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Experimental Investigation and Multi-objective Optimization Approach for Low-carbon Milling Operation of Aluminum

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Abstract. In the past, milling operations have been mainly considered from the economic and technological perspectives, while the environmental consideration has been becoming highly imperative nowadays. In this study, a systemic optimization approach is presented to identify the Pareto-optimal values of some key process parameters for low-carbon milling operation. The approach consists of the following stages. Firstly, regression models are established to characterize the relationship between milling parameters and several important performance indicators, i.e., material removal rate, carbon emission and surface roughness. Then, a multi-objective optimization model is further constructed for identifying the optimal process parameters, and a hybrid NSGA-II algorithm is proposed to obtain the Pareto frontier of the non-dominated solutions. Based on the Taguchi design method, dry milling experiments on aluminum are performed to verify the proposed regression and optimization models. The experimental results show that a higher spindle speed and feed rate are more advantageous for achieving the performance indicators, and the depth of cut is the most critical process parameter because the increase of the depth of cut results in the decrease of the specific carbon emission but the increase of the material removal rate and surface roughness. Finally, based on the regression models and the optimization approach, an online platform is developed to obtain in-process information of energy consumption and carbon emission for real-time decision making, and a simulation case is conducted in three different scenarios to verify the proposed approach.

Keywords: Specific carbon emission, Multi-objective optimization, Dry milling, NSGA-II, Online analysis platform

1. Introduction

With the aggravation of global warming and quick increase of energy cost, research to develop energy-efficient and low-carbon emission technologies for the manufacturing industry, which consume significant raw materials and energy, has been becoming paramount. In the U.S., the manufacturing sector was responsible for 22% of energy consumption in 2006, and the associated energy costs were about $50 billion [1]. Manufacturing results in substantial stress on the environment concerns [2]. Research has been actively carried out to improve the sustainability in manufacturing, such as sustainable production scheduling [3], better workshop management for less energy consumption, and machine parameter optimization for energy efficient machining processes [4].

For machining, research has shown that energy savings up to 6-40% could be obtained based on the optimum choice of cutting parameters, tools and optimum tool path design [4]. Therefore, machining parameters optimization leading to energy saving and minimized carbon emission in manufacturing workshops is imperative.

In machining processes, the most commonly used optimization criteria are material removal rate (MRR), surface roughness (SR), cutting force, tool life and power consumption [5]. Although several optimization approaches have been proposed to reduce the environmental impacts of machining processes, most of them are qualitative analysis methods, such as grey relational analysis [6], response surface methodology (RSM) [7] and factor effect analysis [8]. Through establishing the regression and optimization models, a systemic approach is proposed to analyze and optimize machining parameters quantitatively and achieve a better eco-efficiency which means lower manufacturing costs, better production rate and less carbon emission. Furthermore, an online platform for carbon emission analysis is developed to realize prompt decision-making during the above processes.

The rest of this study is organized as follows. The related research is reviewed in Section 2. In Section 3, regression models of milling processes are constructed to characterize the relationship between the milling parameters and the environmental/productivity/quality objectives firstly. Then a mathematical optimization model is constructed and a hybrid Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is proposed to identify the optimal milling parameters. Section 4 shows the experimental work for establishing the regression models. The regression analysis and optimization analysis are carried out on the basis of the experimental results in Section 5. An online platform for carbon emission analysis is developed and a simulation case is shown to illustrate the feasibility of the method in Section 6. Finally, some conclusions are made in Section 7.

2. Research Background

2.1 Energy reduction of machine tools

Reducing the machining energy of machine tools can significantly improve the environmental performance of manufacturing process [9]. Therefore, several researchers have focused on the energy monitoring and reduction for machine tools. By presenting a detailed description of different test procedures based on standardized workpieces, Behrendt et al.[10] proposed a novel and coherent method to assess energy consumption of machine tools. Hu et al.[11] developed a new on-line energy efficiency monitoring approach without using any torque sensor or dynamometer to minimize the implementation cost and difficulty. Kara and Li [12] presented an empirical model to characterize the relationship between energy consumption and process variables for material removal processes, and tested and validated the model on a number of turning and milling machine tools. In addition, some studies were conducted from the viewpoint of machine tool components and internal energy dissipation units. Through measuring the power consumption of a machining center under different conditions, a new acceleration control method was developed to reduce energy consumption by synchronizing spindle acceleration with the feed system [13]. Newman et al.[4] presented a framework to validate the introduction of energy consumption in the objectives of process planning for Computer Numerical Control (CNC) machining on the basis of the state-of-the-art in process planning and energy consumption in manufacturing research. In addition, a model for the optimization of machining parameters was presented for the minimum energy consumption in a multi-pass turning operation [14], and the model takes into account finishing and roughing passes separately for the energy optimization followed by the dual optimization of the energy functions for a combination of one finishing pass and multiple roughing passes. In order to obtain the optimum machining parameters, Kant and Sangwan [15] provided a multi-objective predictive model for the minimization of power consumption and surface roughness in machining, using grey relational analysis coupled with principal component analysis and response surface methodology. From the above literature, it can be seen that energy modeling and qualitative analysis of machine tools from different viewpoints have drawn much attention, while another important aspect, i.e., the optimization of cutting parameters and quantitative analysis for energy consumption reduction, has not well researched. Therefore, more efforts need to be made to search quantitative methods for the energy conservation and carbon emission reduction of machine tools.

2.2 Low-carbon oriented modeling of machining processes

With the purpose of analyzing machining process and reducing its environmental impact, models have been developed to reveal the relationship between machining parameters and some performances indicators, as shown in Table 1. Choudhury and Appa Rao [16] established a tool life estimation equation from experimental data and the adhesion wear model. Lalwani et al.[17] established a linear model to fit the variation of cutting forces with feed rate and depth of cut by conducting machining experiments based on RSM and the sequential approach. Moreover, Zain et al.[18] established a predicted model of the SR to show its relationship with the decision variables (cutting speed, the feed per tooth, the axial depth of cut, the radial depth of cut and machining tolerance).

In addition, some researchers conducted machining experiment and regression analysis to minimize energy consumption and carbon emission. Campatelli et al.[19] focused on the efficiency of the machining centers and developed a quadratic regression model through an experimental approach to evaluate and optimize the process parameters in order to minimize the power consumption in a milling process performed on a modern CNC machine. An orthogonal array, signal to noise (S/N) ratio and analysis of variance (ANOVA) were employed to analyze the effects and contributions of depth of cut, feed rate and cutting speed on the energy consumption[20]. Bhattacharya et al.[21] outlined an experimental study to investigate the effects of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel by employing the Taguchi techniques and ANOVA. Winter et al.[22] presented a generic regression model to describe and analyze the influence of grinding process parameters in conjunction with different cutting fluids on SR, cost and carbon footprint, and applied the sensitivity analysis to reveal the trends of each process parameter in relation to the preference of technological, economic and environmental objectives. Bhushan[23] conducted experimental investigations to establish relationships between cutting speed, feed rate, depth of cut and nose radius and power consumption and tool life in CNC turning of 7075 Al alloy 15 wt% SiC composite by using the RSM. However, these works considered the power consumption as environmental target which didn't reflect the real energy consumption of machining process directly because the energy consumption is also related to processing time except power consumption. Although Rajemi et al.[24] modelled the total energy of machining a component by a turning process and optimized it to derive a minimum carbon footprint requirement, the carbon emission of cutting tools and cutting fluids were not considered [25].

Table 1: Modeling methods of machining processes.

