

Journal of Materials and Engineering Structures

Research Paper

Experimental and Numerical Characterization of Springback in V-Bending of AISI 304L Stainless Steel Enhanced by Machine Learning Prediction

Mokhtar Bencherif ^{a,*}, Abdelkrim Saidani ^b, Madjid Almansba ^a, Rabah Ferhoum ^a, Amar Boudedja ^a, Khellaf Belmihoub ^b.

^a Laboratory of Elaboration, Characterization of Materials and Modeling (LEC2M), Mouloud Mammeri University Of Tizi Ouzou, Algeria

^b Department of Mechanical Engineering, Mouloud Mammeri University Of Tizi Ouzou, Algeria

ARTICLE INFO

Article history:

Received : 28 February 2026

Revised : 7 March 2026

Accepted : 8 March 2026

Keywords:

Springback

V-bending

ABAQUS

Stainless Steel

Metamodeling

ABSTRACT

Accurate prediction of springback is a major challenge in sheet metal forming due to the material's ductility, strain hardening, and deformation-induced martensitic transformation. In this study, an integrated methodology is proposed, combining experimental measurements, finite element analysis, and machine learning to investigate springback in the V-bending of 1.5 mm thick AISI 304L austenitic stainless steel sheets. V-bending tests conducted at angles from 30° to 90° revealed springback percentages ranging between 20.30% and 37.33%. Subsequently, numerical simulations performed with ABAQUS/Explicit and calibrated using mechanical properties derived from tensile test results showed a good correlation with experimental data (MAE = 9.31%). To address the limitation of the number of physical samples, a data augmentation strategy based on values derived from literature was implemented, generating a training set of 200 synthetic data points. Seven regression models were evaluated via bootstrap validation, identifying degree-2 polynomial regression as the optimal model, with a mean absolute error of $2.98^\circ \pm 0.06^\circ$ and a coefficient of determination (R^2) of 0.985. The statistical validity of the model was confirmed by residual analysis demonstrating normality via the Shapiro-Wilk test ($p = 0.644$). A validated compensation table was generated for the direct calibration of industrial tools, demonstrating that even with a limited number of experimental data points, data-driven models can offer a reliable methodology for optimizing predictive manufacturing processes in sheet metal forming.

1 Introduction

In modern manufacturing, sheet metal bending remains one of the most widely applied processes for producing complex three-dimensional components for the automotive, aerospace and medical sectors [1, 2]. Despite its efficiency, achieving high dimensional precision can be challenging when facing a common defect, such as springback, which consists

* Corresponding author. Tel.: +213 778022739.

E-mail address: mokhtar.bencherif@ummto.dz

in the elastic recovery of the material upon tool removal [1, 3]. Variations in material properties and dimensions often lead to inconsistencies in final bend angles, requiring costly trial-and-error die corrections [1, 4].

Springback prediction is especially complex for austenitic stainless steels such as AISI 304L, which are valued for their excellent corrosion resistance and high strength-to-weight ratios [5, 6]. The mechanical behavior of AISI 304L during V-bending is distinct for its considerable ductility, work hardening, and transformation-induced plasticity (TRIP), where metastable austenite transforms into α' martensite when submitted to plastic strain [7]. This martensitic transformation significantly alters the material's elastic-plastic response, rendering traditional analytical models insufficient for tight industrial tolerances [7]. Recent studies have further shown that surface treatments such as liquid carbonitriding can complicate stress distribution in notched steel specimens under bending [8], while cladding AISI 304L on aluminum introduces complex interfacial behaviors requiring precise accounting in forming operations [5]. To address some of these complexities, Finite Element Analysis (FEA) has become a dominant tool for investigating material responses during loading [2, 9]. Researchers frequently employ ABAQUS/Explicit for numerical investigations of stresses and deflections [10]. FEA has now been successfully applied to parametric studies of cold-formed lipped C-sections under combined bending and shear [11] and to analyze three-dimensional microvoid effects on material behavior [12]. However, while FEA is powerful, its accuracy depends heavily on precise material characterization, remaining computationally expensive for real-time industrial optimization [1, 2].

The integration of Artificial Intelligence (AI) and Machine Learning (ML) offers a transformative approach for in-process springback control [1]. By leveraging Artificial Neural Networks (ANN) and regression models, manufacturers can predict required punch strokes or compensation angles based on in-process load measurements [1]. Studies in this stream have recently demonstrated the high fidelity of ANN in bridging destructive and non-destructive testing results for structural performance prediction [13]. Despite these advances, a primary bottleneck remains, the scarcity of large experimental datasets required to train robust ML models [14]. While optimization strategies such as Response Surface Methodology (RSM) and grid search are used to tune ML hyperparameters, they still require basic high-quality data to avoid overfitting [15–17].

This study contributes to the field by proposing an integrated methodology that overcomes the limitations of restricted physical data. The novelty of this work lies in implementing a Knowledge-Based Data Augmentation strategy. By synthesizing a limited set of experimental V-bending tests with physically grounded literature anchor points, we generated a robust training set of 200 synthetic points to initialize ML models within realistic metallurgical bounds. Seven regression algorithms, from Support Vector Regression (SVR) to Gaussian Process Regression (GPR), are evaluated to identify the optimal predictive framework for AISI 304L. The outcome is a validated Bending Compensation Table, providing a direct and reliable tool for industrial calibration even when experimental resources are limited.

