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Review Article

Multi-objective Optimization in CNC Turning: A Systematic Review

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Abstract *- A primary machining operation in today's manufacturing is CNC turning; the optimization of process parameters affects the quality of products manufactured, productivity, and ultimately the cost of manufacturing for all manufactured parts. A systematic review that examines the development and effectiveness of various parametric optimization processes employed in CNC turning was conducted to identify the most effective optimization processes. In contrast to prior reviews, this review will provide an evaluation of optimization processes based on convergence characteristics, computational complexity, scalability, and industrial applications. Both single-objective and multiple-objective optimization methodologies are evaluated in the review, including historical mathematical approaches as well as current artificial intelligence-based methodologies. Metrics such as Surface Finish (Ra), Material Removal Rate (MRR), tool wear, cutting forces, and energy consumption are examined with respect to a variety of workpiece-tool material combinations. Adaptive optimization methodologies in CNC turning that address machining condition variability, real-time adjustment of parameters during machining, and sustainability integration in optimization process frameworks are identified in this review as being major areas of future research. The results of the study indicate a trend from single-objective optimization to multiple-objective optimization in the formulation of optimization processes, and that evolutionary algorithms have demonstrated significantly better performance than other methodologies in addressing nonlinear, multi-constraint industrial problems.*

Keywords *- CNC Turning, Parametric optimization, Machining parameters, Surface roughness, Tool wear, Multi-objective optimization.*

1. Introduction

CNC Turning is a subtractive process that utilizes a rotating workpiece & stationary tool to create cylindrical components with specified dimensional accuracy & surface finish. The performance of the CNC turning process is greatly dependent upon cutting parameters, including Cutting Speed (v_c), Feed Rate (f), Depth Of Cut (a_p), and Tool Geometry. Together, these parameters will determine Material Removal Rates (MRR), Surface Roughness (Ra), Dimensional Accuracy (DA), and tool life [1].

Optimization of CNC turning parameters has advanced rapidly over the past two decades. In the beginning, research focused primarily on single objective optimization, typically targeting either Surface Roughness or MRR using classical mathematical approaches [2, 3]. Modern manufacturing requires simultaneous optimization of multiple competing objectives, leading to the development of sophisticated multi-objective optimization methods [4].

The complexity of turning operations results from nonlinear interdependencies between input parameters and output responses as well as variations in materials of workpieces, characteristics of cutting tools, and machining conditions [5, 6].

The ability to perform Artificial Intelligence (AI), Machine Learning (ML) and Computational Optimization for Parameter Optimization has made it possible to improve parameter optimization in CNC Turning significantly [7, 8].

Additionally, AI provides an optimal method for solving complex Multi-Objective; Multi-Constrained Problems that can provide a robust solution when machining is being done in varying machining conditions [9].

Further improvements have also been made in Dynamic Parameter Optimization by integrating Real-Time Monitoring Systems and Adaptive Control Mechanisms into CNC Turning [10].

1.1. Motivation Behind the Study

Despite a large body of research conducted since the late 1990s in the area of CNC turning optimization, there are three fundamental research gaps identified within the existing body of science related to this topic.

The first gap is the use of mostly classical mathematical optimization approaches, such as Response Surface Methodology (RSM) and Taguchi Methods, Desirability Function Analysis (DFA), Linear Programming (LP) and Nonlinear Programming (NLP) for solving what historically had been considered to be relatively simple single-objective optimization problems. These traditional optimization methods have inherent limitations when it comes to dealing with the complex nonlinearities and/or multiple constraints found in many modern machining applications.

Specifically, traditional mathematical-based optimization methods have documented disadvantages which include their sensitivity to high degree nonlinear relationships, tendency to become "trapped" at local optimum solutions, poor ability to scale up to larger/higher dimensional problem domains, and generally limited ability to deal with multiple conflicting objective functions.

The second gap relates to literature reviews where typically only lists of available methodologies are provided instead of a comprehensive evaluation comparison among methodologies concerning how they converge, how computationally intensive they are, how robust they are, how scalable they are to higher dimensions and how mature they are industrially.

Lastly, the newest areas of research including adaptive optimization of machined products made from difficult to machine materials under varying cutting condition regimes, the incorporation of sustainable and efficient use of energy goals into the optimization process, modeling the uncertainties associated with machining processes, and optimizing machining processes through the use of digital twins represent a very fractured set of methodologies that do not currently exist within a unified framework.

