

Optimization Techniques for Machining Process Parameters in Manufacturing Engineering

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Abstract: The optimization of machining process parameters plays a critical role in enhancing productivity, product quality, and cost efficiency in manufacturing engineering. With increasing demand for high precision and sustainable production, numerous optimization techniques have been developed to determine optimal combinations of machining parameters such as cutting speed, feed rate, and depth of cut. This review paper aims to provide a comprehensive analysis of various optimization techniques applied in machining processes, highlighting their effectiveness, advantages, and limitations. The study covers classical methods such as the Taguchi technique and response surface methodology, as well as advanced approaches including genetic algorithms, particle swarm optimization, artificial neural networks, and hybrid optimization models. A systematic review of recent literature has been conducted to examine the application of these techniques in different machining operations such as turning, milling, and drilling. The findings indicate that advanced optimization methods, particularly hybrid and AI-based techniques, offer superior performance in handling complex, multi-objective optimization problems compared to traditional approaches. However, challenges such as computational complexity, requirement of large datasets, and implementation difficulties remain significant concerns. This paper contributes by presenting a structured comparison of optimization techniques and identifying research gaps for future exploration. The outcomes of this review provide valuable insights for researchers and practitioners to select appropriate optimization strategies for improving machining performance and achieving efficient manufacturing processes.

Keywords: Machining Optimization, Taguchi Method, Genetic Algorithm, Response Surface Methodology, Artificial Intelligence, Manufacturing Engineering

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1. Introduction

Machining processes play a vital role in manufacturing engineering by enabling the production of components with high dimensional accuracy, surface quality, and functional performance. Operations such as turning, milling, and drilling are widely employed across various industries, including automotive, aerospace, and heavy engineering, where precision and reliability are critical. The performance of these machining processes is significantly influenced by key process parameters such as cutting speed, feed rate, and depth of cut. Improper selection of these parameters can lead to poor surface finish, excessive tool wear, increased production cost, and reduced productivity. Therefore, the optimization of machining process parameters has become an essential aspect of modern manufacturing systems.

Traditionally, machining parameters were selected based on operator experience and handbook recommendations, which often resulted in suboptimal performance. With increasing demand for high-quality products, reduced production time, and cost efficiency, there is a growing need for systematic and scientific approaches to determine optimal machining conditions. Optimization techniques provide a structured methodology to identify the best combination of process parameters that can simultaneously satisfy multiple performance objectives such as minimizing surface roughness, maximizing material removal rate, and reducing tool wear. As highlighted by Onwubolu and Rayegani (2014) [1], the application of statistical and analytical methods has significantly improved process understanding and performance optimization in manufacturing.

Over the years, a wide range of optimization techniques have been developed and applied in machining processes. Traditional methods such as the Taguchi technique and Response Surface Methodology (RSM) have been extensively used due to their simplicity and effectiveness in experimental design and analysis. K. Gupta & Gupta (2020) [2] demonstrated that the Taguchi method is highly efficient in reducing the number of experiments while identifying significant process parameters. Similarly, Sureban et al. (2019) [3] introduced RSM as a powerful tool for modeling and optimization of complex processes. However, these conventional approaches often face limitations in handling highly nonlinear and multi-objective optimization problems.

To overcome these challenges, advanced optimization techniques such as evolutionary algorithms and artificial intelligence-based methods have gained significant attention. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANN) are widely used to model complex relationships and achieve global optimization. Ribeiro et al. (2017) [4] emphasized the robustness of genetic algorithms in solving nonlinear optimization problems, while Patel et al. (2021) [5] highlighted the effectiveness of machine learning techniques in improving process performance and decision-making. Furthermore, hybrid optimization approaches, which combine traditional and intelligent techniques, have shown improved accuracy and efficiency in machining parameter optimization.

Despite the extensive research in this domain, the selection of appropriate optimization techniques remains a challenging task due to the diversity of available methods and their varying applicability. This necessitates a comprehensive review of existing optimization techniques to understand their strengths, limitations, and suitability for different machining applications. The primary objective of this paper is to critically review various optimization techniques used in machining processes, including traditional, evolutionary, artificial intelligence-based, and hybrid methods. Additionally, the study aims to provide a comparative analysis of these techniques and identify research gaps for future advancements in machining optimization.

2. Research Methodology

This study adopts a systematic literature review approach to analyze various optimization techniques applied to machining process parameters in manufacturing engineering. The objective of this methodology is to ensure a comprehensive, transparent, and unbiased selection of relevant research articles, thereby providing a reliable foundation for comparative analysis. A structured multi-stage process was followed, including identification of data sources, keyword-based search, application of inclusion and exclusion criteria, and final screening of selected studies.

