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Springback in sheet metal bending: A comprehensive review of influencing factors, prediction methods, monitoring techniques and compensation strategies

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Abstract

Springback is one of the most significant challenges in sheet metal bending because it adversely affects dimensional accuracy, product quality, and manufacturing efficiency. Its occurrence is governed by the complex interaction of material properties, geometrical characteristics, and forming conditions, making accurate prediction and effective compensation difficult, particularly for advanced high-strength steels and lightweight alloys. This review provides a comprehensive overview of the current state of research on springback in sheet metal bending processes, covering the fundamental mechanisms of elastic recovery, the principal factors influencing springback behavior, and recent advances in prediction, measurement, monitoring, and compensation techniques. Conventional analytical models, finite element analysis (FEA), and emerging artificial intelligence (AI)-based approaches are critically compared in terms of prediction capability, computational efficiency, advantages, limitations, and industrial applicability. In addition, recent developments in optical and laser-based measurement systems, intelligent monitoring technologies, and closed-loop compensation strategies are reviewed to highlight their contributions to improving process accuracy and productivity. The review further discusses the transition toward data-driven and physics-informed modeling, emphasizing the integration of machine learning, digital twins, explainable AI, and real-time sensing within intelligent manufacturing environments. Finally, current research challenges, including computational cost, material uncertainty, model generalization, and real-time implementation, are analyzed, and future research directions are proposed. The findings indicate that hybrid frameworks integrating physics-based modeling, AI, and adaptive process control represent the most promising pathway toward robust, autonomous, and high-precision springback prediction and compensation in next-generation sheet metal manufacturing systems.

Keywords: Springback; Sheet metal bending; Finite element analysis; Springback prediction; Springback compensation; Intelligent manufacturing

1. Introduction

Metal bending processes are among the most important manufacturing techniques used to produce lightweight and high-precision components in various industrial sectors, including automotive, aerospace, transportation, and structural applications. The increasing use of advanced engineering materials such as aluminum alloys, titanium alloys, and advanced high-strength steels (AHSS) has improved the strength-to-weight ratio of formed components. However, these materials commonly exhibit considerable elastic recovery after unloading, resulting in springback, which remains one of the major challenges affecting dimensional accuracy and product quality in bending operations .Such dimensional deviations caused by springback can lead to assembly difficulties, reduced manufacturing accuracy, and additional costs associated with tool modification and compensation procedures [1-3].

Springback occurs due to the redistribution of elastic stresses stored during plastic deformation after the forming load is removed. The magnitude of springback is governed by complex interactions between material characteristics,

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component geometry, and forming conditions. Material-related factors, including Young's modulus, yield strength, strain hardening behavior, anisotropy, and microstructural evolution, have been identified as dominant parameters controlling elastic recovery. In particular, materials with a high yield strength-to-elastic modulus ratio generally experience larger springback due to the increased contribution of elastic strain during unloading [1, 4].

In addition to material properties, process and geometrical parameters significantly influence springback behavior. Parameters such as sheet thickness, bending radius, forming temperature, tool geometry, friction conditions, and applied forming forces affect stress distribution and the final geometry of bent components. Recent studies have demonstrated that optimizing these parameters through experimental investigations and statistical approaches can effectively reduce springback and improve forming accuracy, especially for lightweight alloys and high-strength materials [2, 3].

Due to the high cost and time requirements associated with experimental trial-and-error procedures, finite element analysis (FEA) has become a widely adopted approach for predicting springback behavior in metal forming processes. Accurate numerical prediction strongly depends on appropriate material modeling, including yield criteria, anisotropic behavior, elastic modulus variation, and hardening rules. In particular, the selection of suitable hardening models, such as kinematic and combined hardening approaches, is essential for accurately representing unloading behavior and the Bauschinger effect during springback prediction [4, 5]. Advanced finite element studies have also demonstrated that numerical factors, including mesh configuration, element formulation, and simulation parameters, significantly influence prediction accuracy [6, 7].

Despite significant progress in numerical modeling, conventional finite element simulations still face limitations related to computational cost, model calibration, and real-time industrial implementation. Consequently, data-driven approaches and artificial intelligence (AI) techniques have recently emerged as powerful alternatives for springback prediction and compensation. Machine learning methods, involving artificial neural networks, physics-informed models, and hybrid FEA–AI surrogate models, have demonstrated high efficiency in capturing nonlinear relationships between forming parameters and springback responses while reducing computational effort [8-10].

Although extensive research has been conducted on springback prediction and control, achieving accurate and adaptive compensation remains challenging due to complex interactions among material behavior, forming parameters, and process uncertainties. Therefore, further integration of advanced constitutive modeling, finite element simulation, artificial intelligence, and intelligent monitoring technologies is required to develop robust and reliable springback control strategies.

This review provides a comprehensive analysis of springback behavior in metal bending processes by discussing the fundamental mechanisms, influencing factors, prediction approaches, and reduction strategies. Special emphasis is placed on recent developments in finite element modeling, artificial intelligence-based prediction methods, and intelligent compensation techniques, highlighting current challenges and future research directions toward smart and adaptive forming systems.

To provide readers with a structured overview of the evolution of springback research, Figure 1 illustrates the progressive development of the field from fundamental mechanical studies toward advanced prediction methods, intelligent monitoring, compensation strategies, and smart manufacturing technologies. This conceptual roadmap summarizes the major research stages reviewed in this article and highlights the continuous transition from understanding springback mechanisms to developing intelligent and autonomous manufacturing solutions.

