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Prediction of Springback using the Machine Learning Technique in high-tensile strength sheet metal during the V-Bending Process

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Abstract

Bending is one of the widely used forming processes for sheet metals. However, due to the metal elasticity, the springback characteristic is unavoidable, leading to deviations from the desired final shapes and causing cumulative fitting problems in the assembly stages. Thus, precise predictions of the springback responses will enhance the sheet metal forming and the overall manufacturing processes. This is achieved by employing tree-based machine learning algorithms. These algorithms are used for their simplicity, preciseness, and consistency. Based on the tree-based algorithms, many prediction models are constructed and evaluated. First, experimental setup is established to measure the springback angles for different manufacturing conditions such as: the bending angle, the sheet metal's width and thickness, the machine settings, etc. Then, these data sets are divided into training and testing groups for the prediction models. This division is carried randomly, where 90 % of the data sets are used for training, and 10 % are left for testing the models' accuracy. The models are evaluated by comparing their predicted springback angles with the experimental values. The deviation errors are measured using the Mean Square Error (MSE), the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE).It isrevealed that the LightGBM prediction model is the most accurate model with 0.42 deg., 0.26 deg., and 0.52 deg. for MAE, MSE, and RMSE, respectively. The Gradient boosting comes in the second place with 0.66 deg., 0.760 deg., and 0.80 deg. for MAE, MSE, and RMSE, respectively.

.**Keywords:** Sheet metal bending; springback; high strength steel; machine learning algorithms

1. Introduction

Sheet metal processes had enormous growing in the last few decades for different industrial and commercial applications. Automobile industry is an example where steel sheet metals with high specific strength and high specific toughness are required to enhance the structure to maximize its load capacity and to minimize the fuel consumption [1]. Various sheet metal processes are used such as shaping, drawing, and piercing. Besides, bending is used and considered as a most common process [2]. In the bending process, the sheet is forced to occupy the cavity between the die and the punch. The value of the press load is adjusted in the range of the yield strength and the ultimate strength to re-shape the sheet metal permanently without damage. The bending process produces compression and tension on the inner and the outer faces, respectively (Fig. 1).

The widely used bending operation is the V-bending, where the sheet metal is forced to bend according to the V-shape of the punch and die (Fig. 2). The bending angles can vary widely from very sharp to wide angles depending on the required process and on the metal characteristics.

During the V-bending operation and once the punch is retracted back, the sheet metal tends to partially recover due to its elastic characteristics. This behavior of the metal is known as springback (see Fig. 3). The sheet metal responds according to the tensile characteristic where the springback can either be positive or negative. In other words, the sheet metal recovers outward or inward for positive or negative springback, respectively.

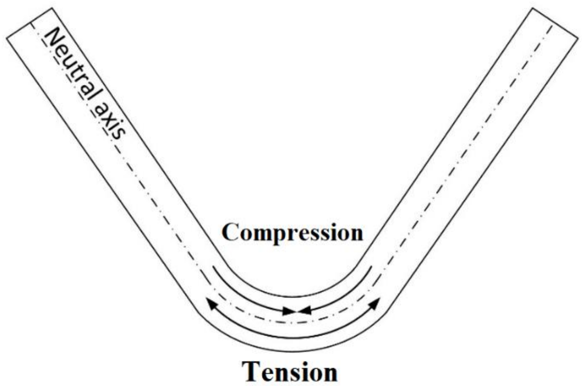

Figure 1. Basic sheet metal bending

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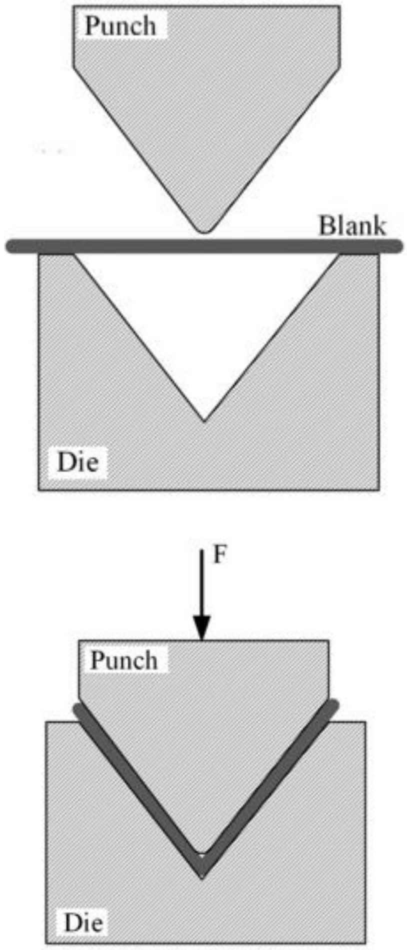

