Design and Implementation of Intelligent Optimization Algorithm for CNC Machine Tool Processing Parameters

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Abstract: *The optimization of CNC machine tool processing parameters serves as a critical link in achieving efficient, high-quality, and low-cost manufacturing. Traditional methods struggle to address its complex characteristics, including multiple objectives, multiple constraints, and strongly coupled parameters. This study aims to design and implement a hybrid intelligent optimization algorithm tailored to this problem. First, by quantitatively characterizing multiple objectives such as processing efficiency, tool life, and surface quality, and strictly defining constraints of the process system including machine power, cutting force, and chatter stability, a high-fidelity multi-objective optimization mathematical model is established. Second, a hybrid intelligent algorithm integrating adaptive global search and local directional development is designed. The algorithm balances exploration and exploitation through an adaptive mechanism based on population distribution entropy, introduces quasi-gradient information to design directional evolution operators for accelerated convergence, and employs a bi-level strategy to handle complex constraints and generate a uniformly distributed Pareto compromise solution set. Finally, the modular software implementation and parallel computing optimization strategies of the algorithm are elaborated; an evaluation system comprising algorithm performance and process gain indicators is constructed; and a framework for an offline integrated verification platform based on high-fidelity process simulation is proposed. This study provides a systematic solution covering algorithm design, implementation, and verification for achieving intelligent and automated optimization of processing parameters.*

Keywords: *CNC machining; parameter optimization; intelligent algorithm; multi-objective optimization; process simulation*

Introduction

The selection of processing parameters for CNC machine tools directly influences the efficiency, cost, and final product quality of the manufacturing process. Its optimization is highly challenging due to the involvement of conflicting process objectives, complex physical constraints, and nonlinear coupling among parameters. Traditional parameter setting methods based on experience or trial-and-error lack scientific rigor and general applicability, while optimization approaches grounded in classical mathematical programming are often inefficient or prone to converging to local optima when dealing with such high-dimensional, non-convex, and computationally expensive "black-box" problems. Therefore, developing intelligent optimization algorithms capable of autonomous optimization, balancing global exploration and local exploitation, and effectively handling multiple objectives and complex constraints holds significant theoretical and engineering importance for enhancing the intelligence level of CNC machining and unlocking the potential of process systems. This study conducts systematic work from problem modeling and algorithm innovation to implementation and verification, aiming to design an efficient and robust hybrid intelligent optimization algorithm, thereby providing a new technical pathway to overcome the traditional bottlenecks in machining parameter optimization.

1. Mathematical Modeling and Constraint Analysis of the Machining Parameter Optimization Problem

1.1 Quantitative Characterization of Machining Process Objective Functions

The core of optimizing CNC machine tool processing parameters lies in the collaborative optimization of multiple, often conflicting, process objectives. The primary objective is to maximize the Material Removal Rate (MRR), whose quantitative expression is typically defined as the product function of cutting speed, feed rate, and depth of cut, directly impacting machining efficiency. Competing with this is the objective of tool life or wear cost, commonly described by an extended Taylor tool life equation. This equation reveals the exponential relationship between cutting parameters and tool durability. The pursuit of a balance between high efficiency and low consumption constitutes the fundamental optimization conflict.

Machining surface integrity and process stability constitute another category of critical objectives. Surface roughness can be predicted through empirical models or theoretical models based on cutting geometry and dynamics, typically expressed as a function of parameters such as feed rate and tool nose radius. Unstable phenomena like chatter are avoided through stability lobe diagram theory, which treats spindle speed and axial depth of cut as key variables, with the objective of maximizing the chatter-free cutting region. These objective functions together form a typical mathematical model for a nonlinear, multi-peak, multi-objective optimization problem[1].

1.2 Mathematical Definition of Hard and Soft Constraints in the Process System

Hard constraints in the process system originate from the physical limits of CNC machine tools and cutting tools, forming the absolute boundaries of the optimization search space. These constraints are typically expressed in the form of inequalities, including the spindle's maximum speed limit, the maximum output power and torque constraints of the spindle motor, and the maximum allowable feed rates and acceleration limits for each feed axis. Constraints related to the cutting tool involve the maximum allowable cutting force, cutting edge strength, and the rigidity threshold of the clamping system. Exceeding these boundaries will lead to equipment damage or machining interruption, and thus must be treated as mandatory constraint conditions within the mathematical model.

