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Research on Optimization of CNC Milling Process Parameters Based on Carbon Emission

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Abstract: In order to achieve the low carbon and efficient working effect of CNC machine tools, this paper takes the 2243 VMC machining centre as the research object to study the problem between carbon emission and time, cost and process parameters in the machining process of machining centre machine tools, and establish the optimization model of CNC milling process parameters based on carbon emission. Carbon emissions, machining cost and machining time are taken as the optimisation objectives, tool life, roughness and machine power are taken as constraints, and spindle speed, feed per tooth, cutting width and depth of cut are taken as optimisation variables. The model is solved using a particle swarm algorithm (PSO) to produce a Pareto solution set for multi-objective optimisation. Finally, the optimisation results were compared with the calculated results for the empirical parameters to verify the feasibility of the model. The results show that the calculated results for the optimised parameters provide a 19.53% reduction in carbon emissions, a 12.96% reduction in processing costs and a 13.72% reduction in processing time after optimisation by the algorithm compared to the calculated results for the empirical parameters, indicating that the algorithm provides a better optimisation than the empirical parameters.

Keywords: Carbon Emissions, CNC Milling, Process Parameter, Adaptive Grid Particle Swarm Algorithm

1. Introduction

Global warming is increasing as a result of increasing CO_2 emissions, affecting our lives and economic development. Data show that China's carbon dioxide emissions in 2020 will be as high as 10.24 billion tons, accounting for 31.7% of the world [1], of which the manufacturing sector accounts for up to 80%. Low-carbon manufacturing, "Industry 4.0" and "Made in China 2025", etc., China proposed these plans are essentially to improve the quality and efficiency of manufacturing [2-4]. The reasonable selection of process parameters, reduction of carbon emission and improvement of processing efficiency in CNC machining have become hot issues for scholars' research and enterprises' production concerns. Therefore, it is important to study how to get a better combination of cutting parameters as well as reduce carbon emissions, reduce machining time, and reduce production costs.

Many scholars have studied low carbon manufacturing and made good progress. Jeswiet J. et al [5] explored the relationship between carbon emission and power consumption in machining process and obtained the carbon emission calculation method about electricity. Munoz et al [6] established a model for evaluating the environmental impact in machine tool processing, and studied and quantified the calculation from the perspectives of energy and material. For the parameter optimization method in machining process, scholars at home and abroad have also conducted a lot of research on it. Chen Zhichu et al [7] optimized the cutting parameters based on imperialistic competition algorithm. Li Xinpeng et al [8] improved the particle swarm algorithm by adding the concept of neighbors to optimize the solution of its cutting parameters. Liu Qiong et al [9] proposed a carbon footprint calculation method for flexible workshops, with carbon emissions as the target, and established a multi-objective optimal scheduling model with the shortest sum of carbon footprints and the greatest energy efficiency of equipment. Mei Zhimin [10] examines methods and strategies for a low-carbon transition in manufacturing from the direction of the actual processing of machinery manufacturing. The process and methods of low carbon transformation are analysed in detail in terms of process, processing design, workpiece materials, and recycling in multiple dimensions. Based on the above studies, further research on carbon-oriented parameter optimization problems has emerged. For example, Li Congbo [11] constructed a multi-objective optimization model for high-efficiency low-carbon emissions and solved it based on particle swarm algorithm. Ni Hengxin et al [12] optimized cutting parameters for hobbing with energy consumption and quality as objectives. The grinding carbon emission model developed by Yulun Chi et al [13] is a research modeling based on power signals, which discards the carbon emissions calculated by empirical formulas. Yi Xi et al [14] constructed a carbon emission model for the hobbing process with low carbon efficiency as the goal, and selected the improved Grey Wolf optimization algorithm to solve it. In this paper, the variables are set as spindle speed, feed rate, milling depth and milling width in milling, and the optimisation objectives are set as carbon emissions, machining cost and machining time. The model is optimally solved using the AGA-MOPSO algorithm and verified experimentally.

