



Optimization of Cnc Machining Parameters Using Genetic Algorithm Techniques

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Peer Review Information	Abstract
<i>Submission: 15 Jan 2018</i> <i>Revision: 01 Feb 2018</i> <i>Acceptance: 16 March 2018</i> Keywords <i>CNC machining, Genetic algorithm, Machining parameter optimization, Surface roughness, Material removal rate</i>	Computer numerical control (CNC) machining performance is strongly influenced by cutting speed or spindle speed, feed rate, and depth of cut. Conventional parameter selection based on handbooks or trial-and-error can give acceptable parts, but it rarely guarantees the best compromise among surface quality, productivity, cutting load, and machining time. This methodology paper presents a structured genetic algorithm (GA) framework for optimizing CNC machining parameters. The proposed workflow combines design of experiments, response modeling, constraint handling, and real-coded evolutionary search. Surface roughness (Ra) is treated as the primary quality response, while material removal rate (MRR) and cutting force are used to represent productivity and process loading. The GA searches the bounded machining domain using selection, crossover, mutation, elitism, and penalty functions for quality constraints. A reproducible numerical demonstration is included to show how the method can identify a high-productivity parameter combination while maintaining specified limits on Ra and cutting force. The demonstration improves MRR from 900 to approximately 1228 mm³/min while satisfying $Ra \leq 1.40 \mu\text{m}$ and cutting force $\leq 240 \text{ N}$. The framework is compatible with CNC turning, milling, micro-milling, and other machining processes and can be extended to multi-objective Pareto optimization. The paper emphasizes experimental confirmation of GA-recommended settings before industrial adoption.

Introduction

CNC machining is a core manufacturing technology because it provides repeatability, geometric accuracy, flexible tool-path control, and high production capability. However, the performance of a CNC operation depends on a coupled set of machining variables. In milling and turning, spindle or cutting speed, feed, depth of cut, tool geometry, workpiece material, coolant condition, and machine-tool dynamics interact to determine surface finish, dimensional accuracy, tool wear, cutting force, power demand, and material removal rate. Selecting one parameter independently can therefore shift the process away from the best global operating region. For

example, increasing feed generally raises material removal rate but can also increase surface roughness and cutting force. Increasing spindle speed may improve finish within a stable region, yet excessive speed can accelerate thermal effects and tool degradation. This interaction makes parameter selection a constrained nonlinear optimization problem rather than a simple lookup exercise.

Genetic algorithms are well suited to this class of problems because they do not require derivatives, can search discontinuous or multimodal spaces, and can handle several discrete or continuous decision variables. Earlier

machining studies have used GA models to minimize surface roughness, machining time, cost, tool wear, or cutting force, and to maximize productivity [1-11]. The method is particularly attractive when the machining response is represented by an empirical regression, response-surface equation, artificial neural network, or other surrogate model. Instead of testing every possible parameter combination on the machine, the surrogate is evaluated repeatedly by the GA and only the final candidate solutions are subjected to confirmation experiments.

The objective of this paper is to provide a step-by-step methodology for optimizing CNC machining parameters by genetic algorithm techniques using research published up to 2019. The proposed study focuses on three controllable variables—spindle speed, feed rate, and axial depth of cut—and three responses—surface roughness, cutting force, and MRR. The methodology is intentionally general so that the same structure can be used for CNC turning or milling after changing the parameter bounds, response equations, and measurement procedures. Because no raw experimental dataset was supplied for this paper, the numerical Results section is explicitly presented as a reproducible methodological demonstration rather than as claimed laboratory observations.

