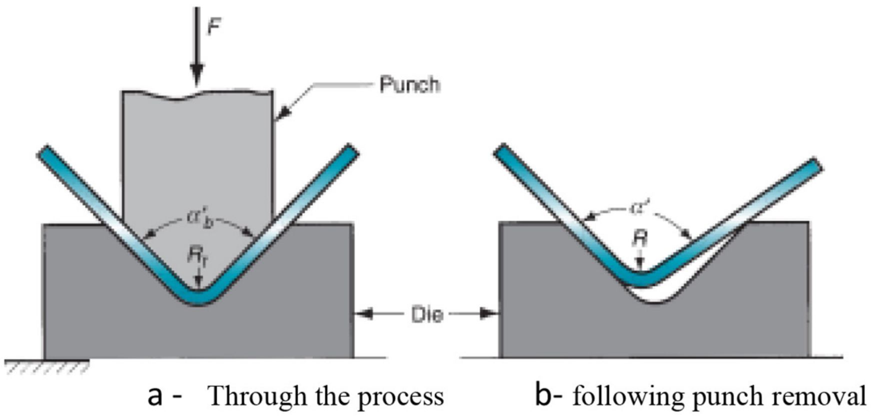

Figure 1. Illustrates the process of v bending production [2]

which impacts the part's dimensional accuracy. Product spring back is therefore determined by process parameters characteristic, which includes tool shape and size, speed, material properties, holding duration, and sheet thickness, as well as design of the tool [6, 7].

The degree of spring-back and the degree of control over this defect are contingent upon the selection of these factors. The parameters of the bending process can have a significant impact on the final product and have been extensively studied. For instance, in their study, Purwatono et al. [8] The spring back decreases with an increase in sheet thickness. In this context, Kartik et al. [9] The variation in spring back with any change in thickness results from the nature of compressive stresses in the sheet metal upper layers and tensile stresses lower layer. Therefore, as the thickness of the used sheet increases, the effects of this thickness play an important role in controlling the elastic recovery process. In this regard, Dametew and Gebresenbet [10], the effect of metal characteristics on spring back was studied. It was found that the spring back of a material increases as its yield strength increases following an unloading situation. The dimensional accuracy of the end product is affected by the spring-back effect, which changes the final shape of a component after sheet metal is produced. Longer holding times help to lower spring back by Khleif et al. [11].

In a study by Pathak et al. [12], artificial neural networks and a finite element technique were used to predict spring back, utilizing 44 examples. This model may be easily implemented for accurate spring-back predictions. In particular, Asmael et al. [13] Study examines how V-bending process factors affect aluminum alloy (AA5052) spring back at varied sheet thicknesses and die-opening times. ANOVA and multi linear regression were used to compare process factors' influence on SB behavior. SB behavior reduced with punch holding duration and sheet thickness, although die opening had the reverse effect. The study indicated that ANN predicted SB better than MLR with 99% accuracy. The study showed cold-work formability of AA5052 aluminum alloy.

In this regard, Hai et al. [14], the finite element method (FEM) analysis and laboratory testing are employed to assess the correctness of the spring-back factor. The revised spring-back factor demonstrated more accuracy than the conventional factor, therefore endorsing its application in V-bending die design. Mesci and Eksi [15] aimed to affect spring back in 1050 aluminum components. Taguchi L9 orthogonal array experiments showed that sheet thickness lowers the spring back angle. On the other hand, Karakaya et al. [16], the finite element studies examine process parameter influences on spring back and maximum load. The bending radius has the greatest spring-back impact (45.2%). The second spring back factor is metal thickness (28.1%). Metal thickness (84.21%) works well at maximum load. Spring back was examined in relation to die diameter and metal properties. Spring back was numerically predicted using Simufact Forming 2022. Experimental results show that steels with higher yield and tensile strength spring back more than those with lower strength by Spišák et al. [17]. The issue lays in the complexity of spring back, prompting research to enhance comprehension and devise solutions through improved predictive tools, a thorough understanding of the material, and the formulation of practical and successful strategies.

In a comprehensive context, it demonstrates how the problem of spring back can be addressed, leveraging the power of analytical software and artificial neural networks in the design and manufacture of a product such as aircraft components require aerodynamic design and precise angles to decrease air resistance. It necessitates very accurate curvatures for best aerodynamic efficacy, and a smartphone case part, which requires smooth, precise curves to fit the internal components and aesthetic appearance. In all of these examples, the parts are formed by bending sheet metal. The primary defect here is spring back, which generates a number of problems. This leads to dimensional inaccuracy, meaning parts do not conform to the required specifications, and to assembly problems, such as parts not fitting together with other parts in the final product. This leads to increased waste and costs, as well as the need to rework or discard non-conforming parts.

Addressing these problems is a crucial first step, as FEA software comes into play. Instead of costly trial and error in the field, use ABAQUS to analyze the bending process and understand the product's rebound behavior under various conditions. Generate massive amounts of accurate data on how various variables (material thickness, rolling direction, holding time) affect spring back. Enhance processing with ANN, obtaining comprehensive spring back data from FEA simulations.

To this end, develop a rapid and precise model in MATLAB capable of swiftly predicting spring back, minimizing analysis duration, and reducing mistakes. Based on the ANN prediction, the system can recommend compensation for the desired angle. Which might suggest to the bending die that its angle is 89 degrees instead of 90 degrees, so that the final angle returns to exactly 90 degrees after the spring back occurs. The result is the ability to manufacture products with precise bends with minimal errors, reducing waste, cost savings, and significantly accelerating product development. The novelty of this research to create ANN model that properly predicts spring back in AA5052 utilizing data collected from FEA as input. This ANN the prediction of spring back, reduce the reliance on time-intensive experiments, and optimize the metal forming process by adjust die dimensions and compensate for spring back, ensuring a product with minimal spring back. Therefore, the research not only contributes to current knowledge but also provides combines the most aspects of simulation and artificial intelligence to address one of the most critical problems spring back in V- bending processes.

