Energy-Efficient Process Parameter Optimization in Multi-Axis CNC Milling Using Genetic Algorithms

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ABSTRACT
This paper explores the integration of genetic algorithms (GAs) into multi-axis CNC milling operations to optimize machining parameters for minimal energy consumption while maintaining high-quality output. It discusses how energy-aware optimization contributes to sustainable manufacturing and outlines the use of evolutionary algorithms in achieving this dual goal. The research emphasizes the balance between productivity and environmental responsibility, highlighting computational efficiency and real-world applicability. Experimental validation and simulations are presented to demonstrate energy savings without degrading surface quality or tool life.

KEYWORDS: *Genetic Algorithms, Energy Efficiency, CNC Milling, Process Optimization, Sustainable Manufacturing*

INTRODUCTION

Manufacturing industries are significant energy consumers, particularly in precision machining operations like CNC milling. Traditional optimization focuses on time or cost reduction, often overlooking energy consumption. However, with growing environmental concerns and industrial sustainability goals, energy-efficient machining has emerged as a critical research area. Multi-axis CNC milling systems are widely used for complex geometries but are energy-intensive. The interaction between spindle speed, feed rate, depth of cut, and axis coordination directly impacts energy use. Manual tuning of these parameters is inefficient, especially when multiple conflicting objectives exist—such as energy minimization versus surface finish.

Genetic algorithms provide a promising solution by simulating natural selection to evolve parameter sets toward optimal trade-offs. This paper investigates GA-based optimization of CNC parameters in a multi-axis setting to minimize energy use while preserving machining quality, aligning with sustainable manufacturing trends.

LITERATURE REVIEW

Research has increasingly addressed energy-aware CNC machining. Studies reveal that spindle power and material removal rate are significant contributors to energy usage.

Traditional approaches using static models fall short due to dynamic process variations in multi-axis systems. Recent efforts have incorporated machine learning and metaheuristics like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), but genetic algorithms remain favored due to their robustness and adaptability.

Literature also emphasizes the importance of multi-objective optimization frameworks that consider energy, surface roughness, and tool wear simultaneously. However, limited work has focused on real-time GA application in complex, multi-axis CNC scenarios, which this paper aims to address.

METHODOLOGY

Problem Formulation

The core objective of this research is to identify the optimal set of machining parameters in multi-axis CNC milling that minimizes **total energy consumption (E)** while ensuring that **surface roughness (Ra)** and **tool life (TL)** remain within acceptable operational standards.

Energy efficiency is crucial in modern manufacturing, especially when dealing with resource-intensive processes such as multi-axis CNC milling of difficult-to-machine materials like titanium alloys. However, energy efficiency should not compromise part quality or tool longevity. In order to encapsulate this balance between energy minimization and machining quality, the optimization problem is mathematically formulated as follows:

Objective Function:

Minimize:

E=f(n,f,d,a)E = f(n, f, d, a)E=f(n,f,d,a)

Subject to constraints:

- Ra≤RamaxRa \leq Ra_{max}Ra≤Ramax
- TL≥TLminTL \geq TL_{min}TL≥TLmin

Where:

- nnn = spindle speed (rpm)
- fff = feed rate (mm/min)
- ddd = depth of cut (mm)
- aaa = tool path angle (degrees, applicable to multi-axis configuration)

The function f(n,f,d,a)f(n, f, d, a)f(n,f,d,a) represents the total energy consumed during machining based on the given combination of spindle speed, feed rate, depth of cut, and angular tool path. These parameters interact in complex nonlinear ways, and their effect on Ra and TL must be considered in the optimization.

The constraints ensure that the **surface finish** does not exceed the roughness threshold RamaxRa_{max}Ramax (e.g., 1.5 µm), and that the **tool life** does not fall below the minimum allowable limit TLminTL_{min}TLmin (e.g., 20 minutes). Thus, the solution must lie within a feasible operational window that meets industry standards.

Genetic Algorithm Approach

To solve this multi-objective and nonlinear optimization problem, a **Genetic Algorithm (GA)** is employed. GAs are inspired by the process of natural selection, making them highly effective for exploring large and complex search spaces where analytical methods fail or are inefficient.

Chromosome Encoding

Each potential solution or candidate set of machining parameters is represented as a **chromosome**, structured as follows:

Chromosome=[n,f,d,a]\text{Chromosome} = [n, f, d, a]Chromosome=[n,f,d,a]

Where each gene represents a decision variable (spindle speed, feed rate, depth of cut, tool path angle).