2 Experiments and methods

2.1 V bending tests

The bending tests were conducted on AISI 304L stainless steel sheets with a thickness of 1.5 mm. Standardized specimens measuring 200 mm $\times$ 20 mm were cut for the experiments. Four different V-die matrices, each corresponding to a specific bending angle (30°, 45°, 60°, and 90°), were used to assess the influence of geometry on springback behavior.

All tests were performed using a universal tensile/compression testing machine (IBERTEST ELIB-200E/W) at the Faculty of Construction Engineering, University of Mouloud Mammeri de Tizi Ouzou. After unloading, each specimen's final bend angle was measured using the ImageJ open-source image analysis software, allowing accurate quantification of springback.

2.2 Finite Element Simulation

Finite element simulations were carried out in ABAQUS/Explicit, using experimentally derived material properties for AISI 304L, including elastic constants, plastic strain data, and ductile damage parameters (Table 1).

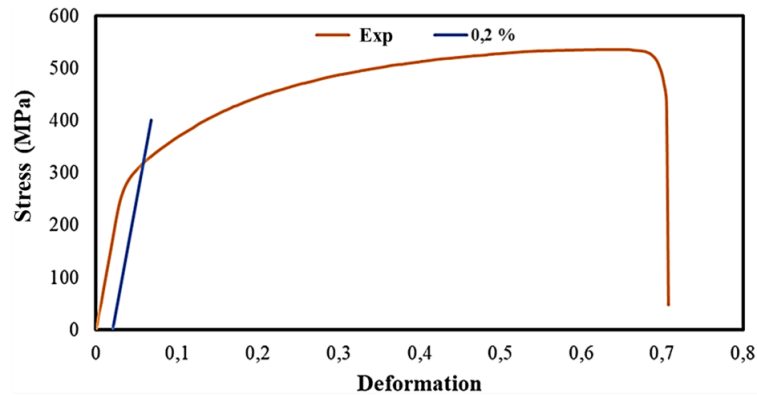


Fig. 1 - Stress Strain Curve for the 304L stainless steel plate.

These properties were calibrated by matching the numerical stress–strain response (Fig. 1) to that obtained from a standard tensile test on a normalized specimen. The simulation model included the punch, die, and specimen, with the specimen meshed using C3D8R elements, while the tools were modelled as rigid bodies.

Table 1: Mechanical Properties of the 304L stainless steel.

Proprieties	E (GPa)	ν	σ_y (MPa)	A%
Value	210	0.3	≈ 320	70%

A general contact interaction with friction was defined between all surfaces. Boundary conditions (Fig. 2) were imposed by fully constraining the bottom die and applying a vertical displacement to the punch, based on the experimental stroke measurements.

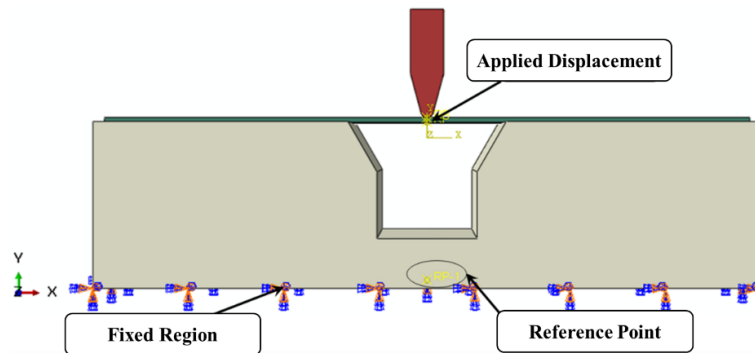


Fig. 2 - Boundary conditions on the modelled assembly.

2.3 Literature Based Data

To address the inherent scarcity of experimental samples for training Machine Learning (ML) models, this study employs a Knowledge-Based Data Augmentation strategy. This approach is grounded in the experimentally reported springback behavior of AISI 304L stainless steel under V-bending conditions. Austenitic stainless steels, specifically the 304L grade, are characterized by high ductility, significant strain hardening, and deformation-induced martensitic transformation, factors that profoundly influence the magnitude of springback and the resulting angular deviation upon unloading.

Experimental evidence consistently indicates that the final angle after unloading (α_d) is greater than the programmed bending angle (α_p) due to elastic recovery. This deviation is a complex function of sheet thickness, die geometry, punch radius, and the target bending angle. In conventional V-bending of thin SUS 304 sheets (1-3 mm), angular deviations typically range between 1° and 5°, with springback factors (k_R) generally observed between 0.96 and 0.98 [4, 6].

Furthermore, Ahmadi et al. [18] demonstrated that in AISI 304L, the relationship between the bending angle and springback is inherently nonlinear. Thinner sheets and lower bending angles typically exhibit more pronounced angular

deviations, a trend also validated by the experimental findings of Nur et al. [3] regarding punch angle influence. By synthesizing these experimentally reported compensations, we established a set of literature-derived anchor points for the ML training phase, as summarized in Table 2.

Table 2: Literature-derived compensation ranges and training anchor points.

Desired Final Angle (α_d)	Programmed Angle Range (α_p)	Representative Anchor Point	Compensation Magnitude ($\Delta\alpha$)
35°	[31.5, 32.5]	32.0°	$\approx 3.0^\circ$
50°	[45.5, 47.0]	46.25°	$\approx 3.75^\circ$
70°	[64.0, 66.0]	65.0°	$\approx 5.0^\circ$
80°	[73.5, 75.5]	74.5°	$\approx 5.5^\circ$

By utilizing these physically grounded data points rather than arbitrary synthetic values, the Machine Learning model is initialized within realistic metallurgical and geometric bounds. This minimizes the risk of non-physical extrapolation while preserving the material-consistent nonlinearity essential for accurate springback correction.