PROBLEM DESCRIPTION

A V-shaped product with an internal angle of 90 is required to be produced using a die and punch with an angle of 90. During the bending process, the component may experience a little expansion, which ultimately leads to a greater final bend angle compared to the initial one. Figure 2 clearly shows that the final radius surpasses the diameter at the start of the process. These are the key challenges that arise when attempting to manage the dimensions of bent parts to satisfy the criteria. SB can be calculated using Equation 1.

$$\Delta\alpha = \alpha_f - \alpha_i \tag{1}$$

where: $\Delta\alpha$ – is angle of spring-bwhere;
α_f – the angle after spring-back, degree;
α_i – is the angle before spring-back, degree.

SB is a large, quantitative variable, making these strategies intriguing. SB has focused on material mechanical qualities and thickness. This defines the final bend radius (Rf) and starting bend radius (Ri). Equation 2[4] shows that T, y, and E matter in determining SB.

$$\frac{R_i}{R_f} = 4\left(\frac{R_i Y}{ET}\right)^3 - 3\left(\frac{R_i Y}{ET}\right) + 1 \tag{2}$$

where: R_f – is final bend radius, mm;
Ri – is the starting bend radius, mm;
E – is modulus of elasticity, GPa;
Y – the yield stress map;
T – thickness of sheet, mm.

To prevent spring-back and ensure the product's engineering acceptability, it must be taken. First, choose a suitable metal for bending. Comprehending the impact of metal properties on resilience should underpin the selection of a metal for a bending-based forming technique. Secondly, select appropriate parameters. ANOVA designs experiments and the impact of these parameters on spring back. Third, design of tools. The use of Solid Works 2022 allows for die and punch design. This simulation includes the process of building the die to achieve the target shape. Make substantial adjustments to the die design when working with metals that have a spring back. This

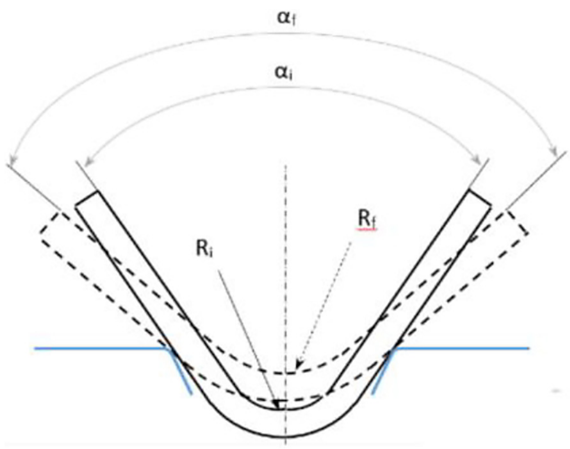

Figure 2. Illustrates the process of v bending production

comprehension aids in enhancing product quality by decreasing the need for trial and error. Work on the ABAQUS program, which gives an impression of the behavior of SB and the extent of the influence of those parameters on spring back. ANN to predict the amount of spring back, reduced duration for both FEA analysis and actual application, and instruct the Solid Works to correct the die angle to achieve product angle values of 90^o from solid Works API. The design, operating technique, parameters, and metal selection procedure will be described in particular in the next paragraph.

MATERIALS AND METHODS

Studying the previous research that had been conducted in the field led to the selection of the design and the metal. Based on theoretical principles, the effective parameters were identified

Specifications of metals

Aluminum, the most abundant metallic element in the Earth's crust, has several industrial applications and is a frequent constituent in various products, including those in the automotive, consumer goods, electronics, and medical device sectors. Cold-forming aluminum is more facile than other materials owing to its flexibility, corrosion resistance, and superior strength-to-weight ratio [18]. This particular metal has demonstrated success in the manufacture of V-shaped structures, in addition to its good qualities and requirements as well as its great formability. In spite of this, the spring back phenomena was seen, which is a phenomenon that is primarily dependent on the conditions under operation, as had been reported and validated in previous research [7, 13]. This investigation utilized AA5052. The choice of these materials was determined by tension test and their widespread use across several industrial domains. Table 1 presents the chemical components of metals that are used in the bending processes.

Selecting parameters

The most successful method for analyzing experimental data is analysis of variance (ANOVA). In experimental contexts, the analysis of variance transforms into a sophisticated and nuanced procedure. ANOVA serves as a fundamental approach for model comparison in experimental design analysis [19]. Methodically adjusting these parameters and examining the impacts of each and their interactions, researchers can identify the critical components for reliably quantifying spring back. This determines the method's relevance to accurate finite element analysis model validation and rigorous experimental design. The study included 27 samples with four variables at three levels in Table 2. After that, using FEA to find values by assessing energy and cost at their lowest. A product with good measurements is available. Finally, use artificial neural networks to forecast spring-back and compare findings to less time.

Design and method

The design of bending dies is predicated on a profound comprehension of the behavior of materials during plastic and elastic deformation. The primary objective is to achieve the desired angle and shape of the part after the forming force is withdrawn, while considering that the metal will have a tendency to spring back. In a typical bending system, the upper instrument, known as a

Table 1. Chemical Composition of AA5052

Si %	Cr%	Mg%	Mn%	Fe %	Cu%	Zn%	Others	Al %
0.216	0.18	2.24	0.04	0.21	0.06	0.05	0.05	Remain

Table 2. The levels of parameters

Parameters	Code/ Levels	L_1	L_2	L_3
Thickness of sheet(mm)	X_1	1	1.5	2
Width-to-thickness ratio	X_2	3/6	4/6	6/6
Angle of rolling	X_3	0°	45°	90°
Holding Time (s)	X_4	0	90	180

punch, is responsible for compressing the sheet metal. It has a strike radius that affects operations. A lower die is the instrument on which the sheet metal is resting. It is equipped with a die angle. The use of Solid Works 2022 allows for process simulation. This simulation includes the process of building the die to achieve the target shape. It is possible to edit the dimensions of dies by using the solid Works API, which allows for significant modifications to be made to the die design. In sheet metal forming, it has shown promise in design [20]. In this work, the convex and concave contact zones constitute the region of curve convergence. The line's midpoint, line-curve intersection, and first-second curve intersection will be crucial components of the tests. Figure 3 shows the die profile of the metal-forming process.