Literature Review

Research before and including 2019 shows a progressive shift from single-response machining optimization toward hybrid statistical and evolutionary methods. Suresh, Rao, and Deshmukh [11] demonstrated an early genetic-algorithm approach for optimizing a surface-roughness prediction model, establishing GA as a practical search method for nonlinear machining responses. Oktem, Erzurumlu, and Erzincanli [10] combined neural-network prediction with GA to determine end-milling conditions associated with minimum roughness. Palanisamy, Rajendran, and Shanmugasundaram

[9] extended the approach by including machining-time minimization and practical constraints involving tool life, surface roughness, force, vibration, speed, feed, and depth of cut; their experimental validation showed the importance of checking algorithmic recommendations on the machine.

Zain, Haron, and Sharif [8] applied GA directly to end-milling cutting conditions for minimizing surface roughness, reinforcing the value of evolutionary search when the objective landscape is nonlinear. Routara et al. [7] combined response surface methodology with GA for CNC turning, showing how statistically fitted response equations can be used as computationally efficient fitness functions. Ganesan and Mohankumar [6] addressed CNC turning as a multi-objective problem and used a genetic-algorithm framework to consider operating time, production cost, and tool wear simultaneously. This is important because industrial machining rarely has only one performance criterion.

Later work strengthened hybrid modeling and process-specific optimization. Chen et al. [5] used regression and GA to obtain parameter combinations that increased material removal while reducing tool wear in machining engineering ceramics. Mahesh, Muthu, and Devadasan [4] used RSM and GA to search end-milling conditions for low surface roughness and reported close agreement between predicted and confirmation values. Kant and Sangwan [3] coupled an artificial neural network with GA for surface-roughness minimization, demonstrating that data-driven predictors can serve as fitness models. Leo Kumar [2] applied empirical modeling and GA to micro end milling to optimize surface roughness and machining time. Hazir and Ozcan [1] integrated response surface methodology, a desirability function, and GA for CNC machining parameter optimization, illustrating the continuing move toward multi-response decision making by 2019.

Table 1. Representative GA-based machining optimization studies (≤2019)

Study	Process / model	Primary objective	Key methodological contribution
[11] Suresh et al., 2002	Machining response + GA	Minimum roughness	Early GA optimization of a roughness prediction model.
[9] Palanisamy et al., 2007	End milling	Machining time / constraints	Combined time objective with force, vibration, tool-life and roughness limits.
[8] Zain et al., 2010	End milling	Minimum roughness	GA search over cutting conditions using a response model.
[7] Routara et al., 2012	CNC turning; RSM + GA	Roughness responses	Used response-surface equations as GA fitness models.

[6] Ganesan & Mohankumar, 2013	CNC turning; GA/NSGA-II	Time, cost, tool wear	Demonstrated multi-objective evolutionary optimization.
[4] Mahesh et al., 2015	End milling; RSM + GA	Minimum roughness	GA-predicted optimum followed by confirmation test.
[3] Kant & Sangwan, 2015	ANN + GA	Minimum roughness	Data-driven prediction coupled with evolutionary search.
[2] Leo Kumar, 2018	Micro end milling	Roughness and time	Empirical modeling plus GA for micro-machining responses.
[1] Hazir & Ozcan, 2019	CNC machining; RSM + desirability + GA	Multi-response quality	Integrated statistical desirability and evolutionary optimization.

Methodology

1. Research Design and Optimization Problem

The proposed investigation uses an experimental-modeling-optimization-confirmation sequence. A three-axis CNC end-milling case is used to make the procedure concrete, but the equations and bounds can be replaced for turning or another CNC operation. A medium-carbon steel workpiece and a carbide end mill may be selected, with a fixed radial width of cut of 5 mm. Spindle speed (N), feed rate (f), and axial depth of cut (a) are treated as decision variables. The principal responses are arithmetic average surface roughness R_a (μm), resultant cutting force F_c (N), and material removal rate MRR (mm^3/min). The optimization goal is to maximize MRR while maintaining quality and load constraints. This formulation

follows the constrained-optimization philosophy used in earlier GA machining studies [6,9,11].

