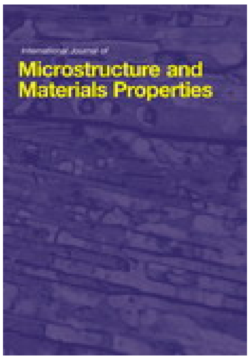

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An optimisation of 3D printing parameters of nanocomposites based on improved particle swarm optimisation algorithm

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An optimisation of 3D printing parameters of nanocomposites based on improved particle swarm optimisation algorithm

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Abstract: In order to overcome the problems of low accuracy, long optimisation time and high printing error of traditional 3D printing parameter optimisation methods, a optimisation method of 3D printing parameters of nanocomposites based on improved particle swarm optimisation (PSO) algorithm was proposed. The 3D mechanism model of nanocomposites 3D printer was constructed, the kinematics of the model was solved, and the calculation results of 3D printing parameters were obtained. The fundamental PSO algorithm is improved by introducing potential drop and contraction expansion factor. The objective function of 3D printing parameter optimisation was constructed, and the improved PSO algorithm was used to solve the function to realise 3D printing parameter optimisation. The test results show that the calculation accuracy of 3D printing parameters of nanocomposites is always higher than 92%, the average optimisation time is 0.72 s, and the maximum 3D printing error is 0.2 mm.

Keywords: improved PSO algorithm; nanocomposites; 3D printing parameters; parameter optimisation; contraction expansion factor.

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1 Introduction

At this stage, science and technology have made great changes in the manufacturing industry, social productivity has been continuously improved, and manufacturing production has become more efficient, economical and flexible. 3D printing technology has become an important symbol of the improvement of social productivity (Deng et al., 2019). However, due to the limited scientific research ability and technical level, 3D printing technology still has some defects in printing accuracy and speed, and the problems of less material selection, low intensity and single function have become important factors limiting the development of 3D printing technology (Vancauwenberghe et al., 2019), which has excellent sound, light, electricity, magnetism, heat the emergence and application of nanocomposites with mechanical properties can effectively solve this problem.

Aiming at the important research topic of 3D printing parameter optimisation of nanocomposites, Cui et al. (2021) proposed a 3D printing parameter optimisation method of nanocomposites based on GPR response surface method. The 3D printing parameters of nanocomposites are calculated, and the 3D printing parameter optimisation model of nanocomposites is constructed based on the response surface method of Gaussian process regression. The result is the optimisation result of 3D printing parameters of nanocomposites. However, in practice, it is found that this method has the problem of long optimisation time of 3D printing parameters of nanocomposites. Ding and Wu (2019) proposed an optimisation method of 3D printing parameters of nanocomposites based on NSGA-II algorithm. The overall configuration of the 3D printer and the internal parts of the nozzle are analysed. Combined with the description of the mechanism, the Jacobian matrix is derived, so as to build the objective function for the optimisation. The optimal solution of the function is solved by NSGA-II algorithm, and the parameter optimisation results are obtained. However, the accuracy of this method is low for 3D printing parameters. Liu et al. (2019) proposed the optimisation method of 3D printing parameters of nanocomposites based on response surface method PLA. The influencing factors of 3D printing of nanocomposites are analysed, the second-order response surface model between different PLA print parameters and surface roughness is constructed, and the relevant parameter optimisation results are obtained when the surface roughness value is the smallest. However, when this method is applied to the 3D printing process of nanocomposites, the printing error is high.

Because the traditional optimisation of 3D printing parameters of nanocomposites is difficult to determine the printing parameters, resulting in the problems of low calculation accuracy, long optimisation time and high printing error of 3D printing parameters of nanocomposites. Therefore, this paper takes solving the problems existing in traditional methods as the research goal, and transforms the engineering problem of 3D printing of nanocomposites into a mathematical optimisation problem, this paper designs a new optimisation method of 3D printing parameters of nanocomposites based on improved PSO algorithm. Therefore, this method has the characteristics of high accuracy of 3D printing parameters of nanocomposites, short optimisation time of 3D printing parameters of nanocomposites and low 3D printing error of nanocomposites. The overall design scheme is as follows

1 Construct the 3D mechanism model of nanocomposites 3D printer, solve the kinematics of the model, and obtain the calculation results of nanocomposites 3D printing parameters.

2 Based on the calculation results of 3D printing parameters of nanocomposites, the fundamental PSO algorithm is improved by introducing potential drop and contraction expansion factor. The optimisation objective function of 3D printing parameters of nanocomposites materials was constructed, and the improved PSO algorithm was used to solve the function to judge whether the number of iterations reached the given threshold. If the conditions were met, the optimal solution, namely the optimisation result of 3D printing parameters of nanocomposites materials, was output.

