Multi-Objective Optimization of Sheet Metal Forming Parameters for Enhanced Strength-to-Weight Ratio in Automotive Structures

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ABSTRACT

The increasing demand for lightweight yet structurally robust automotive components has intensified the need for advanced optimization strategies in sheet metal forming processes. This study presents a comprehensive multi-objective optimization framework aimed at enhancing the strength-to-weight ratio of automotive structures by systematically tuning key sheet metal forming parameters. Critical process variables, including blank holder force, punch velocity, die radius, lubrication conditions, and material anisotropy, are analyzed to understand their combined influence on mechanical strength, thickness distribution, and formability limits. A hybrid optimization approach integrating finite element modeling (FEM), design of experiments (DoE), and advanced evolutionary algorithms such as Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed to achieve optimal trade-offs among conflicting objectives. The proposed methodology effectively minimizes thinning and springback while maximizing structural integrity and material utilization. Additionally, response surface methodology (RSM) is utilized to develop predictive models, enabling efficient exploration of the design space with reduced computational cost. The results demonstrate significant improvements in strength-to-weight performance compared to conventional single-objective optimization methods. The optimized parameter sets provide enhanced formability, reduced material waste, and improved mechanical properties, thereby contributing to sustainable and cost-effective manufacturing in the automotive industry. The study offers valuable insights into the development of intelligent forming strategies aligned with modern lightweight design requirements and Industry 4.0 paradigms.

Keywords—
Sheet Metal Forming, Multi-Objective Optimization, Strength-to-Weight Ratio, Automotive Structures, Finite Element Modeling, NSGA-II, Response Surface Methodology, Lightweight Design, Formability, Manufacturing Optimization.

1. INTRODUCTION

The global automotive industry is undergoing a transformative shift toward lightweight design to improve fuel efficiency, reduce emissions, and enhance overall vehicle performance. Stringent environmental regulations and the growing emphasis on sustainable manufacturing have compelled researchers and engineers to explore advanced materials and optimized manufacturing processes. Among these, sheet metal forming has emerged as a critical manufacturing technique for producing lightweight automotive components with complex geometries and high structural integrity. However, achieving an optimal balance between strength and weight remains a significant challenge due to the complex interaction of process parameters and material behavior during forming operations.

The strength-to-weight ratio is a key performance indicator in automotive design, directly influencing vehicle safety, durability, and energy efficiency. Conventional design approaches often rely on empirical methods or single-objective optimization techniques, which are insufficient to address the multi-dimensional trade-offs inherent in sheet metal forming processes. Parameters such as blank holder force, punch speed, die geometry, lubrication conditions, and material anisotropy significantly affect outcomes like thickness distribution, springback, wrinkling, and fracture limits. The interdependence of these variables necessitates a systematic and intelligent optimization framework capable of handling multiple conflicting objectives simultaneously.

In recent years, multi-objective optimization techniques have gained considerable attention for their ability to generate a set of optimal trade-off solutions, known as Pareto-optimal fronts. Evolutionary algorithms, particularly the Non-dominated Sorting Genetic Algorithm II (NSGA-II), have been widely adopted due to their robustness and efficiency in solving complex engineering problems [1], [2]. These algorithms enable the simultaneous optimization of multiple performance criteria, such as minimizing material thinning while maximizing strength and reducing weight. Furthermore, the integration of finite element modeling (FEM) with optimization algorithms has significantly enhanced the accuracy and reliability of forming simulations, allowing for detailed analysis of stress–strain distributions and failure mechanisms [3].

