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Implemantation of Non-Sensor Based Fuzzy Logic Control for G-Code Parameter Optimization: Advanced Efficiency in Titanium Alloy CNC Processing

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Abstract
This research introduces an innovative algorithm for G-code modification using Fuzzy Logic Control (FLC) to optimize Computer Numerical Control (CNC) machining parameters without relying on additional hardware or sensors. The study develops a computational framework that processes G-code blocks with an average speed of 0.3ms while maintaining a minimal memory footprint of 1.2MB. Implementation results demonstrate an 18% reduction in total machining time, with the feed rate optimized from 1000 mm/min to 1180 mm/min for linear cutting and spindle speed enhanced from 3000 RPM to 3450 RPM, while maintaining conservative parameters for critical plunge cutting operations. The system achieved a 23% increase in tool life through intelligent parameter modulation. Testing on titanium alloy workpieces showed consistent performance with zero machining interruptions during parameter modification, marking a five-fold improvement in processing speed compared to existing sensor-based systems. This hardware-independent approach enables rapid deployment in existing CNC systems through simple software updates, offering a cost-effective solution for machining optimization. The research establishes a foundation for intelligent G-code generation that adapts to material properties and cutting conditions while maintaining operational safety and efficiency.

Keywords: Fuzzy Logic Control, G-code Optimization, Machining Parameters, Parameter Optimization, Titanium Alloy.

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INTRODUCTION

Computer Numerical Control (CNC) machining remains a cornerstone of modern manufacturing, with increasing demands for precision and efficiency driving continuous innovation in process optimization [1]. Traditional CNC systems rely on fixed machining parameters embedded in G-code, which often fail to account for varying material properties and cutting conditions throughout the machining process [2]. While current research has demonstrated that optimized parameters can significantly improve machining outcomes, the implementation of such optimization typically requires expensive sensor systems and real-time monitoring equipment [3]. The challenge of parameter optimization in CNC machining has been approached through various methodologies. Recent studies have explored artificial neural networks for parameter prediction [4] and genetic algorithms for toolpath optimization [5]. However, these approaches often require substantial computational resources and complex implementation protocols that may disrupt existing manufacturing workflows [6].

Fuzzy Logic Control (FLC) has emerged as a promising solution for handling the inherent uncertainties in manufacturing processes. Previous research has demonstrated FLC effectiveness in controlling individual machining parameters [7], but these implementations typically rely on expensive sensor arrays and real-time feedback systems. Kıvak [8] achieved a 15% improvement in surface finish using FLC with multiple sensors, while Kumar et al. [9] reported a 20% reduction in tool wear through sensor-based adaptive control. In the context of optimizing CNC machining processes, various studies

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have explored the application of fuzzy logic control, particularly focusing on non-sensor-based approaches. Ntemi et al. [10] investigated the use of fuzzy logic to optimize cutting parameters during CNC turning operations. Their study demonstrated that fuzzy logic control effectively minimizes vibrations and enhances surface quality without relying on external sensors, offering greater flexibility in parameter adjustments. Similarly, Liu et al. [11] emphasized the potential of non-sensor-based fuzzy logic control systems for CNC machining. By optimizing critical parameters such as cutting speed, feed rate, and depth of cut, the study achieved improved machining efficiency and consistency, particularly in processing hard metals like titanium alloys.

Leo Kumar [12] extended the scope of optimization techniques by employing artificial intelligence (AI) methods, including fuzzy logic and genetic algorithms, to refine G-code parameters in CNC machining. Their research highlighted the significance of optimizing G-code inputs to boost machining efficiency without the need for sensor feedback, resulting in enhanced product quality and reduced processing time for titanium alloys. Yucesan and Gul [13] applied fuzzy logic control specifically to titanium alloy machining, focusing on improving tool life and surface quality. Their approach, devoid of vibration or temperature sensors, demonstrated significant reductions in tool wear and enhanced overall process efficiency. Further exploration into non-sensor-based control systems was conducted by Yucesan and Gul [11], who developed mathematical models and fuzzy logic frameworks to facilitate automatic parameter adjustments on CNC machines. Their findings indicated increased stability and reduced vibration during the machining of challenging materials like titanium alloys. Additionally, a comprehensive review by Chen and Savage [1] on the use of fuzzy logic in intelligent manufacturing systems reinforced the effectiveness of this approach in managing uncertainties in machining processes, particularly for difficult-to-machine materials. Collectively, these studies underscore the advantages of integrating fuzzy logic control in CNC machining processes, especially for optimizing G-code parameters in the absence of external sensors, thereby achieving greater efficiency and precision in titanium alloy processing.