3 Results and Discussions

3.1 Experimental Results

Springback was quantified by analyzing scanned images of the deformed specimens using ImageJ. For each bending angle (30°, 45°, 60°, 90°), the post-unloading angle was measured using a three-point method (Fig. 3).

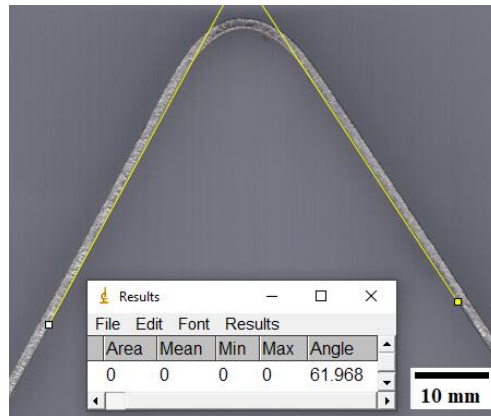


Fig. 3 - Representative image of the spring back angle measuring procedure in ImageJ

The deviation from the theoretical angle was expressed as a percentage, and average values are summarized in the Table 3.

Table 3: Experimental springback values

Theoretical Angle (°)	Average Measured Angle (°)	Average Springback (%)
30	36.96	23.19
45	61.80	37.33
60	75.30	25.50
90	108.27	20.30

3.2 Numerical vs Experimental Results

The simulated V-bent specimens exhibit geometrically consistent and symmetric deformation, confirming the accuracy of the boundary conditions and contact definitions. Von Mises stress is concentrated near the inner bend radius, where plastic deformation is highest, and decreases along the arms of the specimen (Fig. 4).

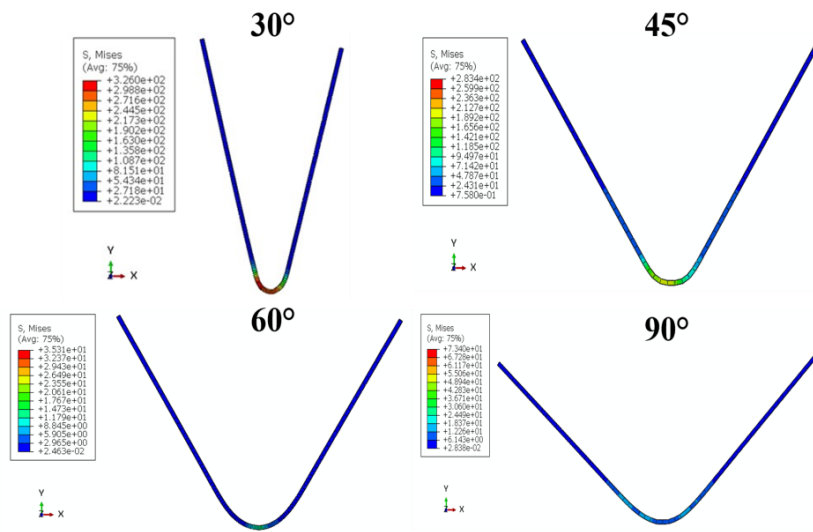


Fig. 4- Stress Strain Curve for the 304L stainless steel plate.

Sharper angles (30° and 45°) exhibit localized stress peaks, while wider angles (60° and 90°) show more uniform stress distribution. This confirms the model's ability to replicate real bending behavior and supports its use in springback prediction and process optimization.

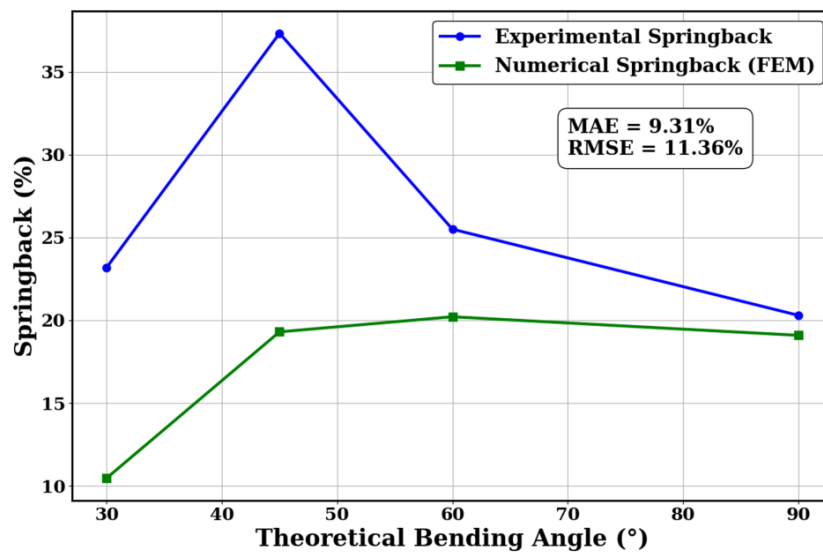


Fig. 5- Comparison between experimental and Numerical Springback values.

The comparison (Fig. 5) shows good agreement between experimental and numerical springback values, especially at 60° and 90°. The simulation slightly underestimates springback, likely due to simplified boundary and contact conditions. With an MAE of 9.31% and RMSE of 11.36%, the results confirm the accuracy of the calibrated material and damage models. Overall, the FEM approach reliably captures the springback behavior of AISI 304L and is well-suited for predictive bending applications.