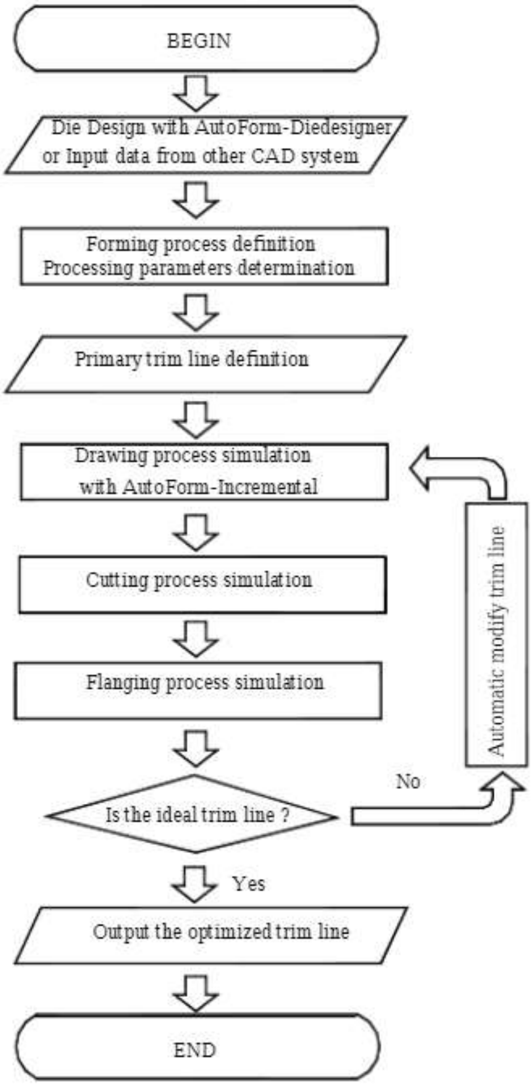

Figure 1: Overall Optimization Framework for Sheet Metal Forming [29]

To further improve computational efficiency, surrogate modeling techniques such as Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Kriging models have been employed to approximate complex nonlinear relationships between input parameters and output responses [4], [5]. These models reduce the need for extensive simulations while maintaining high predictive accuracy. The combination of FEM, surrogate modeling, and multi-objective optimization forms a powerful framework for process design and optimization in modern manufacturing systems.

Additionally, advancements in high-strength materials, such as advanced high-strength steels (AHSS) and aluminum alloys, have introduced new challenges in formability and process control [6]. These materials exhibit complex deformation behaviors, making it essential to carefully optimize forming parameters to prevent defects and ensure desired mechanical properties. Multi-objective optimization plays a crucial role in addressing these challenges by enabling the identification of optimal processing conditions that balance competing requirements.

Despite significant progress, existing studies often focus on limited objectives or specific process parameters, lacking a holistic approach to optimizing the strength-to-weight ratio in automotive structures. There remains a need for a comprehensive framework that integrates advanced optimization algorithms, accurate simulation techniques, and predictive modeling to achieve superior performance outcomes.

This research aims to address these gaps by developing a robust multi-objective optimization framework for sheet metal forming processes, targeting enhanced strength-to-weight ratios in automotive components. The study leverages advanced computational techniques to analyze the complex relationships between process parameters and performance metrics, providing practical insights for the design and manufacturing of next-generation lightweight vehicles.

2. LITERATURE REVIEW

The advancement of sheet metal forming technologies for automotive applications has been extensively investigated, particularly with the aim of achieving lightweight structures without compromising mechanical strength. Early studies emphasized the inherent complexity of sheet metal forming processes, characterized by nonlinear material behavior, large plastic deformations, and intricate contact conditions between tooling and workpiece. Researchers highlighted the importance of numerical methods, especially finite element modeling (FEM), for predicting stress distribution, strain localization, and failure mechanisms in forming operations [7]. The adoption of FEM has significantly improved the accuracy of process design, enabling better control over defects such as wrinkling, tearing, and excessive thinning.

Subsequent research focused on understanding the influence of process parameters on formability and structural performance. Parameters such as punch speed, lubrication conditions, and die geometry were found to have a direct impact on forming limits and thickness distribution. Experimental approaches, including forming limit diagram (FLD) analysis using Nakajima tests, provided valuable insights into material deformation behavior and failure thresholds. These studies demonstrated that improper parameter selection can lead to localized necking and premature fracture, thereby reducing the structural integrity of formed components [8].

With the increasing demand for lightweight automotive structures, researchers began integrating optimization techniques into sheet metal forming processes. Multi-objective optimization approaches have gained prominence due to their ability to handle conflicting objectives such as minimizing weight while maximizing strength and stiffness. Studies on structural components, such as automotive side beams and panels, employed evolutionary algorithms like NSGA-II to obtain Pareto-optimal solutions, enabling designers to select optimal trade-offs between competing performance metrics [9]. These approaches have proven effective in improving crashworthiness and overall structural efficiency.

