




Optimization of NC CAD Machining Parameters Based on Improved Particle Swarm Optimization Algorithm

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Abstract. In this paper, the improved particle swarm optimization algorithm has been used to quickly find the optimal value of the objective function of CNC machining parameters. The proposed method was used to optimize the rough milling, semi-finishing milling and finishing milling operation parameters of S5CK80 NC machine tool, and the accuracy of cutting width and cutting depth was significantly higher than that of substructure coupling method and response surface method. The performance of spindle speed, feed, cutting power and cutting time parameters optimized by this method are superior to those of the other two methods. This method can effectively optimize NC machining parameters, meet the actual machining requirements, and the optimized experimental NC machine tool has good machining performance.

Keywords: Particle swarm optimization; Numerical control machining; Parameter optimization; Objective function; Constraint condition; Mathematical model.

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1 INTRODUCTION

Manufacturing industry is not only an important indicator to measure the level of national productivity, but also a strong guarantee for national prosperity and rejuvenation. Nowadays, with the rapid development of big data, cloud computing, artificial intelligence and other technologies, the manufacturing industry is facing new opportunities and challenges. In order to catch up with the new wave of industrial revolution, the world's major manufacturing countries are actively formulating a series of policies suitable for their own development. In 2003, the United States implemented the "Industrial Internet" strategy, which refers to the development of network security strategies at the national level to ensure the stability and order of the country and society. After the outbreak of the world financial crisis in 2008, the United States formulated the "re-industrialization" strategy and established the "Industrial Internet Alliance" together with Internet giants. In 2013, the German government officially implemented the "Industry 4.0" strategy, which triggered the fourth industrial revolution. It emphasized the integration of information and physical systems to promote the intelligent development of manufacturing industry.

In 2015, The State Council officially put forward the "Made in China 2025" strategy, which emphasizes the establishment of a new industrial production mode combining informatization and industrialization, so as to promote the whole nation from a manufacturing power to a manufacturing power. These strategic goals have in common the application of advanced technological means to the manufacturing field, and the continuous monitoring, guidance and control of the actual production process, so as to drive the manufacturing industry towards a green and intelligent direction [1-2].

As an important processing equipment of modern manufacturing industry, numerical control machine tool integrates the technical achievements of computer technology, mechanical automation technology, information processing technology, sensor technology and many other fields, and has significant advantages in the manufacturing industry. The equipment can analyze the CNC machining program and automatically execute a series of parts processing behaviors, such as milling, drilling, turning, tapping and other operations, which solves the problem of difficult to ensure product quality in complex parts processing often faced by the traditional machinery manufacturing industry [3]

At present, CNC machining technology has been gradually expanded from the original aerospace field to the automotive industry, shipping industry, construction and other mechanical fields; the technology has a broad use space in the manufacturing industry. Advanced numerical control machining technology can bring great economic benefits to manufacturers and has a strategic role in realizing our manufacturing modernization goal. Therefore, on the basis of existing results, it is an important task for our country to realize manufacturing power to further promote numerical control machining performance as shown in Figure 1:

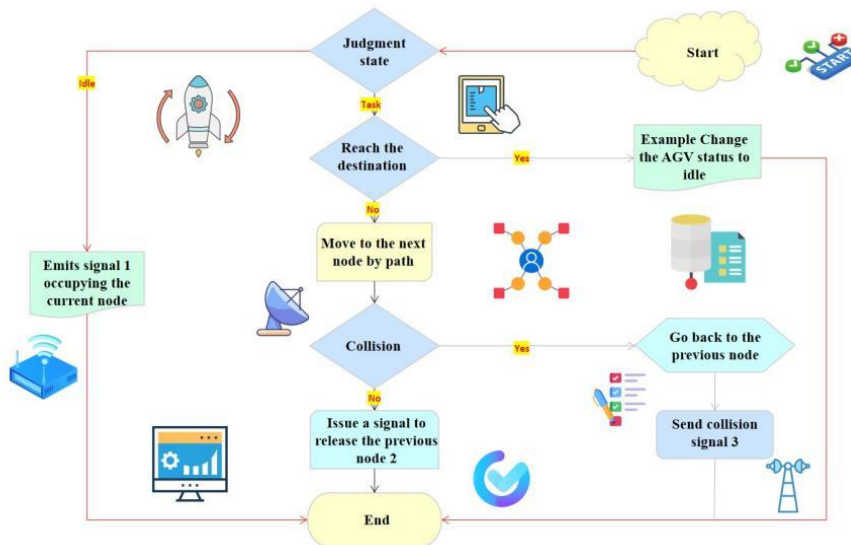


Figure 1: Improved particle swarm optimization algorithm.

