Advances in Science and Technology Research Journal

Advances in Science and Technology Research Journal, 2025, 19(5), 185–199
https://doi.org/10.12913/22998624/202026
ISSN 2299-8624, License CC-BY 4.0

Received: 2025.02.05
Accepted: 2025.03.15
Published: 2025.04.01

A hybrid advanced analysis approach for predicting spring back phenomena existing in metals

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ABSTRACT

Springback phenomenon (SBP) is a critical phenomenon in metal forming processes, influencing the dimensional accuracy and mechanical integrity of manufactured components. This study investigates the springback behavior of aluminum, copper, and pure iron using a hybrid approach that integrates finite element analysis (FEA) and machine learning (ML). The research evaluates key parameters, including material deformation, peak forming force, stress distribution, and thermal effects, under varying thicknesses and punch radii. Results reveal that aluminum exhibits the highest springback (6.2%) due to its ductility, followed by copper (4.0%) and pure iron (2.5%), which demonstrated superior dimensional stability. The forming force requirements were lowest for aluminum (50 kN), moderate for copper (75 kN), and highest for iron (100 kN), reflecting their respective material strengths. Copper recorded the highest temperature rise (350 °C), while iron exhibited the greatest Von Mises stress (420 MPa), emphasizing its robustness but susceptibility to localized stress. The hybrid FEA-ML model effectively predicted springback angles with high accuracy, optimizing forming parameters and minimizing experimental reliance. These findings highlight the significance of material selection and process optimization in industrial applications, where aluminum is ideal for lightweight structures, iron for strength-critical designs, and copper for high-ductility requirements. This study offers a novel framework for enhancing precision in metal forming processes, with implications for automotive, aerospace, and structural industries. Future research can extend this model to complex geometries and multi-material systems, advancing sustainable and efficient manufacturing technologies.

Keywords: finite element analysis, sheet metal forming, spring back phenomenon, mold loading, and manufacturing.

INTRODUCTION

Springback is a critical phenomenon in metal forming processes where materials, after undergoing plastic deformation, experience an elastic recovery, leading to dimensional inaccuracies in the final product. This issue is of particular concern in industries such as automotive, aerospace, and manufacturing, where metals like aluminum (Al), copper (Cu), and iron (Fe) are commonly employed. Each of these materials exhibits distinct mechanical properties, which influence their springback behavior. Aluminum, with its relatively low yield strength and high ductility, tends to show significant springback, particularly in processes like bending and deep drawing. Copper, known for its higher yield strength and pronounced work hardening, demonstrates different springback characteristics than aluminum. Iron, with higher strength and lower ductility, generally experiences less springback, though accurate predictions remain challenging. Therefore, understanding and predicting springback is essential for ensuring dimensional accuracy, minimizing material waste, and improving process efficiency in metal forming operations.

Traditional methods for predicting springback primarily involve analytical and empirical models, which rely on simplified approximations of material behavior and process conditions. While these models are beneficial for basic applications, they often fail to account for the complexities inherent in real-world forming processes. Aluminum, copper, and iron exhibit nonlinear, time-dependent deformation behavior, making it difficult for traditional models to predict springback accurately across varying process conditions. Furthermore, these models often lack the capacity to incorporate material anisotropy, strain rate sensitivity, and thermal effects, all of which significantly influence springback in practical applications. These limitations highlight the need for more sophisticated approaches capable of capturing the intricate relationships between material properties, forming conditions, and springback behavior.

Finite element analysis (FEA) has emerged as a widely adopted technique for simulating metal forming processes, including springback prediction. FEA allows for the detailed modeling of material deformation, incorporating factors such as plasticity, strain rate sensitivity, and material anisotropy. Numerous studies have demonstrated that FEA can provide accurate springback predictions when suitable material models, boundary conditions, and mesh refinements are employed. For example, Zhang et al. (2017) applied FEA to model springback in aluminum deep drawing processes and emphasized the importance of selecting appropriate plasticity models, such as the Hill48 or Barlat48 yield criteria, to accurately represent material behavior. Similarly, Li et al. (2018) utilized FEA to predict springback in copper forming processes, incorporating temperature-dependent material models to account for high strain rates and thermal effects typical in manufacturing environments. Despite its accuracy, FEA is computationally expensive, particularly when dealing with complex geometries, large datasets, or parametric studies. This computational burden limits the practicality of FEA for industries requiring rapid and frequent design iterations or optimization involving multiple process parameters.

To overcome the limitations of FEA, machine learning (ML) systems have gained significant attention in recent years as a promising solution for more efficient springback prediction [1]. Supervised learning algorithms in machine learning can model the complex, nonlinear relationships between process parameters, material properties, and springback behavior without requiring explicit physical modeling [2]. Several studies have explored the application of ML for springback prediction. Bolar et al. [3] developed an artificial neural network (ANN) model to predict springback in V-bending processes for aluminum. Their results showed that ANNs could accurately predict springback by learning from process parameters such as punch speed, sheet thickness, and material hardness. Similarly, Wang et al. [4] applied support vector machines (SVM) to predict springback in copper sheet metal forming, demonstrating that SVM models could generalize well across different forming conditions and material properties, offering accurate predictions with lower computational effort compared to traditional FEA.

While machine learning models are effective in many cases, they require substantial training data, which can be obtained either from physical experiments or simulations [5]. This challenge has led to the development of hybrid models that combine FEA with machine learning to leverage the strengths of both approaches. By using FEA to generate large datasets of simulation results under various process conditions and material properties, machine learning algorithms can be trained to make rapid predictions without the need for complete FEA simulations for every design iteration [6]. He et al. [7] proposed a hybrid model that integrates FEA with support vector regression (SVR) to predict springback in aluminum sheet metal forming. The model, trained on a dataset generated by FEA simulations, demonstrated improved prediction accuracy compared to traditional FEA, while also significantly reducing computational time. Zeinolabedin-Beygi et al. [8] implemented a similar hybrid approach by combining FEA with Random Forest modeling to predict springback in copper and iron forming processes. Their results indicated that this hybrid model reduced the time required for springback predictions by up to 60%, while maintaining high accuracy.

The hybrid approach has proven especially valuable for process optimization in metal forming. By integrating machine learning with FEA simulations, it becomes possible to predict the effects of different process factors, for example die geometry, material thickness, punch speed, and temperature, on springback behavior more efficiently [9, 10]. Additionally, this approach allows for faster and more effective design optimization, as machine learning models can quickly provide predictions across a range of conditions, reducing the need for exhaustive simulations or physical trials [11]. Moreover, hybrid models can be adapted for different metals, including aluminum, copper, and iron, each of which requires distinct material models to accurately capture its unique springback behavior [12].

