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Artificial Intelligence and Data-Driven Optimization for Aluminium Sheet Metal Punching: Current Challenges, Emerging Technologies, and Future Perspectives

Abhinay Agarwal[1], Munna Verma[1], Swapnil Bhoir[2*]
[1]Department of Mechanical Engineering, Bhagwant University, Ajmer, India
[2]Department of Humanities and Applied Science, SIES Graduate School of Technology, Nerul, Navi Mumbai, India
Corresponding Author: Swapnil Bhoir, swapnilbhoir05@gmail.com

Abstract: Sheet metal punching is one of the most widely used manufacturing processes for producing high-volume components with desired dimensional accuracy and edge quality. The increasing adoption of aluminium alloys in automotive, aerospace, packaging, and lightweight structural applications has created a growing need for optimized punching operations capable of minimizing burr formation and improving process efficiency. This paper presents a comprehensive review of conventional and emerging approaches used for modelling and optimization of aluminium sheet metal punching processes. The review covers fundamental mechanisms of deformation and fracture, factors influencing burr formation, and the role of process parameters such as punch–die clearance, sheet thickness, and tool geometry. Traditional optimization techniques including Design of Experiments (DOE), Taguchi methods, ANOVA, and Response Surface Methodology (RSM) are critically evaluated alongside finite element modelling approaches. Recent developments in Artificial Neural Networks (ANN), machine learning, surrogate modelling, and multi-objective optimization techniques such as NSGA-II are also discussed. The review identifies major research gaps related to aluminium-specific process modelling, hybrid AI-driven optimization frameworks, and industrial decision-support systems. Finally, future perspectives toward intelligent, data-driven, and Industry 4.0-enabled punching systems are presented to guide next-generation manufacturing research and applications.

Keywords: Sheet Metal Punching, Aluminium Alloys, Burr Formation, Artificial Neural Network, Machine Learning, Finite Element Modelling, NSGA-II, Multi-Objective Optimization, Data-Driven Manufacturing, Industry 4.0

I. INTRODUCTION

Sheet metal manufacturing processes play a pivotal role in modern industrial production, enabling the fabrication of a wide range of components used across automotive, aerospace, construction, electrical, and infrastructure sectors. Among these processes, punching and shearing operations are widely employed due to their capability to produce high-volume parts with consistent geometry, dimensional accuracy, and cost efficiency. These processes are particularly suited for mass production environments where productivity and repeatability are critical performance indicators. Punching operations involve the separation of material through the application of compressive forces using a punch and die arrangement. The material undergoes elastic and plastic deformation followed by fracture, resulting in the formation of a sheared edge. The stages involved in this process, including rollover, burnish, fracture, and burr formation, are schematically illustrated in Figure 1. Milek et al. (2026) [1] demonstrated that the mechanics of blanking involve complex interactions between material properties, tool geometry, and process parameters.

1.1 Importance of Sheet Metal Punching

The significance of sheet metal processing is further emphasized by its contribution to large-scale manufacturing systems, where millions of components are produced daily with minimal variation. Typical products manufactured using punching operations include perforated plates, structural brackets, and sheet assemblies, as shown in Figure 2. Ma et al. (2024) [2] highlighted that sheet metal operations are integral to sustainable manufacturing practices due to their material utilization efficiency and potential for automation. In industrial settings, particularly in small and medium enterprises (SMEs), punching processes are extensively used for producing structural components that require precise hole geometries and minimal edge defects to ensure proper assembly and long-term performance. However, achieving optimal process conditions remains a challenge due to the variability in material behavior and process dynamics [3–5]. With the increasing adoption of aluminium materials in industrial applications, the importance of optimizing sheet metal processes has become even more pronounced. Aluminium alloys exhibit distinct mechanical characteristics such as lower yield strength and higher ductility compared to steel, which significantly influence the shearing mechanism and burr formation. The growing use of aluminium in lightweight structural applications is illustrated in Figure 3, highlighting its advantages in terms of weight reduction and corrosion resistance. Zhu et al. (2026) [6] reported that material-specific behavior must be considered for accurate prediction of process outcomes.