The remainder of this review is ordered in the following manner. Section 2 introduces the fundamental mechanisms of springback and the factors governing elastic recovery in sheet metal bending. Section 3 reviews the principal factors affecting springback and provides a comparative analysis of representative studies. Section 4 discusses analytical, numerical, and data-driven prediction approaches together with intelligent compensation methods. Section 5 presents representative springback measurement and monitoring techniques used for process evaluation and quality control. Section 6 reviews springback reduction and compensation strategies, while Section 7 outlines the current challenges and future research trends. Finally, the main conclusions of this review are summarized in Section 8.

Figure 1 Evolution of springback research and technological developments in sheet metal bending

2. Fundamentals and Mechanisms of Springback Formation

Springback is an inherent phenomenon in metal bending processes caused by the elastic recovery that occurs after removing the external forming load. During bending deformation, the material experiences non-uniform elastic–plastic deformation through the thickness direction, where tensile stresses are generated on the outer surface and compressive stresses develop on the inner surface. After unloading, the elastic portion of the deformation is recovered, leading to variations in the final bending angle, curvature, and dimensional accuracy of the formed component. Therefore, springback behavior is mainly governed by the relationship between plastic deformation and the remaining recoverable elastic strain stored during the forming process [1, 3].

The development and redistribution of residual stresses are considered the main physical mechanisms controlling springback formation. During bending, non-uniform plastic deformation produces heterogeneous stress distributions within the material. After unloading, these internal stresses redistribute to achieve a new equilibrium condition, resulting in elastic recovery and geometric deviation. From an energy perspective, springback can also be explained by the release of stored elastic energy accumulated during deformation, where a higher amount of residual elastic energy generally increases the tendency for shape recovery after unloading [11, 12].

Accurate representation of material behavior during unloading is essential for reliable springback prediction. Simple elastic–plastic descriptions may be insufficient because many engineering materials exhibit nonlinear unloading behavior, elastic modulus variation, and reverse loading effects. Particularly, the Bauschinger effect plays an important role in springback behavior by modifying the yield response during load reversal. Consequently, advanced constitutive models incorporating kinematic or combined hardening rules have been widely adopted to describe stress evolution and improve springback prediction accuracy [5, 13].

Although the fundamental mechanism of springback is similar in different bending operations, its behavior becomes more complex in tube and profile bending processes due to additional factors such as cross-sectional deformation, wall thickness variation, neutral layer shifting, and multi-axial stress states. These interactions between material response, residual stresses, and geometrical constraints make springback a nonlinear phenomenon that requires accurate modeling before effective prediction and compensation strategies can be developed [14].

3. Factors Affecting Springback Behavior

3.1. Material-Related Factors

Material properties are among the most dominant factors governing springback behavior because they control the relationship between elastic recovery and permanent plastic deformation during bending operations. Young's modulus and yield strength are particularly important parameters affecting the magnitude of springback. Materials with a higher yield strength and lower elastic modulus generally exhibit greater elastic recovery after unloading due to the larger amount of stored elastic strain. Therefore, the yield strength-to-elastic modulus ratio is widely considered an important indicator for evaluating the springback tendency of metallic materials [1, 15].

The increasing demand for lightweight structures has promoted the extensive application of advanced high-strength steels (AHSS), aluminum alloys, and titanium alloys in automotive and aerospace components. Although these materials provide superior strength-to-weight ratios and improved structural performance, their forming accuracy is often limited by significant springback caused by high strength levels and complex deformation characteristics. Therefore, understanding their material response under different forming conditions is essential for improving springback prediction and control [2, 15, 16].

Material anisotropy also has a considerable influence on springback behavior due to the directional variation of mechanical properties introduced during rolling and manufacturing processes. The anisotropic response affects yielding behavior, plastic flow, and stress redistribution during unloading. Consequently, accurate descriptions of anisotropic behavior using advanced yield criteria and constitutive models are required to enhance the reliability of springback prediction in numerical simulations [17, 18].

Another critical aspect affecting springback prediction accuracy is the selection of an appropriate hardening model. Conventional isotropic hardening assumptions are often insufficient for representing complex unloading behavior, particularly under reverse loading conditions. Kinematic and combined hardening models provide improved descriptions of transient material behavior by considering the Bauschinger effect and stress evolution during unloading, resulting in more accurate springback predictions for advanced materials [5, 19].

In addition to macroscopic mechanical properties, microstructural characteristics and deformation history significantly influence springback behavior. Parameters such as grain size, crystallographic texture, and pre-strain conditions modify the evolution of internal stresses and the elastic–plastic response of materials. These effects become more significant in micro-scale forming processes, where size-dependent deformation mechanisms and microstructural heterogeneity strongly affect springback characteristics [20, 21].

3.2. Geometrical and Process Parameters

In addition to material characteristics, geometrical features and forming parameters significantly influence springback behavior by altering the stress distribution, plastic deformation level, and residual stress state generated during bending. The relationship between component geometry and elastic recovery is highly dependent on the deformation severity introduced during forming. Among the geometrical parameters, sheet thickness and bending radius are considered the most influential factors. Increasing sheet thickness generally decreases springback because of the increased bending stiffness and higher plastic deformation ratio, whereas larger bending radii usually increase springback due to the reduction in plastic strain and the higher contribution of elastic recovery [22-24].

Tool-related parameters, including punch radius, die angle, die clearance, and tool configuration, also strongly affect the final springback response. Changes in tool geometry modify the contact conditions, strain distribution, and bending moment applied to the material. Experimental and numerical investigations on V-bending and U-bending processes have shown that optimization of punch and die parameters is an effective strategy to control residual stress formation and minimize dimensional deviations after unloading [6, 25, 26].