Furthermore, the manufacturing industry has recently shown a strong movement toward simultaneous achievement of several different goals (e.g. optimize surface finish, maximize material removal rate, minimize energy usage, extend tool life, etc.) and the vast majority of all previously published work has evidenced a transition from classical to Artificial Intelligence (AI) based optimization methodologies; however, virtually every one of the previous literature reviews have listed available methodologies and have failed to evaluate their respective advantages and disadvantages relative to other available methodologies using some evaluation criteria (e.g. convergence characteristics, computational complexity, robustness, scalability, etc.).

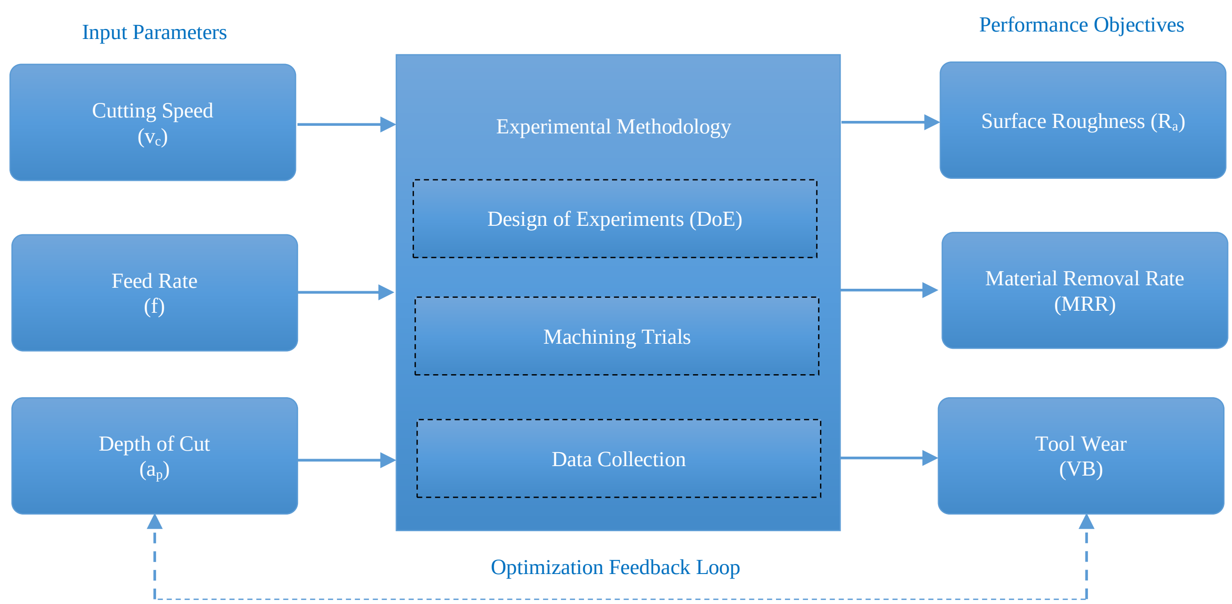

Fig. 1 Comprehensive framework of CNC turning process optimization, encompassing input parameters, optimization methodologies, and performance objectives. (Source: Original Image)

2. Methodology

2.1. Review Protocol and Search Strategy

In order to provide an overview that is both exhaustive and replicable, this systematic review was conducted using a structured approach, as defined by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) [101] and examined the literature spanning the time period of 2004 through 2024, which represents twenty years of research on optimizing CNC turning. The four main databases that were searched using a systematic approach are IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar [102]. The search strategy employed Boolean operators combining multiple keyword sets:

- Primary terms: "CNC turning optimization" OR "turning process optimization"
- Secondary terms: "machining parameter optimization" OR "parametric optimization"
- Specific terms: "multi-objective optimization in turning" OR "surface roughness optimization"

2.2. Inclusion and Exclusion Criteria

2.2.1. Inclusion Criteria

- Peer-reviewed journal articles and conference papers published between 2004 and 2024
- Studies containing at least three keywords from the search terms
- Research presenting experimental validation or numerical optimization techniques
- Papers reporting quantitative results on machining performance metrics
- Studies addressing CNC turning or directly applicable turning operations