The V-shaped object, characterized by a 90-degree internal angle, is both simulated and manufactured using a punch set at a 90-degree angle. Bending operations have been conducted on the initial sheet. The top punch, fabricated from Ck45, features a 90-degree angle and a nose radius of 2 mm. This punch has been employed in this study. Tests on bending have been conducted

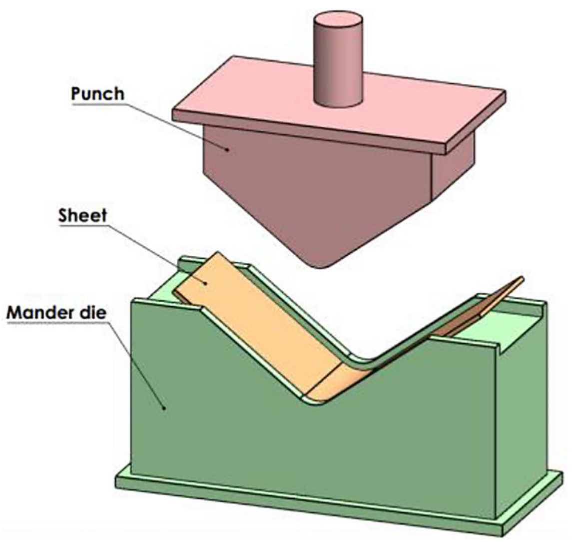

Figure 3. Illustrates the process of V bending production

using the WDW-200E test machine, which has a maximum capacity of 200KN, to produce V-shaped bent components, as seen in Figure 4.

The experiment was conducted at a rate of 20 mm/min, focusing on four factors: thickness (t_0 = 1, 1.5, 2 mm), Width-to-thickness ratio (3/6, 4/6, 6/6), rolling angle (0°, 45°, 90°), and holding time (0, 30, 60 seconds) from AA5052.

The objective was to create a V shape and conduct a practical spring back measurement. The obtained results were compared with the FEA & ANN product; the samples acquired are depicted in Figure 5.

MODEL WITH FINITE ELEMENT

Numerous commercial software applications currently incorporate FEA. Numerical simulation methods are easy to understand and use, setting them apart from the many engineering firms that offer numerical simulation solutions. Developing forming processes now requires FEA. In Sheet metal forming, it has shown promise [21, 22]. The ABAQUS/CAE environment ensures simplicity and consistency in the development, submission, monitoring, and analysis of findings obtained. In the process of finite element analysis, the selection of the element type is of utmost significance since it has a significant impact on the smoothness of the analysis, the correctness of the results, and the achievement of the desired output [23]. In this study, the analysis and simulation of the bending process and predicted spring back behavior of the sheet metals were conducted using the ABAQUS software program. During the course of this investigation, two distinct kinds of elements were utilized: (C3D8R) was utilized to mesh the rigid bodies, and (S8R) was utilized to mesh the deformable bodies. The family of continuum elements, which consists of eight degrees of freedom, incorporates these elements into its classification system. The term "yielding stress" is defined by applying Von Misses yield criteria

Figure 4. Model WDW-200E testing machine

Figure 5. Bending samples after testing

instead. Due to their usage in this finite element model, AA5052 is included as a material in Table 3. The shell meshing and the body sizing are 2.5 × 2.5, determining the AA5052. Determine the dimensions of a punch and die measuring 3.5 × 3.5 using the sweep meshing method. Creating a V-shape out of a sheet is illustrated in Figure 6, which displays the method. Determining the size of the components, making an appropriate mesh, and setting the initial contact conditions are the four primary processes in building the model. To achieve this, use a surface-to-surface dynamic explicit contact approach based on a limited "sliding penalty." It comes with two sets of contacts: one for punch-top sheets and one for die-bottom sheets. The punch maintained a constant speed of 20 mm/min along the y-axis, while the die remained motionless.

Samples of the sheet were cut using a wire and subjected to tensile testing in accordance with ASTM E8M standards. Tensile samples were cut from work pieces using a wire-cut EDM machine in three different rolling directions: 0 degrees, 45 degrees, and 90 degrees. There were three samples taken from each direction. Table 3 provides the results of the tensile test that was performed on the specimens.

The FEA analysis results, analyzed via ANOVA, indicate that the parameters significantly influence SB, with metal thickness exerting the most substantial effect at 38.7%, followed by rolling direction at 32.3%, and subsequently cross-sectional area and, to a lesser degree, holding time, as shown in Table 4.

Figure 7 illustrates the degree to which these parameters have an effect on SB. The metal thickness and rolling direction are the two elements that have the most significant influence on the process, whilst holding time has the least influence.

ARTIFICIAL NEURAL NETWORKS

ANN is a mathematical model that replicates the structure and operation of biological brain networks. It's a form of non-linear mapping structure utilized in classification and predictive modeling. There are many unique varieties of neural networks, each designed to solve a specific sort of problem [24, 25]. This investigation revealed new predictions about spring back in the bending process, demonstrating consistent findings with an error margin of less than 1. Optimal springback necessitates a mathematical model based on bending parameters. This article employs ANN for its mathematical model. It possesses hidden layers situated between the input and output layers. All neurons in the underlying layer communicate with one another. Figure 8 depicts a hidden layer with three inputs and one output that represents the process. The most crucial input and output parameters for the smallest SB are holding of time, the angle of rolling, and thickness. The network was trained using a sequential technique.