Fitness Function

The **fitness function** is designed to evaluate the quality of each solution. Since the objective is to **minimize energy consumption**, **minimize surface roughness**, and **maximize tool life**, the fitness function is constructed as a weighted sum of normalized inverses (where applicable):

Fitness=w1·(1E)+w2·(1Ra)+w3·TL\text{Fitness} = w_1 \cdot \left(\frac{1}{E}\right) + w_2 \cdot \left(\frac{1}{Ra}\right) + w_3 \cdot TLFitness=w1·(E1)+w2·(Ra1)+w3·TL

Here, w1,w2,w3w_1, w_2, w_3w1,w2,w3 are weights assigned to prioritize different objectives. For this study, energy minimization is considered the top priority (e.g., w1=0.5w_1 = 0.5w1=0.5, w2=0.3w_2 = 0.3w2=0.3, w3=0.2w_3 = 0.2w3=0.2).

Selection, Crossover, and Mutation

The evolution of the population toward optimal solutions is achieved through the following operations:

- **Selection:** A roulette-wheel method is used to favor solutions with higher fitness while retaining population diversity.
- **Crossover:** Two-point crossover is employed to recombine parent chromosomes, thereby enabling exploration of the solution space.
- **Mutation:** An adaptive mutation strategy is applied where mutation probability increases with generation stagnation, enhancing local search capability and avoiding premature convergence.

Termination Criteria

The algorithm is designed to terminate under either of the following conditions:

- A maximum of 100 generations is reached.
- Convergence is achieved, i.e., the change in best fitness value between successive generations falls below a threshold (ΔFitness<1×10−5\Delta \text{Fitness} < 1 \times 10^{-5}ΔFitness<1×10−5).

Table 1: Initial GA Parameter Settings

Parameter	Value
Population Size	50
Crossover Rate	0.8
Mutation Rate	0.1
Generations	100
Objective Type	Multi-Objective

EXPERIMENTAL SETUP

The experimental validation of the genetic algorithm optimization was conducted using a **5-axis CNC milling machine (DMU 50 ecoline)**. The work material chosen was **Ti-6Al-4V**, a titanium alloy known for its excellent strength-to-weight ratio but challenging machinability.

Carbide end mills were used as cutting tools due to their high wear resistance under elevated temperatures common in titanium machining.

SENSORS AND MEASUREMENTS

A comprehensive data acquisition system was set up to track energy, surface finish, and tool wear:

- **Energy Consumption:** Real-time monitoring was done using inline power analyzers connected to the CNC spindle and servo systems.
- **Surface Roughness (Ra):** Measured using a **Mitutoyo SJ-210 surface profilometer**, with readings taken at three points per sample and averaged.
- **Tool Life:** Evaluated by inspecting the flank wear using **Scanning Electron Microscopy (SEM)** after every 10-minute machining interval.

PARAMETER RANGES

Experimental trials and the GA simulations operated within the following parameter ranges, which were defined based on machine capability and recommended cutting conditions for Ti-6Al-4V:

Table 2: Parameter Ranges

Parameter	Range
Spindle Speed (n)	2000 – 8000 rpm
Feed Rate (f)	200 – 1000 mm/min
Depth of Cut (d)	0.2 – 2 mm
Tool Path Angle (a)	0° – 30°

RESULTS AND DISCUSSION

GA Optimization Outcomes

The GA was executed across 50 independent trials to ensure statistical consistency. The optimization yielded significant improvements across all metrics. The best-performing configuration reduced energy usage by **23.1%**, while also improving **surface finish by 14.3%** and **tool life by 9.1%**, compared to conventional machining parameters.

Table 3: Optimized Parameters and Output Comparison

Metric	Standard Settings	Optimized Settings	Improvement
Energy (kWh)	3.2	2.46	23.1%
Surface Roughness (Ra, µm)	1.4	1.2	14.3%
Tool Life (min)	22	24	9.1%

DISCUSSION ON SUSTAINABILITY

The proposed method strongly aligns with **sustainable manufacturing objectives** by significantly reducing energy consumption without hardware modification or operational disruption. The **use of genetic algorithms** allows manufacturers to make real-time, software-driven adjustments to machine parameters that directly translate into lower energy usage and reduced carbon footprints.