2 LITERATURE REVIEW

Cutting parameters mainly include cutting speed, feed speed and cutting depth. Reasonable cutting parameters can improve product processing quality, improve processing efficiency and reduce production costs. Therefore, the early research on cutting parameter optimization focused on the machining quality, machining time and production cost as the research objects. Research results on optimization of cutting parameters are mostly based on traditional targets such as processing time, production cost or tool durability, which are difficult to meet the requirements of modern manufacturing industry [4]. With the increasingly serious problem of global warming,

more and more scholars begin to focus on the optimization of cutting parameters, which mainly aims at machine tool energy consumption and carbon emission. In addition to taking machine tool energy consumption and carbon emission as the research direction of cutting parameter optimization, some scholars have taken the negative impact of cutting process on the environment into account and conducted researches on cutting parameter optimization aiming at green manufacturing [5].

There are many research results on the optimization of cutting parameters, some of which are based on traditional indicators (such as production cost, processing time, tool wear degree, etc.). This kind of optimization usually ignores resource consumption and environmental emissions, which has been difficult to meet the requirements of green manufacturing. Part of the optimization is based on the combination of machine tool energy consumption, carbon emissions and other traditional optimization indicators, which can be attributed to the optimization of cutting parameters for low-carbon manufacturing [6].

Compared with green manufacturing, which takes resource consumption and environmental impact into consideration comprehensively, low-carbon manufacturing only focuses on the reduction and control of carbon emissions, without considering the negative impact of waste water, toxic and harmful substances on the environment. At present, the research results of cutting parameter optimization for green manufacturing are limited and need to be further studied [7]. In this paper, an improved particle swarm optimization method for NC machining parameters is proposed.

3 RESEARCH METHOD

3.1 Improved Particle Swarm Optimization (PSO) of NC Machining Parameters

3.1.1 Mathematical model and constraint conditions

<i>Symbol</i>	<i>Meaning</i>
v	Cutting speed
f	Cutting feed in the machining process
T_p	Total working hours
T_s	Cutting time of one machining procedure
T_m	Tool changing time in the process of single process
T_h	Tool changing time between different processes
T_i	Machine tool preparation time, loading and unloading time, tool preparation time and other auxiliary time
D	Tool diameter
L	Cutting length
f_z	Cutter feed per tooth
a_p	Cutting depth
T_R	Tool change time due to tool wear
a_e	Cutting width
B	Tool cost
B_0	Unit time management cost
B_1	Labor cost per unit time
T	Tool wear resistance

Table 1: List of symbols used and their meaning.

3.1.1.1 Mathematical model

In CNC machining, the cutting parameters under step less speed regulation in the NC machining process are set as continuous variables. The lowest production cost and the highest productivity are set as the optimization objectives of CNC machining parameters:

$$T_p = T_s + T_m + T_h + T_i \quad (3.1)$$

In the formula symbols have their meaning as given in Table 1. The formula of process cutting time is as follows (3.2):

$$T_s = (\pi DL)/(1000vf_z Z) \quad (3.2)$$

In (3.3), the tool change time in single process of long-time processing resulting in tool wear is:

$$T_m = \frac{\pi L T_R}{1000 C_V^m} v^{\frac{1}{m}-1} f_z^{\frac{y}{m}-1} a_e^{\frac{y}{m}} Z^{\frac{u}{m}} a_p^{\frac{k}{m}} D^{1-\frac{q}{m}} \quad (3.3)$$