3 The calculation accuracy of 3D printing parameters, parameter optimisation time and 3D printing error of nanocomposites materials of different methods were compared through experiments.

2 Design of nanocomposites 3D printing parameter optimisation method

2.1 Determination of 3D printing parameters of nanocomposites

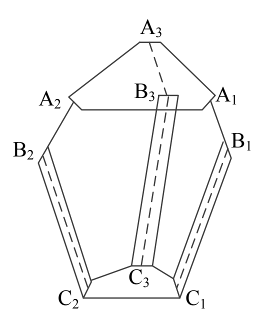
3D printing technology appeared in the 1980s. In recent years, with the gradual popularisation of 3D printing technology, especially the contribution from the network open source community, people can obtain a complete set of 3D printing equipment hardware and software guide, the process is simple and clear, the production cost is low, and the printing model can also obtain relatively high accuracy (Lei et al., 2019). The key step for 3D printing to realise the moulding of complex objects is to transform the moulding of complex objects into an orderly superposition of the moulding of simple objects. The 3D printer studied in this paper is a spatial 3D mechanism. For the spatial 3D mechanism, its model is as follows.

$$F = 6(n - g - 1) + \sum_{i=1}^{g} f_i \tag{1}$$

where n is the total amount of moving rods of 3D printer; g is the total amount of sports pairs; f_i is the degree of freedom of the ith mechanism.

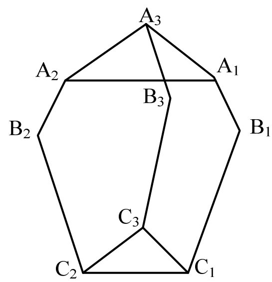
The printer body is simplified to the form shown in Figure 1 (Mendis et al., 2019).

Figure 1 Preliminary simplified diagram of 3D printer body



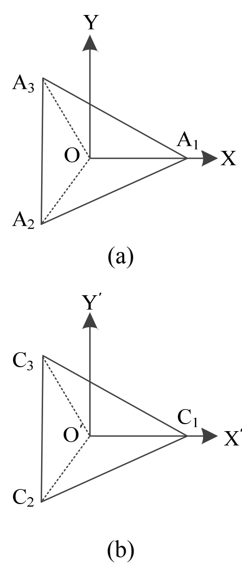
The three driving arms are represented by three straight lines connected with the static platform, and the three driven arms are represented by three parallelograms. In the process of motion, because the moving platform has only plane motion and no rotational motion (Nyuysoni et al., 2022), the three parallelograms can be represented by three dotted lines connected by the midpoints of the upper and lower sides, and Figure 1 can be further simplified to the final form of Figure 2.

Figure 2 Final simplified diagram of 3D printer body



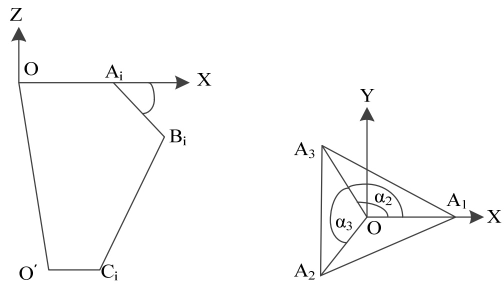
After the simplified structure diagram of the printer is determined, the coordinate systems of the static platform and the dynamic platform are established, which are represented by O-XYZ and O′-X′Y′Z’ respectively. The specific description is shown in Figure 3.

Figure 3 Coordinate system: (a) static platform and (b) moving platform



In order to clarify the kinematic principle of the 3D printer, the single branch chain structure of the printer is analysed (Maniruzzaman, 2021; Somers et al., 2021), as shown in Figure 4.

Figure 4 Single branched chain structure



Among them, the length of driving arm $|A_iB_i| = L_1$ and driven arm $|B_iC_i| = L_2$ and A_i are the connection points between the driving arm and the static platform, α_i is the included angle between the driving arm and the X axis in the static platform coordinate system, and θ_i is the rotation angle of the driving arm under the action of the driving motor (Beregovoi et al., 2021). The coordinate vector of the driving joint in the static coordinate system O-XYZ is $\overline{OA_i}$:

$$\overline{OA} = R \cdot \begin{bmatrix} \cos\alpha_1 & \cos\alpha_2 & 0 \\ \sin\alpha_1 & \sin\alpha_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{2}$$

where α_1 and α_2 is the included angle of different coordinate axes

According to formula (2), the coordinates of the connection point between the driving arm and the driven arm in the static coordinate system are:

$$\overline{OB_i} = \begin{bmatrix} A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \\ C_1 & C_2 & C_3 \end{bmatrix} \tag{3}$$

Assuming that C_i is the connection point between the boom and the moving platform (Ford and Minshall, 2019), $\overline{OC_i}$ represents the coordinate vector of the end of the boom in the moving coordinates O′-X′Y′Z′:

$$\overline{OC} = \begin{bmatrix} x + r\cos\alpha_1 & x + r\cos\alpha_2 & x + r\cos\alpha_3 \\ y + r\sin\alpha_1 & y + r\sin\alpha_2 & y + r\sin\alpha_3 \\ z & z & z \end{bmatrix} \tag{4}$$

where α_3 represents the angle between X and Z axes.