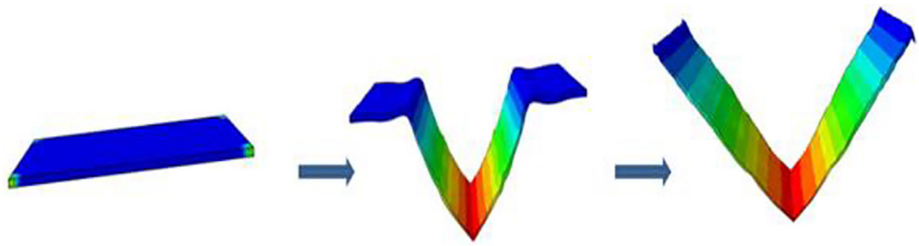

Figure 6. Stages of formation of a shape V-bending

Table 3. Mechanical properties of metal

Properties	0 degrees	45 degrees	90 degrees
Stress yield (MPa)	183	154	168
Modulus of Elastic (GPa)	69	69	69
Density (gm/cm^3)	2.7	2.7	2.7
Poison's ratio	0.33	0.33	0.33

Table 4. NOVA's spring back

Source	DF	Sum of squares	Variance	p %
X1	2	4. 428	2.61	38.7%
X2	2	1.288	0.84	19. 8%
X3	2	3.213	2.17	32.7%
X4	2	0.482	0.05	6.4%
Residual	18	0.198		2.8%
Total	26	9.852		100%

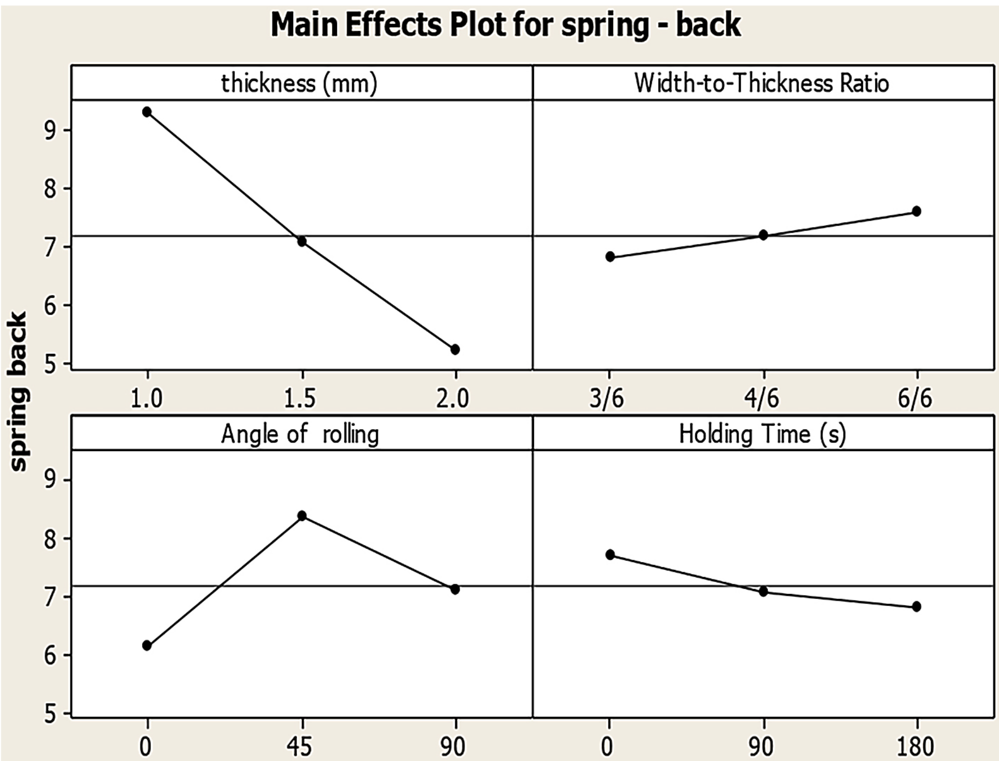

Figure 7. Analyzed of ANOVA

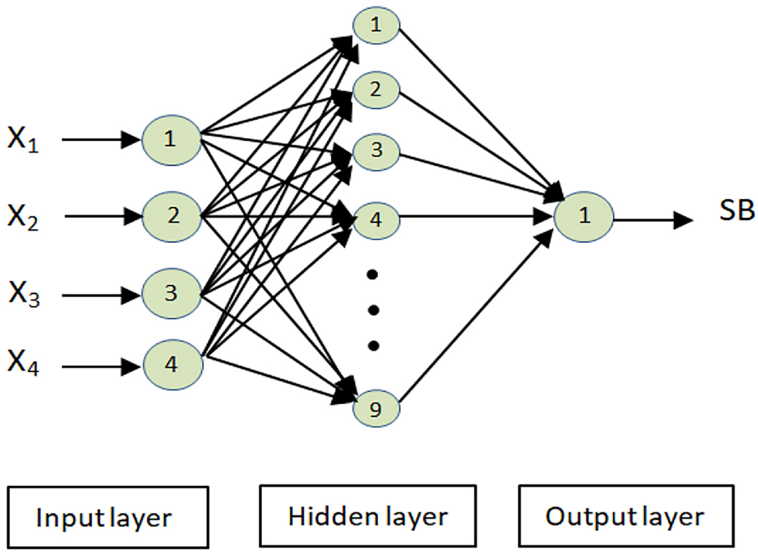

Figure 8. General structure ANN

Various network architectures have been studied in pursuit of the best design. The most appropriate model was found to have a 4-9-1 structure of Number of attempts 100 times. In the 18th try, the results were the best that could be produced.