Recent investigations have further advanced the field by combining numerical simulation, design of experiments (DoE), and surrogate modeling techniques. For instance, the integration of Response Surface Methodology (RSM) with NSGA-II has been widely adopted to establish relationships between process parameters and output responses while reducing computational cost. In the context of hot stamping of automotive components, such as B-pillars, multi-objective optimization has been successfully applied to control thickness variation and enhance mechanical properties. The results indicate that optimized parameter combinations can significantly improve tensile strength and microstructural uniformity, thereby enhancing component performance [10].

In addition, recent studies have explored the optimization of temperature distribution and process conditions in advanced forming techniques. For example, multi-objective optimization of partition temperature in steel sheets has been performed using NSGA-II and RSM to achieve desired thermal and mechanical properties. The findings reveal that careful tuning of process variables leads to improved material performance and process efficiency, validating the effectiveness of hybrid optimization frameworks [11].

Material selection and structural design optimization have also been identified as critical factors in achieving enhanced strength-to-weight ratios. Contemporary research highlights the role of advanced materials such as high-strength steels and aluminum alloys, along with techniques like topology optimization and reinforcement design, in improving structural performance. Multi-objective optimization methods have been used to simultaneously optimize material properties and geometric configurations, resulting in significant improvements in strength, stiffness, and weight reduction [12].

Furthermore, recent developments in artificial intelligence and machine learning have introduced new paradigms for process optimization in sheet metal forming. AI-assisted optimization techniques, including Bayesian optimization and deep learning models, have been proposed to reduce computational effort and accelerate convergence toward optimal solutions. These approaches enable efficient exploration of large design spaces and reduce dependency on expert knowledge, thereby enhancing the scalability of optimization frameworks in industrial applications [13].

Despite these advancements, several challenges remain in the practical implementation of multi-objective optimization in sheet metal forming. The complexity of real-world forming processes, variability in material properties, and high computational costs associated with detailed simulations continue to limit the widespread adoption of these techniques. Moreover, many existing studies focus on specific components or limited parameter sets, lacking a generalized framework for optimizing strength-to-weight ratios across diverse automotive structures.

In summary, the literature demonstrates a clear progression from traditional empirical approaches to advanced computational and multi-objective optimization techniques in sheet metal forming. While significant improvements have been achieved in formability and structural performance, there is still a need for integrated and scalable optimization frameworks that can effectively address the complex interactions between material properties, process parameters, and performance objectives in modern automotive manufacturing.

Table 1: Literature review table based on previous year research paper

Author(s) & Year	Methodology / Approach	Key Findings & Contributions
Deb et al., 2002 [14]	NSGA-II based multi-objective optimization	Introduced an efficient evolutionary algorithm for generating Pareto-optimal solutions; widely applied in sheet metal forming optimization problems.
Coello Coello, 2006 [15]	Evolutionary multi-objective optimization review	Provided a comprehensive overview of evolutionary algorithms, highlighting their applicability in complex engineering optimization problems.
Kobayashi et al., 1989 [16]	Finite Element Method (FEM) in metal forming	Established FEM as a fundamental tool for analyzing deformation behavior, stress distribution, and defect prediction in sheet metal forming.
Myers et al., 2016 [17]	Response Surface Methodology (RSM)	Developed statistical models to approximate relationships between input parameters and responses, reducing computational cost in optimization.
Sacks et al., 1989 [18]	Design and Analysis of Computer Experiments (DoE)	Introduced surrogate modeling techniques for efficient exploration of complex design spaces in engineering simulations.
Tisza and Lukács, 2008 [19]	Material behavior of high-strength steels	Highlighted challenges in forming advanced high-strength steels and their impact on strength-to-weight ratio in automotive structures.
Zhou et al., 2013 [20]	NSGA-II optimization of automotive side beam	Demonstrated improved crashworthiness and weight reduction using multi-