3.3 Machine learning-based prediction

3.3.1 Data preparation and synthetic data generation

To overcome the scarcity of experimental data (only four points), a synthetic training set was constructed by combining experimental measurements with literature information.

Eight reference points (X_i, y_i) were used:

- Four experimental points from V-bending tests at $X = \{30^\circ, 45^\circ, 60^\circ, 90^\circ\}$.
- Four literature-derived points corresponding to desired final angles $\{35^\circ, 50^\circ, 70^\circ, 80^\circ\}$; their initial angles were taken as the centers of published intervals $[31.5^\circ, 32.5^\circ]$, $[45.5^\circ, 47.0^\circ]$, $[64.0^\circ, 66.0^\circ]$ and $[73.5^\circ, 75.5^\circ]$ respectively.

A second-degree polynomial was fitted to these eight points:

$$y_{\text{mean}}(X) = \beta_0 + \beta_1 X + \beta_2 X^2 \quad (1)$$

with coefficients estimated by ordinary least squares ($R^2 = 0.9998$, $\text{MAE} = 0.028^\circ$).

From this trend, 200 input angles X_{train} were uniformly sampled over $[30^\circ, 90^\circ]$. For each $X_{\text{train}}^{(i)}$ the corresponding output was generated as:

$$y_{\text{train}}^{(i)} = y_{\text{mean}}(X_{\text{train}}^{(i)}) + \varepsilon_i, \varepsilon_i \sim N(0, \sigma^2) \quad (2)$$

Where :

- $X_{\text{train}}^{(i)}$ is the i -th sampled initial angle,
- $y_{\text{mean}}(X_{\text{train}}^{(i)})$ is the trend value at that angle,
- ε_i is a random error term representing experimental uncertainty,
- $N(0, \sigma^2)$ denotes a normal distribution with zero mean and variance σ^2 ,
- $\sigma \approx 1.0^\circ$ is the estimated standard deviation of the measurement error, based on preliminary repeatability tests.

This produced a synthetic training set $\{X_{\text{train}}, y_{\text{train}}\}$ of 200 points that follow the physical trend while exhibiting realistic scatter. The four original experimental points were kept exclusively for final validation. The full process is summarized in Fig. 6.

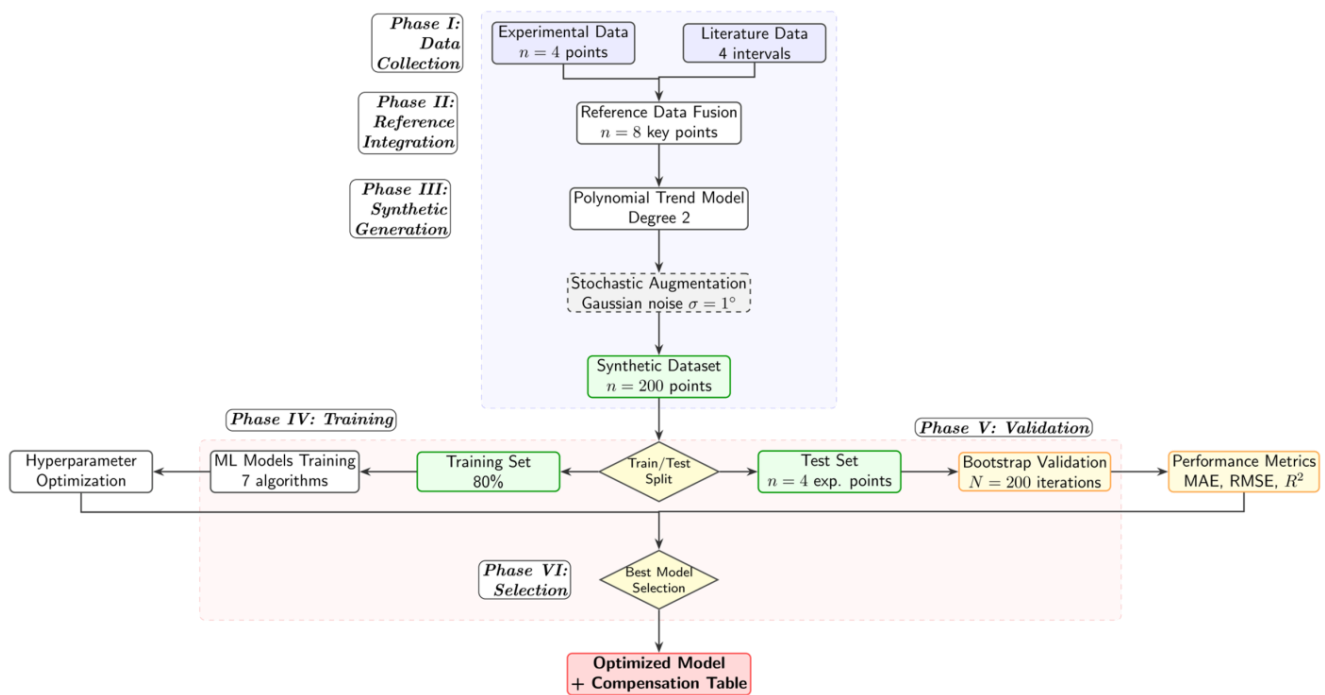


Fig. 6 - Flowchart of the machine learning methodology.