In conclusion, springback prediction remains a significant challenge in metal forming processes, which exhibit distinct mechanical properties and deformation behaviors. While FEA is a powerful tool for simulating springback, its computational expense limits its application in real-time design optimization and iterative testing. Machine learning offers a promising alternative by efficiently learning complex relationships from data, allowing for faster predictions without full physical modeling. When combined with FEA, machine learning can greatly enhance the accuracy, efficiency, and scalability of springback predictions, providing a hybrid approach that offers significant benefits for industries where speed, accuracy, and cost-efficiency are critical. As such, integrating FEA with machine learning techniques holds considerable potential for improving metal forming processes and addressing the challenges associated with springback in materials such as aluminum, copper, and iron.

This research proposes a hybrid analysis approach that combines the predictive power of machine learning with the detailed simulations provided by FEA. The main goal is to develop a robust machine learning model capable of accurately predicting springback in metals, particularly for materials such as aluminum, copper, and iron, using FEA-generated data as input. By coupling supervised learning algorithms with FEA simulations, this approach aims to enhance the prediction of springback angles, reduce the reliance on time-intensive experiments, and optimize the metal forming process. The proposed hybrid model is expected to offer a promising solution for industries that require precise control over material behavior during forming processes, ultimately leading to improved product quality and manufacturing efficiency.

MATERIALS AND METHODS

In this research, three common metals, aluminum (Al), copper (Cu), and iron (Fe), are considered for springback prediction in metal forming processes. These materials were selected due to their distinct mechanical properties, which influence their springback behavior and are commonly utilized in industries such as manufacturing, aerospace, and automotive.

Aluminum is a light, ductile metal with relatively low yield strength and high workability, which makes it prone to springback, particularly in processes like bending and deep drawing. The material is frequently used in aerospace and automotive applications where weight reduction is a priority [13, 14]. Copper is a highly ductile material with excellent thermal and electrical conductivity. It has a higher yield strength compared to aluminum, which results in different springback characteristics. Copper is commonly used in electrical components and plumbing systems [15]. Iron, specifically in its commercial form as mild steel, is stronger but less ductile compared to aluminum and copper. It is commonly used in structural and automotive components. Its springback behavior is influenced by its relatively higher yield strength and lower ductility [16].

The mechanical properties of these metals, including yield strength, Young's modulus, strain-hardening behavior, and Poisson's ratio, were considered when developing the material models for the simulations. These properties were extracted from standard material databases and experimental data.

Finite element analysis simulations

The springback predictions and metal forming processes for the three materials were simulated using finite element analysis (FEA) in ANSYS, a widely used simulation software. FEA is employed to model the forming processes, predict deformation, and evaluate the resulting springback behavior under varying conditions [17].

The metal forming process was modeled as a simple V-bending operation to study the springback phenomenon. A V-die was used with a punch, where the material was subjected to bending at various punch speeds and sheet thicknesses to study the effect of these factors on springback.

The material models used in FEA were chosen to reflect the mechanical properties of aluminum, copper, and iron. For each material, an appropriate plasticity model, such as the isotropic or kinematic hardening models, was employed to simulate the nonlinear behavior under forming conditions [18]. The Johnson-Cook material model was utilized for copper and iron to account for temperature and strain rate effects, while for aluminum, a Hill48 yield surface was used to capture its anisotropic plastic behavior. Table 1 shows the

Table 1. Critical common physical and mechanical properties of the three inspected material

No.	Properties	The name of metal		
		Pure steel	Pure aluminum	Pure copper
1	Vickers hardness	126HV	(150–160)HV	(40–110)HV
2	Thermal conductivity	44 to 52W/m.K	237W/m·K	260W/m·K
3	The strength of tensile	420MPa	90MPa	(200-360)MPa
4	Shear modulus	80GPa	25GPa	44Gpa
5	Poisson’s ratio	0.25	0.36	0.35
6	Modulus of elasticity/ young’s modulus	200GPa	68GPa	120GPa
7	Melting temperature point	(1,205–1,370) °C	660 °C	1,083 °C
8	Density	7,850 kg/m3	2,700 kg/m^3	8,920 kg/m^3
9	Color	Gray	Silvery-White	Red-Orange

critical properties of these metals. Most of these variables and their corresponding values will be utilized for identifying the boundary conditions associated with the three metals examined.

The boundary conditions in the simulation included fixing the die at the bottom and applying a displacement-controlled load to the punch to simulate the bending process. The contact between the punch, sheet metal, and die was modeled using frictional contact, with a coefficient of friction set based on typical values for metal forming processes. A fine mesh was applied to the region of interest (the sheet metal and contact surfaces) to ensure accurate results in terms of stress, strain, and springback predictions [19, 20].

The meshing process is a crucial phase that is meticulously executed to ensure accurate numerical results and high-quality outcomes are achieved. The meshing task can begin with an analysis of the type of structure. In some mechanical problems, such as circular cross-section beams, rectangular parallelepiped mechanical issues, and materials with square-like top and side faces, it can be relatively straightforward [21]. At the same time, mechanical structures can, in certain cases, be quite complex, as they represent larger mechanical systems encountered in real-world manufacturing fields, such as vehicles, ships, or aircraft. For these intricate objects, using mathematical simulations may not yield precise results due to numerous faults and errors when applying a simple design that represents the entire vehicle body of an automobile, ship, or aircraft. Regarding the meshing procedure and the overall shape division related to the three specimens (Al, Cu, and Fe) created and modeled in the SolidWorks® platform, Table 2 presents key meshing variables and their corresponding values utilized in this simulation work.

The mesh was refined in areas with high gradients in stress and strain, and an appropriate mesh size was chosen to balance accuracy and computational efficiency [22]. The simulations were run for various process parameters, including different punch speeds (to assess strain rate sensitivity) and material thicknesses [23]. Temperature effects were considered in simulations for copper and iron due to their high sensitivity to temperature during metal forming processes.