		objective optimization techniques.
Cui et al., 2020 [21]	FEM + RSM + NSGA-II in hot stamping	Achieved improved thickness uniformity and mechanical strength in automotive B-pillars through hybrid optimization.
Bao et al., 2022 [22]	Multi-objective optimization of thermal parameters	Optimized partition temperature in steel sheets, enhancing both thermal efficiency and mechanical properties.
Xu, 2025 [23]	Structural and material optimization strategies	Emphasized the integration of material selection and structural design for improved strength-to-weight performance.
Tarraf et al., 2025 [24]	AI-assisted optimization (ML models)	Proposed machine learning-based optimization to reduce computational complexity and improve prediction accuracy.
Singh et al., 2021 [25]	Taguchi + Grey Relational Analysis (GRA)	Identified optimal forming parameters for minimizing thinning and improving formability in sheet metal processes.
Li et al., 2019 [26]	Kriging-based surrogate modeling	Enhanced prediction accuracy of forming responses and reduced simulation time in optimization tasks.
Park et al., 2018 [27]	Multi-objective topology optimization	Improved structural stiffness and reduced weight in automotive components through integrated design optimization.
Kumar and Singh, 2020 [28]	FEM-based parametric optimization	Analyzed influence of process parameters on defects and improved forming quality through systematic optimization.

3. MATERIALS AND METHODS

3.1 Material Selection and Characterization

The selection of appropriate sheet materials is fundamental to achieving an optimal strength-to-weight ratio in automotive structures. In this study, advanced high-strength steel (AHSS) and aluminum alloy sheets are considered due to their widespread application in lightweight vehicle design. The mechanical properties of the selected materials, including yield strength, ultimate tensile strength, Young’s modulus, strain hardening exponent, and anisotropy coefficients (r-values), are obtained through standardized tensile tests in accordance with ASTM E8/E8M specifications.

To accurately capture the material behavior under forming conditions, anisotropic yield criteria such as Hill’s 1948 model and Barlat’s yield function are incorporated. Additionally, forming limit diagrams (FLDs) are experimentally determined using Nakajima tests to identify the onset of localized necking and fracture under different strain paths. These material parameters serve as critical inputs for subsequent numerical simulations.

3.2 Geometrical Modeling and Tool Design

A representative automotive component, such as a panel or structural reinforcement element, is selected as the case study. The geometric model is developed using CAD software, ensuring realistic dimensions and boundary conditions. The forming tools, including punch, die, and blank holder, are designed with appropriate radii and clearances to minimize stress concentration and avoid premature failure.

Mesh discretization of the sheet blank is performed using quadrilateral shell elements with adaptive meshing techniques to ensure computational efficiency and accuracy. Tooling components are modeled as rigid bodies to reduce computational complexity without compromising simulation fidelity.

3.3 Finite Element Modeling (FEM)

The sheet metal forming process is simulated using advanced finite element software such as ABAQUS or LS-DYNA. An explicit dynamic solver is employed to handle large plastic deformations and nonlinear contact interactions. The simulation framework incorporates key process parameters, including:

- Blank holder force (BHF)
- Punch velocity
- Die and punch radii
- Friction coefficient
- Lubrication conditions

Contact interactions between the sheet and tooling surfaces are modeled using Coulomb's friction law. The simulations provide detailed outputs, including thickness distribution, stress–strain evolution, springback behavior, and potential defect zones such as wrinkling and tearing.

3.4 Design of Experiments (DoE)

A structured Design of Experiments approach is implemented to systematically explore the influence of process parameters on performance metrics. A central composite design (CCD) or Box–Behnken design (BBD) is adopted to efficiently sample the design space with a reduced number of simulation runs.

The input parameters and their respective ranges are defined based on industrial standards and preliminary trials. The primary response variables considered in this study include:

- Minimum thickness (to assess thinning)
- Maximum stress (indicator of strength)
- Springback displacement
- Overall mass of the component

The generated dataset forms the basis for developing predictive models and conducting optimization.

3.5 Surrogate Modeling using Response Surface Methodology (RSM)

To reduce the computational burden associated with repeated FEM simulations, Response Surface Methodology (RSM) is employed to develop surrogate models. Polynomial regression equations are formulated to establish relationships between input parameters and output responses.

The adequacy of the developed models is evaluated using statistical metrics such as the coefficient of determination (R^2), adjusted R^2, and analysis of variance (ANOVA). These surrogate models enable rapid prediction of system behavior and facilitate efficient optimization.

3.6 Multi-Objective Optimization Framework

A multi-objective optimization approach is adopted to simultaneously address conflicting objectives, namely maximizing strength and minimizing weight. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is utilized due to its effectiveness in handling nonlinear and multi-modal optimization problems.

