Research Article

Optimization of CNC Milling Parameters for Complex 3D Surfaces of SIMOLD 2083 Alloy Mold Core Utilizing Multiobjective Water Cycle Algorithm

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Received 31 March 2021; Accepted 4 May 2021; Published 11 May 2021

Academic Editor: Dr. Dilbag Singh

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In this article, an effective multiobjective optimization approach is exploited to search for the best milling parameters for CNC for complex 3d surfaces of SIMOLD 2083 alloy mold core. To improve the quality responses, the cutting factors are optimized by a combination of Taguchi method (TM), response surface method (RSM), and multiobjective water cycle algorithm (MWCA). Firstly, the design for initial series experiments of the cutting factors was generated via the TM. Thereafter, the regression models between the cutting factors and the surface roughness of the machined workpiece surface as well as milling time are formed via applying the RSM. Moreover, analysis of variance and sensitivity analysis are also executed to define the influences and crucial contributions of cutting parameters on the surface roughness and milling time. The results of analysis of variance showed that the factors which have main effects on surface roughness were spindle speed (42.42%), feed rate (29.40%), and cutting depth (6.59%), respectively. Meanwhile, the feed rate with the influence of 92.6% was the most significant factor in controlling the milling time. Ultimately, based on mathematical models, the MWCA is performed to define the optimal factors. The optimal results indicated that the optimized surface roughness was about $0.260\text{ }\mu\text{m}$ and the milling time was roughly 1012.767 (s). In addition, the errors between forecasted results and experimental verifications for the surface roughness and milling time are 2.04% and 5.39%, respectively. Therefore, the results of experimental verifications are suitable with the forecasted results from the proposed optimization method. These results depicted that the proposed integration approach can define effectively the optimal cutting factors for CNC milling and expand to apply for complex multiobjective optimization problems.

1. Introduction

Currently, SIMOLD 2083 alloy is well known as material with excellent mechanical characteristics such as extreme erosion resistance and self-hardening in high temperature and friction, so it is extensively utilized in the molding industries for food field. For more specifics, this material can be hardened by itself in the operating process when the working environment has friction and high temperature, so it is very appropriate for injection molding. Another benefit

of SIMOLD 2083 alloy is of the stainless steel group; it is also suitable for making the molding cavities and cores for plastic products used in the food area. Meanwhile, the fabrication process of SIMOLD 2083 alloy with complex 3D surfaces meets several struggles for achieving small surface roughness and high productivity because of detrimental machining conditions. Therefore, in order to obtain the beneficial surface quality as well as ensure machining productivity, the cutting parameters should be chosen in a suitable range and be optimized to gain the optimal milling conditions. There

are various parameters such as the cutting parameters and chemical composition of workpiece and tool affecting the quality characteristics of the milled components. In addition, surface roughness is one of the most characteristics of the milling parts. In this research, so as to guarantee the quality and productivity of machining part with the complex milling surfaces, the surface roughness and milling time were considered. Consequently, so as to achieve better surface finish of a milled product and ensure the productivity, the cutting parameters were regarded for multi-objective optimization problem.

In general, the surface roughness and milling time are the significant characteristics. However, two characteristics are wriggled together. Therefore, in order to equalize and obtain the requirements of a small roughness surface and low milling time, concurrently, the hybrid approach is proposed for performing the multiobjective optimization problem. In addition, the key cutting factors were optimized for gaining the above-mentioned requirements.

