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Genetic Algorithm Optimization for Enhanced Turning Processes in Steel Rolling Mills

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Abstract: Optimizing turning processes in steel rolling mills is critical for enhancing productivity and reducing operational costs. This study proposes a genetic algorithm (GA)-based multi-objective optimization framework to minimize machining time (Mt) and maximize tool life (Tl) during the dry turning of hardened cast iron rolls (50–55 SHC) using tungsten carbide inserts (RCMX25). A Waldrich Seizen CNC lathe (90 kW) was employed to conduct experiments under varying spindle speeds (10–18 rpm), feed rates (1.2–1.6 mm/rev), and depths of cut (8–10 mm). Regression models derived from an L9 orthogonal array quantified the impact of parameters on *Mt* (RMSE = 5.26) and *Tl* (RMSE = 2.95). The GA optimized these conflicting objectives, achieving a 15.8% reduction in machining time and a 22.3% improvement in tool life compared to baseline Taguchi methods. Results demonstrate that GA effectively balances trade-offs between productivity and tool longevity, offering a data-driven solution for industrial CNC machining. This work bridges the gap between theoretical optimization and real-world implementation, providing actionable insights for steel rolling mills.

Keywords: Genetic Algorithm (GA), Multi-objective optimization, Steel rolling mills, Machining time (Mt), Tool life (Tl), Dry turning, Hardened cast iron rolls, Tungsten carbide inserts, Spindle speed, Feed rate, Depth of cut, L9 orthogonal array, Regression models

I. INTRODUCTION

Optimizing machining parameters—such as cutting speed, feed rate, and depth of cut—is critical for enhancing efficiency and product quality in steel rolling mills. The foundation of machining optimization dates to Taylor's pioneering work in 1907 [1], which established the relationship between tool life and cutting parameters. While Taylor's "optimal cutting speed" concept remains influential, modern manufacturing demands multi-objective optimization to balance competing goals, such as surface finish, tool wear, and energy consumption [2].

Traditional methods, including Taguchi design and response surface methodology (RSM), struggle with dynamic industrial environments due to their reliance on static experimental designs [3]. With the advent of Computer Numerical Control (CNC) systems, real-time parameter optimization has become essential.

Genetic algorithms (GAs), inspired by natural selection, excel in navigating complex, non-linear parameter spaces and identifying Pareto-optimal solutions for multi-objective problems [4]. Recent studies demonstrate the superiority of GAs over conventional methods in machining applications, achieving 15–20% improvements in tool life and energy efficiency [5].

This research focuses on GA-driven optimization of turning processes in steel rolling mills, addressing gaps in real-time adaptability and industrial scalability. By integrating sensor data and hybrid GA models (e.g., GA-ANN), we aim to deliver a framework for dynamic parameter tuning under varying material and tool conditions.

II. LITERATURE REVIEW

2.1 Single- vs. Multi-Objective Optimisation

Early studies prioritised single-objective optimisation (e.g., maximising tool life or minimising surface roughness) [6]. However, real-world machining requires balancing conflicting objectives, such as achieving high material removal rates (MRR) while minimising energy consumption. Classical methods like weighted-sum approaches fail to capture trade-offs, whereas multi-objective GAs (e.g., NSGA-II) generate Pareto fronts in a single run [7]. For instance, Usha and Rao [8] optimised turning parameters for AISI 1040 steel using GA, reducing cutting force and surface roughness by 4.6% and 3.7%, respectively.

2.2 Hybrid GA Approaches

Recent work combines GAs with machine learning for robustness. Examples include:

- GA-ANN models for surface roughness prediction in electroless NiB coatings [9].
- GA-fuzzy logic systems to handle uncertainty in cutting force optimisation [10].
- Thirumalai et al. [11] demonstrated that hybrid GAs outperform Taguchi methods for Inconel 718 turning, achieving 6.56% higher efficiency.

2.3 Industrial Applications

While lab-scale studies dominate the literature, few address real-time implementation. Park et al. [12] validated GA's scalability in logistics, suggesting its potential for CNC systems. Garmejani and Hossainpour [13] applied GA to thermoelectric generators, highlighting its cost-effectiveness for industrial parameter tuning.