3.3.2 ML Models and Hyperparameter Optimization

To capture the non-linear springback behavior of AISI 304L, seven regression models were evaluated: Linear and Polynomial Regression (degrees 2 and 3) as baselines, Decision Tree and Random Forest for non-parametric partitioning, and Support Vector Regression (SVR) with an RBF kernel for high-dimensional mapping [15, 17]. Additionally, Gaussian Process Regression (GPR) was implemented using an optimized **Constant** $\times$ **RBF** + **WhiteKernel** structure to provide probabilistic uncertainty quantification, leveraging log-marginal likelihood maximization for kernel parameter tuning [14].

Table 4: Optimal hyperparameters determined through Grid Search Cross-Validation.

Model	Hyperparameter Search Space	Optimal Configuration
Decision Tree	$max_depth \in \{5, 10, None\}$	$max_depth = 5$
Random Forest	$n_estimators \in \{50, 100\}$	$n_estimators = 100$
	$max_depth \in \{5, 10, None\}$	$max_depth = 10$
SVR (RBF)	$C \in \{10, 100\}, \gamma \in \{'scale', 'auto'\}$	$C = 100, \gamma = 'scale'$
GPR	Log-marginal-likelihood maximization	Kernel optimized internally

Hyperparameters were optimized via Grid Search with 3-fold Cross-Validation on the augmented dataset (N=200), targeting the minimization of the Mean Absolute Error (MAE), a widely adopted strategy for systematic hyperparameter exploration in regression tasks [16, 17]. Stochastic models were initialized with a fixed seed (42) to ensure reproducibility. The resulting optimal configurations are summarized in Table 4.

3.4 Machine Learning Results and Discussion

3.4.1 Model Performance and Selection

The seven machine learning models were evaluated using 200 bootstrap iterations to ensure robust performance estimation despite the limited experimental test data. Table 5 presents the mean and standard deviation of MAE, RMSE, and R^2 for all models, ranked by MAE.

Table 5: Bootstrap performance metrics (mean $\pm$ standard deviation over 200 iterations)

Model	MAE ($^\circ$)	R^2
Polynomial deg. 2	2.9790 $\pm$ 0.0551	0.9849 $\pm$ 0.0005
Linear Regression	2.9872 $\pm$ 0.0826	0.9852 $\pm$ 0.0006
Polynomial deg. 3	3.1748 $\pm$ 0.1364	0.9838 $\pm$ 0.0009
SVR (noyau RBF)	3.4452 $\pm$ 0.2486	0.9813 $\pm$ 0.0019
Arbre de décision	3.6154 $\pm$ 0.4478	0.9794 $\pm$ 0.0045
Forêt aléatoire	3.6923 $\pm$ 0.3809	0.9787 $\pm$ 0.0039
GPR	12.5135 $\pm$ 17.0009	−0.1099 $\pm$ 1.9606

Fig. 7 provides a comprehensive visualization of all seven ML models' predictions across the full range $[25^\circ, 95^\circ]$. The synthetic training points (blue) and reference points (green triangles) are shown alongside the experimental test points (red squares). The best model (degree-2 polynomial) is highlighted with a bold black dashed line.

The degree-2 polynomial model was identified as the best performer, achieving a MAE of 2.9790 ± 0.0551 and a coefficient of determination (R^2) of 0.9849 ± 0.0005 . The nearly identical performance of linear regression ($MAE = 2.9872$) confirms a highly linear relationship between the initial and final angles in this material range. Conversely, the Gaussian Process Regression (GPR) demonstrated extreme instability with a negative R^2 and high standard deviation, indicating it is unsuitable for point prediction with this dataset. Tree-based models (decision tree and random forest) exhibit higher mean errors and larger standard deviations, indicating that their flexibility is not advantageous for this smooth,

monotonic relationship. The Gaussian process regressor shows extremely high variability and negative R^2 values, revealing instability likely due to the small dataset size.

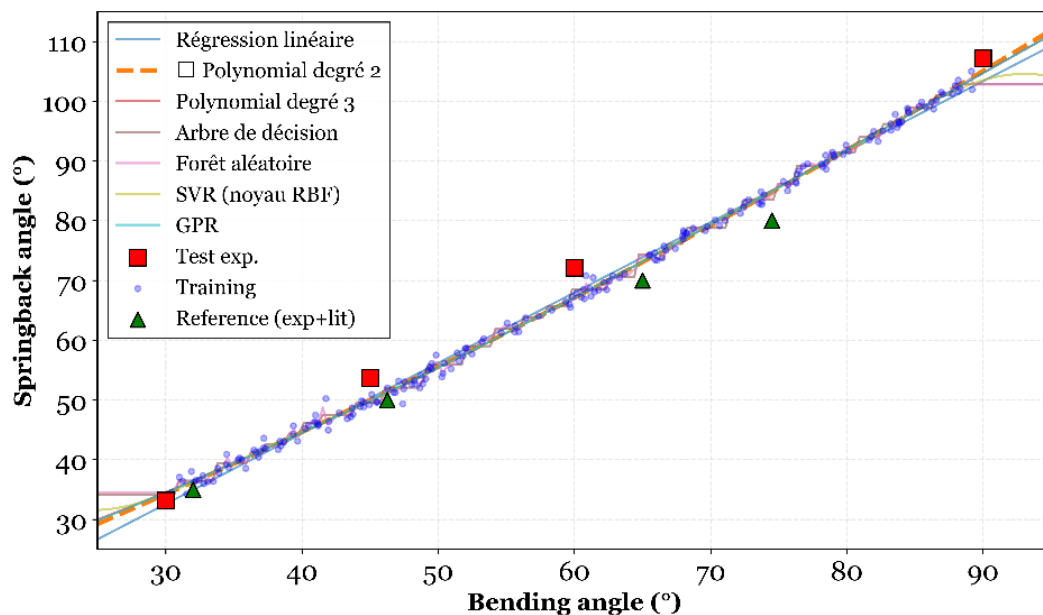


Fig. 7 - Comparison of all seven ML models' predictions

Fig. 8 presents a bar chart comparison of model performance, clearly showing the MAE and R^2 for all seven models. The degree-2 polynomial stands out as the best performer.