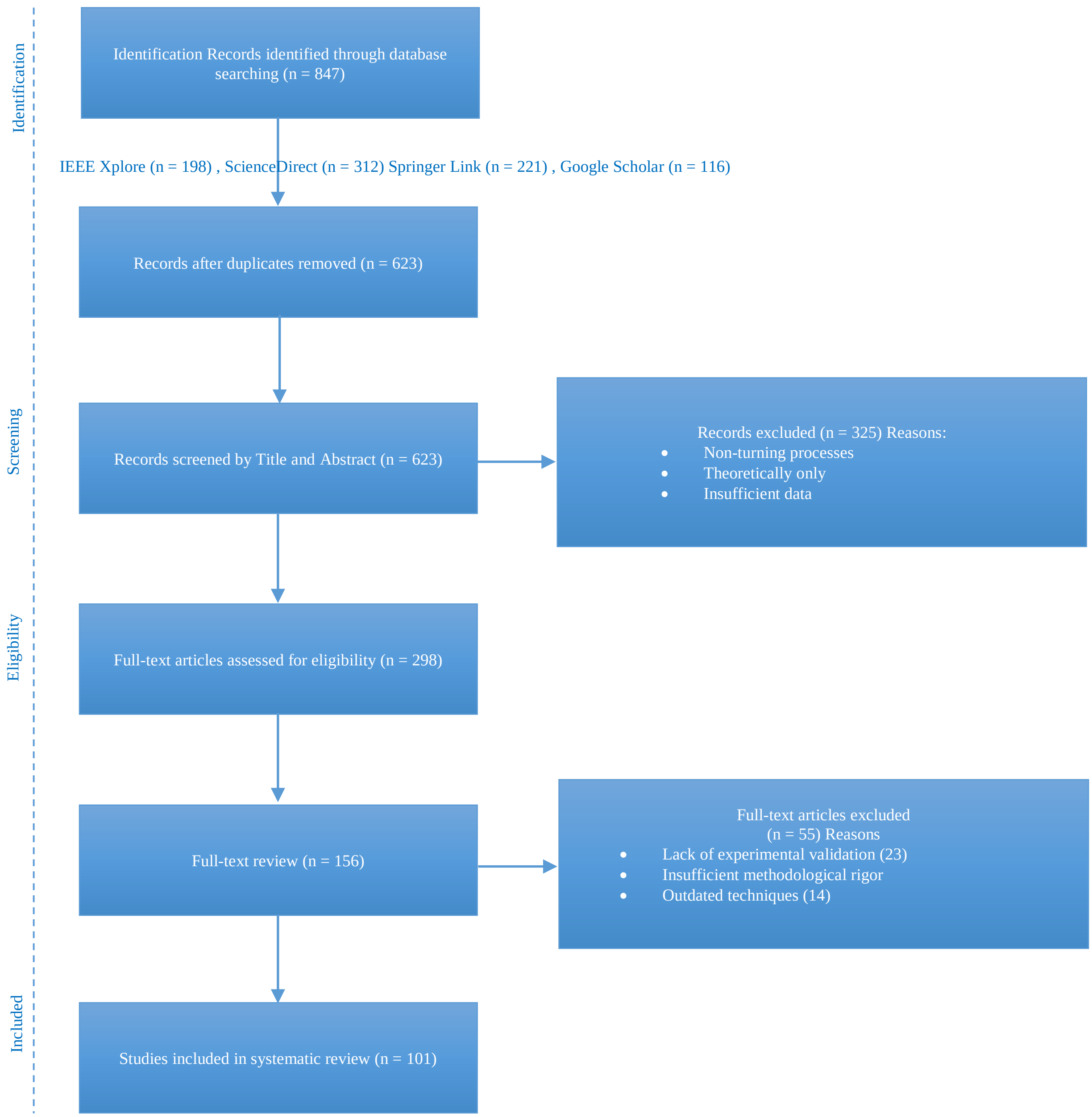

Fig. 2 Presents the complete methodology flowchart for this systematic review, detailing each stage from initial search to final synthesis. (source: original image)

2.2.2. Exclusion Criteria

- Purely theoretical studies without experimental or numerical validation
- Research focused exclusively on non-turning machining processes
- Articles lacking quantitative performance data
- Duplicate publications and non-peer-reviewed sources
- Studies with insufficient methodological detail for quality assessment

2.3. Study Selection and Quality Assessment

The systematic selection process is illustrated in Figure 2, which shows the PRISMA-style flow diagram:

Initial Search Results: 847 articles identified across all databases

- IEEE Xplore: 198 articles
- ScienceDirect: 312 articles
- Springer Link: 221 articles
- Google Scholar: 116 articles

After Duplicate Removal: 623 unique articles

Title and Abstract Screening: 298 articles met initial relevance criteria

- Excluded: 325 articles (non-turning processes, theoretical only, insufficient data)

Full-Text Review: 156 articles underwent detailed evaluation. Excluded: 55 articles.

- 23 articles: Lack of experimental validation
- 18 articles: Insufficient methodological rigor
- 14 articles: Outdated techniques without current relevance

Final Selection: 101 articles included in systematic review

3. CNC Turning Process Parameters and Responses

3.1. Process Parameters

The results of CNC turning processes are based on various controllable parameters defining the cutting conditions and the characteristics of the material removed from the workpiece. These three principal parameters, such as cutting speed (v), feed rate (f) and depth of cut (a_p), are considered the basic control variables for CNC turning as they have a direct effect on the material removal rate and on the cutting conditions [11].