Focus	Authors (Year)	Machine performances	Machining process	Model or methodology
Technical performance	Choudhury and Appa Rao (1999)[16]	Tool life	milling	Experimental methods

	Lalwani et al. (2008)[17]	Cutting forces	turning	RSM, the sequential approach
	Zain et al. (2010)[18]	SR	milling	Artificial Neural Network
Power or energy consumption	Campatelli et al., (2013)[19]	Power consumption	milling	RSM
	Camposeco-Negrete (2013)[20]	Energy consumption and SR	turning	Orthogonal array, S/N and ANOVA
	Bhattacharya et al., (2009)[21]	Surface finish and power consumption	turning	Taguchi technique, ANOVA
	Winter et al. (2013)[22]	SR, cost and carbon footprint	grinding	Regression analysis and sensitivity analysis
	Bhushan (2013)[23]	Power consumption and tool life	turning	RSM, desirability function approach
	Rajemi et al. (2010)[24]	Energy footprint and tool life	turning	$T_{opt-E} = (\frac{1}{\alpha} - 1)(\frac{P_0 t_3 + y_E}{P_0})$

2.3 Mathematical optimization of machining processes

To obtain the optimal cutting parameters and reduce the carbon emission, mathematical optimization approaches were used to identify the optimal or close to the optimal solution of a given task regarding constraints and a set of given functions. The tasks can be generally classified as single-objective or multi-objective optimization, as shown in Table 2. For the former, the aim is to solve a single-objective function by identifying the minimum or maximum value. Nalbant et al.[26] used the Taguchi method to find optimal cutting parameters for SR in turning. Wibowo and Desa[27] presented a technique by using the hybridization of kernel principal component analysis (KPCA) based nonlinear regression and Genetic Algorithms (GAs) to estimate the optimum values of the three parameters (namely radial rake angle, speed and feed rate) such that the estimated SR was as low as possible. In order to get the minimum energy consumption, an experimental study to optimize cutting parameters during turning of AISI 6061 T6 under roughing conditions was presented [20].

However, single objective approaches are limited in identifying the optimal cutting parameters, because several objectives are sometimes contradictory and must be simultaneously optimized. Hence, multi-objective approaches for cutting parameters optimization, which consider multi-objectives were developed. Quiza Sardiñas et al.[28] constructed a multi-objective optimization model to obtain the optimal tool life and operation time, and used a micro GAs to obtain the non-dominated points. Pawade and Joshi [29] applied a new effective approach, named the Taguchi grey relational analysis to experimental results in order to optimize the high-speed turning of Inconel 718 with consideration to multiple performance measures. A new approach for the optimization of the micro wire electric discharge machining process with multiple performance characteristics is attempted based on the statistical-based ANOVA and grey relational analysis [6]. Kuram et al.[30] investigated the effects of cutting fluid types as a function of three milling factors (cutting speed, depth of cut and feed rate) on process responses (specific energy, tool life and SR). Yan and Li[8] presented a multi-objective optimization method based on the weighted grey relational analysis and RSM, and optimized the cutting parameters in milling process by using the sequential quadratic programming (SQP) algorithm. Winter et al.[22] presented an approach to identify the process parameters and developed Pareto-optimal solutions for advancing the eco-efficiency of grinding operations, including SR, cost and carbon footprint. Based on the contour plot methodology, a multi-objective statistical optimization was performed for improving the machining productivity and surface quality of laser milling [7]. It is the fact that most of these studies are limited to qualitative analysis of some optimization objectives by using grey relational analysis, desirability function analysis, sensitivity analysis, RSM, etc. Moreover, many studies transformed multi-objective problems into single-objective problems and employed traditional mathematical programming methods to solve the problems. However, few researchers have used Pareto-optimal methods or intelligent algorithms to optimize machining parameters which are more effective.

Table 2: Mathematical optimization comparison of machining processes.

Focus	**Authors (Year)**	**Objectives**	**Optimization methods**
Single-objective optimization	Nalbant et al. (2007)[26]	SR	Taguchi method
	Wibowo and Desa (2012)[27]	SR	KPCA, nonlinear regression and GA
	Camposeco-Negrete (2013)[20]	Energy consumption	RSM
Multi-objective optimization	Quiza Sardiñas et al. (2006)[28]	Tool life and operation time	micro GAs
	Pawade and Joshi (2011)[29]	SR and cutting forces	Taguchi grey relational analysis
	Somashekhar et al. (2011) [6]	MRR, overcut, SR	ANOVA, grey relational analysis
	Kuram et al., (2013)[30]	Specific energy, tool life and SR	D-optimal method
	Yan and Li, (2013)[8]	Cutting energy, MRR, SR	Weighted grey relational analysis, RSM and SQP
	Winter et al., (2013)[22]	SR, cost and carbon footprint	Geometric programming algorithm
	Bhushan, (2013)[23]	Power consumption and tool life	Desirability function analysis
	Campanelli et al.(2013) [7]	Ablation depth, MRR, SR	RSM (contour plot methodology)

3. Approach

3.1 Workflow of the approach

Figure 1 presents the approach to identify the optimal milling parameters for better quality, higher productivity and lower carbon emission. Firstly, owing to the stochastic nature of milling process, regression models are constructed to characterize the relationship between the milling parameters and the respective objectives. Secondly, based on the regression models, an optimization model is established and a hybrid NSGA-II is adopted to identify the optimal milling parameters. Thirdly, experiments based on the Taguchi design method are designed to identify the levels of experimental variables with the minimal amount of experiments. Fourthly, the milling experiments are performed according to the experimental plan and the regression models are derived from the experimental results with the statistical analyses software SPSS®, and single-objective analysis and multi-objective optimization is carried out to obtain the Pareto-frontier of milling parameters. Finally, an online platform is developed to obtain in-process information about the energy consumption and carbon emission to support above real-time decision making, and a simulation case is conducted in three different scenarios to verify the proposed method. Although Palanikumar et al.[31] applied similar statistical models and NSGA-II to optimize the cutting conditions of glass fiber reinforced plastic composites, they didn't consider the energy consumption and carbon emission.

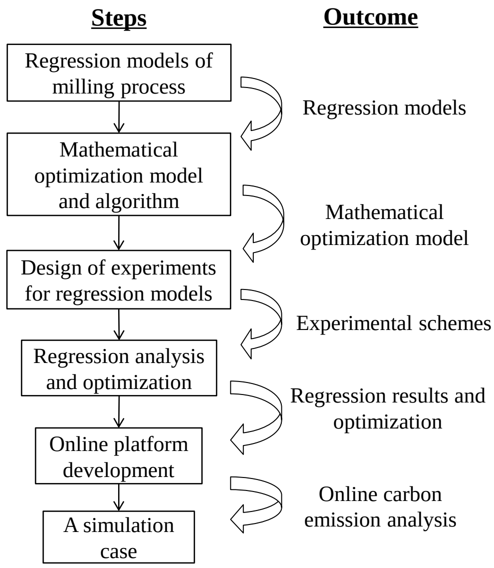


Figure 1: Schematic of the solving approach.

3.2 Regression models of milling process

1. Production rate

The MRR (in mm^3/min), which is the most commonly used optimization criterion of production rate in milling processes, can be computed by the following Eq. 1.

$$MRR = d * f * a_p \tag{1}$$

where d is the cutting tool diameter in *mm*, f means feed rate in *mm/min*, and a_p represents the depth of cut in *mm*.

2. Environmental impact

The power of a milling process is determined by the milling force and milling velocity of machines [32], which can be calculated by Eq.5-2.

$$P_c = 42.4 * 10^{-5} k_p d_0^{-0.3} a_{se} f_z^{0.75} a_{sp}^{1.1} z n_0^{0.8} \tag{2}$$

where k_p, d_0, $a_{se}(a_{sp})$, f_z, z, and n_0 represent correction factor, cutter diameter in *mm*, cutting depth in *mm*, feed rate in *mm/min*, number of teeth and spindle speed in *r/min*, respectively.

According to the above Eq.2, a generic regression model is developed to describe the relationship between the process parameters and the environmental impact, as shown in Eq.3.

$$f(x_1, x_2, x_3) = \alpha_1 * {x_1}^{\alpha_2} * {x_2}^{\alpha_3} * {x_3}^{\alpha_4} \tag{3}$$

where $f(x_1, x_2, x_3)$ denotes an environmental impact such as cutting power, energy consumption, carbon emission, etc., which will be described in detail later. α_i (i=1,2,3,4) is the regression coefficient and x_i (i=1,2,3) represents one of machining parameters including spindle speed (n), feed rate (f) and cutting depth (a_p). The model accuracy or model quality can be ascertained using the coefficient of determination, also known as the R^2 value. The R^2 value describes the consistency between the measurements and the statistical model. The higher R^2 value, the higher degree of consistency.