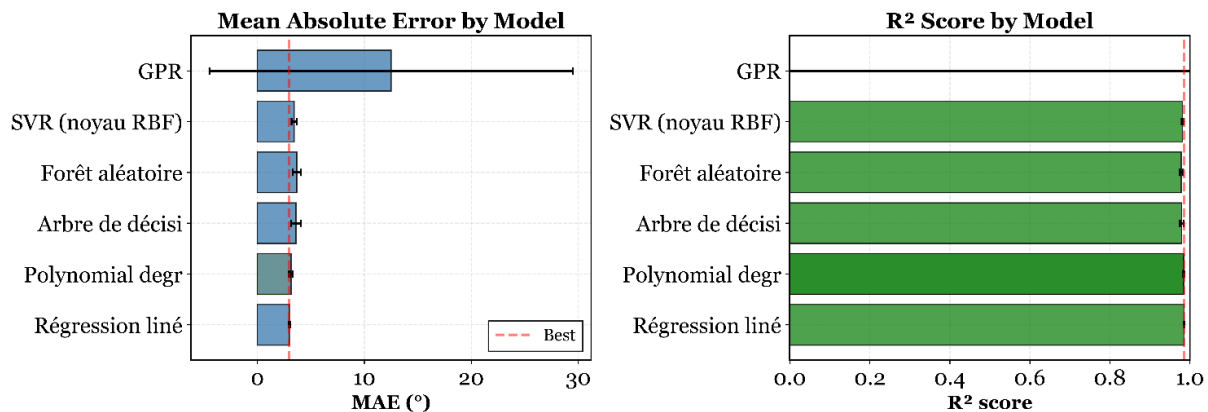


Fig. 8 - Model performance comparison: Mean Absolute Error (left) and R^2 score (right) for all seven ML models

Based on these results, the degree-2 polynomial model is selected as the best-performing model for springback prediction and is used for all subsequent analyses.

3.4.2 Residual Analysis and Model Validation

The selected degree-2 polynomial model was further validated against eight reference points, comprising four experimental and four literature-derived values (Table 6).

Statistical analysis of these residuals yielded a mean of -0.0952° and a standard deviation of 3.1700° . The Shapiro-Wilk test resulted in a p – value of 0.6443, confirming that the residuals follow a normal distribution ($p > 0.05$), thus validating the model's statistical adequacy.

Fig. 9 shows the residuals plotted against predicted values for all eight reference points. Experimental points are marked with squares and literature points with triangles. The random scatter around zero confirms the absence of heteroscedasticity or systematic patterns.

Table 6: Residual analysis of reference points

Point Type	Initial Angle (°)	Actual Angle (°)	Predicted Angle (°)	Residual (°)
Experimental	30	33.14	34.22	-1.085
Experimental	45	53.69	50.01	+3.676
Experimental	60	72.13	67.08	+5.045
Experimental	90	107.18	105.08	+2.102
Literature	32	35	36.25	-1.255
Literature	46.25	50	51.38	-1.384
Literature	65	70	73.06	-3.057
Literature	74.50	80	84.80	-4.804

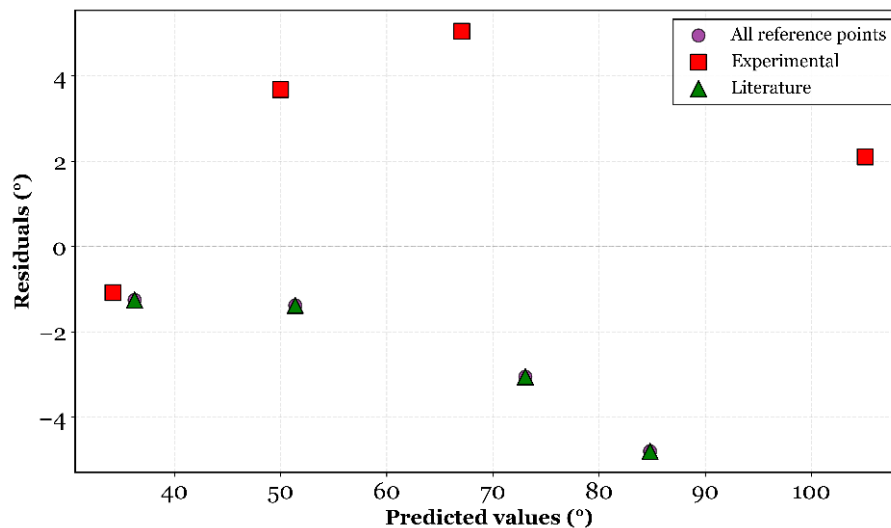


Fig. 9 - Residuals vs. predicted values for the eight reference points

Fig. 10 presents the distribution of residuals alongside a Q-Q plot. The histogram closely follows the normal distribution curve, and the Q-Q plot aligns with the reference line, further supporting the normality conclusion.