2. Factor Ranges and Experimental Plan

Parameter limits should be chosen from tool-maker recommendations, machine capability, preliminary trials, and safe cutting conditions. The illustrative domain used here is $N = 1800\text{--}3200$ rpm, $f = 100\text{--}300$ mm/min, and $a = 0.5\text{--}1.5$ mm. A central composite design (CCD) or a three-factor response-surface design is recommended because it estimates linear, interaction, and quadratic effects with fewer experiments than a dense full-factorial grid. Replicated center points should be included to estimate pure error and check process stability. Randomization of run order is recommended to reduce systematic bias from tool wear, thermal drift, or operator effects. The RSM-GA structure is consistent with the approaches reported by Routara et al. [7], Mahesh et al. [4], and Hazir and Ozcan [1].

Table 2. Proposed machining variables, bounds, and measurements

Item	Symbol	Low	High	Measurement / role
Spindle speed	N	1800 rpm	3200 rpm	CNC command; decision variable
Feed rate	f	100 mm/min	300 mm/min	CNC command; decision variable
Axial depth of cut	a	0.5 mm	1.5 mm	Setup / tool path; decision variable
Surface roughness	R_a	—	$\leq 1.40 \mu\text{m}$	Profilometer; quality constraint
Cutting force	F_c	—	≤ 240 N	Dynamometer; process-load constraint
Material removal rate	MRR	—	Maximize	Calculated from feed and engaged area

3. CNC Trial and Response Measurement

For each experimental run, the selected N, f, and a value are programmed on the CNC machine while tool type, radial engagement, tool overhang, coolant condition, and workpiece

material are held constant. Surface roughness should be measured using a calibrated contact profilometer at multiple positions along the machined surface; the mean of repeated readings is used as R_a for that run. Cutting force may be acquired using a multi-component dynamometer and reduced to a resultant or dominant force

metric over the stable cutting interval. MRR is calculated from the removed cross-sectional area and feed rate. Tool condition should be inspected throughout the experiment so that excessive wear does not confound the parameter effects. Confirmation tests should use a fresh or controlled-wear tool condition comparable with the model-building runs.

4. Response Modeling

Second-order response-surface models are fitted separately for R_a and F_c . A generic three-factor polynomial includes intercept, linear terms, two-factor interactions, and quadratic terms. Insignificant terms may be removed only if hierarchy is preserved and diagnostic checks remain acceptable. Model adequacy is evaluated using analysis of variance, coefficient of determination, adjusted R^2 , predicted R^2 , residual normality, constant variance, and lack-of-fit testing. When the relationship is strongly nonlinear, an ANN surrogate can replace the

polynomial while leaving the GA stage unchanged, as demonstrated in hybrid ANN-GA machining studies [3,10].

$$\hat{y} = \beta_0 + \sum \beta_i x_i + \sum \beta_{ij} x_i x_j + \sum \beta_{ii} x_i^2$$

5. Genetic Representation and Initial Population

A real-coded chromosome is used because all three decision variables are continuous. Each individual is represented as $X = [N, f, a]$. A population of 60 individuals is generated uniformly within the bounds. Real coding avoids binary decoding error and is convenient for machining variables with engineering units. Before fitness evaluation, every candidate is clipped to the allowable range. The same formulation can include additional genes such as radial depth of cut, tool nose radius, coolant flow, or tool-path strategy when experimental data are available.