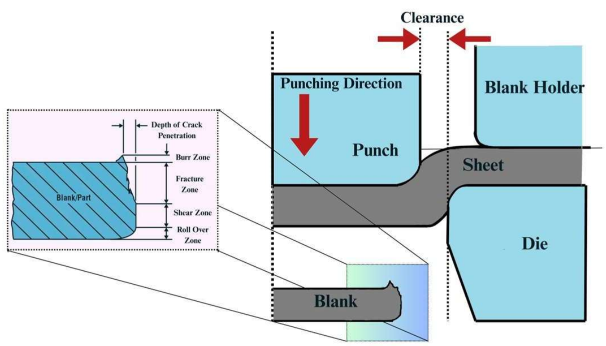

Figure 1: Schematic representation of the sheet metal punching process showing punch, die, clearance, and resulting edge characteristics [7,8]

Figure 2: Typical sheet metal components produced using industrial punching processes

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Figure 3: Increasing adoption of aluminium materials in industrial applications (e.g. automotive) due to lightweight and corrosion-resistant properties [9,10]

1.2 Industrial Challenges in Punching

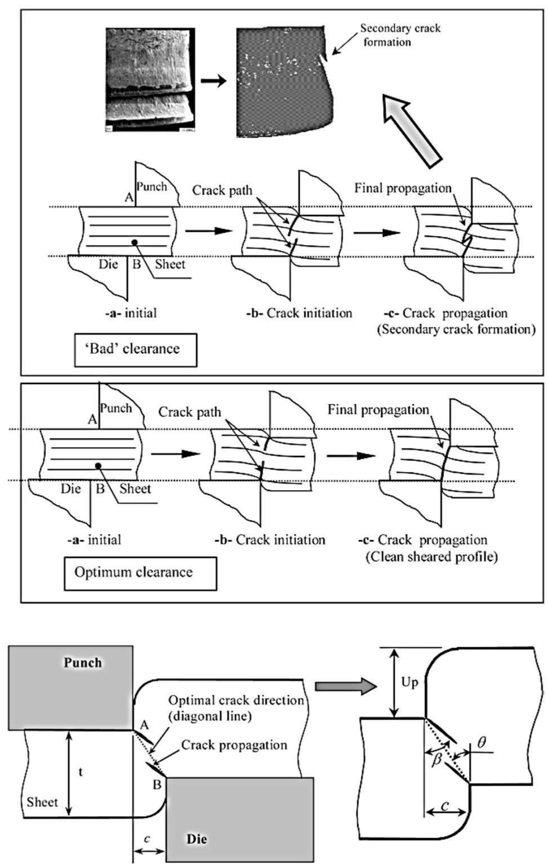

Figure 4: Formation of crack during sheet metal punching showing optimal crack direction and actual crack propogation [11]

Despite the widespread adoption of punching processes in industrial manufacturing, several inherent challenges limit their efficiency, consistency, and product quality. These challenges arise primarily due to the complex interaction between material properties, process parameters, and tooling conditions. Among these, burr formation, tool wear, and

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process variability are the most critical issues affecting industrial operations. One of the most prominent defects in sheet metal punching is burr formation, which occurs at the exit side of the material due to plastic deformation and fracture separation. The burr not only affects the dimensional accuracy of the component but also necessitates secondary finishing operations such as deburring, thereby increasing production time and cost. The mechanism of crack formation and its dependence on clearance and material behavior are illustrated in Figure 4. A critical aspect of achieving clean cuts in blanking is the control over crack initiation and propagation. As shown in Figure 4, successful blanking depends on aligning the crack propagation angle (β) with the diagonal angle (θd) formed between the crack initiation points at the punch and die. Proper punch–die clearance ensures these cracks meet at an ideal depth within the material, resulting in minimal tearing and burr. Conversely, suboptimal clearance can cause the cracks to misalign, producing rough edges, asymmetric fractures, or material pull-down effects Sahli et al. (2021) [12] demonstrated that burr height is significantly influenced by punch–die clearance and material ductility.

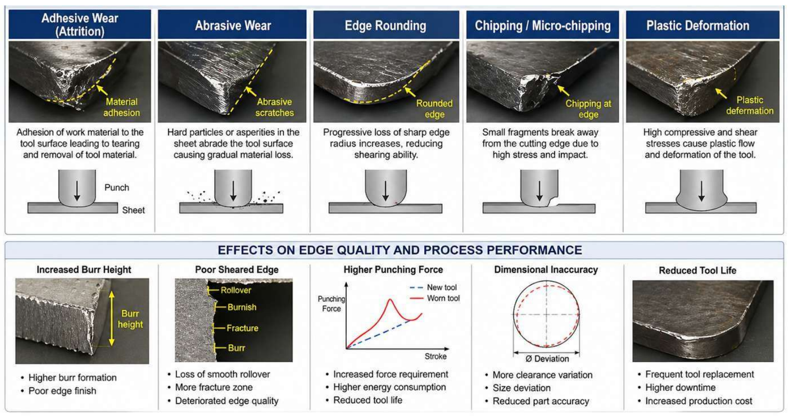

Figure 5: Typical tool wear mechanisms in punching operations affecting edge quality and process performance