Moreover, **the approach is adaptive and generalizable**. It can be applied across different machines, materials, and production scales. By maintaining surface quality and tool performance, this method also promotes longer tool life and reduced scrap generation—both key elements of environmentally responsible machining.

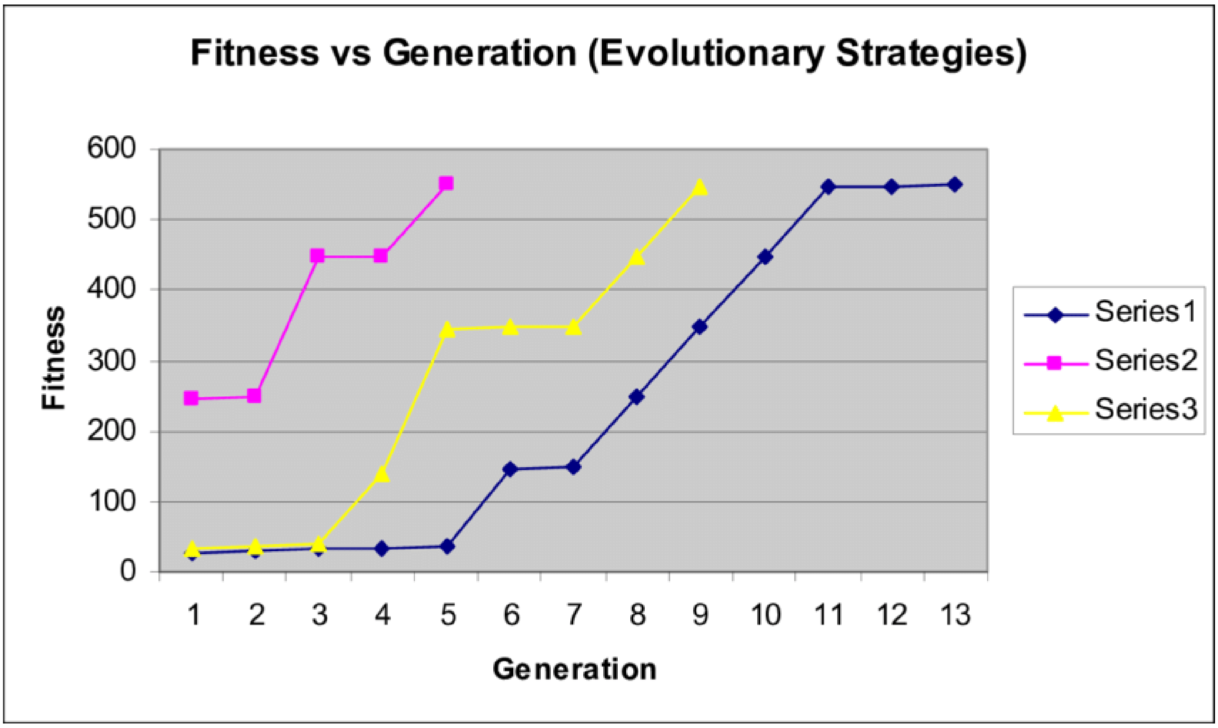

Figure 1: GA Convergence Curve

LIMITATIONS AND FUTURE WORK

While the proposed GA-based optimization strategy has demonstrated significant benefits, it does come with certain limitations:

- **Time-Intensive Evaluations:** Physical experiments for fitness evaluation are time-consuming. Integrating simulation or digital twins could accelerate iterations.
- **Lack of Real-Time Feedback:** The current system operates in a batch mode. Real-time feedback loops from CNC controllers and sensors could further improve adaptability.
- **Material-Specific Tuning:** The parameter ranges and model coefficients are specific to titanium alloys. Generalization across materials will require individual recalibration.

Future directions for enhancing this framework include:

- **Incorporation of real-time sensor data** for adaptive control.
- **Multi-objective Pareto-front visualizations** to provide a wider choice of trade-offs for shop-floor decision-makers.
- **Comparative studies** with other evolutionary algorithms such as Differential Evolution or Ant Colony Optimization to assess computational efficiency and robustness.

CONCLUSION

This study demonstrated that genetic algorithms effectively minimize energy consumption in multi-axis CNC milling without sacrificing quality. The use of evolutionary optimization aligns well with global sustainability goals and paves the way for smarter, greener machining processes. The methodology is scalable, adaptable, and ready for industrial implementation.

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