Process parameters represent another important category affecting springback because they control the deformation history and stress evolution during forming. Variables such as forming force, blank holder force, holding time, friction condition, and forming speed can significantly change material flow and stress relaxation behavior. For instance, increasing holding time or applying appropriate forming forces may enhance stress redistribution before unloading, while the effect of forming speed depends strongly on strain-rate sensitivity and material hardening behavior [27, 28].

Thermal conditions have attracted considerable attention as an effective method for reducing springback, especially in lightweight alloys and high-strength materials with limited room-temperature formability. Warm and hot forming processes reduce flow stress and promote stress relaxation, resulting in lower residual stresses and reduced elastic recovery. However, the effectiveness of temperature-assisted forming depends on the material type, temperature level, and interaction between thermal softening and microstructural evolution during deformation [29-31].

For advanced forming technologies, such as incremental bending, stretch bending, flex forming, and roll bending, springback behavior becomes more complicated because of nonlinear deformation paths and multiple interacting variables. Therefore, optimization-based approaches, including design of experiments, Taguchi methods, response surface, and genetic algorithm methodologies, have been widely applied to determine optimal forming conditions. These approaches provide a systematic understanding of parameter interactions and enable improved springback control in complex forming applications [32-34].

A comparative summary of the representative studies investigating the major factors affecting springback is presented in Table 1. The table highlights the primary investigated factors, their influence on springback behavior, and the key findings obtained from representative experimental and numerical studies.

Table 1 Comparative Summary of the Most Influential Studies on Factors Affecting Springback in Sheet Metal Bending Processes

Ref.	Material	Bending Process	Factor Category	Primary Investigated Factor	Effect on Springback	Verified Main Finding
[1]	Various sheet metals	Sheet bending	Mechanical properties	Yield strength / Elastic modulus	Increased / Decreased	Higher yield strength increases springback, whereas a higher elastic modulus reduces elastic recovery.
[1], [3], [17]	Metallic sheets	Various bending processes	General process interaction	Combined process variables	Variable	Springback is governed by the interaction of material, geometric, and process variables rather than a single dominant factor.

[5]	DP980 steel	Draw-bending	Constitutive behavior	Hardening model	Decreased (prediction error)	The Yoshida–Uemori kinematic hardening model provided more accurate springback prediction than conventional isotropic models.
[15]	Automotive steel sheets	Compression bending	Mechanical properties	Material anisotropy	Variable	Rolling direction significantly affected springback owing to anisotropic plastic deformation.
[20]	JSC590 steel	V-bending	Geometry	Sheet thickness and strip width	Variable	Springback depends on the combined influence of sheet thickness and strip width rather than thickness alone.
[22]	Steel sheets	V-bending	Tool geometry	Punch radius	Increased	Larger punch radius generally increased springback because of reduced plastic deformation.
[24]	Tailor rolled blanks	Cylindrical bending	Geometry	Thickness variation	Variable	Thickness variation caused non-uniform stress distribution and consequently non-uniform springback.
[25]	Sheet metal	Die shoulder patterning	Tool geometry	Die shoulder geometry	Decreased	Optimized die shoulder geometry effectively reduced springback without changing material properties.
[30]	TC4 titanium alloy	Warm tube bending	Thermal-assisted forming	Forming temperature	Decreased	Increasing forming temperature reduced springback, while transient unloading dominated the springback evolution.
[31]	Martensitic 1400 steel	V-bending	Tool and Process	Die angle, temperature, punch radius	Variable	ANOVA identified die angle as the dominant factor, followed by temperature and punch radius; holding time showed negligible influence.
[32]	Flexible stretch-bent profiles	Flexible stretch bending	Geometry	Bending angle	Variable	Larger bending angles altered residual stress distribution and changed springback magnitude.
[33]	SS400 steel	Large-radius V-bending	Optimization	Taguchi method	Decreased	Statistical optimization successfully identified the optimal parameter

						combination for minimizing springback.
[36]	Sheet metal	Flexible stretch bending	Analytical–Numerical	Integrated analytical–FE approach	Decreased	Combined analytical and numerical analysis improved understanding of springback mechanisms and process optimization.
[38]	Profiles	Flexible stretch bending	Process parameters	Stretch strain	Decreased	Higher stretch strain effectively reduced springback but increased the risk of thinning at excessive levels.
[54]	Metallic sheets	U-bending	Process parameters	Blank holder force	Decreased	Increasing blank holder force reduced springback energy and improved dimensional accuracy.
[55]	Sheet metal	V-bending	Multi-factor optimization	ANOVA	Variable	Multi-factor statistical analysis ranked the relative importance of process variables and supported process optimization.
[56]	Sheet metal	V-bending	Optimization	Process parameter optimization	Decreased	RSM effectively quantified parameter interactions and identified optimum process conditions with fewer experiments.

Table 1 summarizes representative studies investigating the factors affecting springback in sheet metal bending processes and highlights the progressive evolution of research from examining individual variables toward integrated process optimization. The reviewed studies consistently demonstrate that springback is a multi-factor phenomenon governed by the interaction of material properties, tool geometry, process parameters, thermal conditions, and geometric characteristics rather than by a single dominant variable.

Material-related factors, including yield strength, elastic modulus, anisotropy, and constitutive hardening behavior, were identified as primary determinants of elastic recovery because they directly influence plastic deformation and residual stress development. In parallel, process parameters such as blank holder force, stretch strain, friction coefficient, and forming temperature were widely reported as effective means of reducing springback when properly optimized. Similarly, geometric variables, including sheet thickness, punch radius, bending angle, and weld-line location, were shown to modify stress redistribution and consequently alter both the magnitude and uniformity of springback.