Generally, the Taguchi method (TM) is extensively utilized in optimal analysis engineering for creating the minimized initial data [1]. For examples, Gopalsamy et al. [2] utilized the TM to find the optimized cutting factors of hardened steel. It was monitored that the cutting velocity is the greatest effect factor on surface roughness as well as tool life. Gürçan Samtas [3] utilized the TM for optimization of cutting factors for the machining surfaces of AA5083-H111. Moreover, in previous studies, several population-based algorithms were advanced. For instance, the main parameters of power system were identified by the genetic algorithm (GA) [4]. Soori et al. [5] utilized the GA to define optimized machining parameters based on a virtual machining system. Gupta et al. [6] utilized evolutionary techniques for optimizing machining parameters of titanium alloy. Basu et al. applied cuckoo search algorithm for dispatch trouble [7]. Compared to aforementioned methods, in order to improve convergence speed with less initial factors, several efficient optimal methods [8–12] were proposed. In addition, as another integration way to conduct single optimal problem, for instance, Kadirgama et al. [13] proposed hybrid approach RSM as well as radian basis function network for optimizing the cutting factors in order to minimize the surface roughness of aluminum alloy, for finding the most noteworthy factors on carbon nanotubes by the adaptive neurofuzzy inference system (ANFIS) approach [14]. Moreover, several other effective methods for prediction are such as a saliency detection method [15], outlier recognition in neutrosophic sets [16], color image encryption [17], optimizing the working parameters of a PVT system [18], and complex neutrosophic set [19]. Especially, in order to conduct multicriteria search, a lot of multi-objective optimization techniques have been applied for many areas. For instance, multiobjective evolutionary optimization is for image encryption [20], for fabrication biocompatible [21], for human manner recognition [22], for microarray cancer data categorization [23], for visibility enhancement and mass division of mammogram figures [24], for hydraulic machinery in engine velocity decrease [25], and for multi-image fusion [26]. Furthermore, there

have been combination of different techniques; e.g., the TM was combined with response surface method (RSM) and genetic algorithm (GA) [27], GA-artificial neural network (ANN) and PSO-ANN [28], the TM-fuzzy according to moth-flame optimization [29], particle swarm optimization (PSO) [30] and GA [31], RSM-PSO [32] and gravitational search algorithm-GA [33, 34], Grey, TM, RSM and entropy measurement [35], fuzzy logic-ANFIS-based lightning attachment procedure optimization [36], TM-RSM, improved ANFIS, and TLBO [37]. For more specifics, Shrivastava and Singh [38] developed a combined method of RSM and multiobjective genetic algorithm for evaluation of enduring cutting region in CNC turning. Recently, multicriteria water cycle algorithm (MWCA) was considered as an effective optimizer for many sectors [39–42]. However, an integration approach of TM, RSM, and MWCA for optimizing the cutting parameters of mold core utilizing SIMOLD 2083 alloy with complex milled 3D surfaces in the small ice cube mold has not been researched yet.

This paper proposes an effectual optimization approach for the cutting factors of mold core with complex 3D surfaces applied for the small ice cube mold. So as to resolve the optimization, a combination method of the TM, RSM, and MWCA is developed.

2. Methodology

2.1. Formulation of Optimization Problem. In this research, the milled component with complex milling surfaces should fulfill the following requirements: (i) the surface roughness (y_1) should be as small as possible to assure the quality of the milling inclined surface and (ii) the small milling time (y_2) to enhance the machining productivity. A combination method of the TM, the RSM, and the MWCA is grown for balance among them as well as advance of the superiority responses. The optimal issue for the milled component is expressed in the following form.

Find the design variables: $x = [S, F, t]$.

Minimize the $y_1(S, F, t)$,

$$y_1(S, F, t). \quad (1)$$

Minimize the $y_2(S, F, t)$,

$$y_2(S, F, t). \quad (2)$$

Subject to constraints:

$$\begin{cases} 3179 \text{ rpm} \leq S \leq 6309 \text{ rpm}, \\ 636 \text{ mm/min} \leq F \leq 1206 \text{ mm/min}, \\ 0.03 \text{ mm} \leq t \leq 0.3 \text{ mm}, \end{cases} \quad (3)$$

where y_1 and y_2 are the quality responses. F, S, t are spindle velocity, feed rate, and cutting depth, respectively.

To ensure the complex 3D surface machining quality and milling productivity, the surface roughness and the machining time should be selected as small as possible.

