Cutting parameter optimization method in multi-pass milling based on improved adaptive PSO and SA

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Abstract. In the production process, cutting parameters greatly affect the production cost and energy consumption, so it is very important for manufacturers to optimize cutting parameters. In this paper, an improved particle swarm optimization (PSO) is presented to optimize cutting parameters for minimizing carbon emissions, production cost and processing time in multi-pass milling. First, a multi-objective optimization model of cutting parameters is established with number of milling passes as one of decision variables. Then, an improved adaptive simulated annealing particle swarm optimization (IAPSOSA) is proposed to obtain the optimal solution of cutting parameters. At last, a case study is given to illustrate that the proposed method is effective to optimize cutting parameters for economic and environmental benefits.

1. Introduction
The CNC machine tool is the core equipment for intelligent manufacturing, and it is developing towards the direction of intelligence, green and service[1]. However, there are still some problems such as expensive cost and environmental pollution in the CNC machining. Related research shows that optimizing cutting parameter can improve machining efficiency and reduce carbon emissions[2]. Forced by market competition and environmental protection policies, the optimization of cutting parameters has attracted extensive attention from academia and industry[3].

Many researchers have focused on parameter optimization for a single pass machining. Yi et al.[4] established a boundary model of carbon emissions to optimize cutting speed and feed rate for carbon reduction. Zhang et al.[5] studied cutting parameter optimization through NSGA-II algorithm to realize a trade-off between energy efficiency, cost and noise. Li et al.[6] established an integrated model of cutting parameter optimization and process optimization to balance energy consumption and workload. To provide convenient methods for manufacturers, Zhou et al.[7] established C-PBOW-W and C-PBOM-P for carbon emissions assessment.

Milling is a widely used machining method, which can be operated by a single pass or multi-pass machining. To ensure the accuracy and quality of products, multi-pass machining is more common in practice. Some researchers have studied parameter optimization in multi-pass machining. Costa et al.[8] adopted hybrid particle swarm optimization to solve multi-constraint process to reduce machining cost. Li et al.[9] investigated the relationship of passes number and cutting parameters, and they used PSO to achieve high energy efficiency and low cost. Moreover, there are many studies on multi-pass parameter optimization by evolutionary algorithms, such as ant colony optimization (ACO)[10], artificial bee colony(ABC)[11], genetic algorithm(GA)[12].

As the above studies show, existing optimization methods on multi-pass machining mainly focus on production indicators such as time and cost. Little research has been done on reducing carbon emissions.
by multi-pass optimization. In this paper, multi-objective parameter optimization is studied to improve machining efficiency, reduce production cost and carbon emissions in multi-pass milling.

The rest of the paper is organized as follows. The mathematical model for cutting parameters optimization is established in Section 2. The solving algorithm is described in Section 3. In Section 4, case study is presented to illustrate the proposed method. In Section 5, the conclusions and future work are given.

2. Multi-objective optimization model for multi-pass milling

In this paper, the decision variables are set as number of milling passes $n$, and cutting speed $V$ (m/min), feed rate $f$ (mm/rev), cutting depth $d_p$ (mm) of each pass.

2.1. Processing time modeling

The processing time $PT$ (s) refers to the time required to complete all machining tasks. It is mainly composed of three parts: material removal time, tool change time and auxiliary time (including tool retracting time), as shown in equation (1).

$$PT = \sum_{i=1}^{n} \frac{\pi D_i L}{1000 V_i f_i} + \sum_{i=1}^{n} \frac{T_{nc} \pi D_i L}{1000 V_i f_i T_{tool-i}} + 60 T_{re} n$$

where $i$ denotes the $i$th milling, $L$ (mm) is milling path length. $T_{nc}$ (min) denotes a single tool change time. $T_{re}$ (min) is a single tool retracting time. $D_i$ (mm) is diameter of cutting tool. $T_{tool-i}$ (min) is tool life of cutting tool.