Another important trend revealed by the reviewed literature is the increasing adoption of statistical optimization techniques, such as Taguchi methods, response surface methodology (RSM), and analysis of variance (ANOVA), to evaluate parameter interactions and determine optimal forming conditions with improved efficiency. Furthermore, recent studies have progressively integrated analytical formulations with finite element simulations, providing deeper insight into springback mechanisms while improving prediction reliability compared with conventional analytical approaches.

Despite these significant advances, most existing investigations remain focused on specific materials, individual process variables, or particular bending configurations. Consequently, the simultaneous interaction among material behavior, tooling conditions, and process parameters has not been comprehensively addressed in a unified prediction framework. This limitation has stimulated the development of more advanced springback prediction methodologies, including finite element modeling, surrogate modeling, machine learning, and intelligent compensation strategies, which are critically reviewed in the following section.

4. Springback Prediction Approaches

Accurate prediction of springback is essential for improving dimensional accuracy and reducing costly trial-and-error modifications in metal bending processes. Over recent decades, different prediction approaches have been developed, ranging from analytical models based on deformation theories to advanced numerical simulations and artificial intelligence-based methods. Each approach offers specific advantages and limitations depending on material complexity, component geometry, computational requirements, and desired prediction accuracy.

4.1. Analytical Prediction Models

Analytical models represent one of the earliest approaches developed for predicting springback behavior in bending processes. These methods are generally based on elastic–plastic deformation theories, stress–strain relationships, and moment–curvature analysis to estimate the amount of elastic recovery after unloading. Due to their relatively simple mathematical formulations and low computational cost, analytical approaches provide efficient tools for understanding the fundamental relationship between material properties, bending conditions, and springback response [35, 36].

Several analytical formulations have been proposed to improve the accuracy of springback prediction by incorporating more realistic descriptions of material behavior and loading conditions. Advanced models considering nonlinear hardening, strain history, and reverse loading effects have demonstrated improved capability compared with conventional elastic–plastic solutions. However, the accuracy of analytical models is strongly dependent on the assumptions used, particularly regarding stress distribution, material homogeneity, and deformation complexity [37, 38].

Energy-based analytical approaches have also been introduced to describe springback from the viewpoint of stored elastic energy generated during forming. These methods relate the magnitude of springback to the residual elastic energy remaining in the component after plastic deformation, providing useful insight into the relationship between stress redistribution and final shape deviation. Such approaches have been successfully applied for predicting springback in complex automotive components and improving process understanding [11].

Despite their advantages in terms of simplicity and computational efficiency, analytical models generally have limited applicability for complex industrial parts involving nonlinear contact conditions, complicated geometries, and multi-axial stress states. Therefore, analytical approaches are often combined with finite element simulations or optimization methods to improve prediction reliability in practical forming applications [3].

4.2. Finite Element-Based Prediction

Finite element analysis (FEA) has become one of the most powerful and widely adopted approaches for springback prediction due to its ability to simulate complex geometries, nonlinear material behavior, and realistic forming conditions. Unlike simplified analytical models, numerical simulations can describe the complete forming process by considering contact interactions, plastic deformation, stress evolution, and unloading behavior. Commercial finite element platforms, including ABAQUS, AutoForm, and LS-DYNA, have been extensively used to evaluate springback characteristics in various bending and sheet metal forming applications [39, 40].

The accuracy of FE-based springback prediction is strongly dependent on the numerical modeling strategy adopted during simulation. Parameters such as element type, mesh density, through-thickness integration points, contact formulation, and unloading procedure can significantly influence the predicted springback response. Therefore, careful selection of numerical parameters is required to achieve a balance between computational efficiency and prediction accuracy, particularly for complex forming operations and high-strength materials [7, 41].

A major challenge in finite element springback simulation is the accurate representation of material behavior during loading and unloading. Since springback is highly sensitive to stress redistribution after forming, the selection of appropriate constitutive models plays a critical role in prediction reliability. Advanced yield criteria combined with kinematic or mixed hardening models have been developed to capture anisotropic behavior, nonlinear unloading, and the Bauschinger effect, leading to improved agreement between numerical and experimental results [3-5].

Experimental validation remains an essential step for ensuring the reliability of finite element predictions. Many studies have combined numerical simulations with experimental measurements to calibrate material models, verify deformation behavior, and evaluate prediction errors. The integration of accurate material characterization with validated FE models has significantly improved the ability to predict springback in advanced high-strength steels, aluminum alloys, titanium alloys, and complex forming processes [2, 42].

Despite continuous improvements, FE-based approaches still present several limitations, including high computational cost, dependency on accurate material parameters, and difficulties in representing complex industrial conditions. Consequently, recent research has focused on combining finite element simulations with optimization techniques and data-driven models to enhance prediction efficiency and enable faster springback compensation strategies [43].

4.3. Artificial Intelligence and Data-Driven Prediction

Although finite element simulations provide reliable springback predictions, their application in real-time manufacturing environments can be limited by high computational requirements and the need for accurate material characterization. Recently, artificial intelligence (AI) and machine learning (ML) techniques have emerged as efficient alternatives by establishing nonlinear relationships between input forming parameters and springback responses. These approaches enable rapid prediction while reducing dependence on repeated numerical simulations and experimental trials [8, 44].

Artificial neural networks (ANNs) represent one of the earliest and most widely applied data-driven approaches for springback prediction. By learning from experimental or simulation-generated datasets, ANN models can capture complex interactions among material properties, geometrical variables, and process parameters. Hybrid approaches combining finite element simulations with neural networks have shown improved capability for predicting springback behavior in complex forming operations where traditional analytical models become less effective [8, 45].