2. Carbon Emission Model

There are many factors that affect carbon emissions in machine tool processing, from different perspectives, there are electrical energy carbon emissions C_{el}, Carbon emissions from raw materials C_{em}, Tool carbon emissions C_{et}, and cutting fluid carbon emissions C_{ef}. Since carbon emissions are not directly available in machining, the above parameters are categorized as indirect carbon emissions. Here, only carbon emissions related to cutting parameters are studied in this paper and carbon emissions from raw materials C_{em} is not considered. The total carbon emissions are:

$$C_p = C_{el} + C_{et} + C_{ef} \tag{1}$$

2.1. Electricity Carbon Emissions

$$C_{el} = E_e \cdot f_e \tag{2}$$

Among them E_e indicates the energy consumption of electrical energy (KWh); f_e Denotes the carbon emission factor of electric energy, $f_e = 0.5722$ (kg/KWh).

The motion state of the machine is divided into three states: standby, no-load, and cutting, where the power in the standby state is stable and can be regarded as a constant and not considered. No-load state is mainly caused by the spindle system and feed system carbon emissions, compared to the two, the latter's impact is much smaller than the former, so the feed system carbon emissions are ignored. The spindle system carbon emission is caused by the spindle motor, and the spindle no-load power is related to the speed, and the relationship between them can be expressed as follows [15]:

$$P_u = P_u^{'} + a_0 n + a_1 n^2 \tag{3}$$

Among them P_u is the spindle no-load power (KW); $P_u^{'}$ is the minimum no-load power (KW); a_0, a_1 is the coefficient.

The energy consumption in the no-load phase can be expressed as:

$$E_u = \int_0^{t_u} P_u dt = \int_0^{t_u} \left(P_u^{'} + a_0 n + a_1 n^2 \right) dt \tag{4}$$

The cutting phase is the process in which the tool and the workpiece are in contact with each other in the cutting state after the workpiece is mounted with the cooperation of the systems of the milling machine. The energy consumption in the cutting phase is expressed as:

$$E_c = \int_0^{t_c} P_c dt + \int_0^{t_c} P_{fz} dt \tag{5}$$

$$P_c = \frac{F_c v_c \times 10^{-3}}{60} \tag{6}$$

Among them P_c is the cutting power (KW); F_c it is the main cutting force (N); v_c is the cutting speed (m/min).

In the cutting phase, the CNC milling machine system is under load, and energy consumption is generated due to the increase in cutting force and torque during machine tool machining. There is a moving linear relationship between additional load energy consumption and cutting power [16], which can be expressed as:

$$P_{fz} = k_m P_c \tag{7}$$

Among them P_{fz} is the additional load power (KW); k_m is the additional load loss factor, the value range is $0.15 \sim 0.25$.

In summary, the carbon emission function of electric energy can be obtained as:

$$C_{el} = E_e \cdot f_e = \left(E_u + E_c \right) \cdot f_e = \left(\int_0^{t_u} \left(P_u^{'} + a_0 n + a_1 n^2 \right) dt + \left(1 + k_m \right) \cdot \int_0^{t_c} P_c dt \right) \cdot f_e \tag{8}$$

2.2. Tool Carbon Emissions

Tools are consumables in the machining process and will be scrapped after a certain period of time. Tool carbon emissions are the indirect carbon emissions caused by tool wear and can be expressed as:

$$C_{et} = \frac{t_c f_t W_t}{T} \tag{9}$$

$$T = \frac{C_T}{a_e^w \cdot n^x \cdot a_p^y \cdot v_f^z} \tag{10}$$

Among them t_c indicates the time of processing $(\min)$; f_t denotes the tool carbon emission factor, $f_t = 29.6$ (kg/KWh), W_t indicates tool quality (kg); T indicates tool life $(\min)$; C_t, w, x, y, z indicates the tool life factor.

2.3. Cutting Fluid Carbon Emissions

$$C_{ef} = \frac{t_c}{T_g} \times (C_{oil} + C_{wc}) \tag{11}$$

$$C_{oil} = f_{oil} \cdot \rho \cdot V \tag{12}$$

$$C_{wc} = f_{wc} \cdot V \tag{13}$$

Among them T_g indicates the interval of cutting fluid replacement $(\min)$; C_{oil}, C_{wc} represent carbon emissions from oil-based cutting fluids and carbon emissions from waste cutting fluids, respectively (L); ρ indicates the concentration of oil-based cutting fluid; f_{oil}, f_{wc} the carbon emission factors of oil-based cutting fluids and waste cutting fluids, respectively; V indicates the volume of cutting fluid. Selection $f_{oil} = 0.2kgCO_2 / L$, $f_{wc} = 2.85kgCO_2 / L$.