Soft constraints primarily concern machining process requirements and quality assurance. Although not absolutely inviolable, violating them will lead to unacceptable consequences. The stability constraint of the cutting process, namely avoiding chatter occurrence, can be transformed into dynamic restriction zones for spindle speed and depth of cut through the stability lobe diagram model. Chip control requirements can be translated into constraint relationships between feed rate and chip breaker geometry. Surface integrity indicators, such as workpiece geometric accuracy and residual stress, are formed into threshold-type constraints by establishing correlation models with cutting force and thermal loads. In algorithm design, soft constraints are often integrated into the optimization process via penalty function methods or feasibility rules.

1.3 Formal Analysis of Parameter Coupling and Problem Complexity

Significant physical coupling effects exist among cutting parameters, resulting in the optimization problem exhibiting a high degree of nonlinearity. Cutting force models, such as classical mechanistic models or artificial intelligence (AI)-based prediction models, clearly reveal the coupling relationships-mediated through cutting coefficients-among cutting speed, feed rate, depth of cut, and tool geometry parameters. This coupling implies that adjusting a single parameter nonlinearly influences multiple output responses. For instance, increasing the feed rate improves efficiency but may also exponentially increase cutting force and thermal load, thereby exacerbating tool wear and degrading surface quality. Consequently, the solution space presents a complex, non-convex landscape.

The aforementioned coupling characteristics directly determine the high-dimensionality and complexity of the machining parameter optimization problem. Design variables not only include direct cutting parameters but may also encompass tool paths and cooling strategies in more refined models, leading to an increase in search dimensions. Objective and constraint functions are mostly defined by implicit or explicit nonlinear equations, and evaluating a single function value often requires invoking complex simulation or empirical models, resulting in high computational cost. This "black-box" or "grey-box" nature, coupled with the prevalence of local optima within the solution space, renders traditional gradient-based optimization methods highly prone to failure. This formally substantiates the necessity of employing intelligent optimization algorithms with global search capabilities[2].

2. Design of a Hybrid Intelligent Algorithm for Machining Parameter Optimization

2.1 Construction of a Global Search Strategy Based on an Adaptive Mechanism

The high-dimensional, nonlinear solution space of machining parameter optimization requires the algorithm to possess robust global exploration capabilities. Fixed-parameter strategies in traditional evolutionary algorithms struggle to adapt to the dynamic changes in population diversity during the search process. To address this, this chapter proposes an adaptive mechanism based on population distribution entropy and evolutionary stagnation detection. This mechanism quantifies population diversity in real-time by calculating the distribution entropy of the solution set. When the entropy value falls below a threshold, it automatically increases the mutation probability and introduces perturbations based on the Cauchy distribution to counter the risk of premature convergence.

This mechanism is further integrated with evolutionary phase identification. By monitoring the improvement rate of historical optimal solutions, the algorithm can dynamically determine whether the search is in a state of global exploration, local exploitation, or stagnation. During the exploration phase, it emphasizes the use of operators such as arithmetic crossover to broaden the search scope; during stagnation phases, it adaptively switches the type of mutation operator based on response surface characteristics, for instance, selecting between Gaussian mutation and Lévy flight mutation, aiming to escape local optima. This strategy, which couples real-time state feedback with operator selection, forms a dynamic closed-loop global search system. It achieves autonomous balance between the breadth and depth of exploration, thereby providing a high-quality initial solution set for subsequent refined search.

2.2 Design of a Directional Evolution Operator Incorporating Local Gradient Information

After global search locates promising potential optimal regions, the convergence accuracy and speed of the algorithm largely depend on its local exploitation capability. Classical evolutionary algorithms primarily rely on probabilistic operators and population competition, lacking directional guidance during the local search phase, which often limits their convergence speed. To enhance the optimization efficiency of the algorithm in the later stages of machining parameter optimization, this section designs a directional evolution operator that incorporates quasi-gradient information[3]. This operator does not require the objective function to be explicitly differentiable. Instead, it strategically samples within the neighborhood of the current optimal individual to construct a linear or quadratic response surface model, thereby estimating the approximate gradient or the direction of steepest descent in that local region. This process is completed through a limited number of additional evaluations of the objective function values, keeping the computational overhead controllable.

Based on the obtained quasi-gradient direction, the operator performs constrained directional mutation. New individuals undergo biased exploration on both the positive and negative sides of the gradient direction, with their step size adaptively linked to the distance to constraint boundaries and the evolutionary generation. To prevent misguidance caused by inaccurate gradient information, this operator is executed in a mixed manner with local random search at a certain probability. Addressing the coupling effects among parameters, the operator constructs an empirical covariance matrix by analyzing historical successful mutation vectors. This matrix is used to adjust the step size ratios across different dimensions during directional mutation, thereby enabling more efficient search along the local ridge directions of the solution space. This design enhances the algorithm's fine-tuning capability near feasible region boundaries or under complex constraint conditions, accelerating the approximation of the Pareto front or the global optimal solution.