Where: C_V, m, y, p, u, k and q are the tool durability coefficients of CNC machine tools. The B_p formula of processing cost of a process in NC machining is as follows (3.4):

$$B_p = T_p \left(\frac{B_t}{T} + B_1 + B_0 \right) \quad (3.4)$$

The feed rate and cutting speed cannot meet the two optimization objectives at the same time, set the coordination coefficient η , use the single objective optimization problem instead of the multi-objective optimization problem, obtain the objective function as follows (3.5):

$$\min F(v, f_z) = T_s + T_m + T_h + T_i + \eta B_p \quad (3.5)$$

Where: when $\eta = 1$ and $\eta = 0$, the objective function takes the lowest production cost and the highest productivity as the optimization objectives respectively; When $0 < \eta < 1$, the objective function exists as a coordination function between different optimization objectives.

Considering the maximum cutting force, spindle speed, work piece quality, feed, maximum cutting power and other factors in the process of machine tool processing, variables v, f_z in the design objective function should meet the following constraints.

1) Cutting speed. The cutting speed is constrained by the following formula: (3.6) and (3.7):

$$g_1(v, f_z) = \frac{\pi O N_{min}}{60 \times 1000} - v \leq 0 \quad (3.6)$$

$$g_2(v, f_z) = v - \frac{\pi O N_{max}}{60 \times 1000} - v \leq 0 \quad (3.7)$$

Where: N_{max} and O , respectively represent the highest spindle speed of CNC machine tool and the diameter of the work piece processed; N_{min} indicates the lowest spindle speed of the machine tool.

2) Supply constraint. Equation (3.8) and (3.9) are as follows:

$$g_3(v, f_z) = f_{min} - f_z \leq 0 \quad (3.8)$$

$$g_4(v, f_z) = f_z - f_{max} \leq 0 \quad (3.9)$$

Where: f_{max} and f_{min} respectively represent the maximum feed and minimum feed of CNC machine tools.

3) Cutting feed force. The cutting feed force is constrained by the maximum feed force of the machine spindle as follows (3.10):

$$g_5(v, f_z) = 9.81 \times 60^n F_c C_{F_c} a_p^x F_c f_z^y F_c v^n F_c k_{F_c} - F_{max} \leq 0 \quad (3.10)$$

Where: $C_{F_e}, n_{F_e}, x_{F_e}, y_{F_e}$ and k_{F_e} are cutting force parameters; F_{max} represents the maximum feeding force of the spindle of the CNC machine tool.

4) Cutting power. The effective power of NC machine tool is used to constrain the cutting power in the following formula (3.11):

$$g_6(v, f_z) = \frac{F_c v}{1000} = \frac{9.81 \times 60^n F_c C_{F_c} a_p^x F_c f_z^y F_c v^n F_c k_{F_c}}{1000} - \mu P_{max} \leq 0 \quad (3.11)$$

Where: P_{max} and μ respectively represent the maximum power and effective coefficient of CNC machine tools.

5) Cutting torque constraints. The cutting torque constraint formula using the maximum spindle torque is as follows (3.12):

$$g_7(v, f_z) = \frac{F_c O}{2 \times 1000} - M_{f_{max}} \leq 0 \quad (3.12)$$

Where: $M_{f_{max}}$ represents the maximum torque of CNC machine tool spindle.

6) Surface roughness constraints. The surface roughness constraints of the work piece processed by CNC machine tools are as follows (3.13):

$$g_8(v, f_z) = \frac{1000 f_z^2}{8 r_\varepsilon} - R_{max} \leq 0 \quad (3.13)$$

Where: R_{max} and r_ε , respectively represent the maximum roughness of work piece surface and the radius of tool tip arc.

3.2 Improved PSO Algorithm

PSO algorithm obtains the optimal solution by iterating random particles initially set. Inertial weight is used to improve the updating speed and position formula of particle swarm optimization algorithm in the iterative process as follows: (3.14) and (3.15):

$$u_{i,k+1} = \omega u_{i,k} + j_1 r_1 (q_i - z_{i,k}) + j_2 r_2 (q_g - z_{i,k}) \quad (3.14)$$

$$z_{i,k+1} = z_i + u_{i,k+1} \quad (3.15)$$

Where: z_i and q_i respectively represent the position of the i th particle and the individual optimal position obtained by the particle through searching; k and q_g respectively represent the number of iterations and the optimal position obtained by all populations through searching. j_1, j_2 and r_1, r_2 respectively represent the habit factor and random numbers $[0,1]$; ω represents the inertia weight that affects the current velocity and the previous velocity. The inertia weight can be used to balance the ratio between local convergence ability and global convergence ability [8-9].