According to the spindle power profile of a machine, a machining process mainly contains five states, that is, the startup state, idle state, cutting state, tool changing state and the shutdown state. Since the power of the startup state, tool changing state and the shutdown state has nothing to do with the milling parameters, only the cutting power (P_c) and air-cutting power (P_a) were chosen to analyze the relationship between machining power and milling parameters, as illustrated in Eq.4 and Eq.5.

$$P_c = \beta_1 * n^{\beta_2} * f^{\beta_3} * a_p^{\beta_4} \quad (4)$$

$$P_a = \theta_1 * n^{\theta_2} * f^{\theta_3} \quad (5)$$

where β_i (i=1,2,3,4) and θ_i (i=1,2,3) denote regression coefficients.

In addition, the specific carbon emission (SCE [$kgCO^2$-e/cm^3]) was used to evaluate the environmental impact of different machining processes, as shown in Eq.6. Here, the carbon emission contains two parts: one from machine tools (SCE_{energy}) and another one from cutting tools (SCE_{tool}) [25]. For the former, only the carbon emission of a machine tool due to the electrical energy consumption was taken in account, while the carbon emission from the production and procurement of the machine tool was not considered because this part of carbon emission cannot be influenced by the machining parameters. For the latter, the carbon emission of cutting tools is calculated by comparing machining time with tool life as the production of cutting tools consumes energy and each cutting tool has a lifetime. Notably, these life cycle analysis of cutting tools only considered the production of cutting tools and the disposal phase was excluded due to the absent data, thus the carbon emission due to cutting tools shown in this study may be underestimated. In order to improve the quality of the analysis, the entire life cycle of the cutting tools was suggested to be considered in the future research.

$$SCE = SCE_{energy} + SCE_{tool} = \eta_1 * n^{\eta_2} * f^{\eta_3} * a_p^{\eta_4} \quad (6)$$

where η_i (i=1,2,3,4) denotes regression coefficients.

3. Product quality

The SR (R_a [um]), which was widely used to assess product quality, was selected to evaluate the production quality target. It was found that the cutting parameters n, f and a_p have a strong effect on SR [33].

In order to characterize the relationships between the SR and the above process parameters, the RSM method was chosen due to its adaptability in applications where several input variables (independent variables) are potentially influence some performance measure or quality characteristic of products or processes [8]. Usually the first-order model of RSM is ineffective because it includes only the main effect of the variables. Here, the second-order model of RSM was adopted based on its flexibility. A general form is shown in Eq.7.

$$R_a = \gamma_0 + \sum_{i=1}^{3} \gamma_i * x_i + \sum_{i \le j} \sum \gamma_{ij} * x_i * x_j \quad (7)$$

where γ_i (i=0,1,2,3) and γ_{ij} are the regression coefficients and x_i (i=1,2,3) represents one of machining parameters.

3.3 Mathematical optimization model

Considering the eco-efficiency of milling processes, an optimization model is established in which the production rate *MRR*, specific carbon emission SCE_{total} and surface roughness R_a are chosen to represent the production target, environmental target and quality target, respectively, as shown in Eq.8. In addition, the total cutting power P_c stands for the real-time machining power reflecting the state of runtime machine. High cutting power can incur the greater vibration of machine tools, or bigger cutting tool wear, so there should be an upper bound limit for the cutting power. Based on the above regression models, the optimization model is shown as follows:

Objectives:

$$\begin{cases} SCE = \eta_1 * n^{\eta_2} * f^{\eta_3} * a_p^{\eta_4} \\ MRR = d * f * a_p \\ R_a = \gamma_0 + \sum_{i=1}^{3} \gamma_i * x_i + \sum_{i \le j} \sum \gamma_{ij} * x_i * x_j \end{cases} \tag{8}$$

Constraints:

$$\beta_1 * n^{\beta_2} * f^{\beta_3} * a_p^{\beta_4} \le \bar{P}_c \tag{9}$$

$$0 < n \le n^{max} \tag{10}$$

$$0 < f \le f^{max} \tag{11}$$

$$0 < a_p \le a_p^{max} \tag{12}$$

$$d > 0, x_i > 0, x_j > 0, \beta_1 > 0, \eta_1 > 0, \gamma_0 > 0 \tag{13}$$

where $\bar{P}_c$ denotes the upper limit of the cutting power which can ensure the machine tool in normal operation state. According to the actual processing capacity of a machine tool, n^{max}, f^{max} and a_p^{max} represent the maximum of spindle speed, feed rate and depth of cut, respectively.

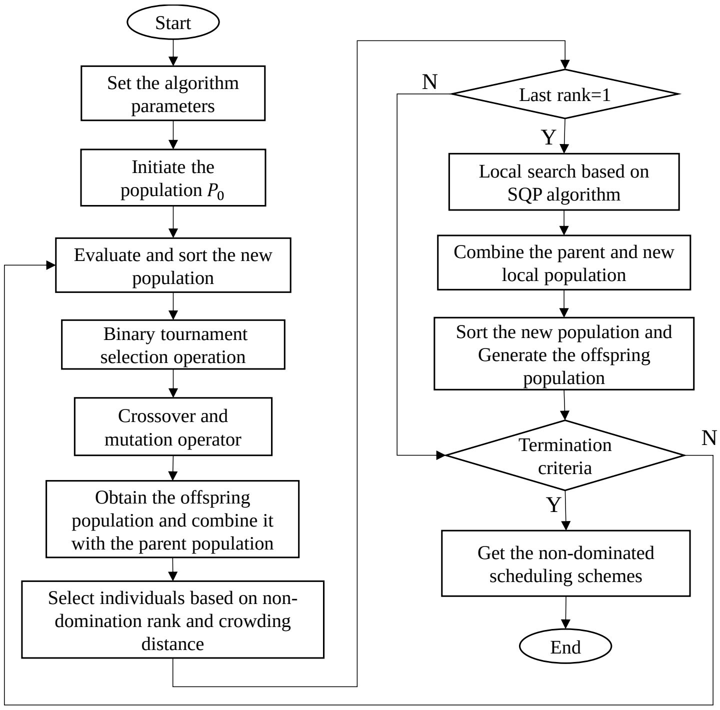


Figure 2: The flow chart of the hybrid NSGA-II.

To solve the above multi-objective optimization problem, a hybrid NSGA-II algorithm is proposed to identify the optimal milling parameters, as shown in Figure 2. NSGA-II can get the Pareto frontier of solutions through non-domination sorting and crowding distance calculation, which allows the operator to choose the appropriate solution according to specific needs. The main components of the proposed algorithm are summarized below:

Step 1: Set the algorithm parameters like number of population, maximum number of generations, crossover and mutation probabilities;

Step 2: Generate the initial population P_0 randomly within the range of parameters;

Step 3: Evaluate the objective functions (i.e. SCE, R_a, MRR), and regard the constraint (P_c) as an additional objective function to conduct the non-dominated sorting, as shown in Figure 3. Then, sort them with the assigned non-domination level number and the value of crowding distance;

```
// Non-dominated sorting of the constrained NSGA-II algorithm
Choose any chromosome C1 and C2;
If (Pc of chromosome C1) ≤ P̄c and (Pc of chromosome C2) > P̄c
    C1 dominates C2;
Else if (Pc of C1) ≤ P̄c and (Pc of C2) ≤ P̄c
    If SCE, Ra, MRR of C1 are all better than that of C2
        C1 dominates C2;
    End if
End if
```

Figure 3: Non-dominated sorting of the constrained NSGA-II algorithm.