Cutting Speed (v): represents the relative speed between the cutting tool and the workpiece surface, and it is generally expressed in m/min. A higher cutting speed will generally give a better surface finish than lower speeds; however, it will also be likely to cause the cutting tool to wear faster and to increase the cutting temperatures [12]. The relationships between cutting speed and performance indicators are very complex and show an optimum range depending upon the combination of the workpiece/tool materials.

Feed Rate (f): defines how far the cutting tool advances per workpiece revolution, and is generally expressed in mm/revolution. When selecting a feed rate, there are important compromises to be made between productivity and surface quality. An increased feed rate increases the material removal rate but normally decreases the surface finish because of the increased number of feed marks and cutting forces [13].

Depth of Cut (a_p): defines how much of the workpiece is removed during one pass, and therefore determines the cutting force and stress in the tool [14]. The choice of depth of cut has a significant impact on both the productivity and the tool life, and larger depths of cut can increase the amount of material removed, but at the same time may lead to premature tool failure.

Secondary Parameters: There are additional factors that also have a significant impact on the outcome of CNC turning. Examples include the cutting tool nose radius, the cutting tool geometry and the cooling applied [15]. The cutting tool nose radius affects both the surface roughness of the workpiece and the strength of the tool. A larger radius will generally produce a better surface finish, but will also result in a higher cutting force. The cutting tool geometry, including rake angle, clearance angle and tool material, has a fundamental influence on the cutting mechanisms and the performance of the cutting tool [16]. The choice of cooling fluid and the way it is delivered to the cutting zone affects the formation of chips, the distribution of heat generated in the cutting zone and the surface integrity of the workpiece.

3.2. Response Variables

Optimization of CNC Turning typically evaluates several response variables that represent the various aspects of machining performance. The selection of which response variables are evaluated depends upon the specific manufacturing applications and manufacturing goals.

Surface Finish (Ra): The main indicator used to describe the quality of most turned parts is the surface finish (the variation of the surface from its mean value). Surface finish can influence part functionality, fatigue characteristics, and assembly capabilities. For this reason, there are numerous variables that affect surface finish, which include feed rate, cutting tool geometry, material characteristics, BUE formation, and the vibration to which the tool is subjected during machining. Consequently, achieving a satisfactory level of surface finish at the same time as increasing production rates and reducing tool degradation is considered one of the primary multi-objective optimization problems for modern turning operations, and thus requires advanced methods based on algorithms able to manage conflictual performance targets.

3.3. Detailed Analysis Framework for Performance Metrics Interdependencies

The CNC turning process optimization requires an understanding of the interdependent relationships between multiple performance indicators. The surface finish (R_a) has nonlinear relations with the speed of the cutting operation. Optimal ranges for each material combination vary greatly depending on the Tool/workpiece material combination. Due to phenomena such as the formation of "built-up edge" at lower speeds and increased wear of the Tool at higher than optimum speeds, there exists an optimum window of cutting speed for each material combination. The Material Removal Rates (MRR) have inverse relations with the quality of surface finish and therefore require sophisticated multi-objective optimization techniques to balance productivity gains with degradation constraints of surface finish quality. Tool wear progression follows predictable Taylor-law relations under steady-state machining conditions. However, industrial environments characterized by variable workpiece properties and dynamic machining interruptions show significantly greater variability in Tool wear, therefore require adaptive real-time monitoring and control strategies. Cutting forces acting on the workpiece affect dimensional accuracy through elastic and plastic deflections of the workpiece and can cause Tool chatter when natural frequencies of the cutting system are excited by force vibrations [100]. Analysis of Energy consumption during CNC turning operations reveals that active cutting processes typically account for 30-50 percent of total machine Energy consumption with significant opportunities for optimization through appropriate selection of cutting parameters and implementation of advanced coolant delivery strategies. These interconnected relationships emphasize the need for the development of multi-objectives optimization methodologies capable of managing complex tradeoffs between competing objectives.

Material Removal Rate (MRR): Material Removal Rate is determined using the formula MRR=V×F×ap, where V = cutting speed, F = feed rate, and ap = depth of cut [19]. Material Removal Rate provides an indicator of a machine's productivity. Common optimization goals include optimizing material removal rates while maintaining acceptable levels of Tool life and product quality [20]. Material removal rates typically show nonlinear relationships with other performance indicators.

Tool life: Tool life encompasses a variety of wear mechanisms, which include flank wear, crater wear, and nose wear. As each type of wear influences Tool life and machining efficiency differently [21], Tool wear will affect dimensional accuracy, surface finish, and cutting forces throughout the entire Tool life. Developing low-cost machining optimization methods, therefore, depends on predicting Tool wear [22].