The change of the global optimal value and the particle movement are determined by the individual optimal value. The current iteration individual optimal value should be superior to and equal to the previous individual optimal value in the iteration process. Whether the particle evolves to the global optimal position can be judged by comparing the previous iteration individual optimal value with the current individual optimal value [10-11]. The judgment formula is as follows (3.16):

$$s(i, k) = \begin{cases} 1 & F(q_{i,k}) < F(q_{i,k-1}) \\ 0 & F(q_{i,k}) = F(q_{i,k-1}) \end{cases} \quad (3.16)$$

Where: Judging whether the particle finds the minimum value by $s(i, k)$; $F()$ and $q_{i,k}$ respectively represent the optimization function and the individual optimal position obtained when the number of iterations is. When $F(q_{i,k}) < F(q_{i,k-1})$ and $F(q_{i,k}) = F(q_{i,k-1})$, respectively represents when the iteration number is k , the particle evolves to the global optimal position and does not evolve to the global optimal position. The particle swarm evolution rate formula is as follows (3.17) when the iteration number is k :

$$W_s(k) = \sum_{i=1}^{n_{pp}} s(i, k) / n_{pp} \quad (3.17)$$

In the formula, $W_s(k)$ and n_{pp} respectively represent the constant between $[0,1]$ and the number of population particles.

According to the above analysis, in order to improve the adaptability of inertia weight, the inertia weight value can be adjusted by evolution rate. The adjustment formula of inertia weight is as follows (3.18):

$$\omega = \frac{(k_{max} - k)(\omega_{max} - \omega_{min})}{k_{max}} + \omega_{min} W_s + 0.2 \quad (3.18)$$

Through the above improvement process, the particle swarm optimization algorithm has strong searching and convergence ability, so as to avoid the particle swarm optimization algorithm falling into the local optimal. The improved particle swarm optimization algorithm can quickly obtain the optimal value of the objective function of CNC machining parameters [10-11].

4 RESULT ANALYSIS

SSCK80 CNC machine tool was selected as an example analysis object, and CAD model was imported to carry out cutting experiments. The machine tool adopted point position control as the motion mode, and the spindle speed range was 1 600 r /min. Open loop control is adopted as the control mode of machine tool. The number of tool is 8, the processing size range is 4 000 mm, and the minimum motor speed and main motor power of machine tool are 35 r /min and 7 respectively. For 8 kW, torque and cutting force are 800 kN·mm and 3 800 N, respectively. Elastic modulus and shear modulus are 170 GPa and 85 GPa, respectively. In order to visually demonstrate the parameter optimization performance of the proposed method, substructure coupling method and response surface method are selected as comparison methods to test the optimization performance of the proposed method. Set the spindle design variable as 1 and particle dimension as 12. Determine the range of different dimensions according to the constraint conditions, set the number of particles in the population and the maximum number of iterations as 25 and 250 respectively, and set the sub factor as 1.6. Numerical control machining parameter optimization curves of different methods are shown in Figure 2 [12-16].

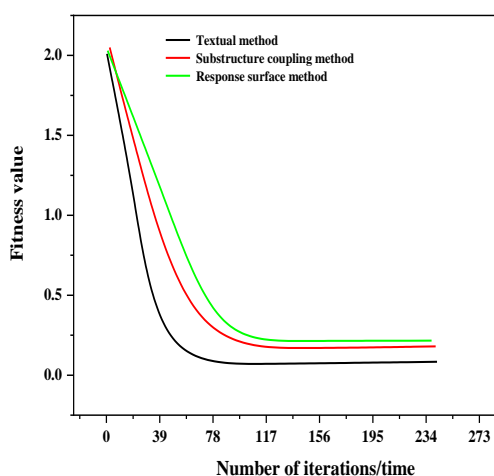


Figure 2: Comparison of results.