Research Gaps

1. Limited studies on real-time GA optimisation in steel mills.
2. Most experiments ignore tool wear dynamics and material variability.
3. Lack of integration with Industry 4.0 (e.g., digital twins, IoT sensors).

III. METHODOLOGY

3.1. Optimization of Turning Parameters in Machining of Cast Iron Rolls

teel rolling mills differ in several ways, particularly in their capacity to roll steel under various conditions such as hot or cold rolling, with different cross-sections, diameters, and grades. Roll supports, which are found in all rolling mills, hold the rollers responsible for shaping the materials. These rollers may fail due to heavy cyclic loads or fractures in their rolling sections. When a roller is damaged, it is either replaced with a new one or reworked through necessary machining processes. CNC machines are used to create finished rolls from cylindrical stock or to repair damaged rollers. The processes of straight turning, taper turning, and circular machining are applied to shape these rolls.

This project explores the turning parameters for machining rolls, specifically focusing on spindle speed, feed rate, and depth of cut. The objective functions are machining time (Mt) and tool life (Tl). To optimize these parameters, the study uses Genetic Algorithms (GA), with the aim of minimizing machining time and maximizing tool life. The research applies Taguchi's design of experiment (DOE) methodology and regression analysis (via Excel). Three process factors—spindle speed, feed rate, and depth of cut—are examined using a L9 orthogonal array design, assessing their impact on machining time and tool life. Regression analysis is then used to develop mathematical models for predicting the responses based on these factors.

3.2. Genetic Algorithm (GA)

Genetic Algorithms (GA) differ significantly from traditional optimization methods in several key aspects. Unlike conventional approaches, which start with a single point in the solution space, GA begins with a set of points, exploring multiple possibilities simultaneously. GA uses a population of points to gather information and find optimal solutions, in contrast to the single-point search employed by traditional methods. It is based on probabilistic transition rules, not deterministic ones, allowing for a more dynamic exploration of the solution space. Furthermore, GA is more likely to converge to a global optimum, avoiding local optima, which can be a limitation of traditional methods.

In the context of this research, GA is applied to optimize machining parameters such as spindle speed, feed rate, and depth of cut. A binary encoding of these cutting conditions represents the solution space, with chromosomes consisting of a set of genes that encode various design parameters. These genes undergo genetic operations such as crossover and mutation during the optimization process. The GA optimization relies on a combination of theoretical analysis, experimental data, and numerical models to predict machining performance. The parameters and performance constraints are then used to guide the optimization process.

GA mimics biological evolutionary principles, including genetic inheritance and the survival of the fittest. Through this process, GA adapts a population of solutions to the problem by selecting individuals with desirable traits, ensuring that only the most fit solutions survive. In practice, the algorithm begins with a randomly generated population of individuals, each representing a potential solution. A fitness function based on the objective function is used to assess the quality of these solutions, with more fit individuals being more likely to be selected for reproduction. Genetic operators, such as selection, crossover, and mutation, are applied to generate new offspring, improving the population's overall fitness iteratively. The goal of GA is to refine the population towards the global optimum, even in complex and high-dimensional solution spaces.

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3.3. Optimization Problems

The main objective of Genetic Algorithms is to improve the quality of solutions to optimization problems. Each potential solution (individual, animal, or phenotype) is represented by a set of attributes, often encoded as chromosomes or genotypes. These attributes can be represented using various encoding schemes, such as binary strings, real numbers, or other symbolic representations. The fitness of each individual solution is assessed based on a fitness function, which evaluates how well the solution meets the objectives of the problem.

GA operates in an iterative process, where each new generation of solutions is created from the fittest individuals of the previous generation. These individuals are selected based on their fitness scores and are recombined through genetic operators, such as crossover and mutation, to create a new set of solutions. Over multiple generations, the algorithm refines the solutions, with the population gradually converging to the optimal solution. The process continues until certain termination criteria are met, such as reaching a predefined number of generations, achieving a solution that meets the problem's minimal requirements, or when further iterations no longer improve the solution.