Another major issue in punching operations is tool wear, which progressively degrades the quality of the produced components. Continuous operation under high contact stresses leads to abrasion, adhesion, and micro-chipping of the punch and die surfaces. This results in increased burr height, poor edge quality, and dimensional inaccuracies. The typical wear mechanisms affecting punching tools are depicted in Figure 5. Leung et al. (2003) [13] reported that tool wear significantly alters the effective clearance and consequently affects the shearing mechanism. In addition to burr formation and tool wear, process variability poses a significant challenge in industrial environments. Variations in material properties, sheet thickness, lubrication conditions, and machine alignment can lead to inconsistent product quality. In many small and medium-scale industries, process parameters such as clearance are often selected based on empirical knowledge rather than systematic optimization, resulting in suboptimal performance. Furthermore, the lack of real-time monitoring and adaptive control in conventional punching systems limits the ability to maintain consistent quality [14]. Modern manufacturing demands high precision and repeatability, which cannot be achieved solely through static parameter selection. The variability in output quality under different process conditions is conceptually illustrated in Figure 6, emphasizing the need for intelligent and adaptive optimization frameworks.

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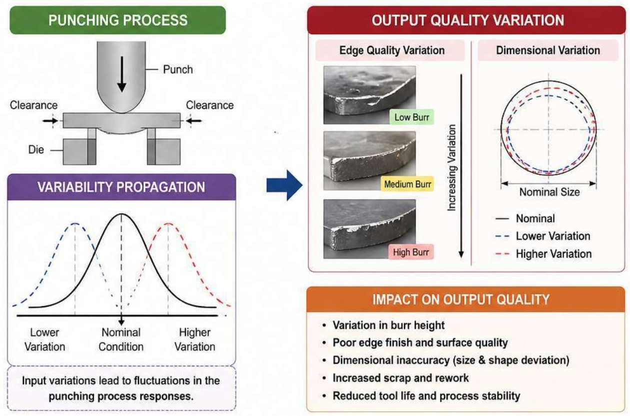

Figure 6: Conceptual representation of process variability and its impact on output quality in punching operations

These challenges collectively highlight the limitations of conventional punching practices and underscore the need for systematic, data-driven approaches for process optimization. Addressing these issues is essential for improving product quality, reducing production costs, and enhancing overall manufacturing efficiency [15].

1.3 Shift Towards Aluminium Materials

In recent years, manufacturing industries have witnessed a significant shift from conventional steel-based materials to aluminium and its alloys, primarily driven by the need for lightweight structures, improved corrosion resistance, and enhanced energy efficiency [16]. This transition is particularly evident in sectors such as automotive, aerospace, electrical enclosures, and infrastructure systems, where reducing component weight without compromising functional performance is a key design objective. The comparative advantages of aluminium over steel, particularly in terms of density and corrosion resistance, are illustrated in Figure 7.

Aluminium alloys, such as AA1100 aluminium alloy and AA5052 aluminium alloy, are increasingly used in sheet form for structural and semi-structural applications due to their favorable strength-to-weight ratio and formability. However, the mechanical behavior of aluminium differs significantly from that of steel, particularly in terms of lower yield strength, higher ductility, and different strain-hardening characteristics. These differences directly influence the shearing mechanism during punching operations, leading to variations in burr formation, edge quality, and process forces [17].

Figure 7: Comparison of aluminium and steel highlighting the advantages of aluminium in terms of weight reduction and corrosion resistance

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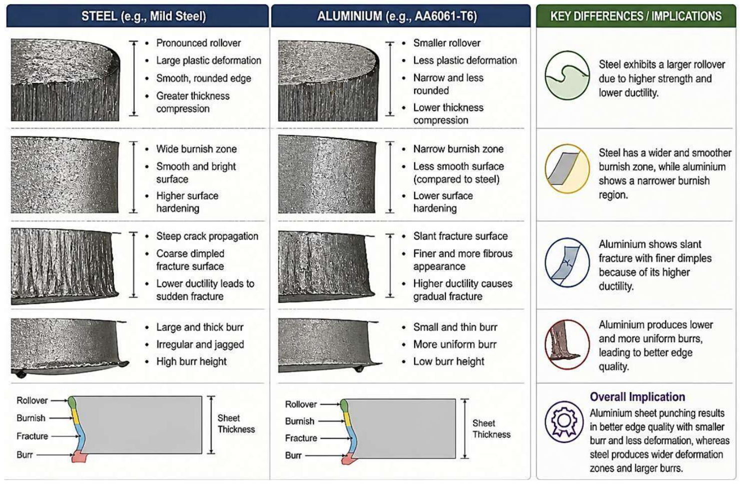

Figure 8: Comparison of edge characteristics in steel and aluminium sheet punching showing differences in deformation zones and burr formation.