The regression equation is a crucial instrument for analyzing and enhancing contemporary industrial processes. ANN offer a mathematical foundation for comprehending the intricate interactions among metal thickness, rolling direction, cross-sectional area, and holding time, facilitating data-driven decisions akin to FEA. These judgments can be juxtaposed with actual outcomes to discern any discrepancies. ANN improves efficiency; decrease expenses, and minimize time requirements. The function may be determined by using the analysis-involved regression models used by SB, as shown in Equation 3.

$$SB = 8.563 + (-0.004X_1) + (-0.0003X_2) + +(-0.00016\,X_3) + (-0.0009\,X_4) + (-0.022\,X_1^2) + 0.0041\,X_1X_2 + (-0.008X_1X_3) + 0.007X_1X_4 + \quad (3)$$

RESULTS AND DISCUSSION

Spring-back of AA5052 is affected by holding time, width-to-thickness ratio, rolling direction, and thickness. A statistical model for predicting SB, obtaining anticipated outcomes, and comparing them to observed values was created using FEA. This model served as the basis for the experiments. The results highlight the SB's responsiveness and efficiency. After the implementation is complete, Table 5 presents the results section, which consists of twenty-seven components and four parameters. One can calculate the error equation using equation number 4, which is the default.

$$Error\ \% = \left(\frac{\left(\begin{array}{c}measured\ value\ - \\ -\ predicted\ value\end{array}\right)}{measured\ value}\right) \times 100 \quad (4)$$

This section will examine the influence of factors on the spring back. Duration required for FEA to conclude, compare it with empirical data, assess the magnitude of its impact, and identify the maximum error percentage between FEA and actual applications. Compare the findings gained from prior research and further enhance these outcomes using ANN and the error % between the model created by the ANN and practical applications, as well as ultimately address the recommendations implemented to mitigate spring back.

Analysis the results

Analyzing of the finite element analysis findings of bending processes enables rapid iteration of design tweaks for parameter optimization. Based on finite element analysis results BS worth fell between 3.447 and 10.096 in Table 5. Thicker materials have less spring-back. A higher width-to-thickness ratio increases cross-sectional area, leading to increased internal stresses and deformation resistance. Due to this, Width-to-Thickness Ratio materials flex more and spring back more.

Table 5. Results of experiments

ON	X_1	X_2	X_3	X_4	Spring back (SB)				
					Practical	FEA	Error%	ANN	Error $_1$%
1	1	6/3	0°	0	8.6	8.288	3.63	8.535	0.8
2	1	6/4	0°	0	8.1	7.956	1.78	8.121	-0.3
3	1	6/6	0°	0	8.2	7.896	3.71	8.228	-0.3
4	1	6/3	45°	90	10.5	10.096	3.85	10.393	1.0
5	1	6/4	45°	90	10.3	10.012	2.80	10.218	0.8
6	1	6/6	45°	90	10.1	9.709	3.87	10.048	0.5
7	1	6/3	90°	180	9.2	8.877	3.51	9.156	0.5
8	1	6/4	90°	180	9.3	9.104	2.11	9.204	1.0
9	1	6/6	90°	180	9.1	8.917	2.01	9.129	-0.3
10	1.5	6/3	45°	180	7.8	7.678	1.56	7.732	0.9
11	1.5	6/4	45°	180	7.2	6.926	3.81	7.225	-0.3
12	1.5	6/6	45°	180	7.4	7.152	3.35	7.372	0.4
13	1.5	6/3	90°	0	7.7	7.398	3.92	7.635	0.8
14	1.5	6/4	90^0	0	7.2	6.948	3.50	7.161	0.5
15	1.5	6/6	90°	0	7.5	7.215	3.80	7.475	0.3
16	1.5	6/3	0°	90	6.5	6.290	3.23	6.453	0.7
17	1.5	6/4	0°	90	6.3	6.078	3.52	6.262	0.6
18	1.5	6/6	0°	90	6.1	6.008	1.51	6.068	0.5
19	2	6/3	90°	90	4.4	4.242	3.59	4.362	0.9
20	2	6/4	90°	90	4.8	4.618	3.79	4.752	1.0
21	2	6/6	90°	90	4.6	4.528	1.57	4.612	-0.3
22	2	6/3	0°	180	3.8	3.736	1.68	3.762	1.0
23	2	6/4	0°	180	3.5	3.447	1.51	3.488	0.3
24	2	6/6	0°	180	4.1	4.026	1.80	4.084	0.4
25	2	6/3	45°	0	7.3	7.153	2.01	7.275	0.3
26	2	6/4	45°	0	7.9	7.691	2.65	7.875	0.3
27	2	6/6	45°	0	6.6	6.456	2.18	6.569	0.5

Material mechanical parameters, including elastic modulus, Angle of rolling, and yield strength, affect the connection between thickness and springback. These qualities show a material's capacity to deform and recover. Higher yield strength and strain hardening characteristics reduce spring back regardless of thickness, as shown in Figure 9.

After analyzing 27 samples, we found that Sample No. 4 had the following characteristics: a medium cross-sectional area, a maximum BS value of 10.5 at 1 mm thickness, a 45° rolling direction, and a 90-second setting time. The thin material has a higher yield point at 45 degrees of rolling, which results in increased internal stresses and resistance to deformation. Additionally, the material has a greater spring-back. This is because of the high spring back. For sample No. 23, we had a lower BS value of 3.5, a 2 mm thickness, straight-line rolling, a lengthy setting time, and a medium cross-sectional area. See the quantity of SB within Figure 10. Because of the nature of compressive stresses in the top layers of the sheet metal and tensile stresses in the bottom layers, rebound changes with thickness variation. Thus, the effects of these stresses become increasingly significant in governing the elastic recovery process as the thickness of the used sheet increases. Decreased thickness leads to an increase in SB, and these findings are consistent with references [8, 9]. Additionally important is a vast cross-sectional area since it stores the delivered force over a big region. The rolling direction, meantime, is correlated with metal characteristics. Less rebound follows from a straight-line rolling direction. Simultaneously, the least important element influencing the process was hold time.