With the advancement of machine learning algorithms, several alternative models such as support vector regression, Gaussian process regression, random forest, gradient boosting, and ensemble learning methods have been introduced to improve prediction accuracy and generalization capability. These approaches provide advantages in handling nonlinear parameter interactions and reducing computational effort compared with conventional simulation-based optimization techniques [46-48].

Recent developments have focused on integrating physical knowledge with machine learning models to enhance prediction reliability and reduce data dependency. He et al. introduced a physics-informed machine learning framework that combines process information with data-driven modeling to achieve efficient real-time springback prediction. Similarly, hybrid surrogate models based on finite element datasets and advanced learning algorithms have demonstrated strong potential for intelligent springback prediction and adaptive forming control [9, 10].

Despite the promising performance of AI-based approaches, several challenges remain, including limited experimental datasets, model transferability between different materials and forming processes, and the need for interpretable prediction models. Therefore, future developments are expected to focus on integrating finite element simulations, machine learning algorithms, sensing technologies, and closed-loop control systems toward smart and autonomous springback compensation strategies [49].

In order to provide a more comprehensive overview of springback, Table 2 presents representative springback prediction and intelligent compensation methods reported in the literature.

Table 2 Comparative Analysis of Representative Springback Prediction and Intelligent Compensation Methods

Ref.	Category	Method	Main Concept	Advantages	Limitations	Typical Applications
[35]	Analytical	Analytical elastic–plastic model	Analytical formulation for predicting springback in arced thin-plate bending	Fast, simple, and computationally efficient	Applicable mainly to simplified bending conditions	Arced thin-plate bending
[36]	Hybrid	Reverse stretch-bending model	Prediction of springback in long-profile	Improved springback	Applicable mainly to	Long-profile forming

			forming using reverse stretch-bending	control for long profiles	profile-forming operations	
[37]	Analytical	Five-point bending analytical model	Theoretical springback prediction for five-point bending	Closed-form and computationally efficient	Limited to FFX pipe preforming	ERW pipe FFX forming
[38]	Analytical	Moment–curvature analytical model	Analytical assessment of springback in flexible stretch bending	Accurate prediction for complex profiles	Limited to stretch-bending processes	Flexible stretch bending
[39]	Finite Element	FE simulation with experimental validation	Numerical prediction validated experimentally	High prediction reliability	Requires experimental validation	Stamping and bending
[40]	Finite Element	AutoForm FE simulation	FE simulation of springback in rubber diaphragm forming	Accurate prediction for aerospace components	Limited to rubber diaphragm forming	Aircraft U-shaped parts
[41]	Finite Element	FE sensitivity analysis	Sensitivity analysis of material parameters affecting springback prediction	Identifies influential material parameters	Limited to simple bending configurations	Simple bending
[42]	Finite Element	Finite Element Method (FEM)	Springback prediction in V-die air bending using FEM	Good agreement with experiments	Limited to V-die air bending	Air V-bending
[43]	AI & Machine Learning	Kriging metamodel	Surrogate modelling for springback prediction	Fast prediction and optimization	Limited extrapolation capability	Air bending optimization
[44]	AI & Machine Learning	Artificial Neural Network (ANN)	ANN-based springback prediction for flexible 3D stretch bending	Captures nonlinear behavior	Requires sufficient training data	Flexible 3D stretch bending
[45]	AI & Machine Learning	FE–BPNN hybrid model	FE-assisted BPNN for springback prediction and automatic forming control	High prediction accuracy with intelligent control	Requires FE-generated training datasets	Multi-point stretch bending
[46]	AI & Machine Learning	Gaussian Process Regression (GPR)	Probabilistic machine learning model for springback estimation	High prediction accuracy with uncertainty estimation	Geometry-dependent performance	Incremental sheet forming

[47]	AI & Machine Learning	Machine learning model	Data-driven springback prediction for automotive body structures	Suitable for industrial applications	Performance depends on training dataset quality	Automotive body-in-white structures
[48]	AI & Machine Learning	Machine learning model	Machine learning analysis of springback under localized heating	Incorporates localized heating effects	Limited to investigated materials and heating conditions	Heated bending
[49]	Intelligent Compensation	Improved Fuzzy PID Control	Closed-loop springback compensation using adaptive fuzzy PID control	Real-time adaptive compensation	Focuses on compensation rather than prediction	Roll forming
[50]	Intelligent Compensation	Experimental–numerical compensation framework	Experimental–numerical framework for springback prediction and angle compensation using additively manufactured polymer tools	Integrates prediction and compensation with flexible tooling	Limited to polymer tools	Air bending
[52]	Intelligent Compensation	Machine learning-supported closed-loop control	Closed-loop springback compensation using machine learning	Adaptive real-time compensation	Requires sensor integration	Intelligent bending systems
[53]	Intelligent Compensation	Knowledge-driven digital twin	Digital twin with graph learning and multi-sensor fusion for real-time springback prediction	High-fidelity real-time prediction	High implementation complexity	Smart manufacturing

Table 2 summarizes the evolution of springback prediction methods from analytical formulations to intelligent machine learning and real-time compensation approaches. Analytical models offer fast predictions with low computational cost but rely on simplified assumptions. Finite element-based approaches significantly improve prediction accuracy at the expense of computational efficiency. Recently, machine learning techniques have emerged as powerful alternatives by providing rapid predictions with high accuracy after training, whereas intelligent compensation strategies extend these capabilities toward adaptive real-time process control.