Machine learning model

To develop a predictive model for springback, a hybrid machine learning approach was employed, combining FEA simulation data with supervised learning algorithms. The primary steps in developing the machine learning model are as follows:

Table 2. Major meshing characteristics of the selected three metals

No.	Category	Aluminum	Copper	Iron
1	Chosen cell type	Hexahedral (for structured meshing)	Tetrahedral (for flexibility in geometry)	Tetrahedral (for flexibility in geometry)
2	Dimensions of the geometric shape	200 mm ×100 mm × 2 mm (for sheet metal)	200 mm × 100 mm × 2 mm (for sheet metal)	200 mm × 100 mm × 2 mm (for sheet metal)
3	The overall number of meshing elements	150,000–250,000 elements (depending on mesh refinement)	150,000–250,000 elements (depending on mesh refinement)	150,000–250,000 elements (depending on mesh refinement)

- Data generation – FEA simulations were performed for a range of process factors, for example, punch speed, material thickness, and die geometry. The simulation data, including the springback angles, were collected for each material (aluminum, copper, and iron) under different forming conditions [24].
- Feature selection – The input features for the machine learning model included process parameters such as punch speed, sheet thickness, material properties (such as yield strength, Young's modulus), and the temperature during forming. These features were chosen based on their known influence on springback behavior. The target output variable was the springback angle, representing the amount of elastic recovery in the metal after forming [25].

Hybrid model integration

The integration of finite element analysis with machine learning (ML) techniques forms the backbone of a hybrid model for predicting springback behavior in metal forming processes [26]. This hybrid approach aims to leverage the strengths of both FEA and ML to overcome their respective limitations while enhancing the accuracy and efficiency of springback predictions. Below, we explore the rationale, methodology, and potential benefits of this hybrid approach.

While FEA is highly effective in modeling the complex physical phenomena in metal forming, including plastic deformation, strain-rate sensitivity, and material anisotropy, it suffers from significant computational cost, especially when simulating large-scale or parametric studies [4]. These computational challenges limit its real-time application and practicality in industrial settings where rapid iterations and optimization are necessary.

On the other hand, machine learning (ML), particularly supervised learning algorithms, can offer quick and efficient predictions by learning complex, nonlinear relationships between input parameters (such as material properties and process conditions) and the output (springback) [27]. However, ML models require large datasets for training, which are often not readily available and must be generated via time-consuming physical experiments or FEA simulations.

Thus, combining FEA with ML can generate high-fidelity data under various forming conditions, which is then used to train machine learning models [28]. This hybridization capitalizes on the predictive capabilities of ML while maintaining the physical accuracy provided by FEA simulations. The proposed hybrid advanced model steps are outlined as shown in Figure 1.

Models and mold mechanical design

In the proposed simulation process, critical graphical data were obtained, reflecting the mechanical properties of various specimens.

For the aluminum specimens, each has a thickness of 2 ± 0.13 mm, with punch radii of 2.0 mm, 3.5 mm, and 4.0 mm for the first, second, and third models, respectively. The bend angles are 92.42° ± 0.50°, 92.62° ± 0.50°, and 93.26° ± 0.50° for the first, second, and third models, respectively. These models were created to conduct a numerical mechanical analysis.

Similarly, the copper specimens also have a thickness of 2 ± 0.13 mm, featuring punch radii of 2.0 mm, 3.5 mm, and 4.0 mm for the first, second, and third models, respectively. The bend angles are 93.75° ± 0.50°, 94.68° ± 0.50°, and 95.05° ± 0.50° for the first, second, and third models, respectively. These copper specimens were analyzed with different dimensions in comparison to the aluminum specimens.

The steel specimens, which were analyzed in the same manner, are presented below. Figures 2, 3, and 4 visually represent the 3D models of the aluminum, copper, and steel specimens, respectively, each designed for specific mechanical analysis.

It can be deduced from Figure 4 that the pure steel specimen models designed for the numerical mechanical analysis exhibit varying dimensions. The pure steel specimens have thicknesses of 2.0 ± 0.13 mm, 3.5 ± 0.13 mm, and 3.5 ± 0.13 mm for the first, second, and third models, respectively. The punch radii are 2.0 mm, 3.5 mm, and 4.0 mm for the first, second, and third models, respectively, with bend angles of 96.00° ± 0.50°, 94.57° ± 0.50°, and 94.94° ± 0.50° for the first, second, and third models, respectively.

The molds designed to apply the required loading in the SMF process are depicted in Figure 5. From Figures 5a to 5c, it can be seen that the 3D mold utilized in this study has a V-shape. The deformations that occurred in this copper specimen following load application are displayed in Figure 5c.