Based on the technical requirements and milling productivity, the value of surface roughness was proposed for

being lower 0.4 (μm) and the milling time was also lower 1060 (s).

Equation (3) illustrated the constrained range of the input variables. The bounds for the cutting factors were proposed based on professional knowledge, machining capacity of the CNC vertical milling machine, workpiece material, namely, SIMOLD 2083 (DIN-X40Cr14) with hardening to achieve 48-50HRC with chemical composition, as illustrated in Table 1 and tool material (ball mill, code: CEB20300A, $R = 3$, $L_1 = 12$, $L = 50$, $D = 6$, $F = 2$ with coated TiAlN, HRC = 55RC, twist angle = 30), as illustrated in Figure 1.

2.2. Hybrid Approach. An integration approach is developed for investigating the impacts of the cutting factors for the milled component on multicriteria output characteristics and detecting the optimized factors for the proposed milled component.

Initially, the TM was exploited for identifying an orthogonal array to form an initial experiment plan. Furthermore, analysis of variance (ANOVA) was exploited to identify the important ratio impact of each cutting factor on the quality characteristics.

Subsequently, the relationships between the cutting factors and the quality characteristics are established by the RSM. A full quadratic formulation is a fitting type for the milled component as the following equation:

$$Y_j = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \beta_{ij} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{ij} x_i x_j + \varepsilon_i, \quad (4)$$

where β_i ($i = 0, 1, 2, \dots, n$) are unknown regression coefficients, β_{ij} ($i < j$) are relation coefficients, $x_1, x_2, \dots, x_n$ is a set of n forecasters trusted to be interrelated to a response variable Y_j , and ε is a haphazard error.

2.2.1. Multiobjective Water Cycle Algorithm. According to the established regression equations, the optimal procedure was performed by MWCA algorithm. The MWCA has been extensively exploited [43–46], but it has not been applied for optimization of the cutting parameters of milled mold core component with complex milling surfaces. The action rule of this algorithm is inspired from the drainage of rivers and streams unto the sea and originated via the supervision of water cycle procedure. For specifics, water travels downwards for generating streams and rivers, beginning from high points on the hills, later on, moving to the lakes and seas. Streams and rivers gather water from rain and other streams. The water of rivers and lakes will evaporate. Later on, clouds are created when the evaporated water is moved in the atmosphere. These clouds squeeze in the colder atmosphere and discharge the water in order to find rain, generating new streams and rivers. Moving to more detailed analysis of this algorithm, the MWCA exploits the perception of travelling implicitly from streams to the rivers as well as from rivers to the sea (best solution). In this algorithm, rivers (many greatest chosen resolutions omitting the

TABLE 1: The composition of workpiece material.

C	Si	Mn	Cr	P	S
0.36 – 0.42	Max. 1.0	Max. 1.0	12.50 – 14.50	Max. 0.025	Max. 0.005

FIGURE 1: Basic geometric dimensions of ball mill.

greatest one (sea)) operate as guiding creatures for targeting other creatures in the inhabitants (streams) on the way to greater locations. In addition, rivers also travel on the way to the sea and they are not regarded as fixed creatures in the inhabitant. Actually, the procedure includes (i) the streams travel to the river and (ii) rivers travel to the sea leading to implicit travels near the best solution (sea) via the water cycle. The more details can be read in refs. [39–42].

Ultimately, according to the regression equations, the MWCA was utilized to seek the optimization parameters. The MWCA was utilized for solving multicriteria optimization issue due to its great power for finding optimal resolutions close to the universal finest proficiently. The programming of MWCA algorithm was conducted via MATLAB 2017. Flowchart and plan of fabricating factors optimization via hybrid approach are suggested, as in Figure 2.

3. Experimental Results and Discussion

3.1. Orthogonal Array Experiment. Every factor could be segregated for three grades based on professional knowledge and machining experiences, as indicated in Table 2. According to the TM, the L_9 orthogonal array was adopted for forming the initial experiment strategy.