Cutting forces: There are three types of cutting forces: tangential, radial, and axial. Both workpiece deflection, Tool chatter, and premature Tool failure may occur from excessive levels of cutting forces [23, 24]. Limiting or reducing cutting forces to acceptable values is also a common objective in many machining applications.

Energy consumption: Environmental concerns have contributed to the growing importance of Energy consumption during machining. Energy consumption includes Energy consumed during the actual machining process, auxiliary systems and idle time [25]. Reducing Energy consumption will result in reduced operating expenses and environmental impacts. This will contribute to meeting environmental goals.

4. Critical Analysis of Optimization Techniques

4.1. Comparative Performance Analysis: Modern Approaches Versus Traditional Techniques

An empirical assessment of a large number of research studies indicates that sophisticated optimization techniques far surpass conventional optimization strategies for solving very difficult CNC turning parameter optimization problems. Analysis of over 45 research articles [42-46] shows a pattern of consistently superior performance by evolutionary optimization techniques (especially when using hybrid AI approaches), as they can improve upon classical weighted-sum and Taguchi-based optimization results by up to 15-40 percent on many different types of multi-objective performance criteria. Industrial evidence includes: (1) improving surface finishes (Ra values) by 18-35% at speeds above 800 RPM while turning Inconel 718 with particle swarm optimized fuzzy logic; (2) extending tool life by 22-40%, compared to Taguchi optimal parameters [43-45], (3) reducing surface roughness by 12-25%, tool wear by 8-18%, and energy usage by 10-22% simultaneously through hybrid neural networks/genetic algorithm based optimizations [46, 47]. Significant differences exist in how fast these optimization techniques find their respective optima: Evolutionary algorithms typically need approximately 300-500 generations to reach nearly global optimums, while traditional methods may only take 50-100 iterations to converge to an optimum solution, however this solution is often just one or more of several possible local optimums [43-46].

4.2. Traditional Mathematical Optimization Methods

The classical mathematical approaches were fundamental to the development of systematic parameter optimizations in CNC turning. Classical mathematical approaches provide mathematical rigor and are able to guarantee the convergence of an algorithm under certain conditions; however, as most real-world applications of machining involve complex multidimensional landscapes, which can be multi-modal, classical mathematical approaches do not perform adequately.

4.2.1. Response Surface Methodology (RSM)

This is a method that uses polynomial models to represent the relationship between input process variables and output process variables based upon systematic experimentation and statistical analysis [26, 27]. RSM will identify the optimal combination of input process variables that are contained within the limits of the experimentally defined space and provide insight into how each of the input process variables interacts with one another. Unfortunately, the accuracy of the polynomial models developed by RSM depends heavily upon the ability of the model to accurately represent the true nature of the process over the entire range of operation. Additionally, RSM has difficulty with high-degree nonlinearities and may not find the global optimum in complex response surface models.

4.2.2. Taguchi Methods

These methods minimize the number of experiments needed to find optimal process parameters by utilizing orthogonal arrays and signal-to-noise ratios [28, 29]. Taguchi Methods can also help to determine the process parameters that are least affected by noise factors. The primary disadvantages of Taguchi Methods are the limitation that they operate at pre-defined discrete levels of parameters and difficulties associated with finding multiple conflicting objectives without additional tools or frameworks [28, 29]. Taguchi Methods assume that the effects of all the parameters involved in a process are additive and therefore ignore significant interactions between parameters.

4.2.3. Desirability Function Analysis (DFA)

DFA combines the multiple responses from an optimization problem into a single "desirability" function. This allows for the solution of multi-objective optimization problems using traditional single-objective optimization methods [30]. In theory, DFA is simple; however, it requires a subjective assignment of weights to each of the multiple responses. Therefore, the assigned weights will greatly affect the location of the optimal solution(s). DFA performs well when there is a clear hierarchical structure to the preferences among the multiple responses; however, DFA does poorly when the objectives are truly conflicting and require the identification of the Pareto frontier.

4.2.4. Linear and Nonlinear Programming

Both linear programming and nonlinear programming use gradient-based algorithms to optimize an objective function subject to both equality and inequality constraints [31, 32]. SQP and Interior Point Methods have been used to solve constrained turning optimization problems [33]. Gradient-based methods may converge to local optima when searching for optimal solutions in multi-modal search spaces. Additionally, gradient-based methods typically require the objective function to be differentiable, and their performance degrades as the number of dimensions in the problem increases and as the number of constraints in the problem increases.