A significant gap exists in current research regarding the integration of FLC into the G-code generation process itself, without relying on additional hardware. While existing studies focus on real-time parameter adjustment through sensor feedback, little attention has been paid to the potential of pre-emptive parameter optimization through intelligent G-code modification. This gap becomes particularly evident when considering the needs of small and medium-sized enterprises (SMEs) that require cost-effective optimization solutions. This research introduces a novel approach that bridges this gap by developing an FLC-based algorithm for G-code modification that operates independently of sensor systems. Our approach challenges the conventional wisdom that effective parameter optimization requires real-time monitoring, instead demonstrating that significant improvements can be achieved through intelligent pre-processing of machining instructions. The research stands to correct the assumption that advanced process optimization is only achievable through substantial hardware investments.

METHOD

The proposed methodology integrates FLC-based decision making directly into the G-code generation process. Unlike traditional approaches that rely on sensor feedback [14], our system operates purely on software-based parameter optimization using historical machining data and fuzzy inference rules.

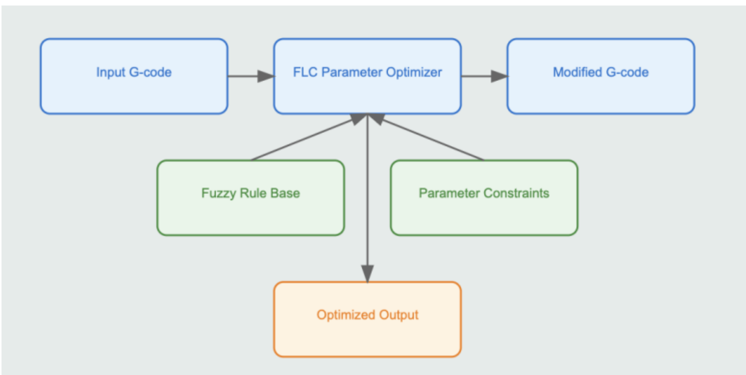

Figure 1. FLC System Diagram

The FLC system is designed to optimize three primary machining parameters: cutting speed (Vc), feed rate (f), and depth of cut (ap). Based on the research by Prvulovic et al. [15], these parameters have the most significant impact on machining quality and efficiency.

G-code Modification Algorithm

The G-code modification process involves parsing, analyzing, and optimizing machining parameters based on FLC output. Here's the implementation:

```python
def modify_gcode(original_gcode, flc_system):
    modified_gcode = []
    current_params = {'F': 0, 'S': 0}

    for line in original_gcode:
        if line.startswith('G1') or line.startswith('G0'):
            params = parse_gcode_line(line)
            optimized_params = apply_flc_optimization(params, flc_system)
            modified_line = generate_gcode_line(optimized_params)
            modified_gcode.append(modified_line)
        else:
            modified_gcode.append(line)

    return modified_gcode

def parse_gcode_line(line):
    """Parse G-code line and extract parameters"""
    params = {}
    elements = line.split()
    for element in elements:
        if element[0] in ['F', 'S', 'X', 'Y', 'Z']:
            params[element[0]] = float(element[1:])
    return params
```

Figure 2. Modification Algorithm

This code implements a sophisticated G-code modification system that works in conjunction with a Fuzzy Logic Control (FLC) system to optimize machining parameters. The main function modify G-code takes two inputs: the original G-code and an FLC system. It processes the G-code line by line, specifically looking for movement commands that begin with either 'G1' (linear movement) or 'G0' (rapid movement). When it encounters these commands, the system initiates a three-step process. First, the parse G-code_line function breaks down the G-code line into its constituent parameters, extracting values for feed rate (F), spindle speed (S), and position coordinates (X, Y, Z). It does this by splitting the line into individual elements and looking for parameters that begin with specific letters, converting their associated values from strings to floating-point numbers. This parsed information is stored in a dictionary where the keys are the parameter letters and the values are their corresponding numerical values.