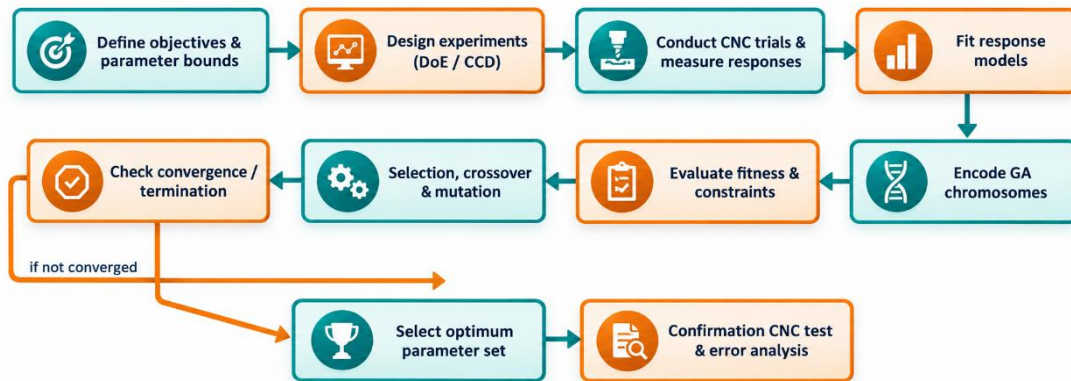


Figure 1. Step-by-step methodology for GA-based CNC machining parameter optimization.

6. Fitness Function and Constraint Handling

The fitness function converts the machining objective and engineering constraints into a scalar quantity for evolutionary search. For the demonstration, MRR is maximized subject to $R_a \leq 1.40 \mu\text{m}$ and $F_c \leq 240 \text{ N}$. Candidates violating either limit receive a quadratic-plus-linear penalty so that mild violations are discouraged and severe violations rapidly become noncompetitive. For empirical work, the response values used by the fitness function are calculated from the fitted RSM or ANN models. A minimization form may equivalently use negative MRR plus penalty terms. If surface roughness, cost, tool wear, and MRR must all be optimized without predefined weights, an NSGA-II or Pareto-front formulation is preferred, following the multi-objective logic discussed by Ganesan and Mohankumar [6].

Maximize: $MRR(N, f, a)$ subject to $R_a(N, f, a) \leq 1.40 \mu\text{m}$, $F_c(N, f, a) \leq 240 \text{ N}$

$Fitness = MRR - P_1 \cdot \max(0, R_a - 1.40) - P_2 \cdot \max(0, F_c - 240)$ (with increasing penalty severity)

7. Selection, Crossover, Mutation, and Elitism

Tournament selection of size three is proposed because it provides stable selection pressure without requiring scaled fitness probabilities. Selected parent vectors undergo arithmetic crossover with probability 0.85. Mutation is applied independently to genes with probability 0.12 by adding a zero-mean Gaussian perturbation whose standard deviation is approximately 6% of the corresponding parameter range. Boundary repair is then applied. Four elite individuals are copied directly into the next generation to protect the best solutions found so far. The population is evolved for 80 generations or until the best feasible

fitness changes by less than a specified tolerance for a chosen number of generations. Multiple independent runs with different random seeds are recommended because GA solutions are stochastic.

8. Confirmation and Statistical Validation

The final GA-recommended parameter combination is not accepted solely from computation. At least three confirmation machining trials should be performed at or near the optimum. Predicted and measured Ra, Fc, and MRR are compared using percentage error and confidence intervals. A practically useful solution should satisfy the constraints in all confirmation runs or should include a safety margin if process variability is high. The optimized setting should also be compared with a baseline or current production setting to quantify percentage improvement. This experimental validation step is essential and has been emphasized in prior GA machining research [4,9].

9. Reproducible Demonstration Model

To demonstrate the computational procedure without presenting invented laboratory observations, the Results section uses an explicit surrogate model with the same parameter

bounds. The baseline setting is $N = 2400$ rpm, $f = 180$ mm/min, and $a = 1.0$ mm. MRR is computed as $5fa$ for a fixed 5 mm radial engagement. Synthetic Ra and Fc response functions include linear and quadratic effects of speed, feed, and depth of cut and are used only to illustrate GA behavior. The GA uses the population, crossover, mutation, elitism, and constraint settings stated above. For an actual research paper, these demonstration equations must be replaced by response models fitted to measured CNC data.