Kannan et al. (2023) [18] demonstrated that aluminium sheets exhibit higher sensitivity to punch–die clearance variations compared to steel, resulting in a wider range of burr heights under similar processing conditions. Additionally, the ductile nature of aluminium often leads to increased rollover and deformation zones prior to fracture, which affects the overall edge profile. The differences in edge characteristics between steel and aluminium punching are schematically represented in Figure 8. From a manufacturing perspective, the adoption of aluminium introduces new challenges in process parameter selection. The conventional clearance values optimized for steel may not yield acceptable results for aluminium sheets, necessitating the development of material-specific optimization strategies [19]. Furthermore, aluminium's tendency to adhere to tooling surfaces can accelerate tool wear and affect process stability. Despite these challenges, the transition towards aluminium is expected to continue due to its advantages in sustainability and lifecycle performance [7]. Industries are increasingly seeking optimized manufacturing processes that can ensure high-quality production of aluminium components with minimal defects and energy consumption. Zhang et al. (2026) [20] highlighted that advanced modeling and optimization techniques are essential for enabling efficient processing of aluminium materials in modern manufacturing systems.

II. CONVENTIONAL APPROACHES FOR MODELLING AND OPTIMIZATION OF PUNCHING PROCESSES

Conventional approaches for process optimization in sheet metal punching have predominantly relied on statistical techniques such as Design of Experiments (DOE), Taguchi methods, Analysis of Variance (ANOVA), and Response Surface Methodology (RSM). These methods have been widely adopted due to their simplicity, structured framework, and ability to identify the influence of process parameters on output responses. However, with the increasing complexity of modern manufacturing systems and the demand for high precision, these traditional techniques exhibit several inherent limitations. Taguchi-based optimization methods are effective in reducing experimental efforts by utilizing orthogonal arrays and signal-to-noise ratios for parameter optimization. Nevertheless, they are primarily designed for single-objective optimization and often struggle to handle conflicting performance measures simultaneously. In punching processes, parameters such as burr height, force, and energy consumption are interdependent and often exhibit trade-off relationships, which cannot be adequately addressed using single-response optimization frameworks. Ram et al. (2025) [21] demonstrated that Taguchi methods may lead to suboptimal solutions when multiple objectives are involved.

Furthermore, ANOVA is commonly used to determine the statistical significance of process parameters and their interactions. While it provides valuable insights into parameter contributions, it does not offer predictive capabilities or

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optimization solutions beyond the experimental domain [21,22]. Similarly, RSM attempts to model the relationship between input variables and responses using polynomial equations, as conceptually illustrated in Figure 9. Although RSM can capture moderate nonlinearities, its accuracy diminishes when dealing with highly nonlinear and complex interactions typical of sheet metal shearing processes [23–26].

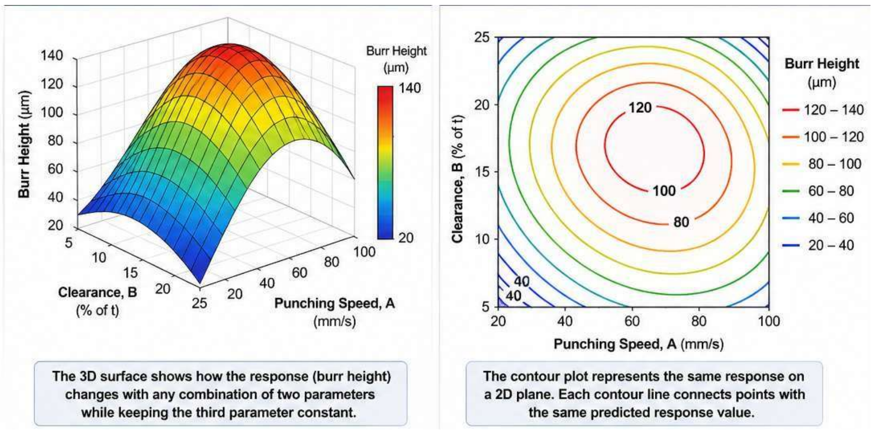

Figure 9: Illustration of response surface methodology (RSM) showing the relationship between process parameters and response using surface and contour plots

Another significant limitation of traditional methods is their dependence on discrete experimental data points. The optimization results obtained from DOE or Taguchi approaches are restricted to the predefined parameter levels, limiting the exploration of the continuous decision space. This constraint becomes critical when fine-tuning process parameters for industrial applications, where optimal settings may lie between the selected experimental levels. The contrast between discrete experimental optimization and continuous parameter exploration is illustrated in Figure 10.