SSCK80 machine tool was used to implement three kinds of CNC machining operations, including rough milling, semi-finishing milling and finishing milling. The machining requirements were as follows: rough milling contour surface roughness was 7.1 μm ; The surface roughness of semi-finished milling is 4.2 μm [17-18]. The finish milling contour surface roughness is 2.8 μm . Three methods were used to optimize the rough milling contour process of SSCK80 machine tool, and the results of numerical control machining parameters optimization were shown in Table 2.

<i>Machining parameter</i>	<i>Textual method</i>	<i>Substructure coupling method</i>	<i>Response surface method</i>
Spindle speed /(r/min)	3398.4243	3125.4825	3054.2817
Cutting width/mm	18.6542	18.4635	18.3754
Cutting depth/mm	6.0004	6.0456	6.0685
Feed rate /(mm/min)	1198.5425	1184.6456	1158.1665
Surface roughness / μm	6.5843	6.8671	6.9785
Cutting power/kW	24.5846	24.1653	23.6481

Cutting time/s	4.0548	4.3548	4.5684
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Table 2: Contour NC parameters optimization of rough milling.

Three methods were used to optimize the shape process of semi-finished milling of SCK80 machine tools. The results of numerical control machining parameters optimization were shown in Table 3.

<i>Machining parameter</i>	<i>Textual method</i>	<i>Substructure coupling method</i>	<i>Response surface method</i>
Spindle speed /(r/min)	3481.5200	3326.8500	3315.8400
Cutting width/mm	2.6002	2.6005	2.6007
Cutting depth/mm	1.9998	1.9884	1.9846
Feed rate /(mm/min)	599.8542	571.6426	561.5817
Surface roughness / μm	3.6841	3.9182	4.0259
Cutting power/kW	4.5136	3.9418	3.8542
Cutting time/s	8.1654	8.8645	9.1546

Table 3: Numerical control parameters optimization results of semi-finished milling.

Three methods were adopted to optimize the finish milling contour process of SCK80 machine tool, and the optimization results of NC machining parameters were shown in Table 4.

<i>Machining parameter</i>	<i>Textual method</i>	<i>Substructure coupling method</i>	<i>Response surface method</i>
Spindle speed /(r/min)	3354.8100	3258.1600	3215.2500
Cutting width/mm	1.5001	1.5004	1.5007
Cutting depth/mm	1.1999	1.1984	1.1846
Feed rate /(mm/min)	499.5842	475.1652	458.6154
Surface roughness / μm	2.6845	2.7659	2.7958
Cutting power/kW	3.5481	3.2546	3.1548
Cutting time/s	13.5846	15.6428	17.8166

Table 4: Numerical control parameters optimization results of finishing milling.

The method presented in this paper was used to optimize the machining parameters of SCK80 CNC machine tool. The blank of the workpiece with a diameter of 60 mm was processed to meet the production demand after 8 times of cutting. Each time, the cutting speed was 58 mm, 54 mm, 52 mm, 48 mm, 46 mm, 43 mm, 41 mm and 39 mm, respectively. The optimization results of cutting speed and feed during 8 times of cutting are shown in Table 5, and the cutting speed and feed of the proposed method are shown in Figure 3. In Table 5, the experimental results once again verify the effectiveness of the proposed method in searching the optimal solution of the objective function of NC machining parameters by using the adaptive decline method of inertia weight value and improved particle swarm optimization algorithm.

<i>Number of strokes</i>	<i>Textual method</i>		<i>Substructure coupling method</i>		<i>Response surface method</i>	
	<i>Spindle speed/(m/s)</i>	<i>Feed rate/(mm/min)</i>	<i>Spindle speed/(m/s)</i>	<i>Feed rate/(mm/min)</i>	<i>Spindle speed/(m/s)</i>	<i>Feed rate/(mm/min)</i>
1	0.85	3.85	0.58	2.85	0.67	3.12
2	0.76	3.83	0.53	2.83	0.64	3.09

3	0.73	3.81	0.52	2.81	0.59	3.07
4	0.72	3.79	0.48	2.79	0.57	3.03
5	0.68	3.78	0.46	2.76	0.51	2.97
6	0.65	3.77	0.42	2.75	0.49	2.94
7	0.62	3.76	0.38	2.71	0.47	2.91
8	0.59	3.75	0.35	2.69	0.41	2.86

Table 5: Results of cutting optimization.