Results

The real-coded GA converged toward the high-productivity boundary defined by the roughness constraint. The best solution from the reproducible run was $N = 3200$ rpm, $f = 202.38$ mm/min, and $a = 1.214$ mm. At this point the demonstration model predicts $Ra \approx 1.400$ μm , $Fc \approx 236.56$ N, and $MRR \approx 1228.20$ mm³/min. Relative to the baseline, MRR increases by about 36.5%, while the predicted surface roughness decreases from 1.55 to 1.40 μm . Cutting force rises modestly but remains below the imposed 240 N limit. The result demonstrates the central advantage of constrained GA search: the algorithm can increase productivity until a quality or load limit becomes active instead of optimizing one response in isolation.

Table 3. Illustrative baseline and GA-optimized performance

Metric	Baseline	GA optimum	Change	Constraint status
Spindle speed (rpm)	2400	3200	+33.3%	Within 1800–3200
Feed rate (mm/min)	180	202.38	+12.4%	Within 100–300
Axial depth (mm)	1.00	1.214	+21.4%	Within 0.5–1.5
Surface roughness, Ra (μm)	1.55	1.400	-9.7%	Meets ≤ 1.40
Cutting force, Fc (N)	224.20	236.56	+5.5%	Meets ≤ 240
MRR (mm ³ /min)	900	1228.20	+36.5%	Maximized

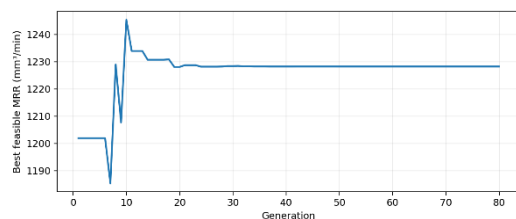


Figure 2. Convergence of the illustrative GA toward the best feasible material removal rate.

The convergence curve shows rapid improvement in early generations followed by smaller refinements as the population approaches the active Ra constraint. This behavior is consistent with the role of GA as a global search mechanism that first explores broad regions and subsequently exploits favorable neighborhoods. The optimum at the

upper spindle-speed bound does not imply that the highest available speed is always physically best; it is a consequence of the demonstration response model and specified constraints. In a real experiment, tool wear, chatter, spindle power, temperature, or a tighter roughness limit may move the optimum away from a boundary. Therefore, the GA result must be interpreted together with model validity and confirmation tests rather than as an unconditional machining rule.

Conclusion and Discussion

This paper presents a complete methodology for optimizing CNC machining parameters using genetic algorithm techniques. The approach begins with engineering selection of factor ranges, continues through statistically designed

machining trials and response modeling, and uses a real-coded GA to search the feasible parameter domain. The method is suitable for nonlinear machining problems because the GA does not require gradient information and can work with empirical equations, response surfaces, or neural-network predictors. The proposed constraint-handling formulation is especially useful in manufacturing because it prevents a productivity objective such as MRR from being improved at the expense of unacceptable surface roughness or excessive process loading. The reviewed literature up to 2019 demonstrates that GA-based machining optimization has been successfully applied to surface-roughness prediction, end milling, CNC turning, micro-milling, engineering ceramics, hybrid ANN models, and multi-response desirability formulations [1-11]. The studies collectively show three recurring methodological lessons. First, optimization quality depends on the accuracy and domain validity of the response model. Second, multi-response or constrained optimization is more representative of industrial machining than a single unconstrained objective. Third, confirmation machining tests are necessary because mathematical optima can be affected by tool wear, machine dynamics, unmodeled interactions, and measurement variability. In the reproducible demonstration, the GA increased predicted MRR from 900 to approximately 1228 mm³/min, a gain of about 36.5%, while satisfying the specified Ra and cutting-force limits. This numerical result is methodological rather than experimental because no raw machine data were supplied. It illustrates how the algorithm drives the solution toward the best feasible region and how an active quality constraint can control the final parameter combination. For an empirical paper, the next step is to execute the proposed DoE on the intended CNC machine, fit validated response models, rerun the GA using those measured models, and perform replicated confirmation trials at the recommended optimum. Future extensions may use NSGA-II to generate a Pareto front among roughness, MRR, energy, cost, tool wear, and machining time; adaptive mutation to improve convergence; robust optimization to account for uncertainty; or online sensor data for dynamic parameter adjustment. Such extensions preserve the same core methodology but improve decision support when production requirements are variable or when multiple objectives are equally important. Overall, GA provides a flexible and computationally practical framework for systematic CNC parameter optimization when it is coupled with sound