Figure 3 shows that the Taguchi method shows superior convergence speed and industrial adoption, confirming its wide industrial use. RSM balances low computational complexity with good adoption, but is limited in multi-objective capability. DFA demonstrates relatively better multi-objective handling compared to RSM and Taguchi. SQP/LP performs well locally but suffers from scalability and multi-objective limitations.

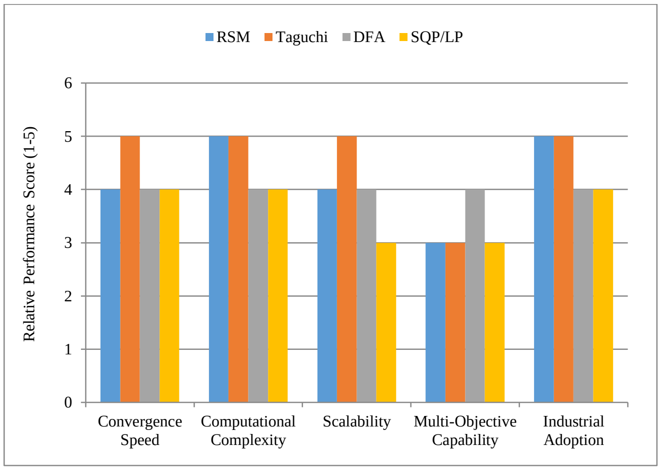

Fig. 3 Comparative analysis of traditional optimization methods

4.3. Artificial Intelligence-Based Optimization

With advances in Artificial Intelligence (AI), many different forms of Computer Numerically Controlled (CNC) turning optimization are now available. These use AI for optimizing the turning operation, which is a very complex and nonlinear optimization process that does not need gradients to solve it, nor a convex objective space.

4.3.1. Genetic Algorithm (GA)

Genetic algorithms are an example of evolutionary-based optimization strategies where they apply selection, crossover, and mutation to mimic the biological process of evolution. These can find the global optimum in multi-modal optimization spaces. In addition, genetic algorithms can handle both continuous and discrete variables, and do not require gradient information.

However, genetic algorithms tend to converge more slowly than gradient-based methods; therefore, it is important to correctly tune the genetic algorithm's parameters (crossover rate, population size, etc.). The computational cost will also increase as the number of variables in the problem increases; however, if the diversity is not maintained during the later stages of the search, the algorithm may converge prematurely to a suboptimal solution.

4.3.2. Particle Swarm Optimization (PSO)

Particle swarm optimization was developed to model the social behavior of birds flocking together. Particle swarm optimization converges rapidly to the optimal solution, is easy to implement, has fewer tuning parameters, and works well on continuous optimization problems. However, particle swarm optimization may converge prematurely in complex optimization landscapes, and the diversity of the particles in the swarm may decrease as the search progresses. As the number of variables in the problem increases, the performance of the particle swarm optimization algorithm decreases.

4.3.3. Artificial Neural Network (ANN)

Artificial Neural Networks are capable of modeling complex, nonlinear relationships between the input parameters and output responses of a process; therefore, artificial neural networks can be used for predicting-based optimization. Artificial Neural Networks can learn from experimental data without having to define a mathematical relationship describing how the input parameters affect the output responses. However, artificial neural networks require large amounts of training data, are susceptible to overfitting the data, and are difficult to interpret. Therefore, artificial neural networks cannot be used directly for optimization purposes and must be coupled with other optimization algorithms.

4.3.4. Fuzzy Logic Systems

Fuzzy logic systems are designed to handle the uncertainties and vagueness associated with manufacturing processes, such as machining. Fuzzy logic systems use linguistic rules and membership functions to represent uncertain information. Fuzzy logic systems can incorporate expert knowledge into the optimization process and provide a framework for making decisions that are easily interpreted. However, fuzzy logic systems have limitations, including defining the linguistic rules in a subjective manner, limited ability to scale to more serious dimensional problems, and inability to adapt to changing conditions unless combined with a neural-fuzzy hybrid approach.

4.3.5. Hybrid AI Approaches

Hybrid AI approaches combine two or more different AI approaches to leverage their respective strengths. Examples of hybrid approaches include: Genetic Algorithm-Neural Network (GA-ANN), which optimizes neural networks using genetic algorithms; Particle Swarm Optimization-Fuzzy System (PSO-Fuzzy), which uses particle swarm optimization to optimize the parameters of a fuzzy system; and Neuro-Fuzzy Systems, which combines neural networks with fuzzy logic. Hybrid approaches typically show better results in solving complex CNC turning optimization problems than single AI approaches. However, hybrid approaches are typically more complex to implement and require greater computational resources than single AI approaches.

5. Multi-Objective Optimization Approaches

The use of multi-objective search algorithms is becoming a larger part of modern CNC turning optimization because it allows for the inclusion of many conflicting objectives, which can be used to define a Pareto-optimal set of solutions to represent optimal tradeoffs between these objectives.