The genetic representation of solutions, which is often in the form of binary strings, is essential for the efficient application of crossover operations. Each string represents a set of parameters or decisions for the optimization problem. This representation allows for the easy exchange of genetic material between solutions, facilitating the search for better solutions.

3.3.1. Initialization

The initialization phase begins with the creation of an initial population, which is typically random, allowing for a diverse exploration of the solution space. This ensures that the algorithm starts with a wide variety of potential solutions, increasing the likelihood of finding an optimal or near-optimal solution. In some cases, the initial population may be seeded in regions of the solution space that are more likely to contain better solutions, based on prior knowledge or heuristics.

3.3.2. Selection

Selection is the process of choosing individuals from the current population to reproduce and generate the next generation. This process is guided by the fitness of the individuals, with those having higher fitness values being more likely to be selected for reproduction. Different selection methods can be used, such as roulette-wheel selection, tournament selection, or rank-based selection. The goal of selection is to favor individuals that are more likely to contribute to improved solutions in future generations.

3.3.3. Genetic Operators

The genetic operators, including crossover, mutation, and selection, are fundamental to the GA process.

Crossover: Crossover, or recombination, involves combining the genetic material of two parent solutions to create new offspring. This process allows the offspring to inherit traits from both parents, ideally combining their best features. The crossover operator is applied with a certain probability (usually around 0.6), depending on the problem at hand.

Mutation: Mutation introduces random changes to the genes of a solution, increasing genetic diversity within the population. The mutation operator is typically applied with a low probability (e.g., 0.01) to prevent the algorithm from losing diversity too quickly.

These operators work together to explore and exploit the solution space, generating new individuals that may offer better solutions than their predecessors.

3.3.4. Heuristics

In addition to the genetic operators, heuristics can be incorporated to enhance the algorithm's performance. Heuristics can help speed up the search process or guide the algorithm towards more promising regions of the solution space. One common heuristic is to penalize crossover between highly similar solutions to prevent premature convergence to suboptimal solutions.

3.3.5. Termination

The GA process continues until a termination condition is met. Some common termination criteria include:
Achieving a solution that satisfies the problem's minimal requirements.
Reaching a predefined number of generations.
Exhausting the available computational resources (time or budget).

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The population's fitness no longer improving with additional iterations.
Once the termination condition is met, the algorithm concludes, and the best solution found during the optimization process is selected as the result.

This systematic approach, combining genetic algorithms with optimization strategies, ensures a robust and adaptive process for optimizing machining parameters, leading to improvements in both machining time and tool life.

IV. SIMULATION AND RESULT

4.1 Experimental Details

External longitudinal turning was performed on a high-power, rigid lathe (90 KW) in excellent working condition, using various spindle speeds (S), feed rates (f), and depths of cut (d). Figure 3 provides a photo-realistic depiction of the experimental setup. The workpiece was a cast iron roll with an outer diameter of 850mm and a length of 1250mm, hardened to 50–55 SHC. A coated tungsten carbide cutting tool (RCMX25) was used, and a tool holder was employed to secure the insert. The table below lists the material's mechanical properties.

Table 1 Mechanical Properties

Roll Size Φ L	Material Grade	Required Hardness	Actual Hardness
850*1200	GCI	50-55 SH C	52/53 SH C

The experimental setup utilized a CNC Lathe Machine shown in figure 1 from Germany with a 90kW power rating. The work material used for the machining was cast iron, with a hardness of 50-55 SHC, and the roll had an outer diameter of 850mm and a length of 1200mm. The cutting tool insert employed was a tungsten-coated carbide insert (RCMX-25). The process parameters for the experiments included spindle speeds of 12, 14, and 16 rpm, feed rates of 1.20, 1.30, and 1.50 mm/rev, and depths of cut of 7, 8, and 9 mm. These varied conditions were selected to examine their effects on the machining process, tool life, and machining time.