Figure 2. V-bending operation (a) before and (b) after punching

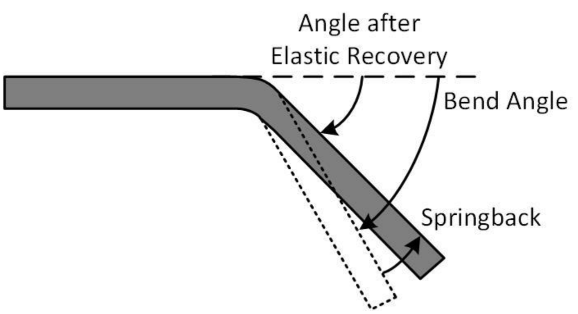

Figure 3. Illustriation of Springback in sheet-metals

Analytical formulations for the bending behavior of simply supported plates using Higher Order Shear Deformation Theory were presented by S. Redddy *et al*. [3]. Another study conducted by Dong-Juan *et al*. investigated the effect of the neutral axis shifting, the sheet metal thickness, the bending arm length, and the contact pressure [4]. An analytical model was established to relate these input parameters with the springback response based on Hill yield criterion under plane strain conditions. The springback response was also investigated by other researchers at varying temperatures ranging from room temperature to 300 ^{o}C on steel sheet metal [5]. Also, the temperature variations during a U bending process and its influence on the spring back response for Aluminum alloy (AA6082) was experimentally investigated by Cai *et al*. They noticed that the springback decreases with the temperature increase [6].

Furthermore, a comparative study was conducted by Da Silva *et al*. to explore the differences in the springback responses between the existing materials of high tensile strength with those of higher tensile strength [7]. Yang *et al*. conducted experimental research to predict the springback response in DP780 during an air bending process. This was challenging due to the fluctuation of the elasticity modulus of the advanced high strength steel during the load application [8]. Another model was established by Jung *et al*. to investigate the anisotropic behavior and to predict the springback response of dual-phase steelsin a U bending process [9]. Experimental validations of the model were conducted.

An analytical model built by Leu and Zhuang enabled the prediction of the springback response for materials of high tensile strength. Their model focuses on many input parameters as the material strength, the sheet metal thickness, and the punch radii [10]. The springback response was also investigated during stamping and successive quenching processes for steel sheets of ultra high tensile strength by Nakagawa *et al.* [11]. They were able to decrease the springback response through many ways by adopting the holding technique during the bending process.

Other studies adopted the analysis of variance (ANOVA) for air V-bending experiment [12]. The obtained data was analyzed to investigate the springback response of different sheet metals according to the workpiece geometry, tools geometry, and the sheet metal materials.

The finite element method (FEM) was also employed for the springback predictions. For example, Ramezani *et al.* employed the FEM to predict the springback response in a V-bending process [13]. This was accomplished for steel sheet metal of high tensile strength by modelling its kinetic friction. FEM was also used by Slota and Jurcisin to predict the springback response for steel sheet metals in an air bending process [14]. Another FEM prediction model was established by Choi *et al*. to investigate the springback response of high tensile steels after a U bending process. They concluded that the loading does not have a proportional effect on the springback response [15]. Noma *et al*. built a finite element model for the investigation of the elastic recovery response in sheet metals by including the strength differentials incorporated from experimental results [16]. Many other FEM models were established to predict the springback response for different sheet metals [17 – 20].

Many other researchers employed the Artifical Neural Network (ANN) and the machine learning algorithms to predict the springback response. They showed that the ANN and the machine learning can provide more accurate and reliable results in comparison with the FEM or the regression models [21 – 25]. Liu *et al*. presented a machine learning model for the prediction of springback in QP1500 steel, where his core objective was to incorporate the Bachinger effect in the sprigback model [26]. Asmael *et al*. also worked on the machine learning for the prediction of springback in AA50552 Aluminum Alloys during the V-bending process [27].