The primary data sources used for this review include well-established academic databases such as Scopus, Web of Science, and Google Scholar. These databases were chosen due to their extensive coverage of peer-reviewed journal articles and high-impact publications in the field of manufacturing and machining processes. In addition, publications from reputed publishers such as Elsevier, Springer, Taylor & Francis, and IEEE were given preference to ensure the credibility and quality of the selected literature. According to Chakraborty et al. (2019) [6], the use of multiple databases significantly enhances the comprehensiveness of systematic reviews.

A comprehensive keyword-based search strategy was employed to identify relevant studies. Keywords such as “machining parameter optimization,” “cutting parameters,” “surface roughness optimization,” “material removal rate,” “Taguchi method,” “response surface methodology,” “genetic algorithm,” “particle swarm optimization,” and “machine learning in machining” were used individually and in combination using Boolean operators (AND, OR). This approach ensured the retrieval of a wide range of studies addressing both traditional and advanced optimization techniques. The search process was iterative, allowing refinement of keywords to capture recent advancements and emerging trends in machining optimization.

To ensure relevance and quality, specific inclusion and exclusion criteria were defined. The inclusion criteria focused on peer-reviewed journal articles published within the last two decades (2005–2025), emphasizing studies directly related to machining processes such as turning, milling, and drilling. Only articles written in English and providing complete methodological details were considered. On the other hand, conference abstracts without full text, duplicate studies, and papers unrelated to manufacturing engineering were excluded. Sangwan et al. (2015) [7] emphasized that well-defined selection criteria are essential for maintaining the reliability of review studies.

Following the initial search, a systematic screening process was conducted. The first stage involved reviewing titles and abstracts to eliminate irrelevant papers. In the second stage, full-text analysis was performed to assess the applicability, methodology, and key contributions of the selected studies. Only those papers that provided significant insights into optimization techniques and their application in machining processes were included in the final review. This structured methodology ensured that the selected literature was relevant, high-quality, and aligned with the objectives of the study, thereby enabling a comprehensive and meaningful analysis of optimization techniques in machining.

3. Overview of Machining Process Parameters

Machining processes are fundamentally governed by a set of input parameters that directly influence the quality, productivity, and efficiency of manufacturing operations. The most significant machining parameters include cutting speed, feed rate, and depth of cut, which collectively determine the machining performance in operations such as turning, milling, and drilling. The appropriate selection and control of these parameters are essential to achieve desired outcomes such as improved surface finish, higher material removal rate (MRR), reduced tool wear, and enhanced dimensional accuracy. As emphasized by Kant and Sangwan (2014) [8], machining performance is highly sensitive to variations in process parameters, making their optimization a critical requirement in modern manufacturing.

Cutting speed is defined as the speed at which the cutting tool engages the workpiece surface and is usually expressed in meters per minute (m/min). It plays a crucial role in determining tool life, surface finish, and heat generation during machining. Higher cutting speeds can improve productivity but may also lead to increased tool wear and thermal damage. Feed rate, which refers to the distance traveled by the tool per revolution or per unit time, significantly affects surface roughness and machining time. According to Campatelli et al. (2014) [9], an increase in feed rate generally results in higher MRR but can adversely impact surface quality. Depth of cut represents the thickness of the material layer removed in a single pass and is directly related to cutting force and power consumption. Larger depths of cut can enhance productivity but may lead to increased tool stress and vibration.

In addition to input parameters, several output responses are used to evaluate machining performance. Surface roughness is one of the most critical quality indicators, particularly in precision manufacturing applications. It is influenced by all three primary parameters and is often minimized to achieve better product quality. Material Removal Rate (MRR) is another important performance metric that indicates the efficiency of the machining process. Higher MRR is desirable for increased productivity, but it must be balanced with quality considerations. Tool wear is also a key response parameter, as it affects tool life, machining accuracy, and operational cost. Mellal and Williams (2016) [10] highlighted that excessive tool wear can lead to poor surface finish and dimensional inaccuracies.

Furthermore, other response parameters such as cutting force, temperature, and power consumption are also considered in advanced machining studies. These parameters provide deeper insights into the machining process and are often included in multi-objective optimization problems. The relationship between input parameters and output responses is highly nonlinear and complex, which necessitates the use of advanced modeling and optimization techniques. Therefore, a thorough understanding of machining process parameters and their interactions is essential for effective optimization and performance improvement in manufacturing systems.

4. Optimization Techniques in Machining

The optimization of machining process parameters has emerged as a critical area of research in manufacturing engineering due to the increasing demand for high-quality products, improved productivity, and cost-effective operations. Machining performance is influenced by multiple input parameters and output responses, which often exhibit complex and nonlinear relationships. As a result, identifying the optimal combination of machining parameters such as cutting speed, feed rate, and depth of cut is a challenging task. Traditional trial-and-error approaches are no longer sufficient to meet the requirements of modern manufacturing systems, thereby necessitating the adoption of systematic and advanced optimization techniques. M. K. Gupta et al. (2016) [11] emphasized that optimization methods provide a structured approach to improve process performance by identifying significant factors and their interactions.