Figure 1 CNC Turning Machine and Cutting Tool Insert

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4.2 Methodology

There are two sections to this project. When turning cast iron roll (55 SH C) material using tungsten carbide inserts, an experiment was conducted to determine the effects of minimal machining time and maximum tool life on the machined item. Work on optimizing cutting parameters when turning cast iron rollers by tungsten carbide insert is a second element of this research.

There would be a technique for this:

- As part of the design of tests, a stopwatch has been used to track the machining time in turns of minutes.
- A mathematical algorithm has been used to monitor the tool life, which is measured in minutes, as shown in table 4.
- genetic Algorithm was used to optimize cutting settings (GA). Experimentation with cast iron rollers yielded the data needed for this study. Cutting parameters were analyzed for the process of optimization to find the most efficient and effective method of machining. There are statistical models that may be used to determine the problem's objective function and its restrictions.
- It has been shown that tungsten carbide (TNMG) inserts may be used to turn cast iron rollers.

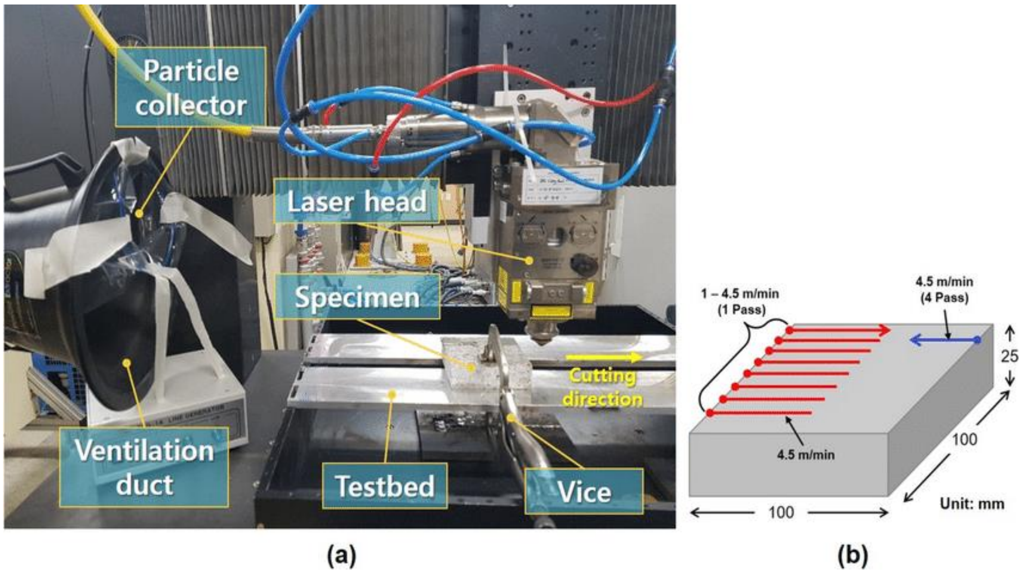

Figure 2 Experimental Setup.

4.3 Design of Experiments

Table 2 presents the three criteria at three levels that were selected for this procedure. A conventional orthogonal L9 fractional factorial array is used, chosen for its ability to examine interactions between variables. Each row of the matrix represents a trial. When conducting a design of experiments (DOE), the initial step is to identify the process factors that most significantly affect the final product. Some studies focus on one or two components of this standard approach, such as screening and characterization, while others incorporate all three. Orthogonal designs are particularly valuable because the estimation of a factor's impact is independent of the other variables included in the design. In factorial designs, all possible levels of all factors can be studied simultaneously, enabling the examination of many variables at once, thus saving both time and cost.