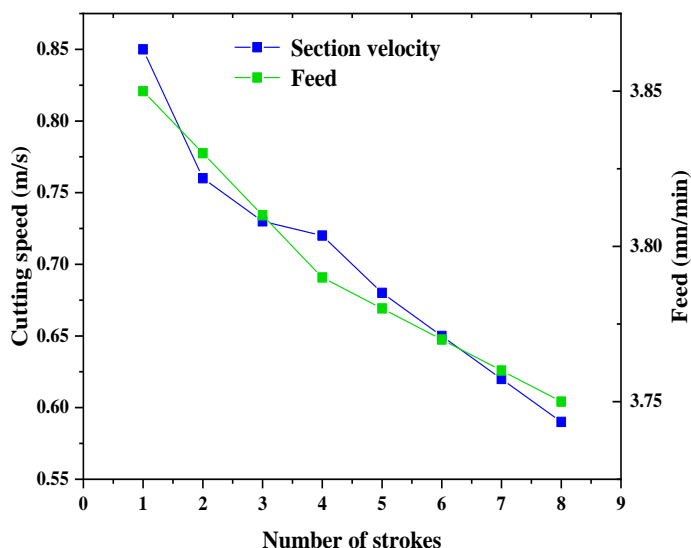


Figure 3: Cutting speed and feed of the proposed method.

5 CONCLUSION

In this essay, the multi-objective optimization problem of minimum production cost and maximum production efficiency is transformed into a single objective optimization problem by using the coordination coefficient. The objective function was established and the relevant constraint conditions were set. The improved particle swarm optimization algorithm was used to find the optimal solution of the objective function of NC machining parameters. SCK80 numerical control machine tool was used to verify the effectiveness of this method in optimizing numerical control machining parameters. The verification results show that the optimization of NC machining parameters by this method can meet the machining requirements and optimize the machining performance of NC machining machine tools, which can provide a reference for the practical application of NC machine tools.

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REFERENCES

- [1] Shami, T.-M.; El-Saleh, A.-A.; Alswaitti, M.; Al-Tashi, Q.; Summakieh, M.-A.; Mirjalili, S.: Particle swarm optimization: A comprehensive survey, *IEEE Access*, 10, 2022, 10031-10061. <https://doi.org/10.1109/ACCESS.2022.3142859>
- [2] Gad, A.-G.: Particle swarm optimization algorithm and its applications: a systematic review, *Archives of computational methods in engineering*, 29(5), 2022, 2531-2561. <https://doi.org/10.1007/s11831-021-09694-4>
- [3] Su, B.; Lin, Y.; Wang, J.; Quan, X.; Chang, Z.; Rui, C.: Sewage treatment system for improving energy efficiency based on particle swarm optimization algorithm, *Energy Reports*, 8, 2022, 8701-8708. <https://doi.org/10.1016/j.egyr.2022.06.053>
- [4] Pozna, C.; Precup, R.-E.; Horváth, E.; Petriu, E.-M.: Hybrid particle filter-particle swarm optimization algorithm and application to fuzzy controlled servo systems, *IEEE Transactions on Fuzzy Systems*, 30(10), 2022, 4286-4297. <https://doi.org/10.1109/TFUZZ.2022.3146986>
- [5] Wang, F.; Wang, X.; Sun, S.: A reinforcement learning level-based particle swarm optimization algorithm for large-scale optimization, *Information Sciences*, 602, 2022, 298-312. <https://doi.org/10.1016/j.ins.2022.04.053>
- [6] Hamdan, A.; Sarhan, A.-A.; Hamdi, M.: An optimization method of the machining parameters in high-speed machining of stainless steel using coated carbide tool for best surface finish, *The International Journal of Advanced Manufacturing Technology*, 58, 2012, 81-91. <https://doi.org/10.1007/s00170-011-3392-5>
- [7] Otair, M.; Ibrahim, O.-T.; Abualigah, L.; Altalhi, M.; Sumari, P.: An enhanced grey wolf optimizer based particle swarm optimizer for intrusion detection system in wireless sensor networks, *Wireless Networks*, 28(2), 2022, 721-744. <https://doi.org/10.1007/s11276-021-02866-x>
- [8] Du, X.; Wang, B.: A C3-continuous NURBS transition scheme for the CNC machining of short linear segments, *Precision Engineering*, 73, 2022, 1-10. <https://doi.org/10.1016/j.precisioneng.2021.08.016>
- [9] Akhtar, W.; Lazoglu, I.; Liang, S.-Y.: Prediction and control of residual stress-based distortions in the machining of aerospace parts: A review, *Journal of Manufacturing Processes*, 76, 2022, 106-122. <https://doi.org/10.1016/j.jmapro.2022.02.005>