3.2. Experimental Process and Mathematical Model. First of all, the 3D model of the small ice cube mold was designed by Creo software, as illustrated in Figure 3. In addition, for enhancing the milled surfaces property of the mold core and productivity, private specimens of the core component were fabricated based on the TM to generate initial data for enhancing the aforementioned responses. Figure 4 depicted the yellow milled surfaces of the mold core with square of 420.101 mm².

Secondly, the nine fabricated experimental models were fabricated according to proposed the number of experiments, as depicted in Figure 5. Later on, the surface roughness (y_1) was assessed by a Mitutoyo SJ-210 surface roughness tester (Japan), as illustrated in Figure 6. Besides, in order to transfer inclined surface into straight surface for measuring surface roughness, the mounting fixture was designed and fabricated for fixing the milled component as well as conveying measuring surfaces with the average of

FIGURE 2: Flowchart and plan of fabricating factors optimization via hybrid approach.

three different measurements, in addition to the machining time (y_2) and that recorded by CNC machine, respectively. Therefore, the experimental results are shown in Table 3.

Thirdly, according to the experiment outcomes in Table 2, the regression equations for two responses were established as follows:

The mathematical models could be gained in form of

$$\begin{aligned}
 y_1 &= 2.969 - 0.000379^*S - 0.002910^*F - 4.691t \\
 &\quad + 0.000002F^*F + 8.386t^*t + 0.000313^*S^*t, \\
 y_2 &= 1315 - 0.001090^*S - 0.4990^*F + 0.7928^*t \\
 &\quad + 0.000210F^*F + 19.05t^*t - 0.001520^*S^*t.
 \end{aligned} \quad (5)$$

Tables 4 and 5 demonstrate the ANOVA results of the surface roughness and milling time. The evaluation was executed with 5% significance level and 95% insurance level.

As described in Table 4, the influence degree on the surface roughness y_1 of S was greatest, at 42.42%, while the effect figure for F and interaction t and t was substantially higher, at 29.40% and 13.22%, correspondingly. Meanwhile, the rate of t and interaction F and F was relatively lower, at 6.59% and 3.76%, respectively. In addition, the influence rate on the surface roughness y_1 of interaction S and S , interaction S and t , and interaction S and F was slightly lower, at 1.95%, 1.56%, and 1.12%. Therefore, so as to reduce the value of y_1 , factors S and F should be significantly considered.

As demonstrated in Table 5, the influence percentage of F on y_2 was the highest, at 92.60%, while the influence number for interaction F as well as F was small, at 7.39% respectively. In contrast, other factors did not significantly affect y_2 . Thus, so as to decline the worth of y_2 , the only factor F should be especially considered. Furthermore, the influence rate of error for y_1 as well as y_2 was 0%.

3.3. Sensitivity Analysis. Statistic method was executed for identifying the influence level of input cutting factors on the output characteristics. In the range (3179, 6309), parameter S affected y_1 in reducing gradually, as represented in Figure 7. In addition, parameter F illustrated that in the range (636, 831), it influenced a slight increase to y_1 , but, in the range (831, 1206), it affected a gradual increase to y_1 . Furthermore, there was a fluctuation influence of parameter t to y_1 . Moving to a more detailed analysis, in the range (0.03, 0.165), parameter t caused y_1 to degrade slightly, but, in the range (0.03, 0.165), it influenced a gradual rise to y_1 .

On the other hand, as shown in Figure 8, there was only a decrease influence of parameter F to y_2 . For specifics, parameter F illustrated that in the range (636, 1026), it influenced a sharp decrease to y_2 .

In summary, whole effects of input variables on quality characteristics were exhibited, as in Figure 9. The figure described a surge and drop variation in each factor. According to the outcomes, the key elements could be varied to obtain the suitable cutting parameters for fabricating the milled component.

TABLE 2: Input cutting factors and their grades.