2.3 Complex Constraint Handling and Generation Mechanism for Multi-Objective Compromise Solutions

CNC machining parameter optimization is inherently a multi-objective optimization problem constrained by multiple complex factors, including machine power, cutting force, surface roughness thresholds, and chatter stability, some of which are nonlinear and conflicting. The algorithm must simultaneously address the dual challenges of constraint satisfaction and multi-objective optimization.

Regarding constraint handling, a dual-layer hybrid strategy is adopted. The first layer is a feasibility-first selection rule, where a feasible solution is always superior to any infeasible solution in any individual comparison. The second layer focuses on the retention and repair of infeasible solutions, designing a tournament selection mechanism based on constraint violation degree ranking. This mechanism allows a small number of borderline infeasible solutions to participate in evolution with a certain probability. The purpose is to utilize the information carried by these solutions, which may guide the search through infeasible regions-this is particularly important for separated feasible regions.

Within the multi-objective optimization framework, the algorithm adopts an elite retention strategy based on non-dominated sorting. Individuals in the population are first stratified according to Pareto dominance relationships, and the distribution density of individuals within the same non-dominated layer in the objective space is measured by calculating the crowding distance. Selection and elite retention operations prioritize non-dominated layers with higher ranks, and within the same layer, individuals with larger crowding distances are preferred. This approach aims to maintain selection pressure towards the Pareto front while preserving the diversity of the solution set as much as possible. To effectively generate compromise solutions, the algorithm introduces reference points or weight vectors to guide the search direction. However, unlike traditional methods, these reference points are not fixed. Based on the shape of the currently discovered front, the algorithm dynamically adjusts the distribution of reference points or the weights of the aggregation function, enabling search resources to adaptively focus on regions of the front that are sparsely distributed or not yet sufficiently explored[4].

Finally, the constraint handling mechanism and the multi-objective search mechanism are organically integrated. The constraint violation degree is treated either as an additional optimization objective or as a penalty term during the non-dominated sorting process, ensuring that the final output solution set consists entirely of feasible solutions. Upon completion of the algorithm's execution, it provides a uniformly distributed Pareto non-dominated solution set. This set clearly reveals the trade-off relationships among multiple objectives such as machining efficiency, machining quality, and tool life. Decision-makers can select the combination of machining parameters that best meets the requirements of the specific production scenario from this solution set, thereby achieving an effective transition from algorithmic optimization to engineering decision-making.

3. Algorithm Implementation and CNC System Integrated Verification Framework

3.1 Software Implementation and Performance Optimization of the Algorithm Core Modules

The engineering implementation of the hybrid intelligent algorithm relies on a modular software architecture design. This architecture encapsulates core functionalities-such as adaptive global search, directional evolution operators, constraint handling, and multi-objective optimization-into independent computational units. Population individuals employ floating-point encoding, where their chromosome structure directly maps to optimization variables like cutting speed, feed rate, and depth of cut. The main algorithm loop control module coordinates the calling sequence and data flow among these units and maintains a global elite solution archive. Key data structures include multidimensional arrays for storing population states, dynamic linked lists for recording the non-dominated solution set, and hash tables for caching historical fitness evaluation results. This approach avoids redundant calculations for identical parameter combinations, significantly reducing the invocation overhead associated with high-fidelity process models or simulation interfaces[5].

To address the characteristic of high computational cost in fitness evaluation for machining parameter optimization, the algorithm's performance optimization focuses on enhancing overall search efficiency. On one hand, multi-threading or parallel computing frameworks are utilized to parallelize the fitness evaluation of population individuals. The calculation of each individual's objective and constraint functions is treated as an independent task, scheduled via a thread pool. This fully leverages multi-core processor resources, reducing the algorithm's runtime from linear to near-constant levels. On the other hand, surrogate model technology is introduced during the iterative process. In the initial stage of the algorithm, a certain number of sample points are obtained using Latin Hypercube Sampling. Approximate models for the objectives and constraints are then constructed via Radial Basis Function networks or Kriging models. In subsequent searches, the preliminary screening of some individuals will be based on predictions from the surrogate models, with precise physical or simulation evaluations conducted only for individuals exhibiting excellent predicted performance. This two-stage strategy of "approximate evaluation followed by precise verification" significantly reduces the number of time-consuming high-fidelity computations while ensuring the reliability of the search direction.