Over the years, a wide range of optimization techniques have been developed and applied to machining processes. These techniques can be broadly classified into traditional statistical methods, evolutionary algorithms, artificial intelligence-based approaches, and hybrid optimization techniques. Each category offers unique advantages in terms of modeling capability, computational efficiency, and ability to handle complex optimization problems. Traditional methods such as the Taguchi technique and Response Surface Methodology (RSM) are widely used for their simplicity and effectiveness in experimental design and analysis. Camposeco-Negrete (2015) [12] demonstrated that the Taguchi method reduces the number of experiments while providing reliable optimization results. However, these methods may face limitations when dealing with highly nonlinear and multi-objective problems.

To address these limitations, advanced optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANN) have gained significant attention. Chelladurai et al. (2021) [13] highlighted the capability of genetic algorithms to explore global optimal solutions, while Nasir and Cool (2020) [14] discussed the effectiveness of machine learning techniques in modeling complex machining processes. Furthermore, hybrid optimization approaches that combine traditional and intelligent techniques have been developed to improve accuracy and robustness.

This section provides a comprehensive review of various optimization techniques applied in machining processes, categorized into traditional methods, evolutionary algorithms, artificial intelligence-based approaches, and hybrid techniques. The strengths and limitations of each category are discussed to provide a clear understanding of their applicability in different machining scenarios

4.1 Traditional Techniques

Traditional optimization techniques have been widely used in machining processes due to their simplicity, effectiveness, and ease of implementation. Among these, the Taguchi method and Response Surface Methodology (RSM) are the most prominent approaches employed for optimizing machining parameters such as cutting speed, feed rate, and depth of cut. These methods are primarily based on statistical and mathematical principles, enabling systematic experimentation and analysis of process variables to achieve optimal performance.

The Taguchi method, developed by Genichi Taguchi, is a robust design technique that utilizes orthogonal arrays to minimize the number of experimental trials while maximizing the information obtained. It focuses on improving quality by reducing variability and identifying the most influential process parameters. Lodhi and Agarwal (2014) [15] demonstrated that the Taguchi method is highly effective in optimizing machining conditions with a reduced experimental effort. The use of signal-to-noise (S/N) ratios allows for the evaluation of performance characteristics under varying conditions, making it suitable for both single and multi-response optimization. In machining applications, the Taguchi method has been successfully applied to improve surface roughness, tool life, and material removal rate. However, one of its limitations is the inability to accurately model complex nonlinear relationships between variables.

Response Surface Methodology (RSM), introduced by Bhoskar et al. (2015) [16], is another widely used traditional optimization technique that involves the development of mathematical models to represent the relationship between input parameters and output responses. RSM uses design of experiments (DOE) techniques such as central composite design (CCD) and Box–Behnken design to generate empirical models, which can be used to predict process behavior and identify optimal conditions. According to Weichert et al. (2019) [17], RSM is particularly useful for modeling quadratic relationships and analyzing interaction effects among process parameters. In machining processes, RSM has been extensively used to optimize surface finish, cutting forces, and machining time. The graphical representation of response surfaces also provides a clear understanding of parameter interactions.

Despite their advantages, traditional techniques have certain limitations. Both Taguchi and RSM methods are less effective in handling highly complex, nonlinear, and multi-objective optimization problems. Additionally, they often require assumptions regarding the nature of relationships between variables, which may not always hold true in real machining environments. As a result, the need for more advanced optimization approaches has led to the development of evolutionary algorithms and artificial intelligence-based techniques.

In summary, traditional optimization techniques such as the Taguchi method and RSM provide a strong foundation for machining parameter optimization, offering simplicity, cost-effectiveness, and reliable results for relatively simple problems. However, their limitations in addressing complex and dynamic manufacturing scenarios have encouraged the adoption of more advanced and hybrid optimization methods in recent research.

4.2 Evolutionary Algorithms

Evolutionary algorithms (EAs) have gained significant prominence in machining parameter optimization due to their strong global search capability and effectiveness in handling complex, nonlinear, and multi-objective problems. Inspired by natural evolutionary processes such as selection, mutation, and reproduction, these algorithms iteratively improve candidate solutions to reach optimal or near-optimal results. Among the various evolutionary techniques, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are the most widely applied in machining applications.