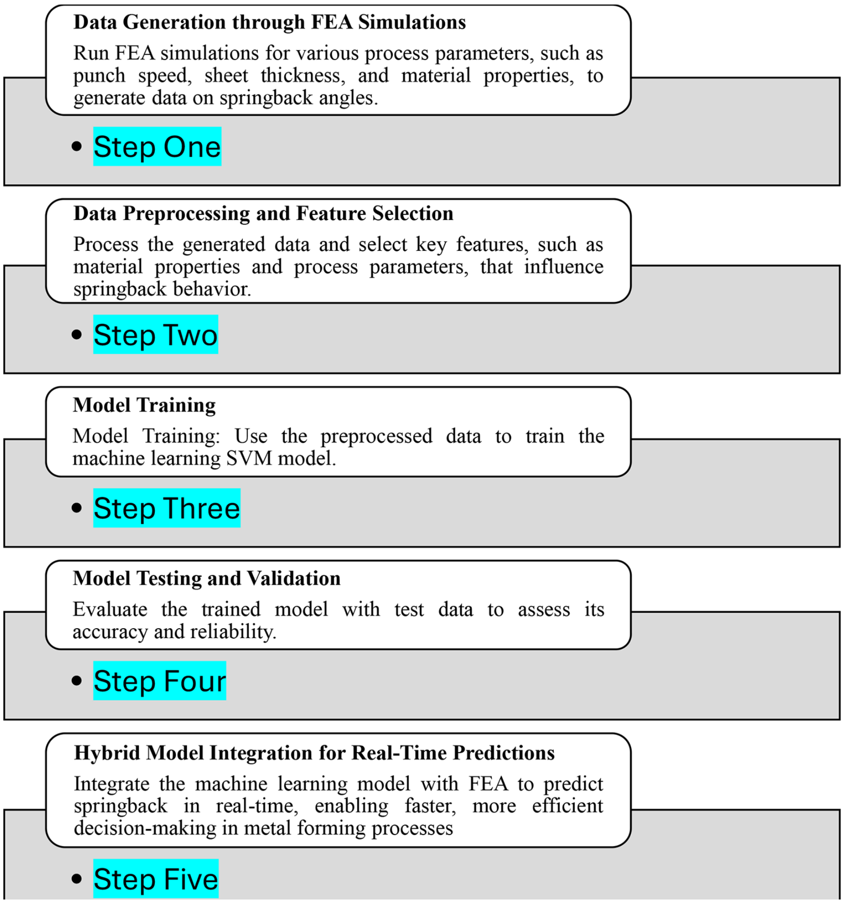

Figure 1. The proposed hybrid FEA-ML model steps

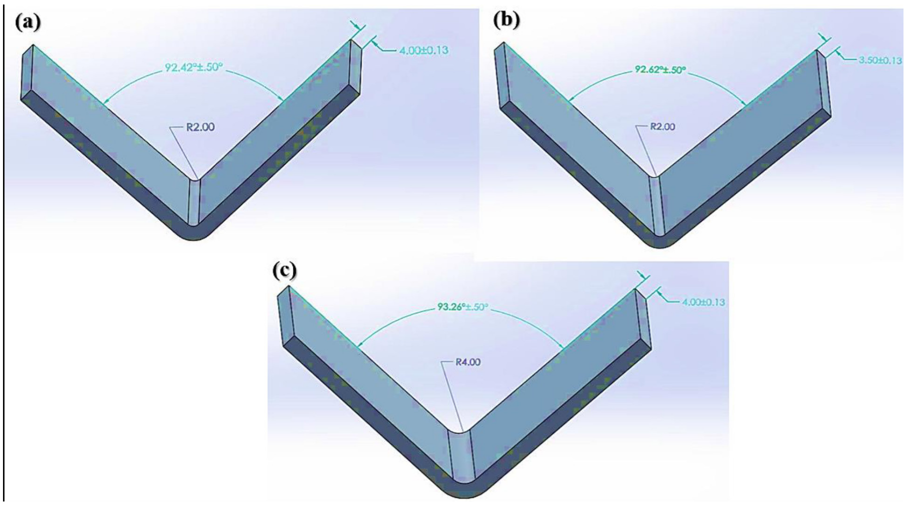

Figure 2. The aluminum specimen models (3D) with varying thicknesses, bend angles, and punch radii

FEM results analysis

The study presents numerical results obtained from ANSYS simulations for six specimens, comprising two samples each of aluminum (Al), copper (Cu), and pure iron (Fe). These findings, detailed in Table 3. Additionally, Figure 6 provides a visual representation of the strain variation over time for each material, underscoring the comparative analysis of their mechanical properties. The results aim to enhance understanding of the material behavior under specific conditions. The analysis of strain rates among various material specimens during a numerical simulation reveals

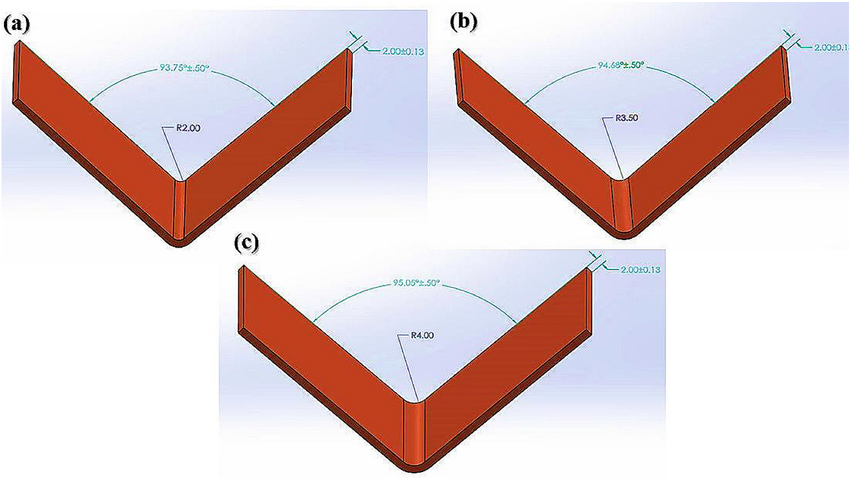

Figure 3. The copper specimen models (3D) with varying thicknesses, bend angles, and punch radii

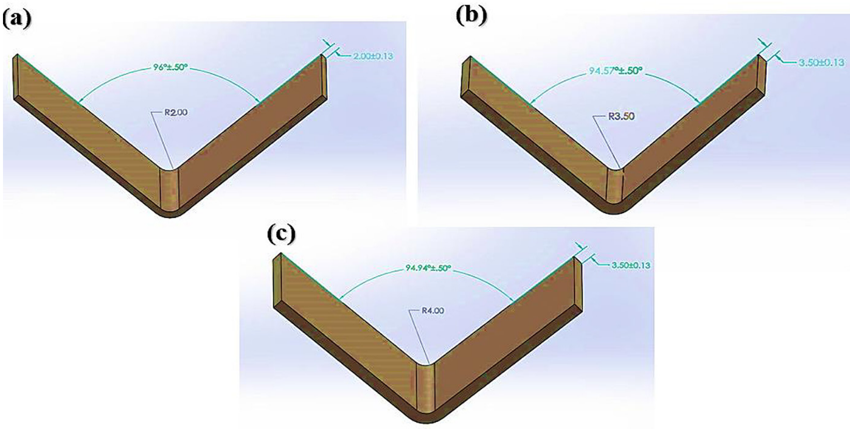

Figure 4. The pure steel specimen models (3 dimensional) with varying thicknesses, bend angles, and punch radii

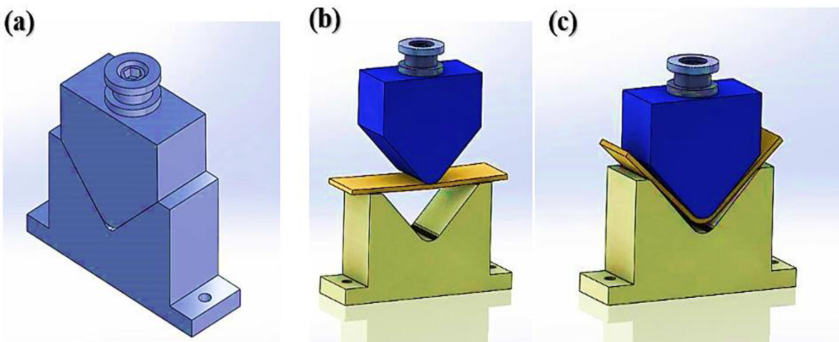

Figure 5. Configurations of (a) the numerical mold (3D), (b) a copper specimen to be bended by the mold, and (c) bended Cu specimen

that the second copper specimen has the highest strain rate at approximately 0.073, followed by the first copper specimen at 0.062 and the second aluminum specimen at 0.0585. In contrast, the first and second pure steel specimens recorded the lowest strain rates of 0.040 and 0.041, respectively. Notably, the first aluminum specimen, which is lighter than pure steel, has a strain rate of 0.045, indicating its potential suitability for lightweight vehicle manufacturing as shown in Figure 7.

Additionally, referring to the numerical simulation results of strain variation in aluminum, copper, and pure steel under load application, as presented in Table 3 and illustrated in Figure 8.