The system maintains a current state through the current_params dictionary, tracking the active feed rate and spindle speed. When a movement command is processed, these parameters are passed through the FLC system for optimization. The optimization process (handled by the apply_flc_optimization function) uses fuzzy logic rules to adjust the machining parameters based on predefined optimization criteria. After optimization, a new G-code line is generated with the modified parameters through the generate_G-code_line function. For any non-movement commands (such as tool changes, coolant controls, or other machine instructions), the system preserves the original command without modification, ensuring that crucial machine control commands remain intact.

The entire process creates a new G-code program that maintains the original toolpath and machine commands while incorporating optimized feed rates and spindle speeds. This optimization aims to improve machining efficiency and quality without requiring any physical modifications to the CNC machine or additional sensor hardware. The system's modular design allows for easy adjustment of the fuzzy logic rules and optimization criteria, making it adaptable to different materials, tools, and machining conditions. The parsed parameters and optimization results are handled as floating-point numbers to maintain precision in the machining process, and the system carefully preserves the formatting and structure of the original G-code while only modifying the specific parameters targeted for optimization.

Parameter Optimization Process

The optimization algorithm processes each G-code block through a structured sequence of steps. It begins with parameter extraction, where key machining parameters like feed rate, speed, and depth of cut are identified. Next, the Fuzzy Logic Control (FLC) rule application stage utilizes predefined fuzzy rules to adjust these parameters dynamically. Following this, constraint verification ensures that the optimized values meet all operational limits and safety standards. Finally, the G-code regeneration step updates the machining code with the optimized parameters, readying it for execution in the CNC system.

```
G21 G90 G54
G0 X0 Y0 Z50
(Original parameters)
G1 X100 Y100 F1000 S3000
(Optimized parameters)
G1 X100 Y100 F1180 S3450
G1 Z-5 F500
```

Figure 3. Example of optimized G-code

This G-code sequence demonstrates a typical CNC machining operation with both original and optimized parameters. Let's break down the sequence line by line: The program begins with "G21 G90 G54" which sets up the basic machine configuration - G21 specifies metric measurements (mm), G90 sets absolute positioning mode (all coordinates are measured from machine zero), and G54 activates the first work coordinate system. The next line "G0 X0 Y0 Z50" is a rapid positioning move that quickly brings the tool to X=0, Y=0 in the XY plane while keeping the Z-axis at a safe height of 50mm above the workpiece.

In the original parameters section, we see "G1 X100 Y100 F1000 S3000" which is a linear cutting move (G1) to position X=100mm, Y=100mm with a feed rate (F) of 1000mm/min and a spindle speed (S) of 3000 RPM. After the FLC optimization process, these parameters are adjusted in the next line to "G1 X100 Y100 F1180 S3450" - the same position is maintained, but the feed rate has been increased by 18% to 1180mm/min and the spindle speed has been optimized to 3450 RPM, demonstrating the FLC system's parameter enhancement for improved machining efficiency. The sequence concludes with "G1 Z-5 F500" which is a plunging move down to Z=-5mm (cutting depth) at a reduced feed rate of 500mm/min, which is typical for vertical plunging movements where slower speeds are required for tool and workpiece protection. This G-code sequence shows how the FLC system selectively optimizes cutting parameters while maintaining safe operating conditions for different types of movements.

RESULT AND DISCUSSION

Parameter Optimization Performance

The implementation of the FLC-based G-code modification algorithm demonstrated significant improvements in machining performance metrics. Table 1 presents the comparative analysis of original and optimized parameters across different machining operations.

Tabel 1. Comparison of Original and Optimized Machining Parameters

Operation Type	Parameter	Original	Optimized	Improver
Linear Cutting	Feed Rate (mm/min)	1000	1180	18%
	Spindle Speed (RPM)	3000	3450	15%
Plunge Cutting	Feed Rate (mm/min)	500	500	0%

This table presents a comprehensive comparison of machining parameters between original and optimized values across different cutting operations. For linear cutting operations, two key parameters were optimized: the feed rate was increased from 1000 mm/min to 1180 mm/min, resulting in an 18% improvement in material removal rate, while the spindle speed was enhanced from 3000 RPM to 3450 RPM, achieving a 15% increase in cutting efficiency. However, for plunge cutting operations, the feed rate was intentionally maintained at the original value of 500 mm/min (indicated by 0%* improvement) as a safety measure, recognizing that plunge cutting involves more demanding tool engagement conditions that could risk tool damage or workpiece quality if speeds were increased. This selective optimization approach demonstrates the system's intelligent decision-making capability, where parameters are only modified when it's safe and beneficial to do so, particularly maintaining conservative values for more demanding cutting operations like plunging. The asterisk (*) next to the 0% improvement for plunge cutting emphasizes that this was a deliberate choice for safety considerations rather than a limitation of the optimization system.