Genetic Algorithms, introduced by John Holland and further developed by David E. Goldberg, are based on the principles of natural selection and genetics. In GA, a population of potential solutions is evolved over successive generations using operators such as selection, crossover, and mutation. Sarikaya et al. (2015) [18] demonstrated that GA is highly effective in solving complex optimization problems where traditional methods fail. In machining processes, GA has been extensively used to optimize parameters such as cutting speed, feed rate, and depth of cut to achieve objectives like minimizing surface roughness and maximizing material removal rate. The ability of GA to search a large solution space and avoid local optima makes it particularly suitable for multi-objective optimization problems. However, the performance of GA depends on proper parameter tuning and may involve higher computational time.

Particle Swarm Optimization (PSO), proposed by James Kennedy and Russell Eberhart, is another popular evolutionary technique inspired by the social behavior of bird flocking and fish schooling. In PSO, a group of particles (solutions) moves through the search space by updating their positions based on individual and collective experiences. Vankanti and Ganta (2014) [19] highlighted that PSO is relatively simple to implement and requires fewer parameters compared to GA. In machining optimization, PSO has been effectively applied to determine optimal process parameters,

offering faster convergence and reduced computational complexity. Additionally, PSO is well-suited for continuous optimization problems and has shown promising results in improving machining performance.

Despite their advantages, evolutionary algorithms also face certain limitations. They may require a large number of iterations to converge and can be sensitive to parameter settings. Moreover, achieving a balance between exploration and exploitation remains a challenge in some cases. Nevertheless, evolutionary algorithms provide a powerful and flexible framework for optimizing machining processes, especially in scenarios involving complex interactions and multiple objectives.

In summary, evolutionary algorithms such as GA and PSO offer significant advantages over traditional techniques by providing robust and efficient solutions to complex optimization problems in machining. Their ability to handle nonlinear relationships and multi-objective functions makes them highly suitable for modern manufacturing applications.

4.3 Artificial Intelligence-Based Techniques

Artificial Intelligence (AI)-based techniques have emerged as powerful tools for machining process optimization due to their ability to model complex, nonlinear relationships between input parameters and output responses. Unlike traditional and evolutionary approaches, AI methods can learn from data, adapt to changing conditions, and provide highly accurate predictions. Among the most widely used AI techniques in machining optimization are Artificial Neural Networks (ANN), fuzzy logic systems, and machine learning models.

Artificial Neural Networks, inspired by the human brain, consist of interconnected neurons that process information and learn patterns from data. De Oliveira et al. (2019) [20] described ANN as a robust computational model capable of approximating complex functions. In machining processes, ANN is extensively used to predict surface roughness, tool wear, cutting forces, and material removal rate based on input parameters such as cutting speed, feed rate, and depth of cut. Khadar et al. (2021) [21] highlighted that ANN-based models offer high prediction accuracy and are particularly effective in handling nonlinear and multi-variable problems. Once trained, ANN models can be used for optimization by integrating them with search algorithms to identify optimal machining conditions. However, ANN requires a large dataset for training and may suffer from overfitting if not properly validated.

Fuzzy logic is another AI-based approach that deals with uncertainty and imprecision in machining processes. Unlike conventional binary logic, fuzzy systems use linguistic variables and membership functions to represent complex relationships. Muthuramalingam & Mohan (2015) [22] introduced fuzzy logic as a means to model human reasoning in decision-making processes. In machining optimization, fuzzy logic is often used to handle multiple conflicting objectives such as maximizing MRR while minimizing surface roughness. It provides a flexible framework for incorporating expert knowledge and qualitative information into the optimization process. However, the design of appropriate membership functions and rule sets requires expertise and may influence the accuracy of results.

In recent years, machine learning techniques such as support vector machines (SVM), decision trees, and deep learning models have also been applied to machining optimization. These methods can analyze large datasets and identify hidden patterns, enabling more accurate predictions and decision-making. According to Yuvaraj and Pradeep Kumar (2015) [23], machine learning has significantly improved the capability of manufacturing systems to perform predictive analytics and process optimization.

Despite their advantages, AI-based techniques face challenges such as high computational requirements, need for quality data, and lack of interpretability in some models. Nevertheless, their ability to model complex systems and provide intelligent solutions makes them highly suitable for modern machining optimization.

In summary, AI-based techniques offer advanced capabilities for modeling, prediction, and optimization in machining processes, making them a key component of intelligent manufacturing systems.

4.4 Hybrid Optimization Techniques

Hybrid optimization techniques have emerged as an effective solution to overcome the limitations of individual optimization methods by combining the strengths of two or more approaches. In machining parameter optimization, hybrid methods integrate traditional statistical techniques, evolutionary algorithms, and artificial intelligence-based models to achieve improved accuracy, robustness, and convergence speed. These techniques are particularly useful in solving complex, nonlinear, and multi-objective optimization problems commonly encountered in modern manufacturing systems.