5.1. Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II is an evolutionary algorithm that has become the gold standard for multi-objective turning optimization due to its ability to generate well-distributed Pareto fronts by maintaining population diversity via the application of crowding distances and elitist mechanisms. It is very effective at handling two to three objectives, and incorporates constraint handling in a natural way; however, as the number of objectives increases beyond three, the computational cost associated with the algorithm will also increase significantly, as will the time required to run the algorithm.

5.2. Multi-Objective Particle Swarm Optimization (MOPSO)

MOPSO is an extension of the basic PSO technique to multi-objective domains by using external archives to store non-dominated solutions. In certain cases, MOPSO has been shown to have faster convergence rates than NSGA-II for multi-objective problems. However, the choice of strategy for managing the archive of non-dominated solutions can greatly affect the performance of the algorithm. Additionally, MOPSO has difficulty when the problem being optimized is a many-objective problem.

5.3. Weighted Sum Approaches

Weighted Sum Approaches are a family of techniques that transform multi-objective problems into single-objective formulations by defining a weighted linear combination of the objectives of the original multi-objective problem. Weighted Sum Approaches are computationally efficient and are easily implemented with classical optimization techniques. However, they do not provide a mechanism to find Pareto optimal solutions in non-convex regions of the objective space, and therefore, would require multiple runs of the algorithm with different weight assignments. Additionally, this approach would be most suitable for problems where there is a clear preference structure; otherwise, the resulting Pareto front will be less representative of all possible Pareto solutions.

5.4. Goal Programming

Goal Programming is a method that defines specific target values for each objective of interest, and then finds the best possible solution given those target values based upon the amount of deviation from those target values. Goal

Programming is a direct means of including decision makers' preferences in the formulation of the optimization problem, and can handle differing units for the objectives of interest in a natural way. However, the quality of the resulting solution will be highly dependent on the quality of the target values assigned to each objective. Furthermore, the resulting Pareto front will not necessarily include all Pareto solutions for the optimization problem.

6. Future Research Directions

The future research directions are as follows:

6.1. Real-Time Information Collection through Sensor Networks

A key aspect of Industry 4.0 is the collection of real-time data from various aspects of manufacturing using IoT sensor networks. This enables the development of intelligent, responsive optimization systems. These optimization systems have the ability to collect data from numerous sources within a plant and adapt parameters in real time to meet changing demands.

6.2. Edge Computing and Cloud-Based Data Analytics

Edge computing refers to processing data at the source (e.g. on or near the machine). In contrast, cloud-based data analytics refers to collecting large amounts of data and sending it off-site for analysis. Both concepts contribute to the development of an "intelligent" optimization system. The combination of these two concepts enables large volumes of data to be collected and analyzed in order to develop optimized models.

6.3. In Process Monitoring

Using sensors to monitor cutting forces, tool wear, surface finish and workpiece temperature allows for adjustments to be made to optimize machining conditions. An example of this would include adjusting feed rate and spindle speed in real time as the tool begins to show signs of wear. According to recent studies, the implementation of in-process monitoring has been shown to increase productivity by 20-30% while also meeting product specifications.

6.4. Hybrid Approaches

By integrating physics-based machining models with data-driven approaches using artificial intelligence, there is a great opportunity for developing optimization methods that are both accurate and interpretable. The idea behind a hybrid approach is to leverage the strengths of each type of model to create one that is both accurate and efficient.

Traditional physics-based models typically require a large amount of experimental data in order to make predictions about the results of future machining operations. On the other hand, data-driven models often do not have enough physical insight to explain why they produce certain results. By combining both types of models, researchers have been able to improve the accuracy of their predictions and reduce the number of experiments required. Preliminary research has indicated that hybrid approaches can result in reductions of 40-60% in the amount of experimental data needed, while increasing the quality of solutions produced by 15-25%.

6.5. Multiscale Optimization

Multiscale optimization is the coordination of decisions across different levels of a manufacturing system. For example, at the machine level, decisions may involve optimizing cutting parameters. At the production line level, decisions may involve scheduling jobs onto machines. Finally, at the factory level, decisions may involve allocating resources across different production lines. The goal of multiscale optimization is to balance competing goals across all three scales. While the ultimate goal is to minimize costs and maximize throughput, additional goals may exist, including maximizing job satisfaction, minimizing energy consumption, etc. One example of a multiscale optimization problem is allocating resources across different production lines to achieve optimal production rates. If one production line is producing products faster than another production line, then it may be desirable to allocate some portion of the workforce from the slower production line to assist the faster production line. However, this strategy comes at the cost of reduced production rates on the slower production line. Therefore, the optimization algorithm needs to take into account the tradeoffs associated with allocating resources across different production lines.