Moreover, traditional statistical models often require assumptions regarding linearity, normality, and independence of variables, which may not hold true for complex manufacturing processes. The interactions between material properties, tool geometry, and process parameters in punching operations are inherently nonlinear and difficult to model using simple regression-based approaches [27–29]. Wen et al. (2013) [30] highlighted that classical models fail to capture complex nonlinear relationships, leading to reduced prediction accuracy in advanced manufacturing scenarios. In addition, these methods lack adaptability and scalability when applied to dynamic industrial environments. They do not support real-time decision-making or integration with intelligent manufacturing systems, which are essential features in modern Industry 4.0 and Industry 5.0 frameworks [31,32].

These limitations necessitate the adoption of advanced data-driven and computational approaches capable of handling nonlinear interactions, multi-objective optimization, and continuous parameter exploration, which will be discussed in subsequent sections.

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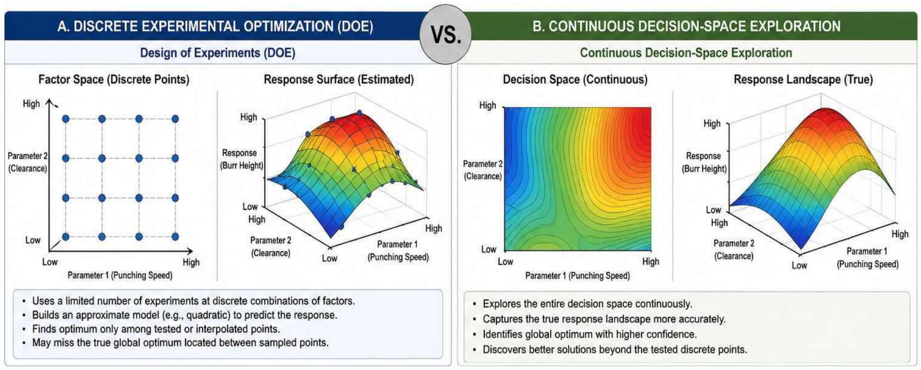

Figure 10: Comparison between discrete experimental optimization (DOE) and continuous decision-space exploration highlighting limitations of traditional methods

III. ARTIFICIAL INTELLIGENCE AND DATA-DRIVEN MANUFACTURING APPROACHES

The limitations of traditional statistical and experimental optimization methods have led to the increasing adoption of Artificial Intelligence (AI) and machine learning techniques in manufacturing systems. These approaches provide powerful tools for modeling complex, nonlinear relationships between process parameters and performance outcomes, enabling more accurate predictions and efficient optimization. Among various AI techniques, Artificial Neural Networks (ANNs) have gained significant attention due to their ability to approximate nonlinear functions and learn from experimental data without requiring explicit mathematical formulations. ANNs can effectively model the intricate relationships between inputs such as thickness, clearance, and material properties, and outputs such as burr height, force, and energy consumption. The general architecture of an ANN model, consisting of input, hidden, and output layers, is illustrated in Figure 11. Elly et al. (2026) [33] demonstrated that ANN-based models outperform traditional regression techniques in predicting manufacturing responses with high accuracy.

In addition to ANN, advanced machine learning techniques such as graph neural networks, deep learning architectures, and ensemble learning models are increasingly being applied to manufacturing processes. These models can handle large datasets and capture complex interactions that are difficult to model using conventional approaches.

Zhao et al. (2026) [34] introduced a graph neural network-based framework for modeling manufacturing processes, demonstrating improved prediction accuracy and scalability.