Table 3. The strain analysis across the specimens

Time (Seconds)	Strain rate Cu (1)	Strain rate Cu (2)	Strain rate Al (1)	Strain Rate Al (2)	Strain rate Fe (1)	Strain rate Fe (2)
1.2	0.06125	0.0725	0.04375	0.05875	0.04	0.04125
1.12	0.06125	0.0725	0.045	0.05875	0.04	0.04125
1.04	0.06125	0.0725	0.04375	0.05875	0.04	0.04125
0.96	0.06125	0.07375	0.045	0.05875	0.04	0.04125
0.88	0.06125	0.0725	0.04375	0.05875	0.04	0.04125
0.8	0.06125	0.0725	0.045	0.05875	0.04	0.04125
0.72	0.06125	0.0725	0.04375	0.05875	0.04	0.04125
0.64	0.06125	0.0725	0.045	0.05875	0.04	0.04125
0.56	0.06125	0.07375	0.04375	0.05875	0.04	0.04125
0.48	0.06125	0.0725	0.045	0.05875	0.04	0.04125
0.4	0.06125	0.0725	0.04375	0.06	0.04	0.04125
0.32	0.06125	0.0725	0.045	0.05875	0.04	0.04125
0.24	0.06125	0.07375	0.04375	0.05875	0.04	0.04125
0.16	0.06125	0.0725	0.045	0.05875	0.04	0.04125

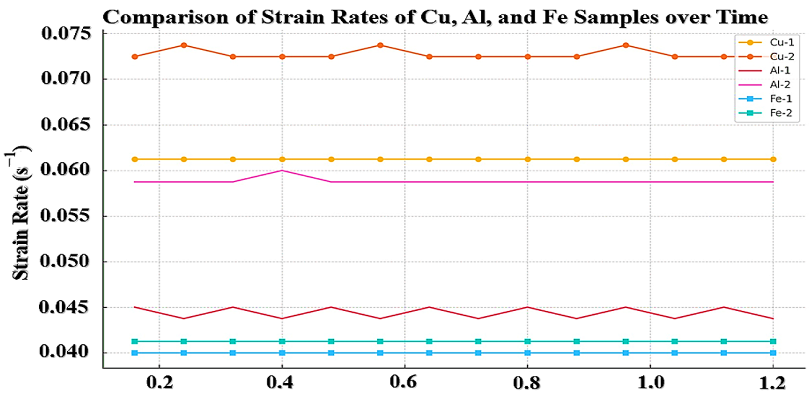

Figure 6. Simulation outcomes of deformation rates varying with time of copper, aluminum, and steel specimens

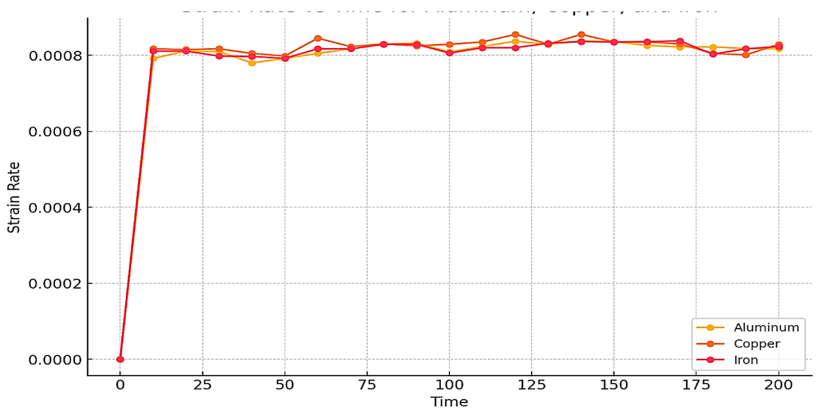

Figure 7. Simulation outcomes of strain rates varying with time of copper, aluminum, and steel specimens, considering short-time load application

The findings show a significant initial increase in strain rates for all three metals, which stabilizes around a steady value after approximately 13 seconds. The similarity in strain response patterns among the metals suggests that they exhibit comparable behavior under load, making them suitable for specific manufacturing applications where load dynamics are critical.

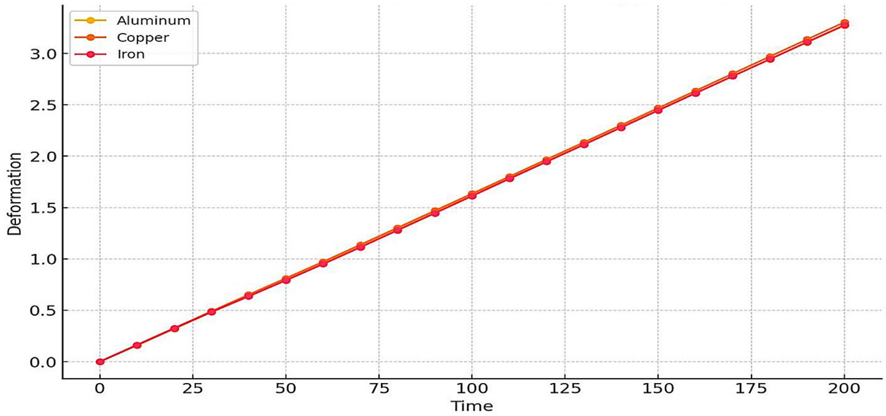

Figure 8. Simulation outcomes of strain rates varying with time of copper, aluminum, and steel specimens, considering long load application interval

The results also investigate the deformation behavior of aluminum, copper, and pure steel when subjected to a sustained load. The findings indicate that the deformation of all three metals increases linearly with the duration of load application. This consistent behavior across the metals suggests that they respond similarly to prolonged stress, highlighting their mechanical properties in terms of time-dependent deformation.

The simulation results provided data on the final surface pressure (SBP) for aluminum samples (Fig. 9). It can be inferred from the results that the behavior related to final surface pressure will increase concerning the dimensions of the metal (radius of indentation). Aluminum samples with lower thicknesses will be affected more significantly and will have noticeable effects on the final surface pressure compared to aluminum samples with greater thicknesses. It was observed that deformation increases with an increase in metal thickness.