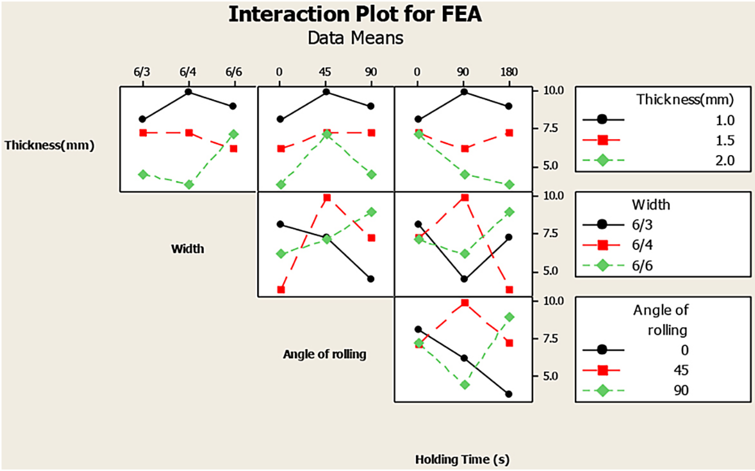

Figure 9. Utilizes the FEA to illustrate the effect of parameters on spring back

Longer holding time contributes to reduce SB, These results agree well with [11, 13]. To ensure the component does not elastically rebound or remain stationary between the punch and die until the plastic deformation is uniformly distributed, a holding period is occasionally employed to reduce or eliminate spring back in the produced item. The findings indicated that holding time exerted significantly less influence compared to the parameters mentioned in the research introduction. A 3.5% decrease in spring back was attained with a 2 mm sheet thickness, a linear rolling direction, and an extension of holding time from 0 to 180 seconds, illustrating the substantial influence of sheet thickness and rolling direction on holding duration. There is agreement between the experimental and finite element analysis results. All of our tests show an error rate of less than 4%. According to earlier studies, this rate is suitable for the transformation processes in question. Alternatively, the maximum SB value with a 3.85% margin of error is (10.5 in practical and 10.096 in FEA). Figure 11 shows that there was a range of errors from a minimum of 1.51% to a maximum of 3.92% when comparing the FEA and practical results.

In comparison to previous research, in Research [7] study the spring back behavior of aluminum, copper, and pure iron is examined in this work by a hybrid technique that combines ML with FEA. According to the results, the ductility of aluminum causes it to have the largest spring back 6.2 at the greatest thickness; this is consistent with the research results. In this regard,

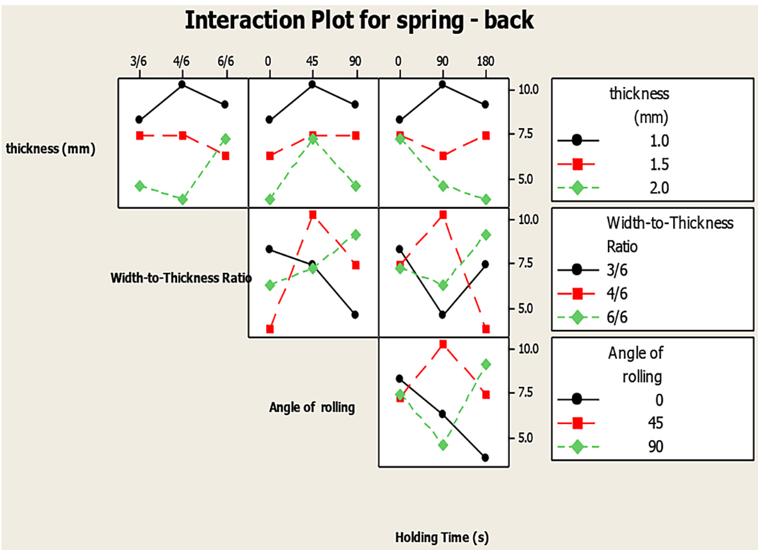

Figure 10. The influence of parameters on spring back

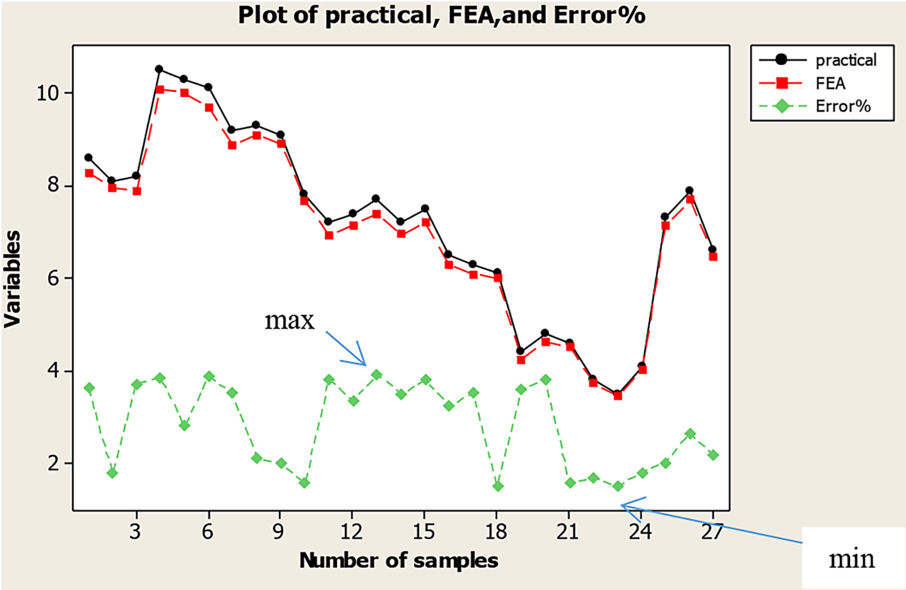

Figure 11. Demonstrates the convergence ratio between FEA and practical

research [26] examined the influence of variables on spring back. The value was determined to be 10.8 at 1 mm and 0 sec, as indicated in Table 3 of the aforementioned research results. The holding time exerted minimal influence on the process, which is consistent with the results obtained, with a rebound value of 8.2 at 1 mm, 0 seconds, and in the straight rolling direction. The researchers in [27] examined the influence of thickness, holding duration, and rolling orientation on two metals. The spring back value was 13 for aluminum at a rolling angle of 45° with minimum thickness and holding time. This investigation demonstrated that a 45° rolling orientation had the largest spring back value. This is consistent with the results obtained, with a maximum of 10.5 at 45°, with the minimum thickness and holding time. While the analysis model matched the practical results, the analysis in the ABAQUS program requires a lot of time to model the die and conduct an analysis of the results. Use ANN to forecast the quantity of SB to circumvent the problem of wasted time and achieve a decreased mistake rate and advise minimizing spring back.