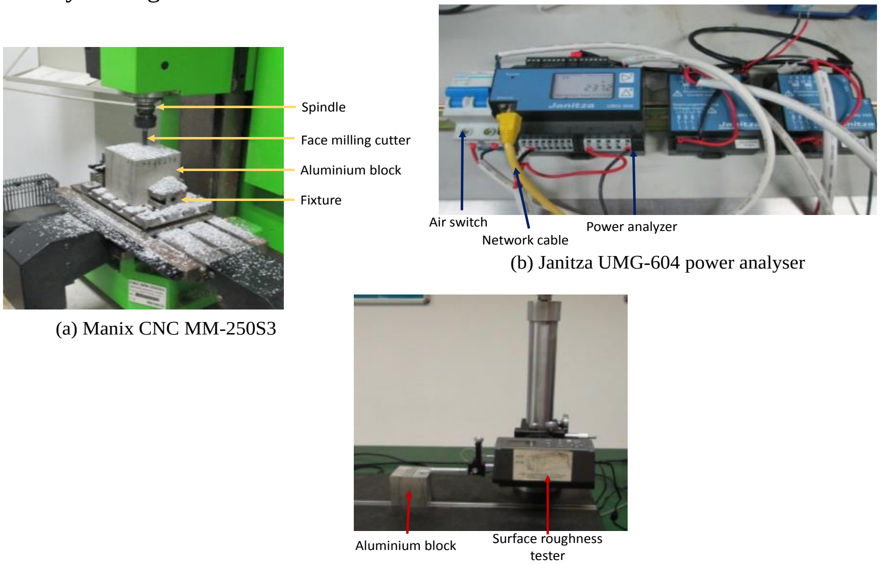
Step 4-6: Perform selection, crossover and mutation operation [34].

Step 7: When ranks of all chromosomes in the parent population equal one, divide the population into three sub populations and perform local search for each sub population based on SQP algorithm. For example, for the first population, the SQP algorithm is used to obtain the best chromosome with the lowest *SCE* and form a new sub population. Similarly, the best chromosome with highest MRR is selected for the second sub population and the one with the best R_a is found for the third sub population. Then, combine the parent and new population, and sort them based on non-domination rank and crowding distance.

4. Experimental Work for Establishing the Regression Models

4.1 Experimental setup

The experimental environment and measurement equipment are shown in Figure 4. The experiments were performed on a CNC micromachining center (Manix CNC MM-250S3, Figure 4a) with 1.2 kW motor rated power and maximum spindle speed of 6400 rpm. The power demand of the milling process was acquired by using the Janitza power analyzer UMG 604 (Figure 4b) and SR was measured by the surface roughness tester TR300 (Figure 4c). Since the main propose of this experiment was to obtain the total power consumption of the micromachining center, the power analyzer was connected with the main input wire of the machine. The used power analyzer with a temporal resolution of 10ms was configured to record the total active power of the MM-250S3. The real-time power data from the power analyzer was recorded through an online platform for energy consumption analysis and process planning, which will be introduced in Section 6.1. Since many problems such as health and environment issues are identified with the use of flood cutting fluids in machining processes, considerable attention has been given to reduce or completely omit the cutting fluids, and meet the demands for environment-friendly cutting processes[35]. Therefore, the dry milling of aluminum is researched in this study. A 7.8*mm* diameter, 4 flutes carbide tool was employed for the dry cutting of an 80*mm*×80*mm*×80*mm* aluminum block.



(a) Manix CNC MM-250S3

(b) Janitza UMG-604 power analyser

(c) Surface roughness tester TR300

Figure 4: The experimental environment and measurement equipment.

4.2 Design of experiments

Taking the actual processing capacity of the MM-250S3 into consideration, the milling parameters were set up in the recommended ranges and the tool wear didn't deteriorate significantly according to preliminary tests. As mentioned before, the spindle speed n (r/min), feed rate f (mm/min) and depth of cut a_p (mm) were chosen due to their major influence on the milling process. The variances of n, f and a_p were customized according to the machine tool's parameter range. The cutting parameters and their levels are shown in Table 3. In order to reduce the times of experiments, the Taguchi design method of experiments was adopted. Since each parameter had four levels, the standard orthogonal array L16(4^5) was chosen. But only three columns in the L16(4^5) were used to obtain the experimental data because there were only three parameters in this experiment. As mentioned before, multiple independent experimental data was measured throughout the experiments, including processing time, air-cutting power, machining power, energy consumption, and SR. Each measurement was taken after removing unit volume of material, namely 1 cm^3, and each experiment was replicated twice in order to reduce the influence of the system errors. For SR, each measurement was taken from three different locations using the surface roughness tester, and the average values were recorded as the final result.

Table 3: Design of experiments.

Parameters	**Range**	**Level 1**	**Level 2**	**Level 3**	**Level 4**
$n[r/min]$	1000-4000	1000	2200	3000	4000
$f[mm/min]$	4-16	4	8	12	16
$a_p[mm]$	0.4-1.6	0.4	0.8	1.2	1.6

5. Regression Analysis and Optimization

5.1 Regression analysis based on experimental results

After carrying out the above experiments, all results of different combinations of milling parameter are shown in Table 4. As aforementioned, the objectives of the mathematical optimization can be expressed as productivity, environmental and quality target functions. Based on the experimental results, a non-linear regression analysis was performed to derive each target function via the IBM SPSS Statistics 19. The regression coefficients and R^2 values of machining power and *SCE* are listed in Table 5. A summary of ANOVA results for the regression models has been presented in Table 6, and it can be clearly seen that the models achieve a great accuracy because of a high R^2 value.

Table 4: Experimental results of different milling parameter combination.

No.	n	f	a_p	P_a	P_c	MRR	SCE	R_a
1	1000	4	0.4	381.756	474.95	12.48	2.931	0.134
2	1000	8	0.8	382.3	502.39	49.92	0.755	0.189
3	1000	12	1.2	384.397	532.73	112.32	0.346	0.234
4	1000	16	1.6	387.319	559.13	199.68	0.200	0.318
5	2200	4	1.2	504.056	661.4	37.44	1.177	0.181
6	2200	8	1.6	506.442	687.93	99.84	0.452	0.21
7	2200	12	0.4	504.63	615.73	37.44	1.128	0.152
8	2200	16	0.8	498.654	656.9	99.84	0.440	0.231
9	3000	4	1.6	578.283	793.03	49.92	0.989	0.231
10	3000	8	1.2	581.997	759.16	74.88	0.641	0.277
11	3000	12	0.8	583.974	733.53	74.88	0.627	0.275

12	3000	16	0.4	585.892	696.65	49.92	0.911	0.216
13	4000	4	0.8	687.115	832.69	24.96	2.041	0.239
14	4000	8	0.4	681.655	797.86	24.96	1.985	0.241
15	4000	12	1.6	686.775	922.19	149.76	0.364	0.292
16	4000	16	1.2	699.73	894.15	149.76	0.357	0.295

Table 5: The regression coefficients of Pa, Pc and SCE.

P_a		P_c		SCE	
β_1	18.46	θ_1	36.421	η_1	1.0577
β_2	0.432	θ_2	0.375	η_2	0.222
β_3	0.007	θ_3	0.021	η_3	-1.01
β_4	/	θ_4	0.099	η_4	-0.965

Table 6: Analysis of variance for Pa, Pc and SCE.

	Factor	DOF	SS	MS	F	Sig. F
P_a	Regression model	2	0.7250	0.3625	387.13	2.6E-12
	Error	13	0.0122	0.0009	-	-
	Total	15	0.7372	-	-	-
	S=0.0306		**R-Sq=98.35%**		**R-Sq(adj)=98.09%**	
	Factor	**DOF**	**SS**	**MS**	**F**	**Sig. F**
P_c	Regression model	3	0.5969	0.1990	246.68	4.81E-11
	Error	12	0.0097	0.0008	-	-
	Total	15	0.6065	-	-	-
	S=0.028		**R-Sq=98.40%**		**R-Sq(adj)=98.01%**	
	Factor	**DOF**	**SS**	**MS**	**F**	**Sig. F**
SCE	Regression model	3	8.2985	2.7662	6118.44	2.28E-19
	Error	12	0.0054	0.0005	-	-
	Total	15	8.3039	-	-	-
	S=0.021		**R-Sq=99.93%**		**R-Sq(adj)=99.92%**	

Based on the experimental data in Table 4, the second-order polynomial regression model of the SR was developed by using the IBM SPSS Statistics 19 software, as shown in Eq.14. The ANOVA for R_a is presented in Table 7, and it can be observed that the coefficient of determination R-Sq (adj) for the regression model of R_a is equal to 0.885, which indicates that the model has good compatibility to the experimental data. Therefore, this regression model based on the Taguchi method and RSM is suitable for establishing prediction models.

$$R_a = 0.04 + 4.615 * 10^{-5} * n - 0.003 * f + 0.147 * a - 2.417 * 10^{-5} * n * a + 0.007 * f * a - 0.05 * a^2 \quad (14)$$