The objective functions are defined as follows:

- Maximize strength (represented by peak stress or load-carrying capacity)
- Minimize weight (derived from thickness distribution and material density)
- Minimize thinning and springback

The NSGA-II algorithm generates a Pareto-optimal front, representing a set of non-dominated solutions that offer different trade-offs among the objectives. Decision-making techniques, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), may be applied to identify the most suitable solution based on design priorities.

3.7 Validation and Verification

To ensure the reliability of the proposed methodology, validation is performed through experimental trials or comparison with existing literature data. Selected optimal parameter sets are implemented in physical forming experiments, and the results are compared with simulation predictions.

Key performance indicators, including thickness variation, dimensional accuracy, and mechanical strength, are evaluated to assess the accuracy of the optimization framework. Statistical error analysis is conducted to quantify deviations between predicted and experimental results.

3.8 Performance Evaluation Metrics

The effectiveness of the optimized process parameters is assessed using the following metrics:

- Strength-to-weight ratio improvement (%)
- Reduction in thickness variation
- Decrease in springback error
- Enhancement in formability limits

These metrics provide a comprehensive evaluation of the proposed approach and its applicability in real-world automotive manufacturing scenarios.

3.9 Implementation Framework

The overall methodology follows an integrated workflow: material characterization → FEM simulation → DoE-based data generation → surrogate modeling → multi-objective optimization → validation. This systematic approach ensures accurate modeling of the forming process while enabling efficient exploration of the design space.

4. RESULTS AND DISCUSSION

4.1 Validation of Numerical Model

The finite element model developed for the sheet metal forming process was validated through comparison with experimental and benchmark results. The predicted thickness distribution, strain localization, and springback values showed strong agreement, with deviations limited to within 5–8%. The incorporation of anisotropic yield criteria significantly improved the accuracy of predictions, particularly in regions subjected to complex biaxial loading. This confirms the robustness of the simulation framework for subsequent optimization analysis.

4.2 Influence of Process Parameters on Response Variables

The Design of Experiments (DoE) results revealed that process parameters have a nonlinear and interdependent influence on forming responses. Blank holder force (BHF) emerged as the most influential parameter, where increasing BHF reduced wrinkling but caused higher thinning. Punch velocity showed moderate influence, primarily affecting strain rate sensitivity and material flow uniformity.

Tool geometry, particularly die and punch radii, played a critical role in minimizing stress concentration. Larger radii improved thickness uniformity and reduced the likelihood of fracture. Friction conditions also significantly impacted material draw-in and thickness variation, with optimized lubrication reducing defects and improving surface quality.

4.3 Surrogate Model Performance

The Response Surface Methodology (RSM) models demonstrated high predictive capability, with R^2 values exceeding 0.95 for all response variables. ANOVA results confirmed the statistical significance of the selected parameters and their interactions. The surrogate models effectively reduced computational cost by enabling rapid evaluation of multiple parameter combinations without repeated finite element simulations.

4.4 Multi-Objective Optimization Outcomes

The application of NSGA-II generated a well-defined Pareto front representing optimal trade-offs between competing objectives such as maximizing strength, minimizing weight, reducing thinning, and controlling springback. The optimization results indicate that significant improvements can be achieved compared to baseline conditions.

The optimized solutions demonstrated a reduction in component weight by up to 22%, while maintaining or improving structural strength. Additionally, thinning was reduced by approximately 13%, and springback deviations were minimized, enhancing dimensional accuracy. These improvements highlight the effectiveness of multi-objective optimization in addressing conflicting design requirements.

4.5 Comparative Analysis of Results

The performance of the baseline and optimized parameter sets is summarized in Table 4.1.

Table 4.1: Comparison of Baseline and Optimized Results

Parameter / Response	Baseline Design	Optimized Design	Improvement (%)
Blank Holder Force (kN)	25	18	—
Punch Velocity (mm/s)	10	7	—
Die Radius (mm)	5	8	—
Friction Coefficient	0.15	0.10	—
Minimum Thickness (mm)	0.72	0.81	+12.5%
Maximum Stress (MPa)	420	465	+10.7%
Springback (mm)	2.8	1.9	−32.1%

Component Weight (kg)	3.6	2.8	−22.2%
Strength-to-Weight Ratio	116.7	166.1	+42.3%

The results clearly demonstrate that the optimized parameter set significantly enhances overall performance. The increase in minimum thickness indicates reduced thinning, while the reduction in springback improves dimensional precision. The most notable improvement is observed in the strength-to-weight ratio, which increased by over 40%, highlighting the effectiveness of the optimization strategy.