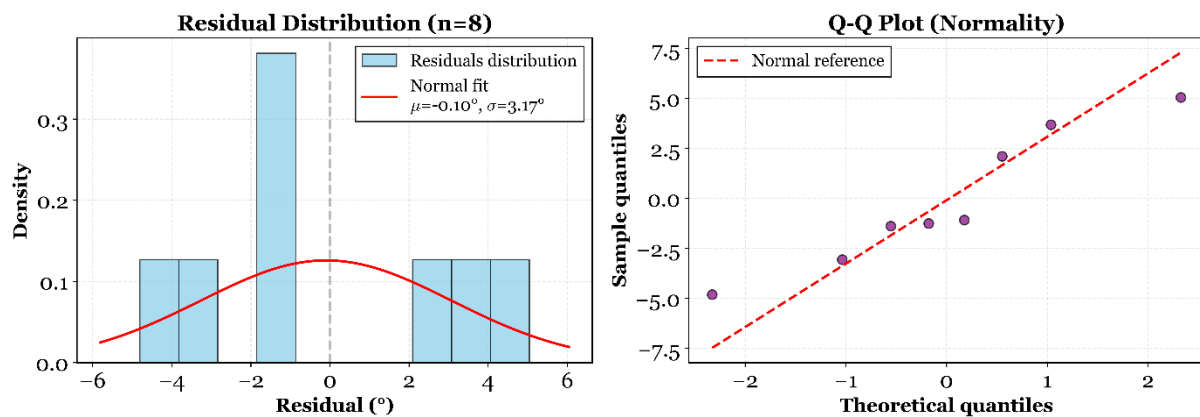


Fig. 10 - Residual distribution analysis: histogram with normal fit (left) and Q-Q plot (right)

3.4.3 Uncertainty Quantification and Inverse Prediction

While the GPR was less accurate for point estimation, it provided critical uncertainty quantification. As shown in Fig. 11 - Gaussian Process predictions with 95% confidence intervals, the 95% confidence intervals remain tight according to the training data but reflect potential variability in the material's elastic recovery.

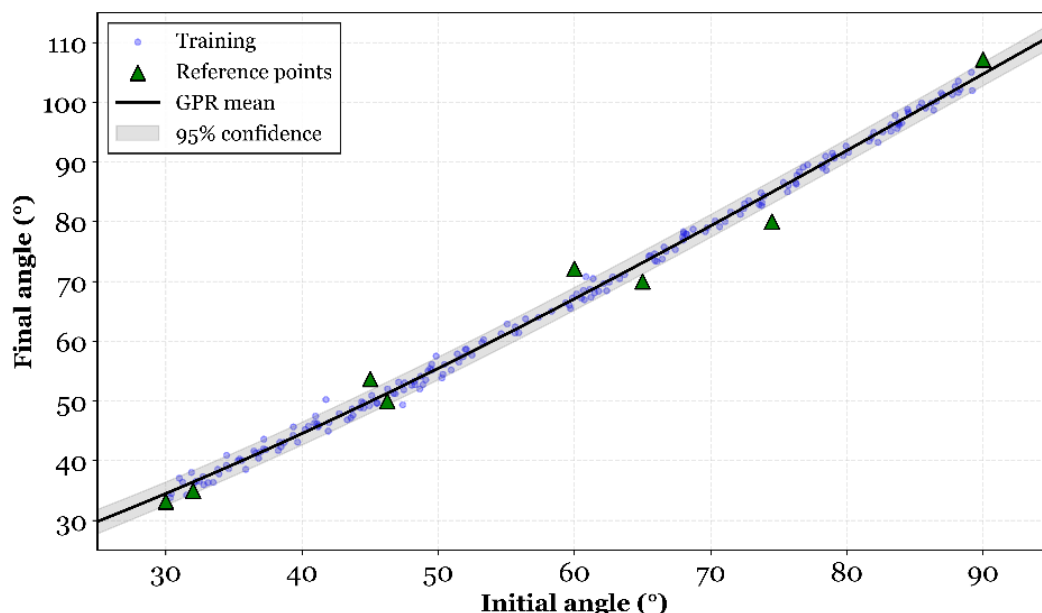


Fig. 11 - Gaussian Process predictions with 95% confidence intervals

The confidence intervals widen near the extremes of the range (below 40° and above 80°), reflecting the lower density of reference data in these regions. This information is valuable for risk-aware decision-making in industrial applications, where safety margins may be required.

To facilitate industrial application, the model was inverted to generate a Bending Compensation (Table 7). This allows operators to determine the exact programmed angle required for a target result.

Table 7: Compensation table for programmed angle determination.

Desired Angle (°)	Programmed Angle (°)	Estimated Obtained Angle (°)
35	30.77	35.00
50	44.99	50.00
70	62.46	70.00
80	70.67	80.01
90	78.57	89.99

4 Conclusion

This study set out to characterize springback in V-bending of AISI 304L stainless steel (1.5 mm) through an integrated experimental, numerical, and machine learning approach. The experimental results indicate that springback percentages ranged from 20.30% to 37.33% across bending angles of 30° to 90°, with ABAQUS simulations demonstrating good predictive capability (MAE = 9.31%).

The machine learning framework developed in this study offers a significant improvement in prediction accuracy. The degree-2 polynomial model emerged as the most robust performer, achieving $\text{MAE} = 2.98^\circ \pm 0.06^\circ$ and $R^2 = 0.985 \pm 0.001$ following bootstrap validation with 200 synthetic training points. These findings suggest that polynomial regression provides sufficient complexity to capture springback behavior without overfitting limited experimental data. The

significance of these results lies in the practical compensation table derived from the optimized model, which enables direct implementation for tool calibration in industrial settings. Importantly, residual analysis confirmed the model's statistical validity, with normality established (Shapiro–Wilk $p = 0.644$) and no evidence of systematic bias.