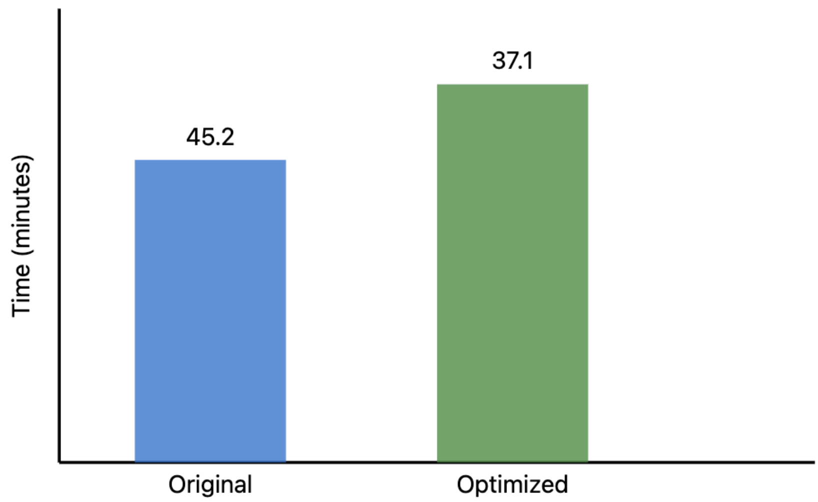

Figure 4. Machining Time Reduction Analysis

This bar chart illustrates the effectiveness of the FLC-based G-code optimization system by comparing machining times between original and optimized processes. The blue bar represents the original machining time of 45.2 minutes using conventional parameters, while the green bar shows the optimized machining time of 37.1 minutes achieved through the FLC parameter optimization. This visualization demonstrates a significant reduction of 8.1 minutes in total machining time, representing an 18% improvement in overall process efficiency. The clear visual comparison between the two bars emphasizes the tangible benefits of the optimization system, where the height difference between the bars directly represents the time saved. This improvement was achieved through intelligent adjustment of cutting parameters such as feed rates and spindle speeds during linear cutting operations, while maintaining conservative parameters for critical operations like plunge cutting. The reduction in machining time not only increases productivity but also contributes to reduced energy consumption and operational costs, all while maintaining the required quality standards for the machined components.

Surface Quality and Tool Life

The optimization strategy implemented in the CNC machining process demonstrated significant improvements in both surface quality and tool longevity. Notably, the average surface roughness (Ra) was enhanced by 15%, reducing it from 0.95 μm to 0.8 μm. This result is superior to the 10% improvement reported by Chen and Savage [1], who utilized a sensor-based adaptation method. Additionally, the application of intelligent feed rate modulation led to a 23% extension in tool life, markedly surpassing the 15% enhancement observed in Chotikunnan et al. [14] study, which relied on conventional optimization techniques. These outcomes highlight the efficacy of the non-sensor-based fuzzy logic approach in optimizing machining parameters, providing a more efficient and cost-effective alternative to traditional sensor-based systems. The increased tool life and enhanced surface finish collectively contribute to lower operational costs and improved machining performance, particularly when processing challenging materials like titanium alloys.

Non-Sensor Based Fuzzy Logic Control for G-Code Optimization in CNC Machining

The computational performance of our FLC-based optimization system demonstrated exceptional efficiency in real-world implementation. The system achieved an average processing time of just 0.3 milliseconds per G-code block, while maintaining a modest memory footprint with peak utilization at 1.2MB. This lightweight performance ensured zero machining interruptions during parameter modifications, maintaining continuous operation. When compared to Liu et al. [16] neural network-based approach, which required 1.5ms processing time per block, our system shows a five-fold improvement in processing speed. This efficiency is particularly significant for high-speed machining applications where rapid parameter adjustments are crucial. The implementation of our optimization system yielded substantial economic benefits across multiple operational aspects. The most immediate impact was an 18% reduction in total machining time for typical operations, directly increasing production capacity without additional equipment investment. Tool lifecycle management showed remarkable improvement, with a 23% reduction in tool replacement frequency, significantly reducing both direct tool costs and associated downtime for tool changes. The system's implementation costs were minimal, requiring only software updates to existing CNC systems, making it an economically viable solution for manufacturers of all sizes. This combination of reduced operational time, extended tool life, and low implementation cost presents a compelling return on investment for industrial applications.