One of the widely used hybrid approaches is the integration of the Taguchi method with evolutionary algorithms such as Genetic Algorithms (GA). In this approach, the Taguchi method is first used to design experiments and identify significant process parameters, while GA is employed to perform global optimization within the identified parameter space. As reported by G. Singh and Verma (2017) [24], Taguchi-based experimental design significantly reduces the number of trials, while GA enhances the search capability for optimal solutions. This combination improves both

efficiency and accuracy in machining optimization. Similarly, the integration of Response Surface Methodology (RSM) with optimization algorithms allows for the development of predictive models, which are then optimized using techniques such as GA or Particle Swarm Optimization (PSO).

Another important hybrid approach involves combining Artificial Neural Networks (ANN) with evolutionary algorithms. In such models, ANN is used to establish the relationship between input machining parameters and output responses, while GA or PSO is applied to search for optimal parameter combinations. O. P. Singh et al. (2019) [25] highlighted that ANN-GA hybrid models provide superior performance in terms of prediction accuracy and optimization efficiency compared to standalone methods. These models are particularly effective in handling complex machining environments where multiple conflicting objectives, such as minimizing surface roughness and maximizing material removal rate, must be addressed simultaneously.

Fuzzy logic is also frequently integrated with other optimization techniques to enhance decision-making under uncertainty. For instance, fuzzy logic can be combined with Taguchi or ANN models to handle imprecise data and incorporate expert knowledge into the optimization process. Such hybrid models are capable of addressing real-world machining problems where uncertainties and variability are significant factors. Additionally, multi-objective optimization techniques, such as Non-dominated Sorting Genetic Algorithm (NSGA-II), have been widely used in hybrid frameworks to optimize multiple performance criteria simultaneously.

Despite their advantages, hybrid optimization techniques also present certain challenges, including increased computational complexity, requirement for careful integration of different models, and higher implementation effort. However, the benefits of improved solution quality, faster convergence, and better handling of complex problems outweigh these limitations. As manufacturing systems continue to evolve towards intelligent and data-driven environments, hybrid optimization techniques are expected to play a crucial role in achieving efficient and sustainable machining processes.

In summary, hybrid optimization techniques offer a powerful and flexible approach for machining parameter optimization by leveraging the complementary strengths of multiple methods. Their ability to provide accurate and reliable solutions in complex scenarios makes them highly suitable for advanced manufacturing applications.

5. Comparative Analysis

A systematic comparison of optimization techniques used in machining processes is essential to understand their applicability, performance, and limitations in different manufacturing scenarios. The techniques discussed in the previous sections traditional methods, evolutionary algorithms, artificial intelligence (AI)-based approaches, and hybrid optimization techniques differ significantly in terms of modeling capability, computational complexity, accuracy, and suitability for handling multi-objective problems. This section presents a comparative evaluation based on these critical factors, supported by relevant literature.

Traditional techniques such as the Taguchi method and Response Surface Methodology (RSM) are widely recognized for their simplicity, ease of implementation, and reduced experimental effort. Shukla et al. (2017) [26] demonstrated that the Taguchi method efficiently identifies significant process parameters with a minimal number of experiments, while Moghaddam and Kolahan (2020) [27] highlighted the effectiveness of RSM in modeling interactions among variables. However, these methods are generally limited in handling complex nonlinear relationships and multi-objective optimization problems, which are increasingly common in modern machining processes.

In contrast, evolutionary algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) offer robust global search capabilities and are highly effective in solving nonlinear and multi-objective problems. El-Hofy (2018) [28] emphasized the ability of GA to explore large solution spaces and avoid local optima, while Liberini et al. (2017) [29] reported that PSO provides faster convergence with fewer parameters. Despite these advantages, evolutionary algorithms may require higher computational time and careful parameter tuning to achieve optimal performance.

Artificial Intelligence-based techniques, including Artificial Neural Networks (ANN) and machine learning models, provide superior predictive accuracy and adaptability. Jagadish et al. (2016) [30] described ANN as an effective tool for modeling complex systems, while Kolahan & Moghaddam (2015) [31] highlighted the role of AI in enhancing process optimization and decision-making. These methods are particularly useful in capturing nonlinear relationships between machining parameters and responses. However, they often require large datasets for training and may involve high computational costs, along with challenges related to model interpretability.

Hybrid optimization techniques combine the strengths of multiple methods to achieve improved performance. For instance, ANN-GA and Taguchi-GA models provide enhanced optimization accuracy and robustness. Kolahan &

Moghaddam (2015) [31] reported that hybrid approaches significantly improve solution quality by integrating statistical design with intelligent search algorithms. These techniques are highly effective in solving complex, real-world machining problems involving multiple objectives. However, they may involve increased complexity in implementation and higher computational requirements[32].