5. Springback Measurement and Monitoring Techniques

Accurate measurement of springback is an essential step for evaluating forming quality, validating prediction models, and developing effective compensation strategies. Traditional springback evaluation methods are mainly based on measuring angular deviation, curvature variation, or dimensional differences between the target and final unloaded geometries. Although these approaches are simple and widely used, they are often limited when applied to complex three-dimensional components because they provide only localized measurements rather than complete shape information [50].

With the development of advanced inspection technologies, non-contact measurement techniques have become increasingly important for accurate springback characterization. Optical measurement systems, three-dimensional scanning, and laser-based techniques allow full-field evaluation of geometric deviations after forming. These methods provide detailed information about shape errors and enable more reliable validation of numerical models compared with conventional contact-based measurement approaches [51].

In recent years, in-process monitoring techniques have gained increasing attention as a key step toward intelligent forming systems. Instead of measuring springback only after unloading, real-time monitoring approaches utilize sensors and online measurement systems to capture forming responses during the process. Such strategies enable adaptive control by adjusting process parameters based on measured deviations, reducing dependence on repeated tool corrections and trial-and-error procedures [49, 52].

The integration of measurement technologies with numerical models and artificial intelligence represents a promising direction for next-generation forming systems. Combining real-time data acquisition, predictive models, and closed-loop control can improve springback compensation accuracy and support the development of smart manufacturing frameworks for high-precision metal forming applications [48, 53].

The reviewed studies indicate that optical and laser-based measurement techniques remain the most reliable approaches for accurately quantifying springback because of their high measurement precision and ability to provide non-contact geometric evaluation. In particular, optical three-dimensional scanning offers comprehensive full-field validation of springback deformation, whereas laser-based in-line systems enable rapid inspection without interrupting the forming process, making them well suited for industrial quality control.

Another important trend highlighted by the reviewed literature is the increasing integration of sensing technologies with intelligent monitoring and adaptive control strategies. Closed-loop monitoring systems utilizing sensor feedback and advanced control algorithms enable real-time process adjustment, thereby reducing springback deviations during manufacturing. More recently, machine learning and explainable artificial intelligence (XAI) techniques have expanded the role of monitoring systems beyond data acquisition by providing accurate prediction, feature interpretation, and intelligent decision support for process optimization and die compensation.

Despite these significant developments, several challenges remain. Most measurement techniques are either limited to offline inspection or designed for specific forming processes, while intelligent monitoring approaches rely heavily on representative training datasets and process-specific validation. Consequently, future research should focus on developing unified monitoring frameworks that integrate high-precision sensing, real-time data acquisition, physics-based modeling, and explainable artificial intelligence to achieve robust and adaptive springback control within smart manufacturing environments.

6. Springback Reduction and Compensation Strategies

Although accurate prediction of springback is essential for understanding forming behavior, practical manufacturing applications require effective strategies to reduce or compensate for the final geometric deviation. Springback reduction approaches generally focus on controlling stress distribution, increasing plastic deformation, or modifying process conditions, while compensation strategies aim to adjust tooling or process parameters to achieve the desired final geometry. These techniques can be broadly classified into process optimization methods, tool-based compensation approaches, and advanced intelligent control strategies.

6.1. Process Optimization-Based Strategies

Optimization of forming parameters is one of the most commonly applied approaches for reducing springback without major modifications to tooling systems. Since springback is affected by complex interactions among multiple variables, statistical and numerical optimization methods have been widely adopted to identify optimal forming conditions. Design of experiments (DOE), Taguchi methods, and response surface methodology (RSM) have been successfully used to analyze the influence of parameters such as forming force, bending radius, sheet thickness, holding time, and temperature on springback behavior [54, 55].

Process optimization approaches are particularly useful because they provide a systematic evaluation of parameter interactions rather than considering individual factors independently. By integrating experimental data with numerical simulations, optimized process windows can be established to minimize elastic recovery while maintaining forming quality. Multi-parameter optimization strategies have demonstrated significant potential in improving dimensional accuracy for various bending operations, including V-bending, U-bending, stretch bending, and roll forming processes [56, 57].

6.2. Tool and Geometry Compensation Methods

Tool-based compensation represents another effective strategy for controlling springback by modifying the initial tool geometry according to the predicted elastic recovery. Traditional methods, such as over-bending and die shape correction, compensate for the expected springback by intentionally introducing an opposite geometric deviation during forming. Although these approaches are relatively simple, their effectiveness strongly depends on accurate prediction of the springback amount and proper adjustment of the tooling design [58, 59].

More advanced compensation techniques have been developed by combining finite element simulations with iterative correction algorithms. Geometry-based compensation methods, including displacement adjustment approaches, modify tool surfaces based on the difference between the target and predicted geometries. Such methods are especially beneficial for complex automotive and aerospace components where conventional trial-and-error tool modifications are expensive and time-consuming [57, 60].

Recently, flexible and additively manufactured tooling systems have attracted attention as promising alternatives for rapid springback compensation. The use of adaptable tools and polymer-based additively manufactured dies allows faster design modifications and reduces manufacturing costs during compensation procedures. These approaches provide greater flexibility for low-volume production and customized forming applications [50].