- [10] Wu, P.; He, Y.; Li, Y.; He, J.; Liu, X.; Wang, Y.: Multi-objective optimisation of machining process parameters using deep learning-based data-driven genetic algorithm and TOPSIS, *Journal of Manufacturing Systems*, 64, 2022, 40-52. <https://doi.org/10.1016/j.jmsy.2022.05.016>
- [11] Yuwen, S. U.-N.; Jinjie, J. I.-A.; Jinting, X.-U.; Mansen, C. H. E.-N.; Jinbo, N. I.-U.: Path, feedrate and trajectory planning for free-form surface machining: A state-of-the-art review, *Chinese Journal of Aeronautics*, 35(8), 2022, 12-29. <https://doi.org/10.1016/j.cja.2021.06.011>
- [12] Singh, Y.; Singh, J.; Sharma, S.; Sharma, A.; Chohan, J.-S.: Process parameter optimization in laser cutting of coir fiber reinforced epoxy composite-a review, *Materials Today: Proceedings*, 48, 2022, 1021-1027. <https://doi.org/10.1016/j.matpr.2021.06.344>
- [13] Mohanty, A.; Nag, K.-S.; Bagal, D.-K.; Barua, A.; Jeet, S.; Mahapatra, S.-S.; Cherkia, H.: Parametric optimization of parameters affecting dimension precision of FDM printed part using hybrid Taguchi-MARCOS-nature inspired heuristic optimization technique, *Materials Today: Proceedings*, 50, 2022, 893-903. <https://doi.org/10.1016/j.matpr.2021.06.216>
- [14] Losper, B; Balyan, V; Groenewald, B.: Development of Distributed Data Acquisition System, *Lecture Notes in Networks and Systems*, 2022, 867-878. https://doi.org/10.1007/978-3-030-93247-3_82
- [15] Mohakud, R.; Dash, R.: Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection, *Journal of King Saud University-Computer and Information Sciences*, 34(8), 2022, 6280-6291. <https://doi.org/10.1016/j.jksuci.2021.05.012>
- [16] Ahmed, N.; Barsoum, I.; Haidemenopoulos, G.; Al-Rub, R.-A.: Process parameter selection and optimization of laser powder bed fusion for 316L stainless steel: A review, *Journal of Manufacturing Processes*, 75, 2022, 415-434. <https://doi.org/10.1016/j.jmapro.2021.12.064>
- [17] Jawad, A.-H.; Abdulhameed, A.-S.; Kashi, E.; Yaseen, Z.-M.; ALOthman, Z.-A.; Khan, M.-R.: Cross-linked chitosan-glyoxal/kaolin clay composite: parametric optimization for color removal and COD reduction of remazol brilliant blue R dye, *Journal of Polymers and the Environment*, 30(1), 2022, 164-178. <https://doi.org/10.1007/s10924-021-02188-1>
- [18] Elfarouk, O.; Wong, K.-Y.; Wong, W.-P.: Multi-objective optimization for multi-echelon, multi-product, stochastic sustainable closed-loop supply chain, *Journal of Industrial and Production Engineering*, 39(2), 2022, 109-127. <https://doi.org/10.1080/21681015.2021.1963338>