Figure 10 illustrates the behavior of the SBP based on the numerical simulation results of three copper specimens with varying thicknesses. The numerical results indicate that the behavior related to the SBP exhibits a slight reduction concerning the metal dimension (the punch radius) [29]. Copper specimens with greater thicknesses demonstrated higher SBP and elastic recovery after deformation compared to those with lesser thicknesses. Consequently, copper deformation showed higher rates with increased thicknesses but lower values with larger punch radius rates [30]. Similarly, as with aluminum and copper, Figure 11 presents the behavior of SBP under different punch radius rates for three pure Fe specimens with varying thicknesses. From the numerical results depicted in Figure 13, it is evident that the pattern concerning the SBP in the three pure steel specimens tends to increase with larger punch radius values. Furthermore, it is observed that pure steel specimens with lower thicknesses exhibit more pronounced effects and observations of SBP compared to those with higher thicknesses.

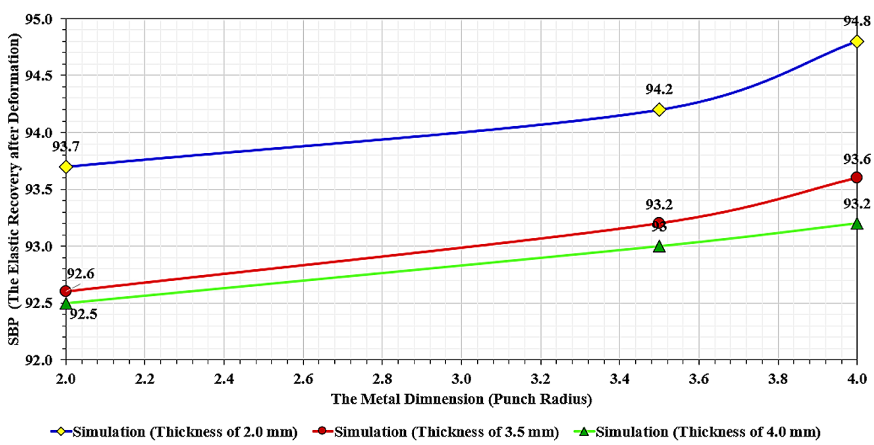

Figure 9. The SBP behavior of the three aluminum specimens with varying punch radius

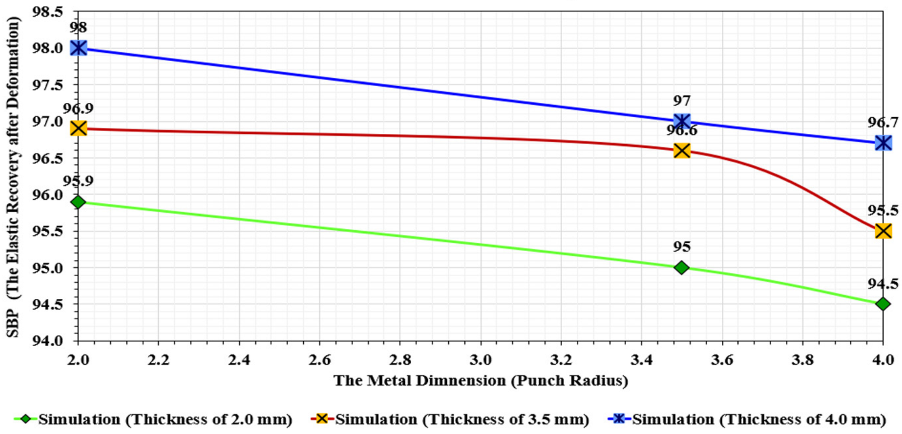

Figure 10. The SBP behavior of the three copper specimens with varying punch radius

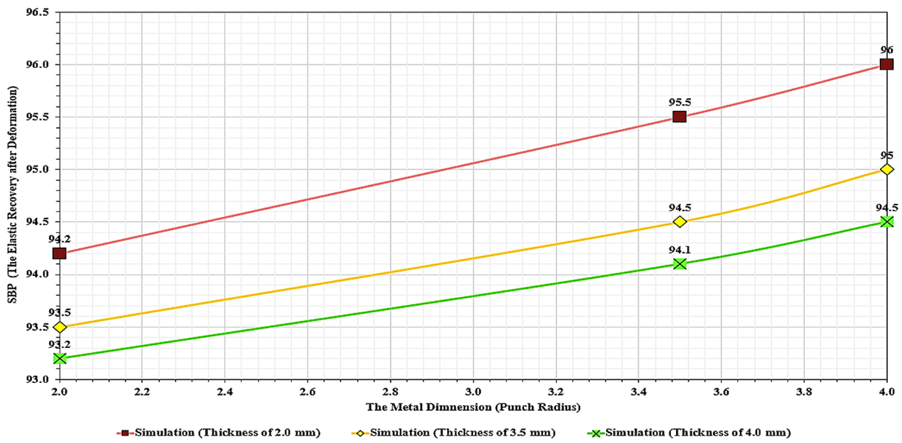

Figure 11. The SBP behavior of the three pure steel specimens with varying punch radius

In conclusion, it can be stated that pure steel specimens with lesser thicknesses are significantly influenced by SBP in comparison to those with greater thicknesses. Additionally, larger punch radius rates lead to a more pronounced occurrence of the SBP.

Hybrid model integration results analysis

In the investigation of the metal forming process using hybrid model integration, the three current study metals, were selected for numerical analysis. These metals were evaluated based on their mechanical and thermal properties, as well as their behavior during the forming process. The main aim of this research was to compare the materials in terms of force, deformation, temperature, stress distribution, springback, and material-specific behaviors, in order to identify the most suitable material for various industrial applications. The results were obtained through detailed simulations that accounted for the intrinsic properties of the materials, and they provide insights into the overall performance of each material in terms of forming efficiency, quality, and computational demands.

Force and deformation

The force and deformation analysis revealed distinct differences in the materials' behaviors under forming conditions, as presented in Figure 12. Aluminum exhibited the lowest peak forming force of 50 kN, which is consistent with its lower yield strength compared to Copper and Iron. As expected, Aluminum also displayed the highest maximum deformation of 4.5 mm, indicating that it is more easily shaped during the forming process. Copper required a higher forming force (75 kN) but demonstrated slightly less deformation (3.8 mm), suggesting that it is more resistant to deformation

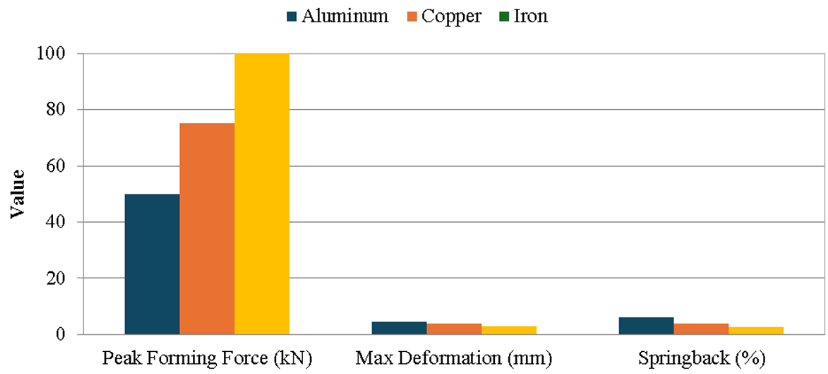

Figure 12. Force and deformation analysis

than Aluminum but still retains a good level of malleability. Iron, being the strongest material, needed the highest forming force (100 kN) and showed the lowest deformation (2.9 mm), highlighting its stiffness and reduced ease of shaping. Springback was also analyzed, with Aluminum exhibiting the highest springback of 6.2%, which can be attributed to its higher ductility. Copper followed with a springback of 4.0%, and Iron had the least springback at 2.5%, which aligns with its lower ductility.