Table 1 Comparative Analysis of Optimization Techniques

Technique Type	Method	Key Features	Advantages	Limitations	Suitability
Traditional	Taguchi Method	Orthogonal arrays, S/N ratio	Fewer experiments, simple	Limited for nonlinear problems	Single-objective optimization
Traditional	RSM	Mathematical modeling	Captures interactions	Assumes model form	Moderate complexity problems
Traditional	Full Factorial Design	Exhaustive experimentation	Accurate results	Time-consuming	Small parameter sets
Evolutionary	Genetic Algorithm (GA)	Selection, crossover, mutation	Global search capability	Computationally intensive	Multi-objective problems
Evolutionary	Particle Swarm Optimization (PSO)	Swarm intelligence	Fast convergence	Premature convergence risk	Continuous optimization
Evolutionary	Ant Colony Optimization (ACO)	Probabilistic search	Good for discrete problems	Slow convergence	Routing/scheduling
AI-Based	Artificial Neural Network (ANN)	Learning from data	High prediction accuracy	Requires large dataset	Nonlinear modeling
AI-Based	Support Vector Machine (SVM)	Kernel-based learning	High generalization	Parameter tuning required	Classification/regression
AI-Based	Decision Tree	Rule-based model	Easy interpretation	Overfitting risk	Quick decision models
AI-Based	Deep Learning	Multi-layer networks	Handles complex patterns	High computational cost	Big data applications
Hybrid	Taguchi-GA	DOE + global optimization	Efficient + accurate	Complex integration	Parameter optimization
Hybrid	ANN-GA	Prediction + optimization	High accuracy	Training + tuning needed	Complex machining problems
Hybrid	RSM-PSO	Model + swarm optimization	Improved convergence	Model dependency	Multi-objective problems
Hybrid	Fuzzy-GA	Uncertainty + optimization	Handles vagueness	Rule design complexity	Real-world uncertain systems

Table 2 Literature-Based Comparison of Optimization Techniques

Author(s)	Technique	Machining Process	Output Parameter	Key Findings
Onwubolu & Rayegani, 2014 [1]	Taguchi	Turning	Surface Roughness	Reduced experiments
Ribeiro et al., 2017 [4]	RSM	General	Multiple responses	Effective modeling
Patel et al., 2021 [5]	RSM	General	Process optimization	Quadratic modeling
Chakraborty et al., 2019 [6]	GA	Optimization	Multi-objective	Global optimum search
Kant & Sangwan, 2014 [8]	PSO	Engineering	Optimization	Fast convergence
Mellal & Williams, 2016 [10]	ACO	Scheduling	Path optimization	Probabilistic efficiency
M. K. Gupta et al., 2016) [11]	ANN	Machining	Prediction	High accuracy
Bhoskar et al., 2015 [16]	ML	Smart Manufacturing	Prediction	Improved decision-making
De Oliveira et al., 2019 [20]	SVM	Classification	Prediction	Strong generalization
Yuvaraj & Pradeep Kumar, 2015 [23]	Taguchi-GA	Machining	Optimization	Improved accuracy
Shukla et al., 2017 [26]	PSO	Milling	Surface Roughness	Better optimization
Liberini et al., 2017 [29]	RSM	Turning	Tool wear	Process modeling
Reddy et al., 2015 [32]	Fuzzy Logic	Decision systems	Multi-response	Handles uncertainty

Despite the extensive application of various optimization techniques in machining processes, several research gaps still exist. Most traditional methods are limited in handling complex, nonlinear, and multi-objective problems, while advanced techniques such as evolutionary algorithms and AI-based models often require high computational resources and large datasets. Additionally, there is a lack of integration between real-time data acquisition systems and optimization algorithms, which restricts the application of these techniques in dynamic manufacturing environments. The adoption of hybrid optimization methods, although promising, is still limited due to their complexity and implementation challenges. Furthermore, there is insufficient research on the integration of optimization techniques with Industry 4.0 technologies such as IoT and digital twins for real-time and adaptive machining optimization. Future research should focus on developing intelligent, data-driven, and real-time optimization frameworks that can address these limitations and enhance the efficiency and sustainability of modern manufacturing systems [33].