6.3. Advanced and Intelligent Compensation Techniques

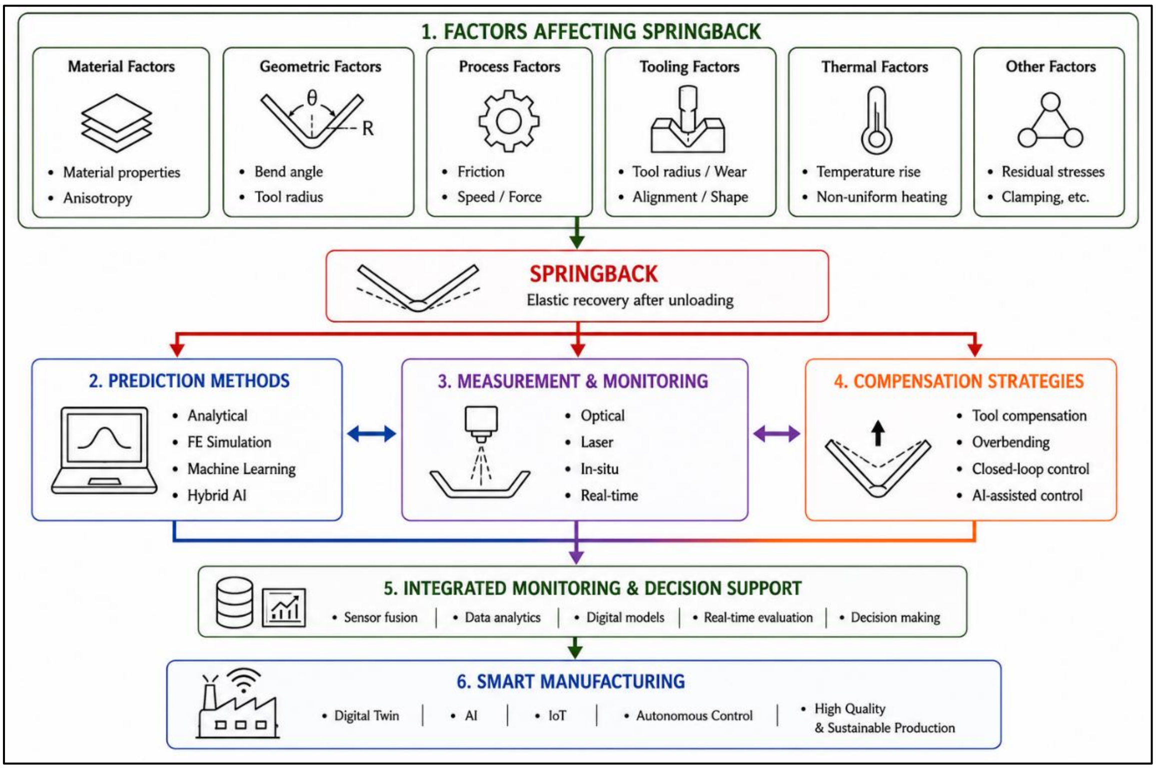

Figure 2 Integrated conceptual framework of springback research

The development of intelligent manufacturing technologies has shifted springback compensation from offline correction methods toward adaptive and data-driven control strategies. Advanced approaches integrate sensors, numerical models, and artificial intelligence algorithms to predict and compensate springback during or immediately after the forming process. Closed-loop control systems can adjust forming parameters based on measured deviations, improving robustness against material variations and process uncertainties [52, 61].

Hybrid strategies combining finite element analysis, machine learning models, and optimization algorithms represent a promising direction for future springback control. These methods enable rapid prediction, automatic parameter adjustment, and adaptive compensation without extensive experimental trials. Therefore, the integration of digital technologies with traditional forming processes is expected to play a key role in achieving intelligent and high-precision sheet metal manufacturing systems [47, 62].

The preceding sections have comprehensively reviewed the key factors influencing springback, the available prediction and compensation approaches, and the measurement and monitoring techniques employed in sheet metal bending processes. Although these aspects are often investigated independently, they are inherently interconnected within the overall springback control framework. To provide an integrated perspective, Figure 2 presents a conceptual framework that illustrates the relationships among the influencing factors, springback prediction, measurement and monitoring, compensation strategies, and intelligent manufacturing technologies. This framework summarizes the major research directions discussed throughout this review and highlights their collective contribution to achieving accurate springback prediction, adaptive process control, and intelligent manufacturing.

7. Current Challenges and Future Trends

Despite significant developments in understanding, predicting, and controlling springback behavior, several challenges still limit the achievement of fully accurate and reliable compensation strategies in industrial forming applications. One of the main challenges is the complex nature of material behavior during deformation and unloading. Factors such as anisotropy, nonlinear hardening, elastic modulus degradation, and loading path dependency make accurate representation of springback difficult, particularly for advanced high-strength steels and lightweight alloys used in modern industries [3, 18].

Although finite element simulation has significantly improved springback prediction capability, its practical implementation still faces limitations related to computational efficiency, model calibration, and uncertainty in material parameters. High-fidelity simulations often require accurate constitutive models and extensive experimental validation, which increases development time and limits their application for rapid process optimization and real-time control [63, 64].