As can be observed from the preceding literature, two main approaches are normally used to predict and simulate the springback response in sheet metals after bending loading; these are the machine learning and the FEM. However, FEM cannot be used simultaneously in the production stages to adapt for the springback due to its inherited efficiency [28]. Moreover, FEM are used for limited type of materials as the high strength steels[1, 29]. On the other side, the machine learning has many drawbacks as many previous attempts used the ANN where huge amount of data is normally needed to train the system, and the results can be quite difficult, or even not possible, to be explained or justified.

Overall, for the increasing demands on competitive and high-quality products, creating final products with exact geometries compared with their designs is very essential. Hence, the springback behavior of the sheet metals should be accurately predicted and compensated during the manufacturing stages to ensure final products with accurate matching with their designs. Thus, to predict this behavior, a new approach based on the machine learning is developed and introduced in this article.

As the name implies, the machine learning provides the system with the ability to learn and adapt for optimal linking between the inputs and the outputs. A fast and efficient family of the machine learning algorithms is the tree-based algorithms which can provide reliable and accurate results at a short time. To elaborate more, the machine learning based on the tree-based algorithms are adopted in this article where small data can be sufficient to provide high level of accuracy for the predicted results. These data were obtained experimentally during a V-bending process for high strength sheet metals. The process includes bending the sheet metals to different angles (60, 90, and 120 degrees). The final angles after the springback recovery are measured using a digital bevel gauge.

The sheet metal conditions should be monitored as the surface finish and the corrosion influence the sheet metals stiffness and their springback behaviors [30]. It is worth to tell that the prediction approach introduced in this work can be extended to be utilized for other materials as composite sheets under bending loads [31].

The article comprises of four sections. The first section had already presented the problem statement and the objective of the study. The following section demonstrates the research design and the experiment setup. Then, the results analysis will be provided in section 3. Finally, the conclusion will be presented in the last section.

2. Methodology

To predict the springback response after the V-bending process, a main framework is established based on the machine learning algorithms (Fig. 4). The framework enables building accurate prediction models by relating the data acquired from the experimental setup with the springback response. The main steps are discussed in the following.

2.1. Design of Experiment

Four grades of sheet metals are considered in this study. These are the steel sheet metals JSC-440, JSH-440, JSC-590, and JSH-590. The geometric parameters (sheet thickness and width) and the process parameters (bend angle, bend load) are listed in Table. 1. Two types of machine press are used; these are the mechanical press and the hydraulic press. The holding time and the gap between the die and the punch are also considered to study their effect on the springback response of the sheet metals after the V-bending process. Once the bending process is completed and the punch is retracted, the final bend angle is measured using an accurate digital bevel gauge, and the springback angle is recorded. Different combinations of the input parameters are considered in this study, where each combination was run twice to ensure the reliability and the accuracy by adopting the two runs' average value. A total of 856 sheet metal bending processes under varying parameters and conditions led to 428 data sets. The data sets are composed of the input parameters listed in Table 1, as well as the corresponding measured values of the springback angles. Here, press #1 is a mechanical press, whereas press#2 is a hydraulic press used in the experiments. The length of the sheet metal strip is 170mm, whereas the internal and the external punch radii are 8 mm and 10 mm, respectively.

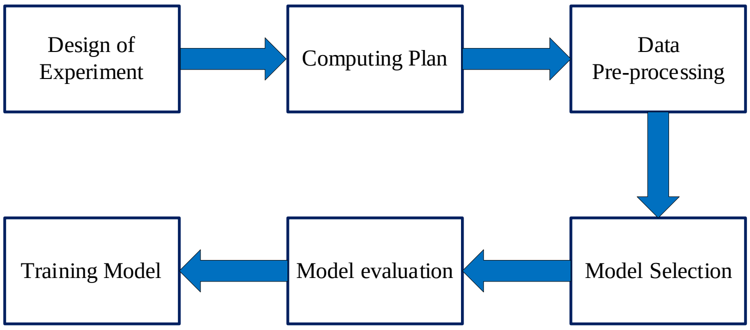

Figure 4. Research Design

Table 1. Controllable Process parameters for the V-Bending

Process Parameters	**Press #1**	**Press # 2**
Applied Load, F (tons)	60	75 Pressure, L (kg/cm^2) of 30 and 180
Load holding time, T (sec.)	0	0 or 10
Die and punch gap, G	= t = 0.7t	= t
Sheet Material	JSC-440, JSH-440, JSC-590, and JSH-590	
Sheet thickness, t (mm)	1.0, 1.2, 1.4, and 1.6	
Width of sheet, w (mm)	20 and 50	
Bend angle (deg.)	60, 90 and 120	

2.2. Computation Plan

The computations were conducted using MacBook pro (Core i5 processor, 8GB DDR3, 3.1 GHz CPU). The programming language adopted was python with the following libraries (Table 2).