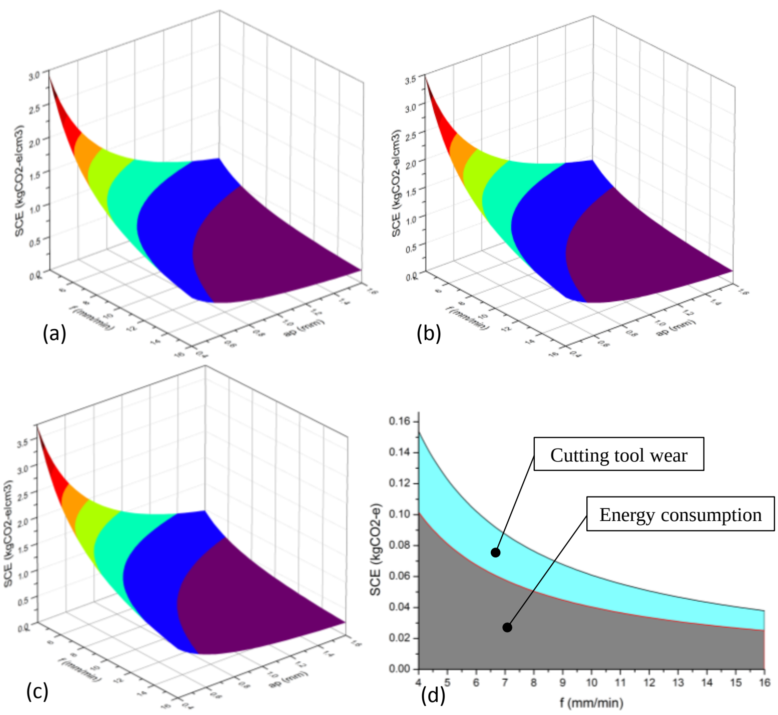
Table 7: The ANOVA for Ra.

	Factor	DOF	SS	MS	F	Sig. F
	Regression model	6	0.0349	0.0058	59.27	1.56E-5
R_a	Error	9	0.0053	0.0006	-	-
	Total	15	0.0402	-	-	-
	S=0.024		**R-Sq=93.11%**		**R-Sq(adj)=88.52%**	

5.2 Single-objective analysis

In order to investigate the contribution and effects of milling parameters on the different objectives including SCE, R_a, P_a and P_c, the surface plots and contour plots were created to perform single objective analysis.

1. Environmental impact analysis



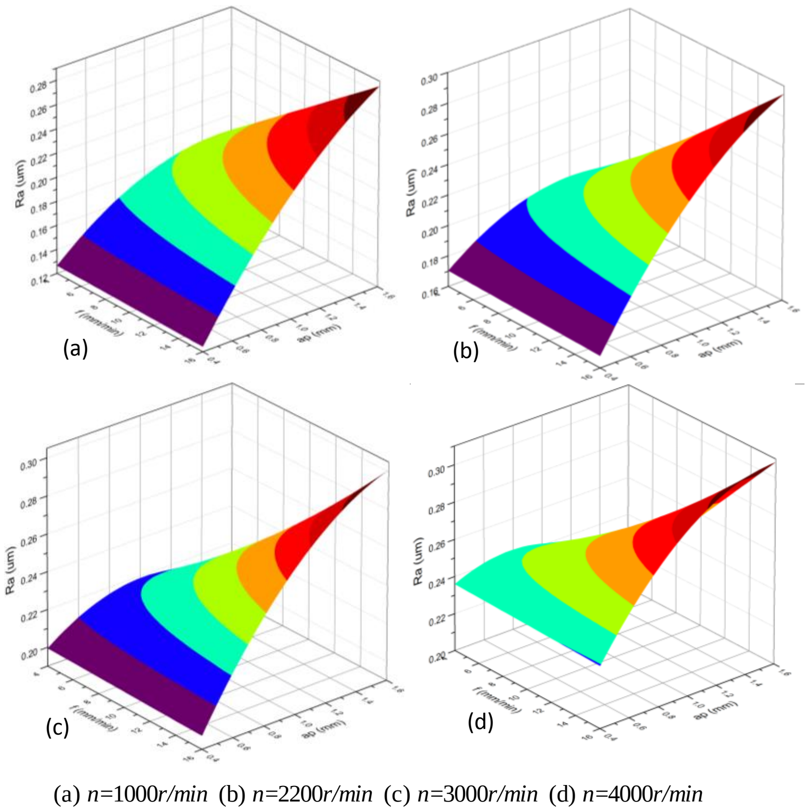
(a) n=1000r/min (b) n=2200r/min (c) n=3000r/min (d) n=4000r/min and a_p=1.0mm sectional view

Figure 5: Specific carbon emission analysis.

The environmental impact is presented in Figure 5 and shows that the *SCE* changes over the depth of cut a_p and the feed rate *f*, with four fixed value for the cutting speed *n*, namely, 1000*r/min*, 2200*r/min*, 3000*r/min* and 4000*r/min*.

It can be observed that the *SCE* decreases with the increase of *f* and a_p simultaneously, and *f* and a_p have an similar effect on the *SCE*. In particular, the *SCE* declines obviously when *f* and a_p are small relatively. If $f > 11$ *mm/min* and $a_p > 1.1$ *mm*, the *SCE* changes very little, which means that $f = 11$ *mm/min* and $a_p = 1.1$ *mm* are the critical points for carbon emission reduction. The influence of *n* on *SCE* is not obvious, especially when *f* and a_p are large relatively. Therefore, compared with the cutting speed, the feed rate and depth of cutting are more important for *SCE*. From the specific carbon emission sectional view in Figure 5d, the carbon emission of energy consumption decreases significantly due to the reduction of processing time; however, the carbon emission of cutting tools decreases not obviously, which shows that the reduction of carbon emission mainly comes from the energy consumption for the chosen parameters.

2. Product quality analysis



(a) *n*=1000*r/min* (b) *n*=2200*r/min* (c) *n*=3000*r/min* (d) *n*=4000*r/min*

Figure 6: Surface roughness analysis.

Figure 6 presents the response surfaces of the empirical regression model for the product quality impact, i.e., SR of the milling process. The impact is also presented over the depth of cut a_p and the feed rate f, with four fixed value for the cutting speed n, namely, 1000*r/min*, 2200*r/min*, 3000*r/min* and 4000*r/min*.

From Figure 6, it can be clearly seen that the increase of a_p and f leads to the increase of the measured SR, and a_p has a more significant impact due to the superposition of geometrical and kinematical effects on the milling process. In particular, the influence of f is not obvious when a_p is small, and the increase of f will cause the changing of SR if $a_p > 0.8mm$. Similarly, when $f < 6mm/min$, the increase of a_p will cause little change of SR, which means there is a critical region ($f < 6mm/min$ or $a_p < 0.8mm$) in which the part has a good quality and the SR changes little due to the increase of f and a_p. Conversely, the influence of the cutting speed is obvious only within the critical region. Overall, when f and a_p are small ($f < 6mm/min$ or $a_p < 0.8mm$), the cutting speed will have more influence on the SR; but f and a_p will affect the SR obviously beyond the critical region.

Moreover, by comparing SR and *MRR*, a_p and f have an opposite effect on them, so that the optimal SR and *MRR* cannot be obtained simultaneously.