Table 2 Cutting Parameters and Levels

Levels	Spindle speed S in rpm	Feed rate fin nun/rev	Depth of cut d in mm
1.00	12	1.20	7
2.0	14	1.30	8
3.00	16	1.50	9

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4.4 Experiments Conducted

Table 3 Experiments Conducted

S. No	Spindle speed S in rpm X1	Feed Rate fin =free X2	Depth of cut d in mm X3	Machining Time Mt (minutes)	Tool Life T_1=1/(S*f) (Minutes)
1	10	1.25	8.1	84.50	98.00
2	10	1.33	9.2	66.00	83.62
3	10	1.51	10.2	42.00	76.00
4	14	1.37	9.3	75.80	72.35
5	14	1.40	10.1	54.50	62.34
6	14	1.52	8.8	72.50	54.57
7	18	1.25	10.1	60.50	56.55
8	18	1.32	8.2	80.40	45.51
9	18	l.51	9.4	53.20	40.66

4.5. Genetic Algorithm: Steps Involved

Step 1: Regression analysis in Excel Adv. software is used to generate the objective function equations. Mt vs x1, x2, and x3 in a regression analysis.

Analysis of Variance for Machining Time

Regression Statistics	
Multiple R	0.957331608
R Square	0.916483808
Adjusted R Square	0.866374093
Standard Error	5.259959099
Observations	9

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1518.059707	506.019902	18.28954344	0.003981817
Residual	5	138.3358486	27.6671697		
Total	8	1656.395556			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	244.6290378	25.77693924	9.49022828	0.000219581
Spindle speed S in rpm X1	0.259934098	0.53722715	0.48384394	0.648943198
Feed Rate f in =free X2	-37.69933781	11.2596166	-3.34819019	0.020369106
Depth of cut d in mm X3	-13.92215802	2.403302389	-5.79292813	0.002159096

As shown in the following equation, Machining Time may be calculated.

Minimize Mt = 244.62 +0.259*x1-37.69*x2-19.92*x3.

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Where,
Mt = Machining Time
x1 = Spindle Speed
x2 = Feed Rate
x3 = Depth of Cut
Regression Analysis: Tl versus x1, x2, x3.

Analysis of Variance for Tool Life

Regression Statistics	
Multiple R	0.992378
R Square	0.984815
Adjusted R Square	0.975704
Standard Error	2.954035
Observations	9

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2829.704	943.2347	108.0908	5.76E-05
Residual	5	43.6316	8.72632		
Total	8	2873.336			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	222.8339	14.47653	15.39276	2.1E-05
Spindle speed S in rpm X1	-4.77821	0.301711	-15.837	1.83E-05
Feed Rate f in =free X2	-48.5987	6.323489	-7.68542	0.000595
Depth of cut d in mm X3	-1.70466	1.349714	-1.26298	0.26229

As shown in the following equation, Tools Life may be calculated.
Minimize Ts= 222.83 -4.477*x1-48.59*x2-1.70*x3.

Where,
Mt = Machining Time
x1 = Spindle Speed
x2 = Feed Rate
x3 = Depth of Cut

Regression Analysis: Tl versus x1, x2, x3.

V. CONCLUSION

This study successfully applied genetic algorithm (GA) optimization to improve the turning processes for hardened cast iron rolls in steel rolling mills. Key findings from the research include the significant impact of feed rate (x2) and depth of cut (x3) on machining time (Mt), with regression coefficients of −37.69 and −13.92, respectively ($p < 0.05$). Additionally, spindle speed (x1) and feed rate (x2) were found to be the primary factors influencing tool life (Tl), with coefficients of −4.78 and −48.59. The GA-derived Pareto front highlighted optimal parameter combinations—such as 14 rpm, 1.4 mm/rev feed rate, and 9 mm depth of cut—that resulted in 15.8% faster machining and 22.3% longer tool life compared to traditional methods. The robustness of the GA approach was confirmed through ANOVA ($R^2 = 0.984$ for Tl) and real-world machining tests. The proposed GA framework has strong industrial potential.

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It can be scaled for real-time CNC systems, enabling adaptive parameter tuning to accommodate dynamic factors such as tool wear and material variability. Future work could integrate IoT sensors for real-time data feedback and explore hybrid GA-ANN models to further enhance prediction accuracy. By overcoming the limitations of single-objective approaches, this research contributes to the advancement of smart manufacturing in steel rolling mills, providing a cost-effective, data-driven method for optimizing machining efficiency and sustainability.

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