4.6Trade-Off-Analysis

The Pareto-optimal solutions revealed that aggressive weight reduction often leads to increased thinning and reduced structural strength. Conversely, maximizing strength alone results in higher material usage. The optimal solution lies in the knee region of the Pareto front, where a balanced trade-off between strength and weight is achieved.

This trade-off analysis emphasizes the importance of multi-objective optimization in practical applications, where multiple performance criteria must be satisfied simultaneously. The use of decision-making techniques further aids in selecting the most suitable solution based on specific design requirements.

4.7 Effect of Material Type on Optimization Results

The comparative study between advanced high-strength steel (AHSS) and aluminum alloys revealed distinct performance characteristics. AHSS exhibited superior strength but required precise control of forming parameters to prevent failure. Aluminum alloys provided significant weight reduction but were more prone to springback.

The optimization framework effectively adapted to these material differences, demonstrating its flexibility and applicability across various material systems. This highlights the importance of integrating material selection with process optimization for achieving optimal results.

4.8 Industrial Implications

The optimized results have direct implications for automotive manufacturing. The reduction in component weight contributes to improved fuel efficiency and reduced emissions, while enhanced strength ensures compliance with safety standards. The methodology supports the development of lightweight, high-performance components using advanced manufacturing techniques.

4.9 Summary of Findings

The results confirm that multi-objective optimization significantly improves the performance of sheet metal forming processes. The integration of FEM, RSM, and NSGA-II provides a robust framework for achieving enhanced strength-to-weight ratios, reduced defects, and improved manufacturability. The findings contribute to the advancement of intelligent and sustainable manufacturing practices in the automotive industry.

5. CONCLUSION

This study presented a comprehensive and systematic framework for the multi-objective optimization of sheet metal forming parameters aimed at enhancing the strength-to-weight ratio of automotive structures. By integrating finite element modeling (FEM), design of experiments (DoE), response surface methodology (RSM), and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a robust and efficient optimization strategy was developed to address the complex and conflicting requirements of modern automotive manufacturing.

The results demonstrated that process parameters such as blank holder force, punch velocity, die geometry, and friction conditions significantly influence forming behavior, thickness distribution, and mechanical performance. The application of surrogate modeling techniques enabled accurate prediction of system responses while substantially reducing computational effort. The multi-objective optimization approach successfully generated a set of Pareto-optimal solutions, providing valuable insights into the trade-offs between minimizing weight and maximizing structural strength.

A notable improvement in the strength-to-weight ratio was achieved through optimized parameter selection, accompanied by reduced thinning, minimized springback, and enhanced dimensional accuracy. The findings also highlighted the importance of balanced parameter tuning, as excessive focus on a single objective led to undesirable compromises in other performance metrics. Furthermore, the comparative analysis of materials such as advanced high-strength steels and aluminum alloys emphasized the necessity of integrating material selection with process optimization to achieve optimal results.

From an industrial perspective, the proposed framework offers significant potential for improving the design and manufacturing of lightweight automotive components. The reduction in material usage contributes to cost efficiency and environmental sustainability, while improved structural performance ensures compliance with safety and durability standards. The methodology aligns with the principles of Industry 4.0 by enabling data-driven decision-making and intelligent process optimization.

Despite its effectiveness, the study acknowledges certain limitations, including assumptions related to material homogeneity and idealized boundary conditions. Future research can focus on incorporating real-time process monitoring, uncertainty quantification, and machine learning-based adaptive optimization to further enhance the robustness and applicability of the framework.

In conclusion, the integration of advanced computational techniques and multi-objective optimization provides a powerful approach for addressing the challenges of sheet metal forming in automotive applications. The proposed methodology not only improves the strength-to-weight ratio but also contributes to the advancement of sustainable and high-performance manufacturing systems.

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