3. Minimum Cost Function

In this paper, we only study the production cost, including the cost of electricity, labor, tool wear, cutting fluid, and machine depreciation.

$$C_T = C_e + C_{la} + C_{to} + C_{fd} + C_{mt} \tag{14}$$

(1) Electrical energy cost

$$C_e = \frac{C_p \times E_e}{3600} \tag{15}$$

Among them C_p indicates the price of electricity ($); E_e for electrical energy consumption (KW h)

(2) Labor cost

$$C_{la} = T_w (C_a + C_1) \tag{16}$$

Among them T_w indicates the total processing time; C_a indicates time management costs; C_1 indicates the labor cost of time (yuan/hour).

(3) Tool wear cost

$$C_{to} = \frac{T_w}{T} C_{tc} \tag{17}$$

Among them C_{tc} denotes the tool cost price ($); T indicates tool life; T_w indicates the total processing time.

(4) Cutting fluid cost

$$C_{fd} = C_{fc} \frac{T_w}{T_g} \tag{18}$$

Among them C_{fc} indicates cutting fluid cost.

(5) Depreciation cost of machine tools

$$C_{mt} = C_b \cdot T_w \tag{19}$$

Among them C_b represents depreciated cost based on time depreciation.

4. Minimum Processing Time Function

Machining time in the milling process includes cutting time t_c, assist time t_{ot} and tool change time t_h, The average total processing time T_w expression is given by:

$$T_w = t_c + t_h \frac{t_c}{T} + t_{ot} \tag{20}$$

(1) Cutting time

Cutting time refers to the milling machine from the beginning of a certain processing moment to the completion of a process time, cutting time is calculated as follows:

$$t_c = \frac{L}{f_v} = \frac{L}{f_z n z} \tag{21}$$

Among them L is the cutting length (mm); f_z is the feed per tooth (mm/z); n is the spindle speed (r/min); z is the number of teeth of the milling cutter.

The cutting length affects the cutting time, and a reasonable de-definition of the cutting length can effectively save the cutting time. Cutting length can be expressed by the following equation:

$$L = l_a + a + e \tag{22}$$

Among them l_a is the length of the workpiece being machined (mm); a is the approach length, e is the safety distance.

For the approach length a, the calculation is as follows:

$$a = \frac{d}{2} - \sqrt{\left(\frac{d}{2}\right)^2 - \left(\frac{a_e}{2}\right)^2} \tag{23}$$

The cutting time for a single tool walk can be expressed as:

$$t_c = \frac{\pi d \left(l_a + \frac{d}{2} - \sqrt{\left(\frac{d}{2}\right)^2 - \left(\frac{a_e}{2}\right)^2} + e \right)}{1000 v_c f_z z} \tag{24}$$

(2) Auxiliary time

Auxiliary time of the work process refers to the auxiliary time other than tool change, such as workpiece clamping time, auxiliary time can be treated as a constant in the calculation.

(3) Change time

Tool change time mainly considers the apportionment of one tool change time in one machining time, the calculation formula is:

$$t_h = \frac{t_c}{T} \tag{25}$$

5. Build Cutting Parameter Optimization Model

5.1. Determination of Variables

In CNC milling, the four elements of milling are used as variables.

5.2. Optimization Objectives

Establish the cutting parameters model with the lowest carbon emission and the least machining cost and machining time as the optimization objectives, namely:

$$\min\left(n, f_z, a_p, a_e\right) = (\min C_p, \min C_T, \min T_w) \tag{26}$$

5.3. Constraint Conditions

While satisfying the optimization objectives during the milling process, the optimization results should be made to conform to the actual machining as much as possible, and the machining conditions should be constrained.

(1) $n_{\min} \le n \le n_{\max}$, $n_{\min}$, $n_{\max}$ denote the minimum and maximum spindle speed, respectively.

(2) $a_{p\min} \le a_p \le a_{p\max}$, $a_{p\min}$, $a_{p\max}$ denote the minimum and maximum back draft, respectively.

(3) $a_{e\min} \le a_e \le a_{e\max}$, $a_{e\min}$, $a_{e\max}$ denote the minimum and maximum cutting width, respectively.

(4) $f_{\min} \le f \le f_{\max}$, $f_{\min}$, $f_{\max}$ denote the minimum and maximum feeds, respectively.