2.2. Production cost modeling

The production cost $UC$ ($) mainly includes raw material removal cost, tool change cost, other auxiliary cost and tool production cost, as shown in equation (2).

$$UC = k_p \times PT + \sum_{i=1}^{n} \frac{k_d \pi D_i L}{1000 V_i f_i T_{tool-i}}$$

where $k_p$ ($$/min$$) is direct labour cost and other indirect costs per minute. $k_d$ ($$/edge$$) is cutting tool unit cost.

2.3. Carbon emissions modeling

The carbon emissions $CE$ (kgCO$_2$) are consisted of electric energy emission, tool preparation emission and cutting fluid loss emission, as shown in equation (3).

$$CE = \sum_{i=1}^{n} \frac{\pi D_i LW_{tool-i}}{60000 V_i f_i T_{tool-i}} \times CEF_{tool} + \frac{PT \times V_{fluid}}{T_{fluid}} \times CEF_{fluid} + E_p \times CEF_{elec}$$

where $CEF_{tool}$ (kgCO$_2$/kg), $CEF_{fluid}$ (kgCO$_2$/m$^3$) and $CEF_{elec}$ (kgCO$_2$/J) are carbon emission factors. $W_{tool-i}$ (kg) is cutting tool weight. $T_{fluid}$ (s) and $V_{fluid}$ (m$^3$) are replacement cycle and volume of cutting fluid. $E_p$ (J) is electrical energy from the milling process. Yi et al.[4] made a detailed explanation for the calculation process of $E_p$.

2.4. Objective function evaluation strategy

The cutting parameters optimization model is established with processing time, production cost and carbon emissions as objectives. In addition, it should take into account constraints including machine specifications, workpiece quality and tool life. Therefore, the problem has the characteristics of multi-objective and multi-constraint. In this paper, the weight coefficient method and penalty function method is used to solve the problem. The extended objective function $Q(x)$ is obtained as follows.
$$Q(x) = u_1 \left( w_1 \times PT^* + w_2 \times UC^* + w_3 \times CE^* \right) + u_2 \sum_{i=1}^{m} \left( \max \left[ 0, f_i(x) \right] \right)^2 + u_3 \sum_{j=1}^{n} \left[ g_j(x) \right]^2$$  \hspace{1cm} (4)$$

where $w_1$, $w_2$ and $w_3$ are weighting coefficients, and $w_1 + w_2 + w_3 = 1$. $PT^*$, $UC^*$ and $CE^*$ are the normalized values of $PT$, $UC$ and $CE$, respectively. $x = (x_1, x_2, \ldots, x_n)$ is the vector composed of decision variables. $f_i(x)$ and $g_j(x)$ are $i$th inequality constraint and $j$th equality constraint in the proposed problem. $m$ and $n$ are number of constraints. $u_1$, $u_2$ and $u_3$ are penalty factors.

3. The IAPSOSA algorithm

PSO is a kind of random search method. It relies on a group of particle swarms, which can move around the solution space to find the best solution. In the search process, each particle can remember its history best point $pbest$ and the optimal point $gbest$ of entire population. The particles update their speed $v$ and position $x$ by the following equations.

$$v = w_I \times v + c_1 \times rand() \times (pbest - x) + c_2 \times rand() \times (gbest - x), \hspace{0.5cm} x = x + v$$  \hspace{1cm} (5)$$

where $w_I$ is inertia weight. $c_1$ and $c_2$ are acceleration constants.

To improve the convergence speed and accuracy of PSO, IAPSOSA algorithm is proposed in this section. Firstly, adaptive inertia weight and acceleration constants are used to make them nonlinear change with the number of iterations. Then, to prevent PSO from falling into the local optimum, $gbest$ and $pbest$ are updated based on SA mechanism. Finally, roulette selection operator is used to improve convergence speed. The procedure of IAPSOSA is executed according to figure 1 as follows.