3. Other measurands

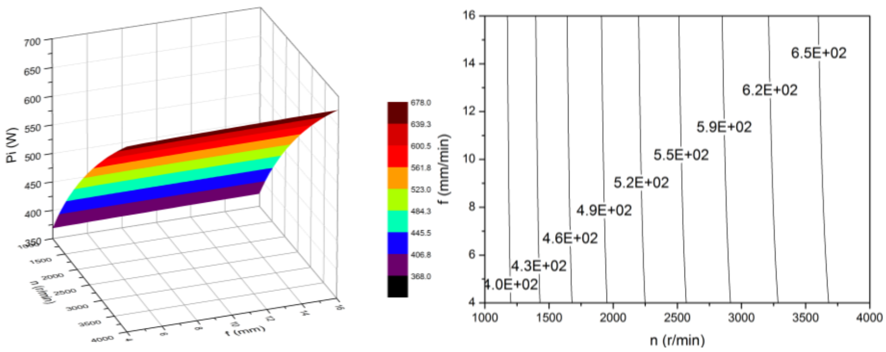
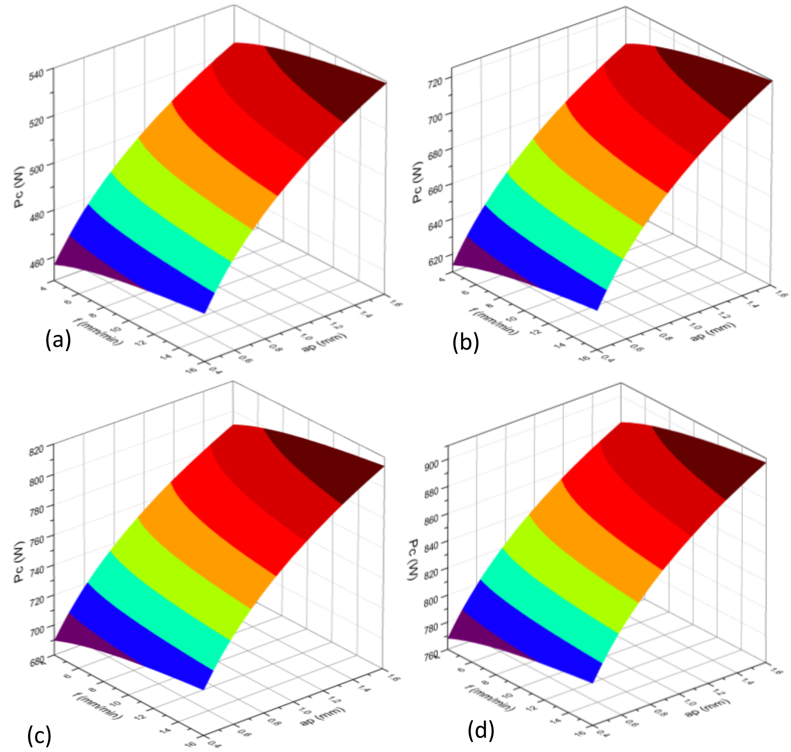


Figure 7: Air-cutting power analysis (left side response surface and right side contour plot).



(a) n=1000*r/min*; (b) n=2200*r/min*; (c) n=3000*r/min*; (d) n=4000*r/min*

Figure 8: Cutting power analysis.

Based on the aforementioned experimental results, some other measurands were also analyzed in this research. First, the air-cutting power is presented in Figure 7. The impact is shown over the cutting speed n and the feed rate f. The air-cutting power is mainly related to the cutting speed, and increases apparently with the increase of n. For feed rate, the change of air-cutting power is little since the selected feed rates are relatively small and have a little change in the experiment.

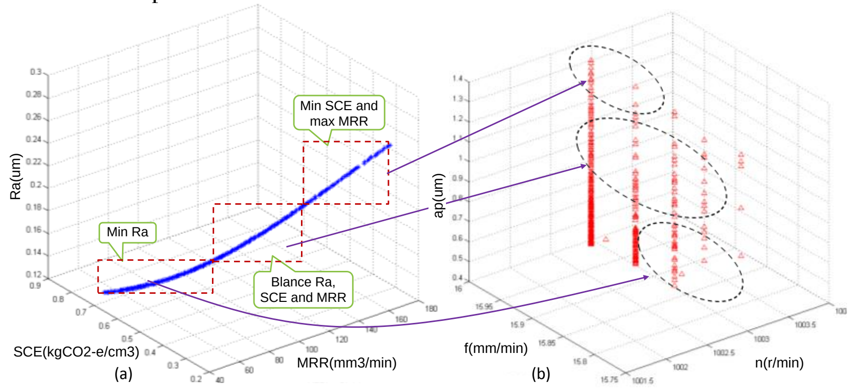
In addition, the total cutting power analysis is presented in Figure 8. The impact is shown over the depth of cut a_p and the feed rate f, with four fixed value for the cutting speed n, that is, 1000*r/min*, 2200*r/min*, 3000*r/min* and 4000*r/min*.

In Figure 8, the increase of f and a_p results in a higher cutting power, and a_p plays a main role because they will increase the cutting force which is directly related to the cutting power. In particular, the cutting power increases obviously when f and a_p are small. Through the comparison of Figure 8(a) – Figure 8(d), the cutting speed has a same effect on the cutting power whether it is small or large relatively. Comparing the *MRR* with cutting power, they have the same variation trend with the changing of the feed rate and depth of cut.

5.3 Multi-objective optimization result

In this study, since there is a trade-off between *MRR*, *SCE* and *SR*, a multi-objective optimization becomes necessary. Finding the optimal process parameters to achieve the desired level of response (maximum *MRR*, minimum *SCE* or minimum *SR*) can be performed.

The multi-objective optimization model has been described in Section 3.3. According to the actual operation of the milling machine, the total power is constrained to be less than or equal to 530W. The simulations were run by using the hybrid NSGA-II with a population of 80 chromosomes and a maximum number of 500 iterations. After obtaining the best milling parameter combinations, the Pareto frontier was plotted in a three-dimensional objective space for viewing (shown in Figure 9a). The simulations usually took less than 20 minutes in a PC with an Intel Dual-Core 2.40 GHz processor.



(a) Pareto front of optimal objective values; (b) Optimal solutions in variable domain

Figure 9: Results of the multi-objective optimization.

The Pareto frontier of the non-dominated solutions for maximum *MRR*, minimum SR and minimum *SCE* is presented in Figure 9. Three distinct regions are identified along the Pareto frontier of the non-dominated solution set in Figure 9a. These regions are marked as "Min *SCE* and max *MRR*", "Balance R_a, *SCE* and *MRR*" and "Min R_a". Corresponding regions in the solution (decision variable) space are also indicated in Figure 9b. Milling process parameters that maximize *MRR*, minimize SR and minimize *SCE* are identified in the variable domain at a lower spindle speed 1002.93*r/min* and at a higher feed rate 15.75-16.00*mm/min* (see Figure 9b). However, the depth of cut a_p varies hugely from 0.4*mm* to 1.28*mm*, which means a_p has the most important influence on the optimal results.

Table 8: A set of non-domination solutions.

No.	*n*	*f*	a_p	*MRR*	*SCE*	R_a
1	1002.93	15.99	0.40	49.92	0.722	**0.124**
2	1002.93	15.99	1.32	**164.99**	**0.228**	0.261
3	1002.93	15.99	1.02	127.48	0.292	0.226
4	1002.93	15.81	0.95	116.62	0.319	0.215
5	1002.93	15.86	0.51	62.74	0.579	0.144
6	1002.93	15.81	0.79	97.91	0.377	0.193
7	1002.93	15.99	1.11	138.79	0.269	0.238
8	1002.93	15.99	1.29	160.80	0.233	0.258
9	1002.93	15.99	1.09	135.52	0.275	0.234
10	1002.93	15.86	0.66	81.70	0.449	0.171
11	1002.93	15.99	0.41	51.76	0.697	0.127
12	1002.93	15.86	1.14	140.48	0.266	0.240
13	1002.93	15.99	0.64	79.96	0.458	0.168
14	1002.93	15.86	0.63	77.89	0.470	0.166
15	1002.93	15.99	0.42	52.91	0.682	0.129

Furthermore, a feasible solution set with 15 combinations of milling process parameters is provided for the operator to achieve desired *MRR*, *SCE* and SR, as shown in Table 8. From Table 8, it can be seen that the No.1 solution has the minimum R_a, and No.2 solution has the maximum *MRR* and minimum *SCE*, which have been marked with bold. At different times or in different scenarios, the operator can choose different solutions to achieve different targets. Therefore, compared to other traditional multi-objective optimization algorithms such as desirability analysis [23] and weighted grey relational analysis [8], the multi-objective optimization model based on the constrained NSGA-II can get a Pareto optimal set which includes all possible optimal solutions and the operator can make the final decision up to the practical situation and specific demands.