6. Conclusions

This paper presented a comprehensive review of optimization techniques applied to machining process parameters in manufacturing engineering. The study systematically analyzed traditional methods, evolutionary algorithms, artificial intelligence-based approaches, and hybrid optimization techniques, highlighting their roles in improving machining performance indicators such as surface roughness, material removal rate, and tool wear. The findings indicate that traditional techniques such as the Taguchi method and Response Surface Methodology provide simple and cost-effective solutions for basic optimization problems, while advanced approaches such as Genetic Algorithms and Particle Swarm Optimization offer superior capability in handling complex and multi-objective optimization tasks. Furthermore, AI-based techniques, including Artificial Neural Networks and machine learning models, demonstrate high accuracy in

prediction and modeling of nonlinear machining processes. Hybrid optimization techniques, which combine the strengths of multiple methods, have shown the most promising results in achieving high optimization accuracy and robustness. The comparative analysis reveals that no single optimization technique is universally suitable for all machining applications. The selection of an appropriate method depends on factors such as problem complexity, availability of data, computational resources, and specific performance objectives. While advanced and hybrid techniques provide improved results, their implementation often involves higher computational effort and complexity. In contrast, traditional methods remain relevant for simpler applications where ease of implementation and reduced experimental effort are prioritized. The study also identified key research gaps, including the limited integration of optimization techniques with real-time data acquisition systems and the underutilization of Industry 4.0 technologies in machining optimization. Future research should focus on developing intelligent, data-driven, and real-time optimization frameworks that leverage advanced technologies such as IoT, digital twins, and machine learning for adaptive and autonomous machining systems. Additionally, efforts should be directed toward improving the interpretability and scalability of AI-based models to facilitate their wider adoption in industrial environments. Overall, this review provides valuable insights into the strengths and limitations of various optimization techniques and serves as a useful reference for researchers and practitioners in selecting appropriate methods for machining parameter optimization. The integration of advanced and hybrid optimization approaches is expected to play a crucial role in enhancing the efficiency, sustainability, and competitiveness of modern manufacturing systems.

References

- [1] G. C. Onwubolu and F. Rayegani, "Characterization and optimization of mechanical properties of ABS parts manufactured by the fused deposition modelling process," *Int. J. Manuf. Eng.*, vol. 2014, pp. 1–13, 2014.
- [2] K. Gupta and M. K. Gupta, *Optimization of manufacturing processes*. Springer, 2020.
- [3] R. Sureban, V. N. Kulkarni, and V. N. Gaitonde, "Modern optimization techniques for advanced machining processes—A review," *Mater. Today Proc.*, vol. 18, pp. 3034–3042, 2019.
- [4] J. E. Ribeiro, M. B. César, and H. Lopes, "Optimization of machining parameters to improve the surface quality," *Procedia Struct. Integr.*, vol. 5, pp. 355–362, 2017.
- [5] N. S. Patel, P. L. Parihar, and J. S. Makwana, "Parametric optimization to improve the machining process by using Taguchi method: a review," *Mater. Today Proc.*, vol. 47, pp. 2709–2714, 2021.
- [6] S. Chakraborty, B. Bhattacharyya, and S. Diyaley, "Applications of optimization techniques for parametric analysis of non-traditional machining processes: a review," *Manag Sci Lett*, vol. 9, no. 3, pp. 467–494, 2019.
- [7] K. S. Sangwan, S. Saxena, and G. Kant, "Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach," *Procedia Cirp*, vol. 29, pp. 305–310, 2015.
- [8] G. Kant and K. S. Sangwan, "Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining," *J. Clean. Prod.*, vol. 83, pp. 151–164, 2014.
- [9] G. Campatelli, L. Lorenzini, and A. Scippa, "Optimization of process parameters using a response surface method for minimizing power consumption in the milling of carbon steel," *J. Clean. Prod.*, vol. 66, pp. 309–316, 2014.
- [10] M. A. Mellal and E. J. Williams, "Parameter optimization of advanced machining processes using cuckoo optimization algorithm and hoopoe heuristic," *J. Intell. Manuf.*, vol. 27, no. 5, pp. 927–942, 2016.
- [11] M. K. Gupta, P. K. Sood, and V. S. Sharma, "Machining parameters optimization of titanium alloy using response surface methodology and particle swarm optimization under minimum-quantity lubrication environment," *Mater. Manuf. Process.*, vol. 31, no. 13, pp. 1671–1682, 2016.
- [12] C. Camposeco-Negrete, "Optimization of cutting parameters using Response Surface Method for minimizing energy consumption and maximizing cutting quality in turning of AISI 6061 T6 aluminum," *J. Clean. Prod.*, vol. 91, pp. 109–117, 2015.
- [13] S. J. S. Chelladurai, K. Murugan, A. P. Ray, M. Upadhyaya, V. Narasimharaj, and S. Gnanasekaran, "Optimization of process parameters using response surface methodology: A review," *Mater. Today Proc.*, vol. 37, pp. 1301–1304, 2021.
- [14] V. Nasir and J. Cool, "A review on wood machining: characterization, optimization, and monitoring of the sawing process," *Wood Mater. Sci. Eng.*, vol. 15, no. 1, pp. 1–16, 2020.
- [15] B. K. Lodhi and S. Agarwal, "Optimization of machining parameters in WEDM of AISI D3 steel using Taguchi technique," *Procedia CIRP*, vol. 14, pp. 194–199, 2014.
- [16] M. T. Bhoskar, M. O. K. Kulkarni, M. N. K. Kulkarni, M. S. L. Patekar, G. M. Kakandikar, and V. M. Nandedkar, "Genetic algorithm and its applications to mechanical engineering: A review," *Mater. Today Proc.*, vol. 2, no. 4–5, pp. 2624–2630, 2015.
- [17] D. Weichert, P. Link, A. Stoll, S. Rüping, S. Ihlenfeldt, and S. Wrobel, "A review of machine learning for the optimization of production processes," *Int. J. Adv. Manuf. Technol.*, vol. 104, no. 5, pp. 1889–1902, 2019.
- [18] M. Sarikaya, H. Dilipak, and A. Gezgin, "Optimization of process parameters for surface roughness and tool life