Optimized results by ANN

Production wants to acquire a product with exact, inflexible dimensions and achieve a product with a reduced value SB. Consequently, it was imperative to achieve a reduced error rate and minimize the duration for analyzing the outcomes of the FEA analysis and energy consumption, attainable just by ANN. Multiple regression models are utilized to analyze data from primary quantitative research designs, such as surveys and experiments, to identify correlations between a criterion variable and predictor variables. At least 15% of the data is used for testing, 15% for validating, and 70% for training the model. Table 6 displays typical output response observations.

Figure 12 suggests that the optimal choice for this study was epoch 0, with the lowest mean absolute prediction error of 0.0688897.

The Levenberg-Marquardt approach produced the best overall results (R = 0.99094). The validation data set has a regression coefficient of R = 0.99136, indicating a strong connection between ANN and experimental outcomes as shown in Figure 13. The maximum percentage error values was 1% as shown in Figure 14 illustrates the difference between experimental, ANN. The greatest SB value, accounting for a 1% margin of error, is 10.5 in practical and 10.393 in ANN. The range of errors is from a minimum of 0.3% to a maximum of 1% in the comparison between the

Table 6. Observation on the output response

Settings for the network	4-9-1
The type of transfer function	Sigmoid
The number of epochs	100
The factor of learning rate (α)	0.001
Quantity of training trials	20
Quantity of testing trials	4

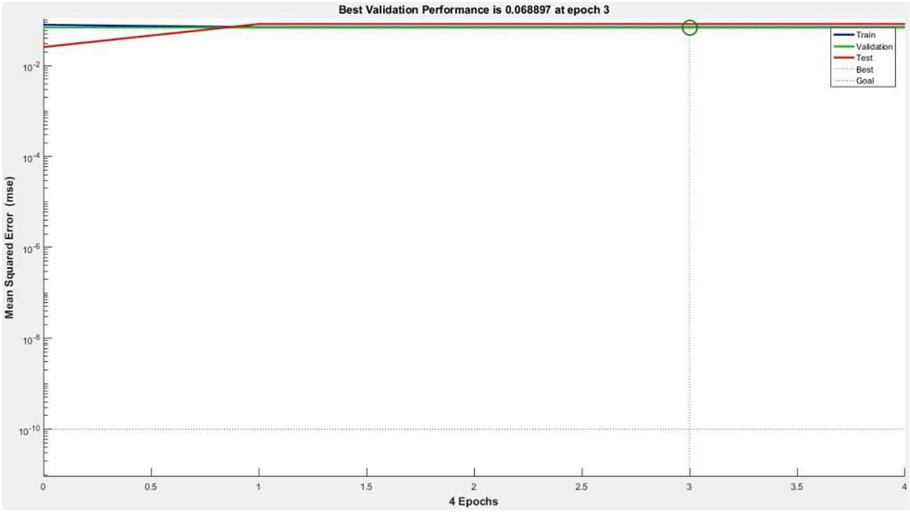

Figure 12. Spring back performance plot

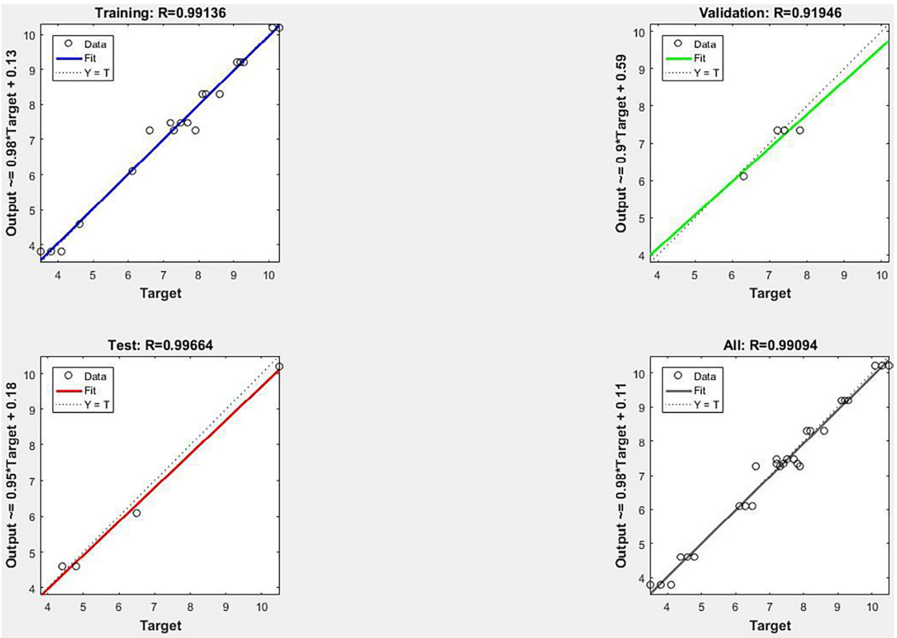

Figure 13. The envisioned network's visual representation

ANN and practical outcomes, these results agree well with [13]. With a decreased error rate of 2.8 percent compared to sample No. 4, the results show that the ANN model performs better than FEA. In comparing the outcomes of the ANN with other studies, the lowest error rate recorded was 0.27 in the previous research [28], but the minimum rate in our research was 0.3.

Comparison between SB values

In Table 5, see the expected and measured values for the SB side by side. Figure 15 shows the results of comparing the actual values with the predicted values. Results from SB were quite similar to those predicted by the design model. The ANN prediction model and the practical were in perfect agreement, with a minimum error of 0.3%. While the minimum error of 1.56% between FEA and practical. The results show that the ANN model is superior to the FEA analysis.