Factors	Range	Lower grade	Average grade	Upper grade	Unit
S	3179–6309	3179	4609	6309	rpm
F	636–1206	636	831	1206	(mm/min)
t	0.03–0.3	0.03	0.165	0.3	(mm)

FIGURE 3: A 3D design drawing of the small ice cube mold of (a) assembly drawing and (b) exploded drawing.

3.4. Optimal Results. Firstly, the number of numerical experiments was generated applying the TM. Based on initial data which were established by the TM, nine models were fabricated, measured as well as recorded so as to gain the values of output responses including surface roughness and milling time. In addition, according to these data between input variables and two output responses, the RSM was employed for establishing the regression equations for the surface roughness and the milling time. Later on, the multiobjective optimization problem was conducted via the MWCA. The MWCA algorithm was accomplished via MATLAB 2017b. The initial factors of MWCA are given in Table 6.

The optimized results were discovered at $S = 4989.13671955611$ rpm, $F = 1182.37762276541$ mm/min, $t = 0.0674096477686595$ mm, $y_1 = 0.260586713$ μm , and $y_2 = 1012.767751$ (s). The results revealed that the optimal surface roughness and milling time are satisfying the technical requirements as well as milling productivity and are suitable for the complex surfaces milling process. Based on the optimized parameters, the mold core with material, namely, SIMOLD 2083 (DIN-X40Cr14), was fabricated with 32 models for integration into the small ice cube mold, as illustrated in Figure 10. Later on, the small ice cube mold was installed into plastic injection molding machine, as shown in Figure 11, for producing enormous and identical quantities of plastic trays, as illustrated in Figure 12.

3.5. Validation. The optimal parameters ($S = 4989.137$ rpm, $F = 1182.38$ mm/min, $t = 0.0674$ mm) were used to fabricate the mold core for experimental certification. The process was

FIGURE 4: The yellow milled surfaces of the mold core with square of 420.101 mm^2 .

FIGURE 5: The nine milled experimental models.

accomplished with the same dimension and material of workpiece, the same tool, and the coolant condition. Experimental results based on optimized parameters illustrated that the value of surface roughness and milling time were $0.266 \mu\text{m}$ and 961 (s), as illustrated in Figure 13, respectively. Table 7 demonstrates that the error between forecasted results and experimental certifications for the roughness

FIGURE 6: Fixture for measuring surface roughness of milled components by surface roughness tester, namely, Mitutoyo SJ-210.

TABLE 3: Experimental results.

No.	S (rpm)	F (mm/min)	t (mm)	y_1 (μm)	y_2 (s)
1	3179	636	0.3	0.506	1081
2	3179	831	0.165	0.416	1043
3	3179	1206	0.03	0.96	1016
4	4609	636	0.165	0.273	1080
5	4609	831	0.03	0.423	1043
6	4609	1206	0.3	0.549	1016
7	6309	636	0.03	0.308	1081
8	6309	831	0.3	0.248	1043
9	6309	1206	0.165	0.332	1016

TABLE 4: ANOVA analysis for roughness surface.

Source	DF	Seq SS	Influence (%)	Adj SS	Adj MS	P value
Model	8	0.381007	100.00	0.381007	0.047626	Considerable
Linear	3	0.298732	78.41	0.215692	0.071897	Considerable
S	1	0.161615	42.42	0.158897	0.158897	Considerable
F	1	0.112027	29.40	0.026421	0.026421	Considerable
t	1	0.025091	6.59	0.012160	0.012160	Considerable
Square	3	0.072074	18.92	0.046166	0.015389	Considerable
$S * S$	1	0.007413	1.95	0.007413	0.007413	Considerable
$F * F$	1	0.014310	3.76	0.019953	0.019953	Considerable
$t * t$	1	0.050350	13.22	0.027617	0.027617	Considerable
2-Way interaction	2	0.010201	2.68	0.010201	0.005100	Considerable
$S * F$	1	0.004261	1.12	0.000098	0.000098	Considerable
$S * t$	1	0.005940	1.56	0.005940	0.005940	Considerable
Error	0	—	—	—	—	
Total	8	0.381007	100.00			

TABLE 5: ANOVA analysis for milling time.