Table 2. Python's Libraries

Library	Revision
Pandas	1.1.3
NumPy	1.19.2
Scikit-learn	0.23.2
Matplotlib	3.3.2
LightGBM	3.2.1
Flaml	0.3.6

2.3. Data Preprocessing

To simplify the model, instead of using the 7 varying parameters listed in Table 1, the machine parameters are combined to form a single parameter called "the machine settings". Here, the machine settings combine the applied load, the holding time of load, and the gap between the die and the punch. To elaborate more, five parameters are considered in the prediction model, these are: (1) width of sheet metal, (2) thickness of sheet metal, (3) bend angle, (4) sheet metal material, and (5) the machine settings. While the first three parameters are treated as continuous parameters where scikit-learn's Standard Scaler was used, the last two parameters are treated and encoded as integer arrays where scikit-learn's OrdinalEncoder was used.

Regarding the continuous parameters, their data are transformed into a normal distribution with a mean value of 0, and a standard deviation of 1.

The five parameters mentioned are spread over 2 - 6 attributes of the features. For example, the width parameter has two attributes as only two values of width are considered, whereas the machine settings are spread over 6 attributes to cover all the different combinations. The detailed attributes are listed in Table 3.

2.4. Model Selection

Tree-based algorithms are adopted in this research for their wide capabilities of solving linear or non-linear, continuous or discrete problems with high precision and good consistency. In general, tree-based algorithms can adapt to establish mapping between the input parameters and the output results for any type of problems efficiently and simply. The prediction models constructed according to the tree-based algorithms and the corresponding libraries used are listed in Table 4.

Table 4. Machine Learning Models according to the tree-based algorithms

Machine Learning model	Python's Library
Decision tree, **D**	Scikit-learn
Random forest, **R**	Scikit-learn
Extra tree, **E**	Scikit-learn
Light gradient boostingmachine (lightgbm), **L**	Lightgbm
Gradient boosting, **G**	Scikit-learn

2.5. Model Evaluation

To evaluate the prediction models constructed and to assess their accuracy, statistical measures were performed. These measures are the MSE, MAE and RMSE. The mathematical expressions for these measures are expressed as

$$MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^{\,2} \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \left| e_i \right| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^{\,2}} \tag{3}$$

where e_i is the difference error between the experimental result and the predicted result of the springback angle for each data set i. N is the number of samples of the testing data.

In this work, these measures (MSE, MAE, and RMSE) are considered for monitoring and evaluating the prediction model's accuracy and performance.

2.6. Model training

For training purpose, 90% of the data sets are considered (i.e. 385 data sets). All the prediction models listed earlier in Table 5 were trained on these data sets using the corresponding libraries mentioned (i.e. the Scikit-learn and the Lightgbm libraries). Tuning the models' parameters was conducted using hit and trial for both decision tree and Gradient boosting models, whereas flaml was used for the remaining models. The optimal values for the parameters of the different models after the tuning are listed in Table 5.

Table 3. Controllable Parameters for the V-bending

Feature parameter	Attribute 1	Attribute 2	Attribute 3	Attribute 4	Attribute 5	Attribute 6
Material	JSC-440	JCS-590	JSH-440	JSH-590		
Sheet thickness, t (mm)	1.00	1.20	1.40	1.60		
Sheet Width, w(mm)	20	50				
Bend angle, A (degree)	60	90	120			
Machine settings (M)	**Press#1**		**Press#2**			
	F =60 tons, G = t	F =60 tons, G=0.7t	F=75 tons, G = t, T=0 sec, HL=30 kg/cm^2	F=75 tons G = t T=10sec HL=30 kg/cm^2	F=75 tons G = t HT=0 sec HL=80 kg/cm^2	F=75 tons G = t HT=10 secHL=80 kg/cm^2