The graphic clearly illustrates that both the FEA and ANN models successfully forecast the SB with a high level of accuracy. The tight correspondence between the anticipated and observed values confirms the efficacy of these models for this specific application, corroborating the study paper's conclusions.

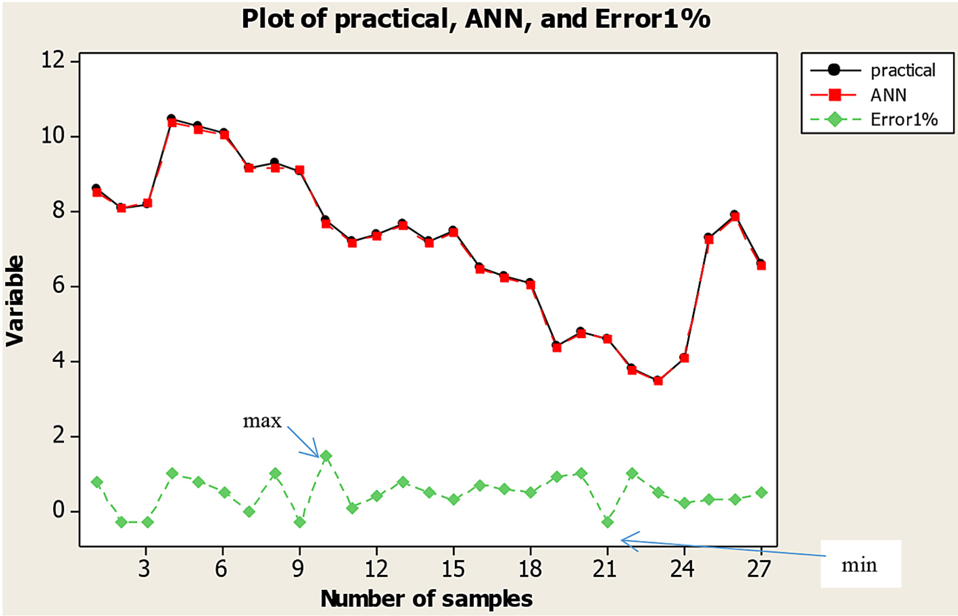

Figure 14. Demonstrates the convergence ratio between ANN and practical

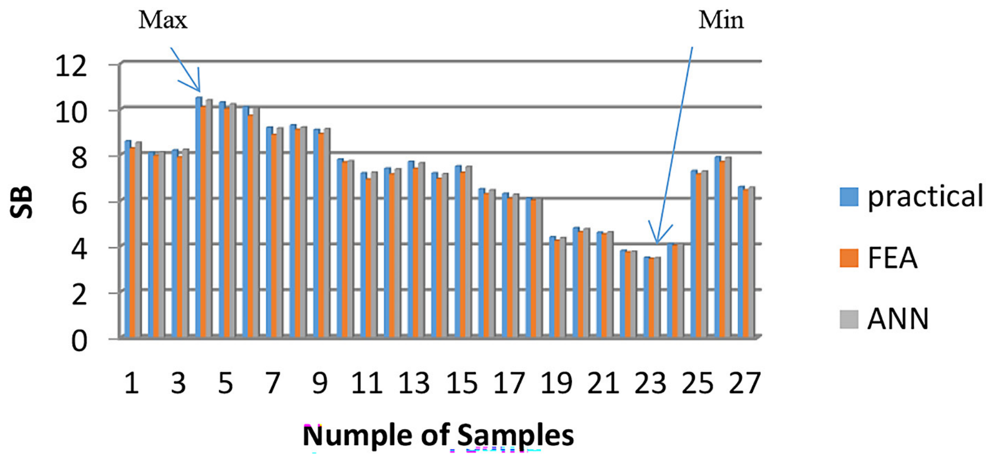

Figure 15. SB amount between practical, FEA and ANN

TO solve the problem an approach was established to tackle this phenomenon, use ANN to rectify the spring back, so assuring that components are manufactured with little departure from the required angle. The artificial neural network was trained with experimental or simulated data, utilizing Equation 2, in which the network modifies the R value. The outcomes derived from training the neural network indicated that reducing the bottom die angle significantly yields a final output with minimal spring back. If the target angle for the component is 90 degrees, the ANN may suggest a die angle of 89 degrees to account for the anticipated rebound. This indicates that the punch will deform the material at an angle somewhat less than 90 degrees. Upon removal of the force, this adjustment is implemented inside the design environment, immediately transmitting a command to Solid Works to modify the die angle in the 3D model of the die. This facilitates the automation of the design process and embodies the optimal recommendations obtained from ANN. It is important to highlight that the laboratory die utilized in this work was constructed with a fixed angle of 90 degrees. In light of the findings demonstrating the efficacy of decreasing the angle in mitigating spring back, it is recommended to produce a new 89-degree bending die. This alteration to the die's physical configuration will markedly diminish spring back in production processes, hence improving product precision and manufacturing efficacy.

CONCLUSIONS

ANN models may precisely evaluate product spring back, allowing effective modifications during the production. Implementing ANN can enhance product quality, reduce human error, and augment productivity. Future integration is essential for industrial superiority and global competitiveness.

The results indicated that the spring back phenomenon varied considerably according to thickness and rolling angle. The following are some of the most important conclusions drawn:

1. The ANOVA results demonstrated that the metal thickness significantly influences the spring back value by 38.7%, the angle of rolling by 32.3%, and the cross-sectional area by 19.8%. The least significant factor affecting the process was hold time.
2. Reduced spring back value of 3.5, a thickness of 2 mm, linear rolling, and an extended holding time.
3. The ANN model is capable of accurately projecting spring back in a short amount of time, reducing the amount of time spent on analysis, minimizing errors, lowering costs, and accelerating product success.
4. Comparing the experimental, FEA, and ANN values for SB, it was found that the ANN model had error of 0.3% and the FEA model had an error of 1. 56%. However, adding more test patterns can further decrease this error.

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