experimental design, validated predictive models, and confirmation testing.

Research-use note: The numerical values in Section 7 are an illustrative reproducible demonstration, not claimed laboratory measurements. Replace them with measured data and confirmation results before submitting the paper as an empirical experimental study.

References

- Hazir, E., & Ozcan, T. (2019). Response Surface Methodology Integrated with Desirability Function and Genetic Algorithm Approach for the Optimization of CNC Machining Parameters. *Arabian Journal for Science and Engineering*, 44, 2795–2809. DOI: 10.1007/s13369-018-3559-6.
- Leo Kumar, S. P. (2018). Experimental investigations and empirical modeling for optimization of surface roughness and machining time parameters in micro end milling using Genetic Algorithm. *Measurement*, 124, 386–394. DOI: 10.1016/j.measurement.2018.04.056.
- Kant, G., & Sangwan, K. S. (2015). Predictive Modelling and Optimization of Machining Parameters to Minimize Surface Roughness using Artificial Neural Network Coupled with Genetic Algorithm. *Procedia CIRP*, 31, 453–458. DOI: 10.1016/j.procir.2015.03.043.
- Mahesh, G., Muthu, S., & Devadasan, S. R. (2015). Prediction of surface roughness of end milling operation using genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, 77, 369–381. DOI: 10.1007/s00170-014-6425-z.
- Chen, X., Ma, L., Li, C., & Cao, X. (2014). Experimental study and genetic algorithm-based optimization of cutting parameters in cutting engineering ceramics. *The International Journal of Advanced Manufacturing Technology*, 74, 807–817. DOI: 10.1007/s00170-014-5979-0.
- Ganesan, H., & Mohankumar, G. (2013). Optimization of Machining Techniques in CNC Turning Centre Using Genetic Algorithm. *Arabian Journal for Science and Engineering*, 38, 1529–1538. DOI: 10.1007/s13369-013-0539-8.
- Routara, B. C., Sahoo, A. K., Parida, A. K., & Padhi, P. C. (2012). Response Surface Methodology and Genetic Algorithm used to Optimize the Cutting Condition for Surface Roughness Parameters in CNC Turning. *Procedia Engineering*, 38, 1893–1904. DOI: 10.1016/j.proeng.2012.06.232.

Zain, A. M., Haron, H., & Sharif, S. (2010). Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. *Expert Systems with Applications*, 37(6), 4650–4659. DOI: 10.1016/j.eswa.2009.12.043.

Palanisamy, P., Rajendran, I., & Shanmugasundaram, S. (2007). Optimization of machining parameters using genetic algorithm and experimental validation for end-milling operations. *The International Journal of Advanced Manufacturing Technology*, 32, 644–655. DOI: 10.1007/s00170-005-0384-3.

Oktem, H., Erzurumlu, T., & Erzincanli, F. (2006). Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm. *Materials & Design*, 27(9), 735–744. DOI: 10.1016/j.matdes.2005.01.010.

Suresh, P. V. S., Venkateswara Rao, P., & Deshmukh, S. G. (2002). A genetic algorithmic approach for optimization of surface roughness prediction model. *International Journal of Machine Tools and Manufacture*, 42(6), 675–680. DOI: 10.1016/S0890-6955(02)00005-6.