Table 5. Values for the machine learning parameters after tuning

Model name	Parameters used	Value
Decision Tree	Maximum depth of the decision tree	4
	Minimum nos. of samples to be in a leaf node	8
	Minimum weighted fraction to be in a leaf	0.0 (equal weight)
	Growth of tree up to maximum number of nodes	10,000
	Minimum cost complexity pruning	0.0
	Error criterion	MSE
Random Forest	Control of sub-sample size with the maximum sample size	True
	Error criterion	MSE
	Minimum nos. of samples to be in a leaf node	1
	Minimum number of sample size to split an internal node	2
	Maximum features weights to decide the split	0.511992
	Number of trees	35
	Number of parallel jobs	-1
LightGBM	Subsample ratio of columns in each tree	0.950267
	Learning rate	0.236847
	Number of bins to construct histogram	127
	Minimum data points needed in a leaf node	21
	Number of boosting stages to perform	49
	Number of leaves	
	Objective	'regression'
	Weights of regularization Alpha	0.2424801
	Weights of regularization Lambda	0.0009765
	Fraction of rows used per tree building	0.6374486
Extra Tree	Bootstrap	False
	Maximum feature (in fraction)	0.61700764
	Number of trees	100
	Number of parallel jobs	-1
	Error criterion	MSE
	Minimum nos. of samples to be in a leaf node	1
	Minimum number of sample size to split an internal node	2
Gradient Boosting	Learning rate	0.1
	Error criterion	Friedman MSE
	Loss	Ls
	Maximum depth of the individual regression estimators	3
	Minimum nos. of samples to be in a leaf node	1
	Minimum number of sample size to split an internal node	2
	Number of trees	100
	Subsample	1.0
	Tolerance	0.0001
	Validation Fraction	0.1

2.7. Discussion

As the decision tree model is the core to all other tree-based models, understanding its role is important to understand the other prediction models. Training of the decision tree is performed using experimental data sets. In the training stage, the decision tree model continuously and iteratively generates split decisions which lead to cumulative branching until the success criteria or ending criteria is reached. This is carried using the binary recursive partitioning which is a part of python's scikit-learn. As a result of the branching tree, the most significant predictor parameters are expected to be generated at the upper level of the tree. Whereas the non-dominant parameters can appear on the lower levels or even completely disappear. For example, if the sheet thickness is a dominant factor for the prediction of the springback response, it comes on the top layers of the tree.

One drawback of the decision tree model is its instability. That is; small variations in the values of the input parameters can lead to significant changes in the decision tree and in the results concluded. Hence, using one prediction model is not recommended, and several tree models can be established and combined to enhance the prediction process and to improve its stability and robustness. This combination is known as ensembling approach and it is used by all the tree-based models adopted in this work. There are two ensembling approaches; these are the boosting and the bagging approaches.

In boosting approach, a series of small trees, normally with only one node, is established. Each tree is constructed by considering the net error of the previous tree. This will enhance the construction of the subsequent tree as it will be able to recognize the misclassified data points of the previous tree occurred during the branching. The final solution is the weighted average of all considered individuals. Gradient boosting and LightGBM models are famous extends of the boosting approach.

The bagging is an approach for creating different decision tree models simultaneously by random replacement of the sampling data from the original data set. This leads to variety in trees' sizes and branching. Some of the famous bagging approaches are the extra tree and the random forest models.

3. Discussion and Conclusion

As discussed earlier, the models are trained using 90% of the data sets. Once these models are constructed, their predictions' accuracy should be evaluated. A testing sample representing 10% of the main data sets (43 data sets) is used for evaluation. However, seeking abbreviations, a sample of 9 data sets are used first as a demonstrative example. The results of the full testing sample will be discussed next.

3.1. Demonstrative example for evaluation

To validate the constructed models and to evaluate their accuracy, a sample of 9 random data setsisfirst considered. The springback predictions of these data sets were compared with the experimentally measured springback values. The data sets' sample considered for this exampleis listed in Table 6.

Using the input parameters for these 9 data sets, the values of the springback angles were predicted for the five models constructed in this work. These predicted values are listed in Table 7 along the experimental values for comparison.The letters in the Table is representing the initial letters of the model's names.