3.2 Algorithm Performance Evaluation Indicator System for CNC Machining

To comprehensively and objectively evaluate the effectiveness of the proposed algorithm, it is necessary to construct a multi-dimensional performance evaluation indicator system. This system first encompasses metrics for the algorithm's own convergence and diversity. Convergence is quantified using indicators such as Generational Distance or Inverted Generational Distance, which measure the closeness between the non-dominated solution set generated by the algorithm iteration and a reference Pareto front. Diversity is assessed through indicators of the solution set's distribution uniformity, such as the Spacing metric or the Maximum Spread metric, to ensure that the final set of parameter solutions covers a wide range of trade-off choices. The Hypervolume indicator is used as a comprehensive evaluation criterion because it simultaneously reflects both convergence and distribution; it measures the size of the hypervolume dominated by the solution set in the objective space.

Beyond general algorithm metrics, the system places greater emphasis on specialized verification indicators directly linked to the physical process of CNC machining. These indicators include the expected process gains from the computed optimal parameter sets, such as the predicted percentage increase in material removal rate, the reduction in surface roughness, or the extension ratio of tool life compared to empirical parameters. Algorithm robustness is examined through the stability of its optimization results across multiple sets of different initial populations and different workpiece-tool material combinations, calculating the standard deviation or success rate of the objective function values. The algorithm's time complexity and computational resource consumption are recorded and analyzed to evaluate its engineering applicability. Finally, the evaluation system employs a weighted composite scorecard encompassing all the aforementioned indicators to provide a quantitative and structured basis for comparing the performance of different intelligent optimization algorithms within the specific domain of CNC machining parameter optimization[6].

3.3 Construction of an Integrated Verification Platform Based on Machining Process Simulation

Before applying the algorithm to actual machine tools, constructing a simulation-based offline integrated verification platform is crucial. The core of this platform is a standardized data exchange and process execution engine. The algorithm module serves as an optimization server, receiving optimization task configurations-including objective function weights, constraint thresholds, and machine-tool-workpiece combination parameters-through predefined application programming interfaces (APIs). The candidate machining parameter sets generated by the optimization are automatically packaged by the platform and passed to the downstream high-fidelity machining process simulation module. This simulation module integrates commercial or self-developed components for cutting mechanics simulation, thermo-mechanical coupling simulation, and geometric accuracy simulation. It is capable of simulating cutting forces, temperature fields, vibration states, and the final workpiece morphology and dimensional errors under the given parameters.

The key to constructing the platform lies in achieving seamless conversion from optimized parameters to executable simulation instructions. This is typically accomplished through a neutral process description layer, such as the extended STEP-NC standard or a custom XML process template. The parameters output by the algorithm are populated into this template, generating an intermediate file containing complete process information. The simulation platform parses this file, drives the various simulators to execute sequentially, and collects simulation result data such as forces, thermal effects, vibrations, and roughness. This data is fed back to the evaluation module, which calculates performance based on the established indicator system and generates visualization reports. These reports may include comparison radar charts of parameter sets before and after optimization, Pareto front distribution diagrams, and comparative simulation cloud plots. This closed-loop verification process not only confirms the effectiveness and safety of the algorithmic optimization outcomes in a virtual environment-avoiding costly physical trial cuts-but also provides an efficient experimental setting for iterative algorithm improvement and parameter tuning. It thus constitutes a reliable bridge connecting intelligent algorithm design with practical machining application.

Conclusion

This study addresses the intelligent optimization problem of CNC machine tool processing parameters, completing systematic work spanning mathematical modeling, algorithm design, software implementation, and verification framework construction. The proposed hybrid intelligent algorithm, through the integration of an adaptive global search mechanism and directional evolution operators incorporating local gradient information, effectively balances the breadth and depth of the search. Its innovative framework for handling complex constraints and dynamic multi-objective optimization is capable of generating well-distributed Pareto-optimal solution sets. The modular software implementation and performance optimization strategies ensure the algorithm's engineering practicality, while the simulation-based integrated verification platform provides a reliable environment for evaluating and iterating on the algorithm's performance. Future research can focus on the following directions: exploring real-time interaction mechanisms between the algorithm and online monitoring data to achieve adaptive optimization based on dynamic perception of machining states; investigating the application of the algorithm to more complex multi-process, full-process-chain collaborative optimization; and advancing the deep integration of the algorithm with digital twin systems to construct more autonomous intelligent machining systems.

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