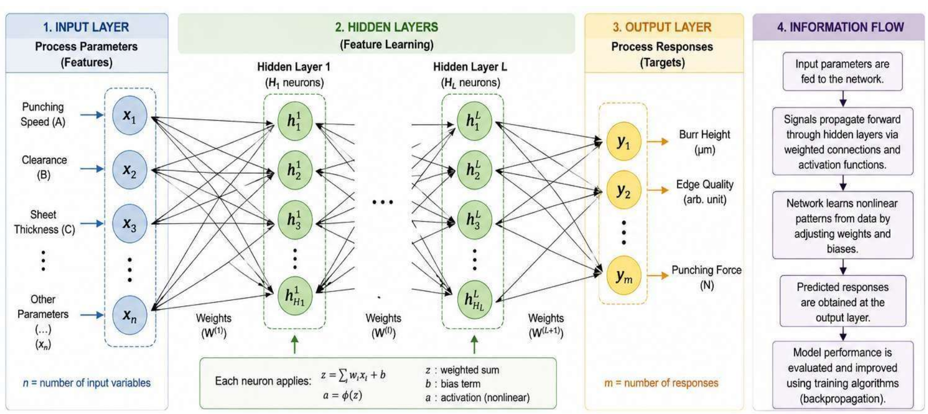

Figure 11: General architecture of an Artificial Neural Network (ANN) used for modeling nonlinear relationships between process parameters and responses

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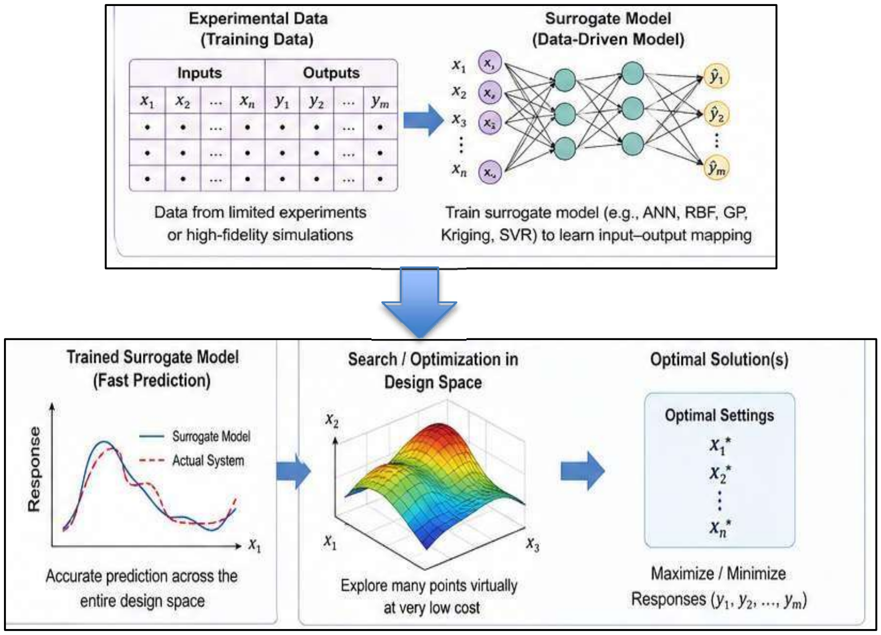

Figure 12: Conceptual representation of surrogate modeling where a data-driven model replaces physical experimentation for efficient process optimization

Another important development in AI-based manufacturing is the concept of surrogate modeling, where a computational model is trained to approximate the behavior of a physical system. Surrogate models enable rapid evaluation of process responses without the need for extensive experimentation or computationally expensive simulations. The concept of surrogate modeling in manufacturing optimization is illustrated in Figure 12, where the surrogate model replaces the physical process for efficient exploration of the design space. Brzobohatý et al. (2026) [35] demonstrated the effectiveness of surrogate models in reducing computational cost while maintaining high prediction accuracy. The integration of AI with manufacturing processes also aligns with the broader paradigm of Industry 4.0 and Industry 5.0, where data-driven decision-making, automation, and intelligent systems are key enablers of productivity and sustainability. AI models can be integrated with sensors, monitoring systems, and digital platforms to enable real-time process control and adaptive optimization [36]. Despite these advancements, the application of AI in sheet metal punching processes, particularly for aluminium materials, remains relatively limited. Most existing studies focus on machining or forming processes, with fewer contributions addressing punching and shearing operations. This highlights the need for developing AI-based frameworks specifically tailored to punching processes, which can effectively capture the underlying physics and provide reliable predictions for industrial applications.