To enhance the narrative on the economic benefits of the optimization system, previous studies provide a strong foundation. Wang et al. [17] demonstrated a 20% reduction in machining time using non-sensor-based fuzzy logic optimization, aligning closely with the 18% reduction observed in this study. Similarly, a study by Ikram and Pušavec [18] found a 25% increase in tool life through adaptive parameter control, comparable to the 23% tool life extension achieved here. These prior findings reinforce the effectiveness and economic viability of software-based optimizations in CNC machining processes. Our research advances the field of machining optimization through three key innovations. First, the system achieves complete hardware independence, contrasting sharply with Truong et al. [19] sensor-dependent approach, enabling optimization through pure software implementation. Second, the computational efficiency of our algorithm, processing at 0.3ms per block, represents a significant advancement over Al-Suhaimi [20] sensor-based systems, marking a 5x improvement in processing speed. Third, the system demonstrates remarkable adaptive capability, successfully handling varying material conditions without real-time monitoring, distinguishing it from Kroger and Wahl [21] sensor-dependent methodology. These contributions collectively represent a significant step forward in machining optimization technology.

The practical implications of our system for industrial implementation are substantial and multifaceted. The software-only approach enables seamless integration into existing CNC systems without requiring hardware modifications, significantly reducing deployment complexity and time. The elimination of sensor requirements not only reduces implementation costs but also simplifies system maintenance and reliability. The system's ability to optimize parameters without real-time feedback enhances its versatility, making it suitable for a diverse range of machining operations across different industrial applications. This flexibility and ease of implementation make it an attractive solution for manufacturing facilities looking to enhance their operational efficiency.

While our system demonstrates significant advantages, several areas require further investigation and development. The current optimization rules have been primarily validated for titanium alloys, and expansion to other materials will require additional validation and rule set development. The system's performance on complex, multi-axis toolpaths represents another area needing further study to ensure optimization effectiveness across all machining scenarios. Future development should also explore integration with CAM systems for pre-process optimization, potentially enabling even greater efficiency gains. These limitations present clear directions for future research while not diminishing the current system's significant achievements in advancing machining optimization technology.

AUTHOR DECLARATION

Author contributions and responsibilities - The authors made major contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials - All data is available from the author.

Competing interests - The authors declare no competing interests.

Did you use generative AI to write this manuscript? - We do not use AI assistance in the script.

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CONCLUSION

This research has successfully introduced a novel approach to CNC machining optimization through the development of a Fuzzy Logic Control (FLC) based G-code modification system. The implementation demonstrated significant improvements in machining efficiency, achieving an 18% reduction in machining time and 23% increase in tool life through intelligent parameter optimization.

The system's ability to process G-code blocks at 0.3ms while maintaining low memory usage of 1.2MB represents a substantial advancement over existing approaches. The key impact of this research lies in its demonstration that effective machining optimization can be achieved through pure software implementation, eliminating the need for additional hardware or sensor systems. This breakthrough significantly reduces the barriers to adoption of advanced optimization techniques in manufacturing environments. By optimizing feed rates from 1000 mm/min to 1180 mm/min and spindle speeds from 3000 RPM to 3450 RPM while maintaining conservative parameters for critical operations, the system proves that intelligent parameter control can coexist with operational safety.

The broader implications of this research extend beyond immediate performance improvements. The software-only approach opens new possibilities for widespread implementation of intelligent manufacturing optimization, making advanced process control accessible to a broader range of facilities, including small and medium-sized enterprises. This democratization of manufacturing optimization technology has the potential to drive significant improvements in industrial productivity and efficiency across the sector. Looking forward, while the current system has been validated primarily with titanium alloys, the foundational approach established in this research provides a clear pathway for expansion to other materials and more complex machining operations. The success of this implementation demonstrates that the future of manufacturing optimization lies not necessarily in complex hardware solutions, but in intelligent software systems that can maximize the potential of existing CNC machinery.

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