In conclusion, this work demonstrates that machine learning approaches, even when trained on restricted experimental datasets supplemented by synthetic data, can deliver fast and reliable springback predictions suitable for process optimization. The methodology presented here has the potential to be extended to other material grades and thicknesses, offering a scalable framework for predictive manufacturing.

REFERENCES

- [1]- K.-J. Fann, L.-P. Chen, C.-Y. Yang, C.-Y. Lee, C.-Y. Tsai, J. Wang, An Artificial Intelligence Application for In-Process Springback Control of Sheet Metal Bending, *J. Manuf. Sci. Eng.* 147(2025). <https://doi.org/10.1115/1.4067740>.
- [2]- B. Sarema, S. Matope, M. Nagel, A. Sterzing, Material Characterisation Experiments and Data Preparation for a Finite Element Analysis of the Deep Drawing Process Using AA 1050-O, *J. Manuf. Mater. Process.* 9(2025) 33. <https://doi.org/10.3390/jmmp9020033>.
- [3]- R. Nur, M.A. Suyuti, M.R. B, M. Misbahuddin, Pengaruh Sudut Punch dan Ketebalan Pelat terhadap Springback pada Bending V, *J. Tek. Mesin Sinergi* 17(2019) 57–64. <https://doi.org/10.31963/sinergi.v17i1.1593>.
- [4]- N. Rahdiana, Sukarman, Khoirudin, Amri Abdulah, Apang Djafar Shieddieque, Spring-back analysis of the vee bending process for high-strength stainless steel. *J. Teknol.* 85(2023) 135–144.
- [5]- Y. Gabsi, S. Zouari, M. Abdennadher, L. Dieng, R. Elleuch, Development and Characterization of Cladding AISI 304L Stainless Steel on Aluminum, *J. Manuf. Mater. Process.* 9(2025) 30. <https://doi.org/10.3390/jmmp9020030>.
- [6]- S. Sukarman, C. Anwar, N. Rahdiana, K. Khoirudin, A.I. Ramadhan, Analisis Pengaruh Radius Dies terhadap Springback Logam Lembaran Stainless-steel pada Proses Bending Hidrolik V-die, *J. Teknol.* 12(2020) 123–132.
- [7]- M. Ahmadi, B. Mohammad Sadeghi, H. Arabi, Experimental and numerical investigation of V-bent anisotropic 304L SS sheet with spring-forward considering deformation-induced martensitic transformation, *Mater. Des.* 123(2017) 211–222. <https://doi.org/10.1016/j.matdes.2017.03.040>.
- [8]- S.H. Nasser, D.H. Shakir, Experimental study on notch shape and liquid carbonitriding specimens under bending loading, *J. Teknol. Sci. Eng.* 87(2025) 373–380. <https://doi.org/10.11113/jurnalteknologi.v87.22683>.
- [9]- K. Shah, M.U. Rehman, Finite Element Analysis of Custom Designed and Additive Manufactured Total Surface Bearing Prosthesis for Trans-Tibial Amputees, *Appl. Sci.* 15(2025) 1284. <https://doi.org/10.3390/app15031284>.
- [10]- K. Senthil, S. Rupali, Crashworthiness of highway lamp post against vehicle impact, *J. Mater. Eng. Struct.* 5(2018) 371–385.
- [11]- T.M. Raka, K.M. Amanat, Parametric study with FE model of cold-formed plain lipped C-section in shear, and combined bending and shear, *J. Mater. Eng. Struct.* 6(2019) 259–268.
- [12]- L. Zouambi, N. Mahmoudi, M. Bourdim, B. Serrier, FEM analysis of the tridimensionnel effect of microvoids on the PMMA behaviour in PTH., *J. Mater. Eng. Struct.* 5(2018) 97–109.
- [13]- P. Gangele, A.K. Patel, Prediction of Compressive Strength by Considering Practical Consideration Non-destructive Test by Artificial Neural Network, *J. Mater. Eng. Struct.* 12(2025) 47–62.
- [14]- Y. Zebin, Z. Aijun, Hyperparameter tuning methods in automated machine learning, *Sci. Sin. Math.* 50(2020) 695. <https://doi.org/10.1360/N012019-00092>.
- [15]- G.A. Lujan-Moreno, P.R. Howard, O.G. Rojas, D.C. Montgomery, Design of experiments and response surface methodology to tune machine learning hyperparameters, with a random forest case-study, *Expert Syst. Appl.* 109(2018) 195–205. <https://doi.org/10.1016/j.eswa.2018.05.024>.
- [16]- N. Subaşı, Comprehensive Analysis of Grid and Randomized Search on Dataset Performance, *Eur. J. Eng. Appl. Sci.* 7(2024) 77–83. <https://doi.org/10.55581/ejeas.1581494>.
- [17]- H. Kaneko, K. Funatsu, Fast optimization of hyperparameters for support vector regression models with highly predictive ability, *Chemom. Intell. Lab. Syst.* 142(2015) 64–69. <https://doi.org/10.1016/j.chemolab.2015.01.001>.
- [18]- M. Ahmadi, B. Mohammad Sadeghi, H. Arabi, Experimental and numerical investigation of V-bent anisotropic 304L SS sheet with spring-forward considering deformation-induced martensitic transformation, *Mater. Des.* 123(2017) 211–222. <https://doi.org/10.1016/j.matdes.2017.03.040>.