IV. MULTI-OBJECTIVE OPTIMIZATION FRAMEWORKS

In sheet metal punching processes, achieving optimal performance is inherently a multi-objective problem, as several output responses must be considered simultaneously. Key performance indicators such as burr height, punching force, energy consumption, and tool wear are often interdependent and exhibit conflicting behavior. For instance, reducing burr height may require smaller punch–die clearance, which can increase punching force and accelerate tool wear [8]. Traditional optimization techniques, such as Taguchi or RSM, are generally limited to single-objective optimization or require the conversion of multiple objectives into a single composite index, which may lead to loss of information and biased solutions. In contrast, multi-objective optimization approaches aim to identify a set of optimal solutions, known as the Pareto front, where no single solution can be improved without compromising at least one other objective. Among various multi-objective optimization algorithms, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has

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emerged as one of the most effective and widely used methods. NSGA-II is an evolutionary algorithm that uses principles of natural selection and genetic operations to explore the solution space and identify Pareto-optimal solutions. The working mechanism of NSGA-II, including population initialization, selection, crossover, mutation, and non-dominated sorting, is schematically illustrated in Figure 14. Chowdhury et al. (2026) [37] demonstrated that NSGA-II provides a robust framework for solving complex multi-objective problems in manufacturing processes.

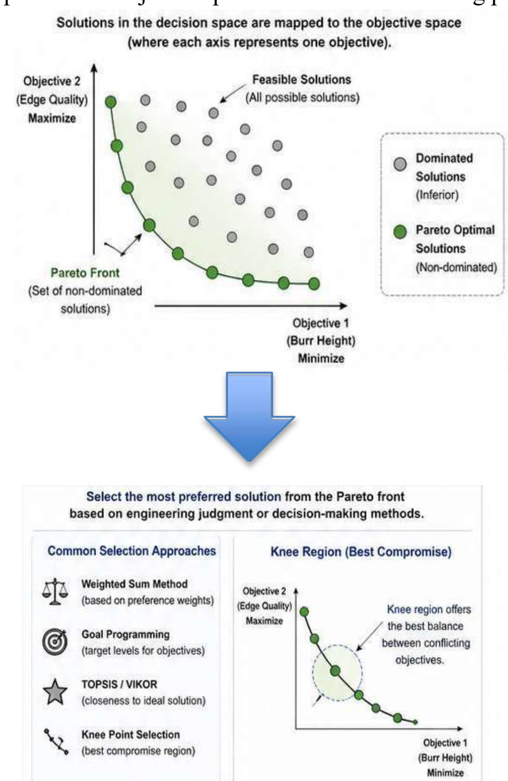

Figure 13: Illustration of trade-offs between conflicting objectives in manufacturing processes represented using Pareto optimal solutions [38]

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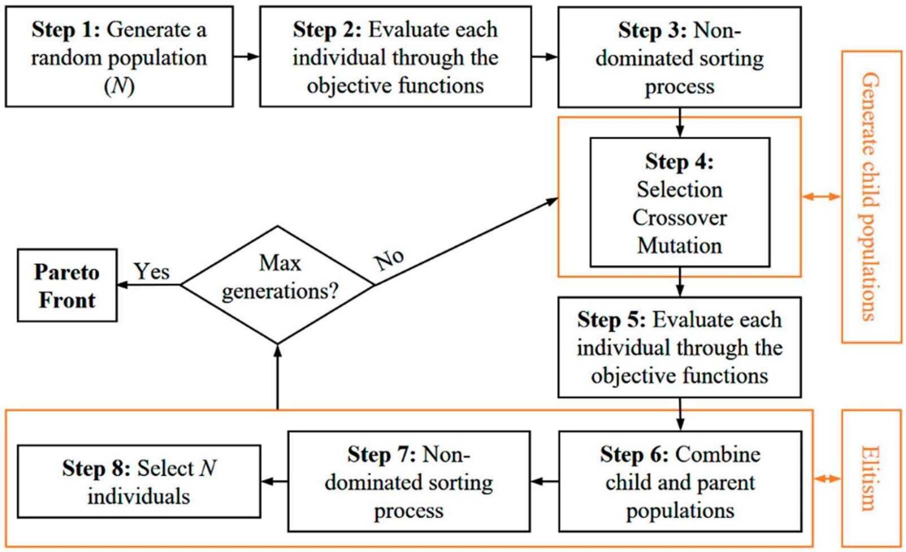

Figure 14: Flowchart of the NSGA-II algorithm showing evolutionary operations and Pareto-based selection [39]

The integration of surrogate models, such as ANN, with NSGA-II further enhances the optimization process by enabling rapid evaluation of multiple design alternatives without the need for repeated physical experimentation. This combination allows for efficient exploration of the continuous decision space and identification of optimal parameter settings that balance multiple objectives. Han et al. (2025) [3] demonstrated that hybrid ANN–NSGA-II frameworks significantly improve optimization efficiency and solution quality in manufacturing applications.