In addition, since convergence performance is an important criterion to evaluate optimization algorithms, many methods are proposed to assess it. Generational distance (*GD*) is widely used for the assessment [36] which has the following representation:

$$GD = \sqrt{\sum_{i=1}^{n} d_i^2 / n} \tag{15}$$

where n is the number of the solutions in the current Pareto front, d_i stands for the Euclidean distance between ith solution in the current Pareto front and the nearest solution in the reference set. And the *GD* with higher value means worse convergence performance to the reference set.

In order to compare the performance of original NSGA-II and the proposed hybrid approach, both approaches are implemented 10 times for the low-carbon optimization model which is discussed in Section 3.3, and the results are listed in Table 9. The simulation results show that the proposed hybrid NSGA-II algorithm has better convergence performance than the original NSGA-II.

Table 9: The generational distance of the original NSGA-II and this approach.

/	Generational distance									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Original NSGA-II	0.047	0.048	0.055	0.060	0.056	0.053	0.060	0.058	0.042	0.060
Proposed algorithm	0.037	0.034	0.050	0.050	0.044	0.041	0.058	0.039	0.029	0.046

6. Online Platform Development and Simulation Case

6.1 Online platform for carbon emission analysis and optimization

Since there are many kinds of data about carbon emission which need to be analyzed, such as machining power, air-cutting power, energy consumption, we require a platform to satisfy the demand of data collection and analysis. Meanwhile, the real-time data need to be gathered to validate and amend the proposed models because different parts and processes may influence the regression models and optimization results. Therefore, an online platform for carbon emission analysis was developed to analyze the carbon emission and optimize the process parameters. Moreover, it can provide the function of early warning of fault through the monitoring and simple analysis of the processing power, which can reduce accidents during machining processes. Also, it is simple and convenient for field operation since mobile devices such as smart phones can access the platform.

The schematic diagram of the online platform is shown in Figure 10. Firstly, the power sensor receives the data of power of the milling process in real time. The platform can analyze the original power data for making statistics related to machining power, air-cutting power, energy consumption and total carbon emission, and further optimize process parameters. Then it deposits the results into the database which will be passed to the operator through the Internet. The operator can monitor the carbon emission information and process planning results via his/her hand-held tablets or PCs.

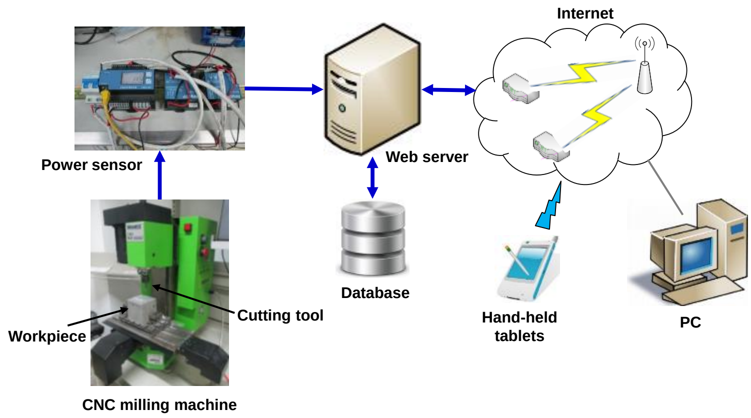


Figure 10: Schematic diagram of the online platform.

Based on the above schematic diagram, the operation procedure of the platform mainly contains five steps, as shown in Figure 11:

(1) Machine configuration: mount sensors to machines for performance monitoring;
(2) Real-time power curve: when the machine starts, the real-time power curve will be plotted and the frequency of data collection is three in one second;
(3) Breakpoint energy consumption statistics: when the machining process is finished and the sensor is stopped, the real-time power curve will end and several parameters will be calculated automatically, such as processing time, total energy consumption/carbon emission, average energy consumption, the average power, and so on;
(4) Machine carbon emission analysis: based on the statistics, the analysis module can analyze the relationship between cutting power, energy consumption, carbon emission, MRR, etc. and milling parameters, namely, the regression models;
(5) Optimization and real-time decision making: based on the analysis of the new data, the regression models will be amended to reduce the error. Then, the optimization process will be performed again to obtain the new and accurate parameters. In accordance with the new Pareto-optimal results, the operator will change the machining parameters according to their specific requirement. For example, if jobs are urgently demanded and the laws and regulations are strict with carbon emission of the plant, solutions with the higher MRR and lower SCE will be chosen; and if jobs are in finishing stage, the solutions with smaller SR will be adopted. Considering diverse production occasions, there different scenarios are considered in Section 6.2.

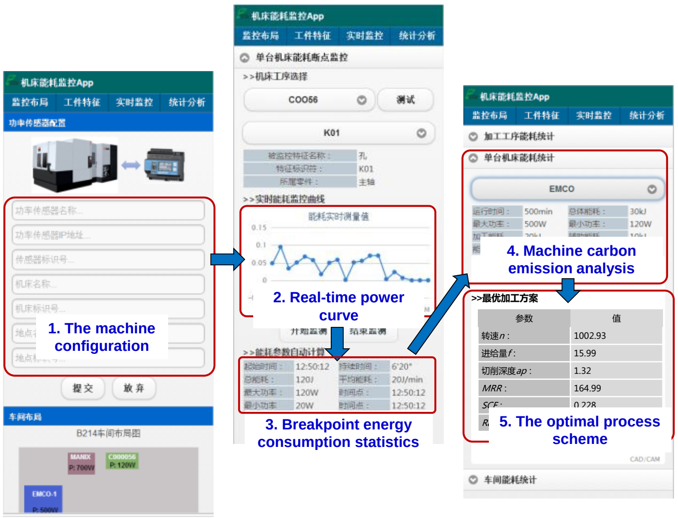


Figure 11: Operation procedures of the online platform.

6.2 A simulation case

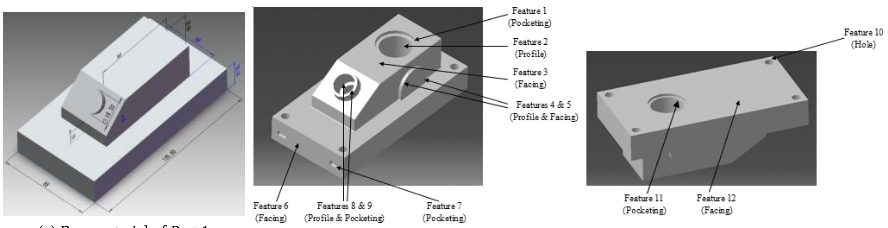
To verify the rationality and availability of the proposed methods, a simulation case with two parts is simulated. Part 1, Part 2 and their manufacturing features are shown in Figure 12 and Figure 13, respectively. The main dimensions of the raw material of Part 1 are illustrated in Figure 12a, and the raw material of Part 2 is a bar material with the dimension of D34*mm* * 30*mm*. The relevant removal volume of each feature can be obtained through calculating the difference between the raw material and the machined part, as shown in Table 5.10. Since the proposed model mainly takes the milling process into account, the features of holes are not considered in this study, i.e., feature 10 of Part 1, feature 10/11 and feature 12/13 of Part 2. The parts will be machined on the CNC MM-250S3 milling machine. Considering the different importance of *MRR*, SR, and *SCE* under diverse production conditions, three different scenarios are considered as follows:

Scenario 1: *MRR* and *SCE* are the main concern;

Scenario 2: SR is mainly concerned;

Scenario 3: *MRR*, *SCE* and SR are equally important;

For the Scenario 1 and Scenario 2, the No.2 and No.1 processing schemes in Table 8 are appropriate respectively, while the No.6 is suitable for the Scenario 3 since its *MRR*, *SCE* and R_a are 97.91mm^3/min, 0.377$kgCO^2\text{-}e/cm^3$ and 0.193*um* which are all medium. The operator can browse the optimization schemes through accessing the online platform.



(a) Raw material of Part 1

(b) Features of Part 1

Figure 12: The raw material and features of Part 1.