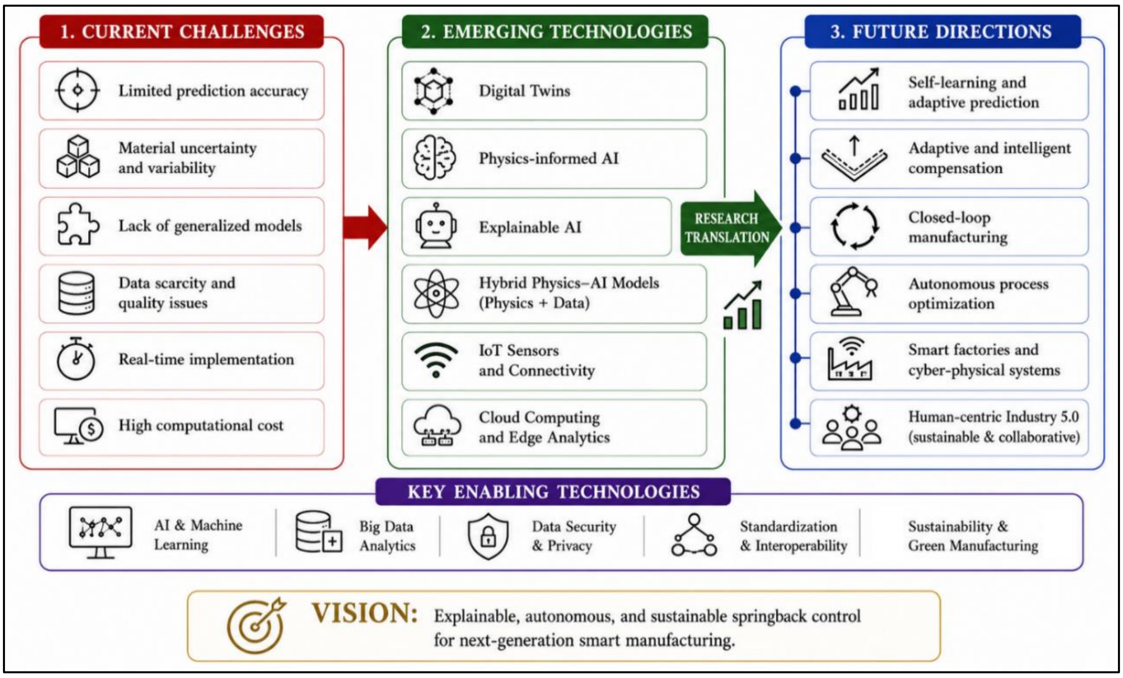

Figure 3 Roadmap for future research in intelligent springback control

The rapid development of artificial intelligence and data-driven techniques has provided new opportunities for overcoming these limitations; however, several challenges remain before widespread industrial implementation. Machine learning models often require large and reliable datasets, while their prediction accuracy can decrease when applied to materials, geometries, or forming conditions outside the training domain. Therefore, improving model generalization and interpretability remains an important research direction [65, 66].

Future developments in springback prediction and compensation are expected to focus on hybrid approaches that combine the advantages of physics-based modeling and data-driven techniques. Physics-informed machine learning, hybrid FEM–AI frameworks, and surrogate models provide promising solutions by reducing computational cost while maintaining prediction accuracy. These approaches can support faster optimization and more efficient compensation strategies for complex forming operations [67, 68].

Furthermore, the integration of real-time monitoring, digital twin technologies, and closed-loop control systems represents a key direction toward intelligent sheet metal forming. Future smart manufacturing systems are expected to continuously collect process data, predict springback evolution, and automatically adjust forming parameters to achieve high dimensional accuracy with minimal human intervention [69, 70].

The preceding discussion has highlighted the major limitations of current springback prediction, monitoring, and compensation approaches, together with the rapid emergence of advanced digital technologies. To summarize these perspectives and illustrate the future evolution of the field, Figure 3 presents a research roadmap linking current challenges with enabling technologies and future research directions toward intelligent, autonomous, and sustainable springback control.

As illustrated in Figure 3, future research is expected to shift from conventional springback prediction toward intelligent and autonomous manufacturing systems by integrating physics-informed artificial intelligence, digital twins, IoT-enabled sensing, and closed-loop adaptive control. These developments are anticipated to improve prediction accuracy, enhance manufacturing flexibility, and support the realization of next-generation smart factories.

8. Conclusions

Springback remains one of the most critical challenges limiting dimensional accuracy and product quality in sheet metal bending processes. Despite significant advances in manufacturing technologies, the complex interaction between material behavior, geometrical characteristics, and process parameters continues to make accurate springback prediction and compensation a difficult task. This review has comprehensively analyzed the fundamental mechanisms governing springback formation and critically discussed the effects of material properties, geometrical features, and processing conditions on springback behavior.

The review has shown that springback is strongly influenced by multiple interacting factors rather than by a single dominant parameter. Material-related characteristics, including yield strength, elastic modulus, anisotropy, and hardening behavior, significantly affect elastic recovery during unloading. Likewise, geometrical and process variables such as sheet thickness, bending radius, tool geometry, friction conditions, forming temperature, and loading history play essential roles in determining the final dimensional accuracy of bent components. Therefore, reliable springback control requires simultaneous consideration of material, tooling, and process characteristics.

Various prediction techniques have been developed to estimate springback with increasing levels of accuracy. Analytical models provide rapid and computationally efficient estimations but are generally limited to simplified loading conditions and geometries. Finite element analysis has become the dominant prediction tool because of its capability to simulate complex material behavior and forming conditions, although its effectiveness depends heavily on accurate constitutive modeling, numerical parameter selection, and experimental validation. More recently, artificial intelligence and machine learning techniques have demonstrated considerable potential for improving prediction efficiency while reducing computational cost, particularly when integrated with finite element simulations.

This review has also highlighted the evolution of springback reduction strategies from conventional process optimization and tool compensation methods toward intelligent and adaptive compensation systems. The integration of numerical simulation, optimization techniques, sensing technologies, and data-driven models provides new opportunities for achieving more accurate and efficient springback control in industrial applications. However, challenges related to material uncertainty, model generalization, computational efficiency, and real-time implementation still require further investigation.

Future research should focus on developing hybrid prediction and compensation frameworks that combine physics-based modeling, artificial intelligence, digital twin technologies, and closed-loop process control. Such integrated approaches are expected to improve prediction robustness, enable adaptive manufacturing, and support the realization of intelligent sheet metal forming systems capable of producing high-quality components with minimal dimensional deviation.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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