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**Figure 1. The flowchart of IAPSOSA algorithm.**
Step1: Initialize the number \( N \) of particles, maximum iteration number \( G_{\text{max}} \), initial temperature \( T_0 \), lower limit \( T_L \) of temperature, and others. The calculation process of \( w_I \), \( c_1 \) and \( c_2 \) are as follows.

\[
\max_{1} \max_{L} (1 - \frac{G}{G_{\text{max}}} - 1) \times (w_U - w_I) \\
\]

\[
c_1 = c_{1L} + (c_{1U} - c_{1L}) \times \left( \frac{G}{G_{\text{max}}} - a + 1 \right), \quad c_2 = c_{2U} - (c_{2L} - c_{2U}) \times \left( \frac{G}{G_{\text{max}}} - a + 1 \right)
\]

where \( w_I \) and \( w_U \) are bounds of inertia weight, \( G \) is the number of current iteration. \( c_{1L} \) and \( c_{1U} \) are bounds of \( c_1 \). \( c_{2L} \) and \( c_{2U} \) are bounds of \( c_2 \). \( a \) is a constant greater than 1.

Step2: Initialize particle swarm and compute the fitness \( Q(x) \), and initialize \( pbest \) and \( gbest \).

Step3: Update position \( x \) and velocity \( v \) of each particle by equations (5), and evaluate \( Q(x) \).

Step4: Compare \( Q(pbest) \) with \( Q(x) \). If \( Q(pbest) > Q(x) \), then accept the new position \( x \). If \( Q(pbest) < Q(x) \), then execute SA algorithm (see Algorithm 1). \( pbest \) is determined by comparing the fitness values of \( x \) and its neighbourhood \( x_r \). \( x_r \) is calculated as follows.

\[
x_r = x + (v_{\text{max}} - v_{\text{min}}) \times \text{rand}(0, 1)
\]

Step5: Compare \( Q(gbest) \) with \( Q(x) \). If \( Q(gbest) > Q(x) \), then \( gbest = x \). If \( Q(gbest) < Q(x) \), then execute SA algorithm and obtain \( gbest \).

Step6: Execute roulette selection operator based on fitness value of each particle. Replace 1/3 of particles with excellent particles.

Step7: Execute cooling operation, i.e. \( T = \text{frac} \times T \), where \( \text{frac} \) is cooling factor.

Step8: Output optimal solution when the stop condition is reached. Otherwise, return to Step3.

### Algorithm 1: Simulated annealing (SA)

**Input:** current particle \( x \), current best particle (\( pbest \) or \( gbest \)) \( x_{\text{best}} \)

**Output:** new best particle \( x_{\text{ret}} \)

1. Generate the neighbourhood particle \( x_r \) of \( x \) by equation (8)
2. Compute fitness \( Q(x_r) \), \( dE = Q(x_r) - Q(x) \), and \( P(dE) = \exp(-dE/(KT)) \)
3. If \( dE < 0 \) \( \quad x_{\text{ret}} = x_r \)
   Else
   \quad If \( P(dE) > \text{rand}(0, 1) \) \( \quad x_{\text{ret}} = x \) \quad Else \( x_{\text{ret}} = x_{\text{best}} \) \quad End
   End

4. Case study
To validate the proposed method, a milling experiment is performed on a milling machine with cemented carbide tool and S45C carbon steel workblank. In this milling, we consider that the whole machining process is composed of one pass finishing and multi-pass roughing, and cutting parameters of each roughing are the same.

4.1. Validation of necessity of the optimization model
To demonstrate the effectiveness of multi-objective optimization, three single-objective optimization models (Min \( PT \), Min \( UC \), Min \( CE \)) are used to the same milling process. In table 1, \( (V_r, f_r, a_{pr}) \) and \( (V_s, f_s, a_{ps}) \) are the solution sets of cutting parameters for roughing and finishing respectively. The study results show that the proposed model achieves a balance among processing time, cost and carbon emissions.