Considering the predicted values for the springback angles listed in Table 7. Their deviations from the experimental values can be described using many statistical measures such as the MAE, MSE, RMSE, etc. These measures are listed in Table 8. It is obvious that Lightgbm model has the least deviations from the experimental values in comparison with the remaining models regarding MAE, MSE, and RMSE. This indicates that Lightgbm can be adopted as the most accurate and reliable prediction model for the springback of sheet metals after the V-bending process. However, before generalizing this conclusion, the full testing data sets' sampleshould be evaluated first.

Table 6. Data sets for the input parameters with the experimentally measured springback

Set No.	Thickness (mm)	Width (mm)	Initial angle (deg.)	Material	Machinesettings	Springback angle (deg.)
1	1.2	20	60	JSC-440	Press#275 - 0 - 180	2.500
2	1.6	50	60	JSH-590	Press#2 75 - 10 - 180	1.458
3	1.4	50	120	JSC-440	Press#160 - 0.7t	0.333
4	1.4	20	90	JSC-440	Press#1 60 -t	0.208
5	1.2	20	120	JSC-440	Press#1 60 - 0.7t	-3.333
6	1	20	60	JSC-590	Press#1 60 - 0.7t	-0.833
7	1.2	50	120	JSC-440	Press#2 75 - 10 - 30	-3.083
8	1	50	60	JSC-590	Press#1 60 - t	1.917
9	1.2	20	60	JSC-440	Press#2 75 - 10 - 180	2.250

Table 7. Predicted vs. experimental springback angles (in degree)

Set	R	G	L	E	D	Exp.
1	-0.280	0.682	1.650	1.876	-1.417	2.500
2	0.972	0.440	1.148	0.020	0.396	1.458
3	0.310	0.596	0.614	1.393	-1.000	0.333
4	1.418	0.680	1.051	1.409	1.750	0.208
5	-3.977	-3.768	-3.132	-4.344	-3.417	-3.333
6	-0.453	0.129	-0.662	-1.027	0.396	-0.833
7	-2.767	-3.620	-2.895	-2.729	-3.417	-3.083
8	2.732	1.984	1.661	2.127	0.396	1.917
9	-0.765	-0.210	1.215	-0.051	-1.417	2.250

Table 8. MAE, MSE, and RMSE measures of the predicted models (in degree) for 9 random data sets

Prediction model	MAE	MSE	RMSE
Lightgbm, L	0.459	0.317	0.563
Gradient boosting, G	0.892	1.344	1.159
Random forest, R	1.074	2.205	1.485
Extra tree, E	0.932	1.283	1.133
Decision tree, D	1.632	4.224	2.055

3.2. Evaluating the prediction models

Using the same statistical measures as had already been done in the previous section, however on all the testing data sets instead of 9 data sets, it was confirmed that the most accurate predictive machine learning model was the Lightgbm with values of 0.42, 0.26, and 0.52 for MAE, MSE, and RMSE, respectively. The Gradient boosting revealed values of 0.66, 0.76, and 0.80 for MAE, MSE, and RMSE, respectively, placing it as the second reliable predictive model. The different models and their corresponding evaluation values are listed in Table 9.

Table 9. MAE, MSE, and RMSE measures of the predicted models (in degree) for full testing data sets

Prediction model	MAE	MSE	RMSE
Lightgbm, L	0.41667	0.25689	0.516
Gradient boosting, G	0.66322	0.75954	0.803
Random forest, R	0.70593	0.97595	0.875
Extra tree, E	0.77252	1.01941	0.924
decision tree, D	0.91667	1.69012	1.347

This article introduced an approach which employs the tree-based learning algorithms for the prediction of the springback response of the sheet metals after the V-bending process. The approach demonstrated good accuracy and reliability to be adopted as a predictive model for the springback response. Different combinations of the input parameters were considered. The outputs (springback angles' values) were obtained through experimental setups. 90% of the data sets generated were randomly selected for training purposes. The remaining 10% were used for testing.The testing process revealed that the closest results to the experimental values was delivered by the lightGBM model. The statistical measures on the testing data revealed values of 0.42, 0.26, and 0.52 for MAE, MSE, and RMSE, respectively. Hence, LightGBM can be adopted for the springback prediction of the sheet metal after the V-bending process. Although this approach was dedicated for sheet metals of high-strength steel, different data sets can be fed to the model to establish prediction models for other sheet metal materials.

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