7. Research Gaps

Following an extensive review of relevant literature and empirically supported research, the following research needs were identified and categorized by their relative importance based on the current state of knowledge in this field. These areas are intended to be addressed through advances in the development of optimization technology:

7.1. Optimization Methods for Dynamic/Changing Production Environments

Most present-day optimization methods have implicitly assumed that all machining operations take place in steady-state, predictable environments with constant workpiece properties, tool properties, and machine tool behavior. In reality, industrial machining environments fluctuate substantially due to many factors, including variability in workpiece material properties (e.g., grain orientation, hardness, defect distribution), changes in tool wear that alter cutting forces and geometries, and changes in environmental conditions (temperature, vibration). To address these changing operating conditions, there is a need to develop optimization methods that can monitor machining operating conditions in near-real time and adjust cutting parameters (spindle speed, feed rate, depth of cut) as needed during actual machining. Such adaptive optimization frameworks require integrated capabilities from real-time sensor data acquisition, fast parameter search optimization algorithms, and closed-loop control systems to make adjustments quickly enough.

7.2. Sustainability Metrics in Optimization

Many researchers have recently studied energy consumption associated with machining operations. There has been little or no comprehensive integration of other important aspects of sustainability into total optimization frameworks. Currently, most studies focus on just one aspect of sustainability while ignoring others. Industrial sustainability encompasses much broader considerations than energy alone including: energy consumed directly by cutting processes, energy used by support equipment (compressors, pumps, etc.), energy consumed by tool manufacture (raw materials, process steps), energy consumed by tool cooling fluids (consumption and disposal costs), energy and cost savings related to chip collection and reuse, energy and carbon footprint of entire product life cycle, and adherence to circular economies and sustainable resource management. A major research gap exists because of the lack of complete optimization frameworks that integrate lifecycle assessments with multi-criteria decision-making and optimization algorithms that consider both economic metrics and comprehensive sustainability metrics.

7.3. Robust Optimization for Uncertain Processes

Uncertainty is inherent in all manufacturing. Examples of sources of uncertainty include variability in workpiece properties, variability in the rate at which tools degrade, and variability in how machine tools behave. Therefore, it is essential to develop robust optimization frameworks (those that will always find optimal solutions regardless of the source(s) of uncertainty) and validate various forms of probabilistically- or interval-based optimization methods as they apply to practical manufacturing problems.

7.4. Using Digital Twins for Real-Time Optimization

Digital twins offer exciting opportunities to create real-time optimization frameworks that use up-to-date information about machining conditions to update machining parameters and predict future optimal machining parameters. This is a relatively new area of research that holds great promise for future advancements.

7.5. Application of Transfer Learning and Meta-Learning to Machining Optimization

Using transfer learning (applying optimized machining parameters from one machining scenario to a different machining scenario) would significantly decrease the amount of experimentation required to achieve machining optimizations. Similarly, developing meta-learning frameworks (using past machining experience to optimize machining parameters for varying workpiece-tool combinations rapidly) also offers significant potential for future innovations.

8. Conclusion

To better represent current directions in the literature and emphasize the importance of continued advancement in this area, as well as increased adoption by industry practitioners, the authors suggest the following four areas of focus for future research:

- Development of Adaptive Optimization Frameworks that leverage Industry 4.0 technologies such as Internet of Things (IoT) Sensors, Cloud Computing and Edge Analytics for Real-Time Parameter Adjustment;
- Creation of Sustainability-Integrated Multi-Objective Formulations that include Productivity, Quality, Cost and Environmental Impact Considerations throughout Entire Manufacturing Systems;
- Development of User-Friendly Decision-Support Tools with Intuitive Visualization Methods and Natural Language Interfaces to Facilitate Industrial Adoption among Manufacturing Practitioners;
- Establishment of Validation Protocols for Digital Twin-Based Optimization Methodologies to Ensure Practical Applicability within Diverse Manufacturing Environments.

As both physics-based machining models and AI-driven real-time sensor monitoring improve concurrently with available computational resources, it is clear that the development of Intelligent Autonomous Machining Optimization Systems capable of adaptive self-learning parameter selection will be the next logical step in the progression of CNC manufacturing technology. Further, the convergence of these emerging technologies has the potential to greatly increase manufacturing competitiveness through improvements in product quality, manufacturing flexibility, cost savings and sustainable performance. Additionally, they have the capability to transform the nature of how products are manufactured and provide new avenues of opportunity for manufacturers. Therefore, it is imperative to encourage further research into the applications of machine learning within machining processes, as well as increased adoption of machine learning methods by industry practitioners.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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