Temperature and stress distribution

The temperature and stress distribution analysis provided further insights into the thermal and mechanical responses of each material during forming, as presented in Figure 13. Copper, with its superior thermal conductivity (398 W/m·K), experienced the highest temperature rise (350°C) during the process. Aluminum, with a lower thermal conductivity of 237 W/m·K, reached a maximum temperature of 300 °C. Iron, which has the lowest thermal conductivity (80 W/m·K), experienced the least temperature rise of 250 °C, making it more resistant to heat during the forming process. The stress distribution data indicated that Iron had the highest maximum Von Mises stress (420 MPa), as expected due to its higher strength, while Aluminum experienced lower stress (280 MPa). Copper's stress was intermediate, with a maximum of 350 MPa. The stress concentration was highest in Iron (450 MPa), which suggests that while it is a strong material, it is more prone to localized stress accumulation during the forming process.

Springback and post-processing

The springback and post-processing behavior table emphasized how each material behaves once the forming force is removed, as presented in Figure 14. Aluminum showed the largest springback angle of 4.5°, which is indicative of its high elasticity and tendency to return to its original shape after deformation. Copper, with a springback angle of 3.2°, exhibited moderate recovery, and Iron showed the least springback at 1.8°, reflecting its reduced ability to return to its original shape. The final shape deviation was also evaluated, with Aluminum showing the

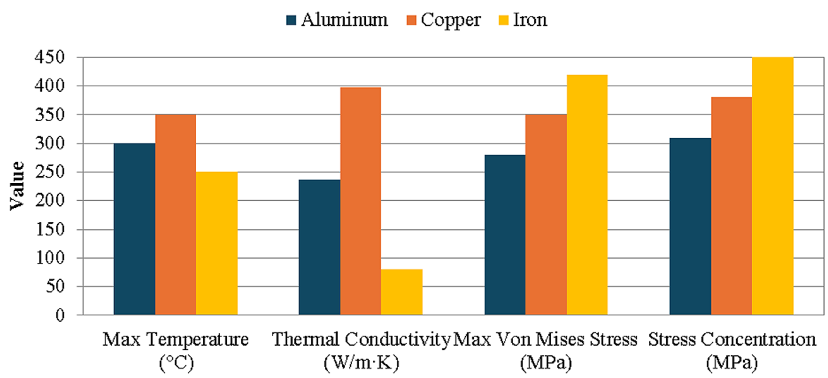

Figure 13. Temperature and stress distribution

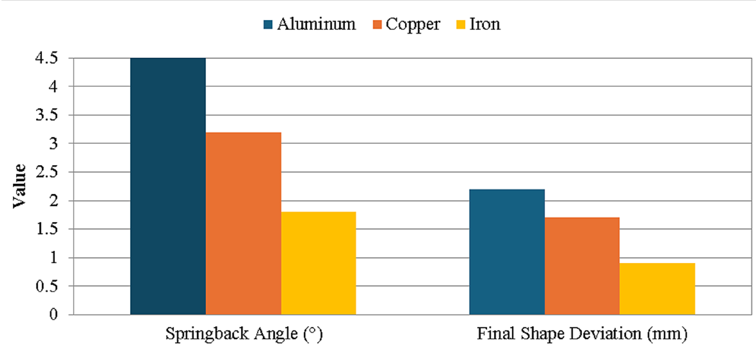

Figure 14. Springback and post-processing behavior

largest deviation (2.2 mm), followed by copper (1.7 mm) and Iron (0.9 mm). This suggests that aluminum, despite its higher formability, may result in less precise final shapes compared to copper and iron.

Material-specific

The material-specific behavior analysis, as shown in Table 4, showed that copper is the most ductile material, with a high elongation at break of 35% and superior overall ductility. Aluminum, while still relatively ductile, had a lower elongation at break (25%), and iron had the lowest ductility with only 15% elongation at break. Yield strength was highest in iron (350 MPa), followed by aluminum (250 MPa), and copper (210 MPa). These results are consistent with the general understanding that Iron is stronger but less ductile than aluminum and copper.

Computational performance

Finally, the computational performance analysis indicated the time and mesh size required for each material during the simulation process, as shown in Table 5. As expected, the simulation time increased with the complexity of the material, with Iron requiring the longest time (5 hours) due to its larger mesh size (250,000 elements) and more complex behavior. Copper and Aluminum, with smaller mesh sizes (200,000 and 150,000 elements respectively), required less time, but Copper still took more time than Aluminum due to its more complicated stress and temperature distribution. Solver efficiency decreased slightly with the increasing number of elements, but the hybrid model remained efficient for industrial applications despite the increased computational demand for more complex materials.

In summary, each material, aluminum, copper, and iron, demonstrated unique advantages and limitations in terms of forming force, deformation, stress distribution, and post-processing behavior. These findings provide critical insights for selecting the appropriate material based on specific forming requirements, whether it be ease of shaping (aluminum), superior ductility (copper), or higher strength (iron).

Table 4. Material-specific behavior

No.	Material	Yield strength (MPa)	Elongation at break (%)	Ductility
1	Aluminum	250	25	High
2	Copper	210	35	Very High
3	Iron	350	15	Low

Table 5. Computational performance

No.	Material	Simulation time (hrs)	Mesh size (Elements)	Solver efficiency
1	Aluminum	3.5	150,000	85%
2	Copper	4	200,000	80%
3	Iron	5	250,000	75%

Comparative analysis of the SBP between the three metals

To provide a better understanding of how each metal responds to mold loading and the resulting springback (SBP), the elastic recovery ratios for the three metals at different thicknesses (2.0 mm, 3.5 mm, and 4.0 mm) are now expressed in percentage terms. This allows for a more quantifiable comparison of how each material behaves under the applied loads. The results of the SBP behavior for each metal at different thicknesses are shown in Figure 15.