In the machining process, the number of milling passes \( n \) and cutting parameters for each pass largely affect values of optimization objective (see Table 2). In this experiment, the optimal solution is \( n = 3 \). This further proves that it is necessary to study multi-pass machining problem.
Table 1. The comparison with single objective optimization model.

| Models         | n   | \((V_r, f_s, a_p)\) | \((V_s, f_s, a_p)\) | PT(s) | UC($) | CE \((10^{-3}\text{kgCO}_2)\) |
|----------------|-----|----------------------|----------------------|-------|-------|-----------------------------|
| Min PT (M1)    | 3   | (132.9, 2.67, 3.69)  | (334.9, 1.35, 0.62)  | 93.16 | 46.65 | 44.61                       |
| Min UC (M2)    | 3   | (139.4, 2.68, 3.51)  | (292.2, 1.36, 0.98)  | 94.19 | 46.51 | 45.10                       |
| Min CE (M3)    | 3   | (30.0, 0.60, 3.79)   | (30.0, 0.60, 0.42)   | 155.45| 77.73 | 37.30                       |
| Proposed model | 3   | (52.1, 2.68, 3.85)   | (285.1, 1.36, 0.30)  | 96.65 | 48.34 | 39.36                       |

Table 2. The comparison of different milling passes.

| Schemes       | n   | \((V_r, f_s, a_p)\) | \((V_s, f_s, a_p)\) | PT(s) | UC($) | CE \((10^{-3}\text{kgCO}_2)\) |
|---------------|-----|----------------------|----------------------|-------|-------|-----------------------------|
| S1            | 3   | (52.1, 2.68, 3.85)   | (285.1, 1.36, 0.30)  | 96.65 | 48.34 | 39.36                       |
| S2            | 4   | (30.1, 2.60, 2.10)   | (302.8, 0.62, 1.70)  | 137.20| 68.63 | 50.60                       |
| S3            | 5   | (56.1, 2.42, 1.88)   | (126.7, 1.12, 0.48)  | 164.35| 82.18 | 63.63                       |

4.2. Validation of necessity of the proposed algorithm

To prove the convergence of the proposed algorithm, PSO and PSOSA\[13\] are used to optimize milling parameters, and the result is shown in figure 2. The convergence speed of PSO is faster, and convergence speed of PSOSA is relatively slow. At the 26th iteration, IAPSOSA converges to 41.60. Therefore, the proposed algorithm has better convergence performance.

To further test the solution accuracy of the proposed algorithm, GA, ACO, PSO and PSOSA algorithms are used to solve the optimization model. As seen in table 3, the proposed algorithm searches better cutting parameters.

![Figure 2. The convergence processes.](image)

Figure 2. The convergence processes.

Table 3. The comparison of optimization results for different algorithms.

| Methods   | n   | \((V_r, f_s, a_p)\) | \((V_s, f_s, a_p)\) | PT(s) | UC($) | CE \((10^{-3}\text{kgCO}_2)\) |
|-----------|-----|----------------------|----------------------|-------|-------|-----------------------------|
| GA        | 3   | (33.7, 2.40, 3.78)   | (365.6, 0.82, 0.44)  | 101.05| 50.54 | 38.36                       |
| ACO       | 3   | (53.7, 2.48, 3.60)   | (274.2, 1.17, 0.80)  | 97.13 | 48.57 | 39.70                       |
| PSO       | 3   | (55.9, 2.37, 3.70)   | (352.2, 1.20, 0.60)  | 97.69 | 48.87 | 39.71                       |
| PSOSA\[13\]| 3  | (53.3, 2.55, 3.83)   | (488.0, 0.66, 0.34)  | 97.04 | 48.54 | 39.57                       |
| IAPSOSA   | 3   | (52.1, 2.68, 3.85)   | (285.1, 1.36, 0.30)  | 96.65 | 48.34 | 39.36                       |

5. Conclusions

In this paper, cutting parameter optimization problem for multi-pass machining is solved by an improved PSO. First, a model for cutting parameters optimization is established. The result of milling experiment shows that the model can realize a balance between machining efficiency, cost and carbon emissions. Then, IAPSOSA algorithm is proposed to solve the above model. Compared with other algorithms, the
algorithm has good convergence speed and solution precision, and can find better solution set of cutting parameters. In the future, IAPSOSA will be studied and applied in more cutting parameter optimization problems.

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