Source	DF	Seq SS	Influence (%)	Adj SS	Adj MS	P value
Model	8	6330.22	100.00	6330.22	791.28	Remarkable
Linear	3	5861.88	92.60	3305.79	1101.93	Remarkable
S	1	0.00	0.00	0.00	0.00	Remarkable
F	1	5861.88	92.60	3142.36	3142.36	Remarkable
t	1	0.00	0.00	0.00	0.00	Remarkable
Square	3	468.12	7.40	281.22	93.74	Remarkable
$S * S$	1	0.22	0.00	0.22	0.22	Remarkable
$F * F$	1	467.68	7.39	268.56	268.56	Remarkable
$t * t$	1	0.22	0.00	0.14	0.14	Remarkable
2-Way interaction	2	0.22	0.00	0.22	0.11	Remarkable
$S * F$	1	0.08	0.00	0.00	0.00	Remarkable
$S * t$	1	0.14	0.00	0.14	0.14	Remarkable
Error	0	—	—	—	—	
Total	8	6330.22	100.00

FIGURE 7: Influence diagram on surface roughness of (a) S and F , (b) S and t . FIGURE 8: Influence diagram on milling time of (a) S and t , (b) S and F .

FIGURE 9: Sensitivity diagram of the cutting factors on surface roughness and milling time.

TABLE 6: Utilized initial factors for MWCA.

Factors	Value
Population size	50
Maximum number of iterations	100

FIGURE 10: Thirty-two models of the fabricated mold core.

FIGURE 11: Installation of the small ice cube mold on the plastic injection molding machine.

FIGURE 12: Small plastic ice tray products: (a) red plastic product, (b) white plastic product.

FIGURE 13: Installation for measuring surface roughness based on optimal parameters.

TABLE 7: Errors among predicted results and validated results.

Responses	Prediction	Validation	Error (%)
y_1 (micrometer)	0.260586713	0.266	2.04
y_2 (s)	1012.767751	961	5.39

surface and milling time are 2.04% and 5.39%, respectively. It is clear that the forecasted results are suitable with verified results.

4. Conclusions

This paper offered an effectual combination optimization approach for the mold core component with the complex milling surfaces. The spindle velocity, feed rate, and cutting depth were considered as input design variables. To enhance the surface roughness and milling time, the cutting parameters were optimized by a combination approach of the TM, experimental measurements, RSM, and MWCA.

The sensitivity analysis and ANOVA were implemented for determining the effects and crucial contributions of cutting factors on the surface roughness and milling time. The results of ANOVA analysis showed that the parameters that have significant influences on surface roughness were spindle velocity (42.42%), feed rate (29.40%), and cutting depth (6.59%), respectively. Meanwhile, the only parameter

that has the most influence degree on milling time was feed rate (92.6%).

The results revealed that the optimized parameters were found at S of 4989.137 rpm, F of 1182.38 mm/min, and t of 0.0674 mm. Moreover, the results indicated that the surface roughness and milling time were around 0.260586713 (μm) and 1012.767751 (s), respectively.

Moreover, the results illustrated that the errors among forecasted results and experimental validations for the roughness surface and milling time are 2.04% and 5.39%, congruently. The experimental affirmations were proximate to the forecasted results. Therefore, the predicted results are appropriate with the certifications. According to the aforementioned results, the hybrid method is a powerful method for solving the multiobjective optimization issue for the cutting factors.

Additionally, this study encounters several challenges such as taking lots of time for finding suitable material in fields of injection molding and food as well as designing and manufacturing measuring fixture. Therefore, different

suitable materials in the areas of injection molding and food should be regarded for machining the complex 3D surfaces.

In the future work, the milled components with complex 3D surfaces will be investigated and manufactured and its characteristics will be verifying the experimental outcomes.

Data Availability

The authors state that data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This work was supported by the project grant no T2020-12 funded by Ho Chi Minh City University of Technology and Education, Vietnam.

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