The elastic recovery ratios for the three metals at different thicknesses demonstrate varying levels of springback behavior.

At a thickness of 2.0 mm, aluminum exhibits the highest elastic recovery ratio of 85%, showing that it responds well to mold loading and recovers most of its shape after deformation. Copper follows with a moderate recovery of 60%, while Iron shows the lowest recovery at 35%, indicating significant deformation that does not fully recover after the mold loading.

For a thickness of 3.5 mm, aluminum still maintains the highest springback at 75%, but this is a decrease from its performance at 2.0 mm. Copper's recovery ratio decreases to 55%, and Iron continues to show the lowest recovery at 30%, further emphasizing its poor performance in terms of elastic recovery.

At 4.0 mm thickness, the springback behavior of aluminum is again reduced to 65%, while Copper experiences a slight decrease to 50%. Iron still has the lowest elastic recovery at 25%, confirming that it exhibits the least ability to recover from mold loading among the three metals. This analysis indicates that Aluminum consistently performs the best in terms of springback across all thicknesses, while Iron exhibits the poorest elastic recovery, especially as the thickness increases. Copper lies between the two, with moderate springback across the different thicknesses.

The numerical simulation results and ML classification procedures obtained from this study are consistent with the experimental outcomes attained by Cinar et al. (2021) [13], who found that the scale of SBP occurring to A6061 aluminum samples formed by V-shaped die relies on specific critical variables, including the bending angle, die shoulder force, amount of the applied die load, annealing temperature, strain hardening, material's properties (like Poisson's ratio, yield strength, modulus of elasticity), die and punch radius, friction coefficient, and aluminum sheet thickness. Additionally, Cinar et al. (2021) [13] confirmed that throughout the load implementation process, small sheet metal's changes and deviations in its thickness could result in considerable variations in the behavior of the SBP. Furthermore, the authors elucidated that undesired elastic recovery during SMF from the target shape, which can result in assembly problems, SBP, and inaccuracy issues, might take place because of lower metal thicknesses.

The numerical simulations of this work are consistent as well with the findings of Pandit et al. (2020) [16], whose experimental work affirmed that galvanized iron sheet metal SBP properties, such as die corner radius, punch radius, and dimensions could affect the behavior of SBP. Strictly speaking, their experimental study revealed that the sheet thickness would have a significant impact on the pattern of SBP. Also, it was realized that the effect of some variables, like the punch radius and the die corner radius, is relatively lower if it is individually considered. Nonetheless, when considering all SBP properties and indices, the combined effect of all of them would be more remarkable.

Also, the numerical simulation outcomes and ML prediction activities of this research are

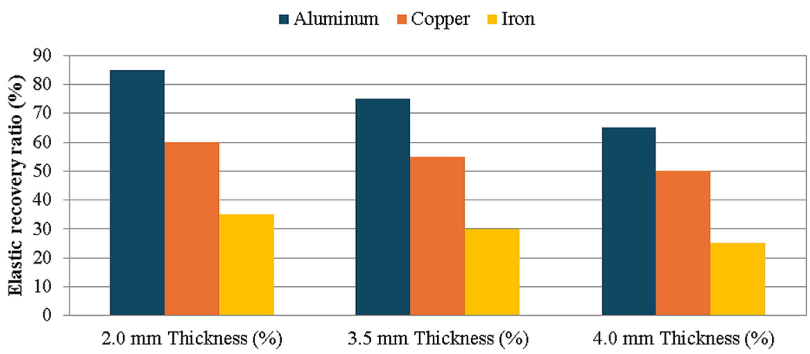

Figure 15. SBP behavior for different thicknesses (2.0 mm, 3.5 mm, 4.0 mm)

compatible with the results of Cinar et al. (2021) [13], who reported that with a rise in the metal thickness, corresponding bending angle would increase. Certainly, for aluminum, it was found that greater thickness would be correlated to raised values of bending angle. Nonetheless, these results are not compatible for the simulation outcomes related to steel and copper.

In addition, it was found that the temperature effect had a significant impact on the deformation, Von Mises stress, and elastic strain. Particularly, when the metal has larger thermal conductivity, like copper compared with aluminum and steel, its response to deformations would be more significant. When the metal's temperature is at the ambient degree, its corresponding deformations and elastic strain would be low. These results are identical to the experimental outcomes realized by Cinar et al. (2021) [13], who found that a temperature increase in aluminum specimen A6061 would cause a rise in the elongation of the aluminum specimen.

CONCLUSIONS

This study explored a hybrid advanced analysis approach combining finite element analysis (FEA) and machine learning to predict springback phenomena (SBP) in metals. The research revealed several critical findings regarding the mechanical behavior of aluminum, copper, and pure iron under forming conditions. The conclusions are summarized as follows:

1. Springback behavior varied significantly among the three metals, with aluminum exhibiting the highest springback (6.2%) due to its high ductility, followed by copper (4.0%) and iron (2.5%).
2. Pure iron demonstrated the least springback, indicating its suitability for applications requiring precise dimensional control post-forming. Aluminum required the lowest peak forming force (50 kN) and showed the highest deformation (4.5 mm), making it the most easily formable material. Copper required a higher forming force (75 kN) with moderate deformation (3.8 mm), while iron, being the strongest material, exhibited the highest forming force (100 kN) and the least deformation (2.9 mm).
3. Copper experienced the highest temperature rise (350 °C) during the forming process due to its superior thermal conductivity, followed by aluminum (300 °C) and iron (250 °C).
4. Thinner specimens exhibited more pronounced springback effects across all three metals, while increased punch radii enhanced the springback behavior.
5. Copper demonstrated the highest ductility (35% elongation at break), making it ideal for applications requiring significant deformation without failure. Aluminum exhibited good ductility (25% elongation) and high formability but showed larger shape deviations post-forming. Iron, with the highest yield strength (350 MPa) and lowest elongation (15%), provided excellent strength and dimensional stability but reduced malleability.
6. The integration of FEA and machine learning proved effective in accurately predicting springback angles, reducing reliance on time-intensive experiments, and optimizing the metal forming process.

The findings of this study provide actionable insights for industries requiring precise material behavior control during forming processes. Aluminum is suitable for lightweight applications such as automotive manufacturing, while iron is preferred in scenarios requiring high strength and dimensional stability. Copper, with its balance of ductility and strength, is well-suited for intricate forming processes.

This hybrid analysis approach offers a promising tool for optimizing manufacturing processes, improving product quality, and enhancing efficiency across various industrial sectors. Future research could expand the applicability of this model to more complex geometries and multimetal systems, further advancing the field of metal forming technology.

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