(5) Roughness constraint:

$$R_a = 318 \frac{f_z^2}{\tan(\gamma) + \cot(\alpha)} \le [R_a]$$

Where: γ, α are the front and back angles of the tool, $[R_a]$ respectively; the maximum allowed surface roughness.

(6) $P_c \le \eta P_0$, Machine power constraint, where η, P_0 are the machine efficiency and machine power rating, respectively.

(7) Tool life constraint: $T \ge T_0$, T_0 is the maximum economic life of the tool.

6. Particle Swarm Algorithm

The Particle Swarm Optimisation (PSO) algorithm has the advantage of being simple, fast and advantage seeking, and it is also often used in conjunction with other algorithms. Therefore, in this paper, the particle swarm algorithm is used to solve the cutting parameter optimisation model.

6.1. Simulation Experiments

The Matlab software simulation was used to write the program about the PSO algorithm, setting the population population to 50 and the number of iterations to 200, $w = 0.3$, $c_1 = c_2 = 2$. Finally, the Pareto diagram obtained by the algorithm is recorded, as shown in Figure 1 below.

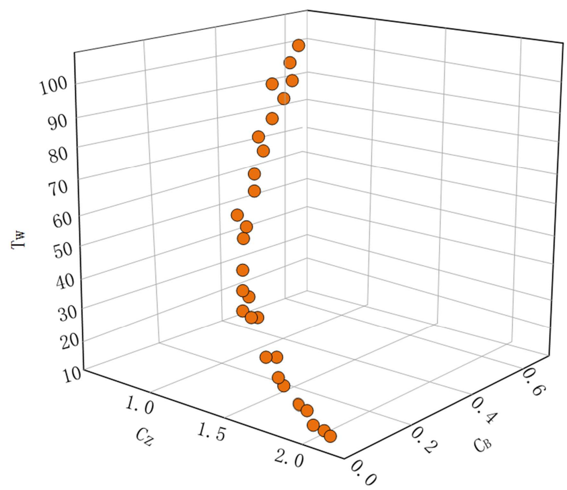

Figure 1. *Pareto diagram of particle swarm algorithm.*

6.2. Analysis of Optimization Results

From the empirical parameters selected from the cutting dosage manual, the calculation results are shown in Table 1 below.

Table 1. *Calculated results of selected parameters.*

$n(r/\min)$	$f_z(mm/r)$	a_p (mm)	$a_e(mm)$
251.734	0.1	4	2

The results of the optimized parameters of the standard particle swarm algorithm are shown in Table 2 below.

Table 2. *Parameter optimization results.*

	$n(r/\min)$	$f_z(mm/r)$	a_p (mm)	$a_e(mm)$
PSO	256.8274	0.27	1.58	1.4756

The results of optimizing the three objectives, i.e., cost, time, and carbon emissions, are shown in Table 3 below.

Table 3. *Calculation results of optimization objectives.*

	T_w	C_T	C_P
Before optimization	27.510	0.634	6.3829
After optimization	23.942	0.547	5.1364

As can be seen in Table 1, Table 2 and Table 3, PSO algorithm can be seen that the local optimum is avoided to some extent and the optimization is better. Compared to the parameters selected from the cutting parameters manual, the particle swarm algorithm resulted in a 12.96% reduction in machining costs, a 13.72% reduction in time, and a 19.53% reduction in carbon emissions.

7. Conclusion

In CNC cutting, CNC milling is used as an example to analyze the influencing factors of carbon emission, analyze the factors causing carbon emission from different perspectives, and establish a carbon emission model. Combining the machining cost and machining time, the multi-objective optimization model of the green-oriented milling process parameters in the machining process is further constructed with machine tool, cutting parameters, tool life and roughness as constraints and the four elements of milling as variables. By solving the optimization model with the PSO algorithm and compared with empirical parameters, the results show that the algorithm can obtain relatively better results. the milling parameters obtained by the PSO algorithm are better than the values selected in the manual and the milling parameters obtained by the standard particle swarm algorithm. Compared to the parameters selected from the cutting parameters manual, the particle swarm algorithm resulted in a 12.96% reduction in machining costs, a 13.72% reduction in time, and a 19.53% reduction in carbon emissions, which has certain application value and significance.

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