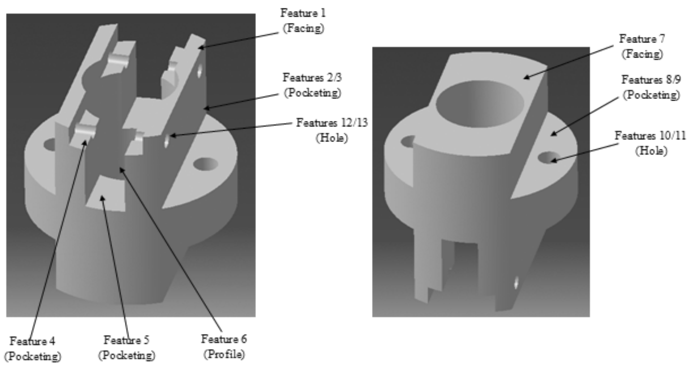


Figure 13: Features of Part 2.

Table 10: Removal volume of each feature of Part 1 and Part 2.

Part 1		Part 2	
Features	**Volume (mm^3)**	**Features**	**Volume (mm^3)**
1	760.3	1	960.0
2	8906.0	2/3	2900.0
3	3562.4	4	802.4
4	1022.5 x 2	5	1245.3
5	917.6 x 2	6	1102.8
6	2968.7	7	960.0
7	55.8	8/9	2780.5
8	235.9		
9	502.7		
11	760.3		
12	14925.0		

Through the proposed empirical modelling and optimization methodology, the processing results of Part 1 can be predicted without the actual processing, as shown in Table 11. Except the completion time, the carbon emission, the SR and further measurands are presented to describe the influence of the process parameters on the energy consumption factors, including air-cutting power and cutting power. Also these empirical modelling methods and processing results are beneficial to the low-carbon design of products.

Table 11: The simulation results of Part 1.

Results	Scenario 1	Scenario 2	Scenario 3	Traditional optimization	Another scheme[8]
Cutting speed(r/min)	1002.93	1002.93	1002.93	1002.28	1000
Feed rate(mm/min)	15.99	15.99	15.81	15.78	16
Depth of cut(mm)	1.32	0.40	0.79	1.05	1.6
Completion time(min)	221.57	732.32	373.38	282.31	183.08
Carbon emission($kgCO^2$-e)	8.34	26.39	13.78	10.6	6.92
SR(um)	0.261	0.124	0.193	0.228	0.286
Air-cutting power(W)	372.6	372.6	372.5	372.4	372.1
Cutting power(W)	529.7	470.7	503.4	517.7	539.3

After analyzing the results, it can be clearly seen that the completion time of Scenario 1 is the shortest, and its carbon emission is also less than other scenarios. However, its product quality is poorer, whose SR is 0.261um. If the machining scheme of Scenario 2 is adopted, Part 1 can obtain the best machining quality, but its completion time is the longest and its carbon emission is 26.67$kgCO^2$-e, which is the highest. Comparing with Scenario 1 and Scenario 2, Scenario 3 is a compromise choice, whose results of completion time, carbon emission and SR are all medium. Overall, the increase of depth of cut will lead to the decrease of completion time and carbon emission, but will result in a clear opposing impact on the SR.

In addition, for the three scenarios, the difference of their air-cutting power is very small, while the cutting power will decrease with the increase of the depth of cut. Due to the constraint of the maximum cutting power, the cutting powers in these three scenarios are all less than 530W.

In order to highlight the difference between traditional optimization method and this eco-efficiency method, the optimal milling parameters determined by traditional method was also obtained, as shown in Table 11. As previously mentioned, the traditional optimization problem means cutting parameter optimization based on traditional optimization objectives such as MRR, SR, and cutting force, which doesn't take environmental impact into consideration. In this study, the traditional objective optimization of milling parameters was executed using the similar algorithm. Moreover, MRR and SR were employed as the traditional optimization objectives, and it is assumed that the two objectives are equally important (i.e. weight=1:1). As noted from Table 11, the results of the traditional method are similar to that of the Scenario 1, but the total carbon emission of the latter decreased

21.3%. It is obvious that the results of the proposed method is obtained after the trade-offs between *MRR*, SR and carbon emission. Since considering environmental impact shifts the balance to the carbon emission optimization, the SR becomes a little larger when the carbon emission decreases compared to the traditional optimization result. However, this problem could be solved if the constraint of SR is considered.

Furthermore, referring to Yan and Li [8], the machining result by using their optimal milling parameters is also listed in Table 11. Although its completion time and carbon emission are optimal, its SR increases from 0.261 to 0.286 comparing to the result of Scenario 1. Meanwhile it doesn't consider the cutting power constraint. In a word, their method only considered one situation, but the actual requirement may be varying, and this developed methodology can provide many alternatives for the operator. In other words, the operator can adopt different processing parameters from the non-dominated solutions according to various processing requirements and different processing stages which fit for dynamic manufacturing.

Table 12: The simulation results of Part 2.

	Scenario 1	**Scenario 2**	**Scenario 3**
Completion time(*min*)	65.16	215.36	109.80
Carbon emission($kgCO^2$-*e*)	2.45	7.76	4.05
SR(*um*)	0.261	0.124	0.193

The simulation results of Part 2 are shown in Table 12. The similar conclusion can be drawn from Part 2. Comparing Part 2 with Part 1, it can be seen that the total completion time of Part 2 is shorter, so as for its carbon emission. The main reason is that the total volume of Part 2 is much smaller than Part 1.

6.3 Discussions

As summarized in Section 2.3, there are many multi-objective optimization methodologies in manufacturing technologies, such as the Taguchi grey relational analysis for high-speed turning [29], grey relational analysis for micro wire electric discharge machining [6] and contour plot methodology for laser milling [7]. Through the analysis above, it can be observed that the proposed systemic optimization method has two advantages respect to other multi-objective optimization models:

(1) Most of these optimization methodologies focus on the qualitative analysis of some optimization objectives, which can only reflect the influence trend of the different parameter combinations on the objectives. The proposed method in this study is an accurate method for the parameter optimization;

(2) Considering the conflict among multiple objectives, the proposed optimization method can generate different Pareto-optimal results, and the operator can choose the suitable parameters according to different requirements.

However, there are also some drawbacks in the proposed method if applied in other manufacturing technologies. Firstly, the universality of the method needs to be validated in different machine tools and different manufacturing technologies because only a simulation case was studied. So various experiments and applications need to be performed in the future work to improve the universality of the proposed method. Then, the multi-objective decision method needs to be established to help the operator to choose a better parameter combination.

7. Conclusions

Carbon emission reduction in manufacturing industry is imperative. In this study a systemic optimization approach is presented to identify the values of some key process parameters leading to low-carbon milling operation. By considering production rate, carbon emission and product quality concurrently, regression models are constructed to characterize the relationship between environmental/productivity/quality objectives and milling parameters. Then, a multi-objective optimization model is further constructed for identifying the optimal process parameters, where the *MRR* is maximized, and the carbon emission and SR are minimized simultaneously. After several dry milling experiments of different combinations of milling parameters, the regression models are derived and they have a great reliability for depicting behavior of tested milling processes because of a high R^2 value. The hybrid NSGA-II is adopted to solve the optimization model and the Pareto frontier of the non-dominated solutions are obtained. Finally, based on the regression models and the optimization approach, an online platform is developed to obtain in-process information about the energy consumption and carbon emission for real-time decision making.

Some conclusions are drawn as follows:

(1) The Pareto frontier of non-dominated solutions show that when the optimal spindle speed is 1002.93*r/min*, feed rate is 15.99*mm/min*, and depth of cut ranges from 0.4 *mm* to 1.28*mm*, the biggest effect on the objectives is achieved. The increase of depth of cut results in the decrease of SCE and the increase of MRR and SR;
(2) The simulation case shows that in the optimal solutions MRR has a positive correlation with carbon emission, and there is an oppose relationship between MRR and SR;
(3) Comparing to other existing methods, the results of the simulation case indicates that the proposed method can obtain multiple eco-efficient milling

schemes through only one calculation which is more efficient for dynamic manufacturing.

Comparing to existing process models and optimization methods for manufacturing process, this research derives some regression models for characterizing milling processes. As a general recommendation, empirical process models need to be developed for other cutting tools, workpiece materials, cutting fluids and machine tools. The analysis of cutting tools impact also requires improvements by considering its entire life cycle, since it is one of the main contributors regarding the environmental impacts. Therefore, a more accurate analysis can be achieved in the future.

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