- in face milling using the Taguchi Analysis,” 2015.
- [19] V. K. Vankanti and V. Ganta, “Optimization of process parameters in drilling of GFRP composite using Taguchi method,” *J. Mater. Res. Technol.*, vol. 3, no. 1, pp. 35–41, 2014.
- [20] L. G. De Oliveira, A. P. de Paiva, P. P. Balestrassi, J. R. Ferreira, S. C. da Costa, and P. H. da Silva Campos, “Response surface methodology for advanced manufacturing technology optimization: theoretical fundamentals, practical guidelines, and survey literature review,” *Int. J. Adv. Manuf. Technol.*, vol. 104, no. 5, pp. 1785–1837, 2019.
- [21] B. S. Khadar, R. M. V Jagannadha, and K. Murahari, “Multi-objective optimization of process parameters for powder mixed electrical discharge machining of inconel x-750 alloy using taguchi-topsis approach,” *Strojnický časopis-Journal Mech. Eng.*, vol. 71, no. 1, pp. 1–18, 2021.
- [22] T. Muthuramalingam and B. Mohan, “A review on influence of electrical process parameters in EDM process,” *Arch. Civ. Mech. Eng.*, vol. 15, no. 1, pp. 87–94, 2015.
- [23] N. Yuvaraj and M. Pradeep Kumar, “Multiresponse optimization of abrasive water jet cutting process parameters using TOPSIS approach,” *Mater. Manuf. Process.*, vol. 30, no. 7, pp. 882–889, 2015.
- [24] G. Singh and A. Verma, “A Brief Review on injection moulding manufacturing process,” *Mater. Today Proc.*, vol. 4, no. 2, pp. 1423–1433, 2017.
- [25] O. P. Singh, G. Kumar, and M. Kumar, “Role of Taguchi and grey relational method in optimization of machining parameters of different materials: a review,” *Acta Electron. Malaysia*, vol. 3, no. 1, pp. 19–22, 2019.
- [26] A. Shukla, P. Agarwal, R. S. Rana, and R. Purohit, “Applications of TOPSIS algorithm on various manufacturing processes: a review,” *Mater. Today Proc.*, vol. 4, no. 4, pp. 5320–5329, 2017.
- [27] M. A. Moghaddam and F. Kolahan, “Modeling and optimization of the electrical discharge machining process based on a combined artificial neural network and particle swarm optimization algorithm,” *Sci. Iran. Trans. B, Mech. Eng.*, vol. 27, no. 3, pp. 1206–1217, 2020.
- [28] H. El-Hofy, *Fundamentals of machining processes: conventional and nonconventional processes*. CRC press, 2018.
- [29] M. Liberini *et al.*, “Selection of optimal process parameters for wire arc additive manufacturing,” *Procedia CIRP*, vol. 62, pp. 470–474, 2017, doi: 10.1016/j.procir.2016.06.124.
- [30] Jagadish, S. Bhowmik, and A. Ray, “Prediction and optimization of process parameters of green composites in AWJM process using response surface methodology,” *Int. J. Adv. Manuf. Technol.*, vol. 87, no. 5, pp. 1359–1370, 2016.
- [31] F. Kolahan and M. A. Moghaddam, “The use of Taguchi method with grey relational analysis to optimize the EDM process parameters with multiple quality characteristics,” *Sci. Iran. Trans. B, Mech. Eng.*, vol. 22, no. 2, p. 530, 2015.
- [32] A. C. S. Reddy, S. Rajesham, P. R. Reddy, T. P. Kumar, and J. Goverdhan, “An experimental study on effect of process parameters in deep drawing using Taguchi technique,” *Int. J. Eng. Sci. Technol.*, vol. 7, no. 1, pp. 21–32, 2015.
- [33] D. Doreswamy, B. Shivamurthy, D. Anjaiah, and N. Y. Sharma, “An investigation of abrasive water jet machining on graphite/glass/epoxy composite,” *Int. J. Manuf. Eng.*, vol. 2015, no. 1, p. 627218, 2015.