V. RESEARCH GAPS AND FUTURE PERSPECTIVES

Despite significant advancements in sheet metal punching research, several critical gaps remain in the development of efficient and intelligent optimization frameworks for aluminium-based punching processes. The literature reveals that a large proportion of existing studies focus on steel materials, while comparatively fewer investigations have addressed aluminium alloys and aluminium matrix composites. Considering the increasing industrial adoption of aluminium for lightweight applications, the lack of material-specific optimization frameworks represents an important research challenge.

Conventional optimization approaches such as Design of Experiments (DOE), Taguchi methods, Analysis of Variance (ANOVA), and Response Surface Methodology (RSM) have been widely applied for process parameter optimization. Although these methods effectively identify significant parameters and interactions, they are inherently limited in handling highly nonlinear relationships and multiple conflicting objectives. Furthermore, their dependence on discrete experimental levels restricts exploration of the continuous design space required for industrial parameter optimization.

Finite Element Modelling (FEM) has significantly improved understanding of deformation, fracture, and stress distribution during punching operations. However, FEM-based approaches are computationally expensive, require extensive material characterization, and are generally unsuitable for rapid optimization and real-time decision-making. Consequently, their industrial implementation remains limited, particularly for small and medium-scale manufacturing enterprises.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated considerable potential for overcoming the limitations of traditional modelling techniques. Artificial Neural Networks (ANN), deep learning models, and surrogate modelling approaches have shown superior capability in capturing nonlinear relationships between process parameters and manufacturing responses. Nevertheless, their application to aluminium sheet punching remains relatively limited, and comprehensive datasets suitable for model development are still scarce. Similarly, multi-objective optimization algorithms such as NSGA-II, NSGA-III, and reinforcement learning-assisted optimization frameworks have been successfully applied in machining, welding, and forming processes. However, only limited research has explored their application in sheet metal punching operations, particularly for aluminium alloys and composite materials. Furthermore, most existing studies investigate modelling and optimization independently rather than integrating them into a unified framework. Future research should therefore focus on developing hybrid experimental–AI optimization frameworks that integrate process understanding, predictive modelling, and multi-objective optimization. The combination of ANN-based surrogate models with evolutionary optimization algorithms offers significant potential for rapid and accurate parameter selection. In addition, the integration of digital twins, real-time monitoring systems, explainable artificial intelligence (XAI), and Industry 5.0 concepts can further enhance process adaptability and decision-making capabilities.

The future of aluminium sheet punching is expected to move towards intelligent manufacturing systems capable of self-learning, adaptive optimization, and autonomous process control. Such developments will support higher productivity, improved edge quality, reduced production costs, and sustainable manufacturing practices.

VI. CONCLUSIONS

This review presented a comprehensive assessment of conventional and emerging approaches used for modelling and optimization of aluminium sheet metal punching processes. The study highlighted the growing industrial significance of aluminium alloys and composite materials owing to their lightweight characteristics, corrosion resistance, and suitability for sustainable manufacturing applications. The review demonstrated that burr formation, tool wear, and process variability remain the primary challenges affecting punching performance and edge quality. Conventional optimization techniques such as DOE, Taguchi methods, ANOVA, RSM, and FEM have contributed significantly to process understanding and parameter optimization. However, these approaches exhibit limitations in handling complex nonlinear interactions, continuous design-space exploration, and multi-objective decision-making. Recent developments in Artificial Intelligence, Machine Learning, and surrogate modelling have created new opportunities for predictive modelling and intelligent process optimization. Artificial Neural Networks and advanced machine learning algorithms have shown superior capability in modelling manufacturing processes with high accuracy and reduced computational effort. Furthermore, evolutionary optimization techniques such as NSGA-II have enabled efficient handling of conflicting performance objectives through Pareto-based optimization. The review identified several important research gaps, including limited focus on aluminium-specific punching behaviour, insufficient integration of AI-driven predictive models with optimization algorithms, and the lack of industrially applicable decision-support systems. Addressing these challenges requires the development of unified hybrid frameworks that combine experimental investigation, data-driven modelling, and multi-objective optimization.

Overall, the integration of Artificial Intelligence, machine learning, and advanced optimization techniques represents a promising pathway toward intelligent and sustainable aluminium sheet punching systems. Future developments involving digital twins, explainable AI, and Industry 5.0 technologies are expected to further transform manufacturing processes by enabling adaptive, autonomous, and data-driven decision-making.

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