The coordinates of the driven arm B_iC_i are:

$$\overline{B_iC_i} = \begin{bmatrix} D_1 & D_2 & D_3 \\ E_1 & E_2 & E_3 \\ F_1 & F_2 & F_3 \end{bmatrix} \tag{5}$$

Since the length of the driven arm rod is $\left|B_i C_i\right|^2 = L_2^2$, there is:

$$\begin{cases} L_2^2 = G_1^2 + H_1^2 + S_1^2 \\ L_2^2 = G_2^2 + H_2^2 + S_2^2 \\ L_2^2 = G_3^2 + H_3^2 + S_3^2 \end{cases} \tag{6}$$

Simplify the above formula to obtain:

$$I_i \cos\theta_i - J_i \sin\theta_i - K_i = 0 \tag{7}$$

According to the assembly relationship of the printer, the kinematics solution result is:

$$\theta_i = 2\arctan\frac{-J_i - \sqrt{J_i^2 + I_i^2 + K_i^2}}{K_i + I_i} \tag{8}$$

Combined with the kinematics solution results, the 3D printing quality is affected not only by the printing speed, but also by other different printing parameters. Based on the previous research results, this paper determines the 3D printing parameters as layer thickness, printing speed, nozzle temperature and hot bed temperature, expressed by d_i, k_i, t_i, r_i respectively.

2.2 3D printing parameter optimisation based on improved PSO algorithm

Inspired by the phenomenon of bird predation, particle swarm optimisation (PSO) algorithm has developed into an artificial intelligence algorithm to solve optimisation problems (Cai and Li, 2021; Song et al., 2021). Due to the uncertainty of particles, the application of PSO algorithm is limited. Therefore, this paper introduces quantum behaviour into basic PSO algorithm to form quantum PSO algorithm. This algorithm is used to optimise 3D printing parameters, so as to improve the effect and efficiency of 3D printing parameter optimisation.

$$v_{id}(k+1) = v_{id}(k) + c_1 rand()\left(p_{id}(k) - x_{id}(k)\right) + c_2 rand()\left(p_{gd}(k) - x_{id}(k)\right) \tag{9}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \tag{10}$$

where $v_{id}(k)$ and $x_{id}(k)$ are the current particle velocity and position (Xu, 2021; Nabi and Ahmed, 2021), $p_{id}(k)$ represents the local optimum, $p_{gd}(k)$ is the global optimum, and c_1 and c_2 are different constants, $rand()$ is a random number between 0 and 1.

Due to the uncertainty of particles, the application of PSO algorithm is limited. Therefore, this paper introduces quantum behaviour into basic PSO algorithm to form quantum PSO algorithm. Assuming that the particle's wave function is $\phi(Y)$ at a potential of δ, there is the following relationship:

$$\phi(Y) = \frac{1}{\sqrt{L}} e^{\frac{-|Y|}{L}} \tag{11}$$

where $L = \frac{1}{\beta} = \frac{h^2}{mr}$ is the relative point position probability of particles. Then the particle position equation is expressed by the following formula:

$$X = P \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \tag{12}$$

where P is the potential drop vector, and the particle position at this time can be calculated by the following formula:

$$X_{t+1} = P \pm \frac{L(t)}{2} \ln\left(\frac{1}{u(t)}\right) \tag{13}$$

where t represents discrete time.

Assuming that there is an attractor, represented by $P_i = (P_{i1}, P_{i2}, \ldots, P_{iN})$. For $P_{i,j}$, each dimensional wave function with particles i is represented by the following formula:

$$\phi\left[x_{i,j}(t+1)\right] = \frac{1}{\sqrt{\left[L_{i,j}(t)\right]}} \exp\left[\frac{\left|x_{i,j}(t) - P_{i,j}(t)\right|}{L_{i,j}(t)}\right] \tag{14}$$

The position equation is:

$$x_{i,j}(t+1) = P_{i,j}(t) \pm \frac{L_{i,j}(t)}{2} \ln\left(\frac{1}{u_{i,j}(t)}\right) \tag{15}$$

The average best position is introduced to optimise the particle optimisation performance.

$$mbest = \frac{1}{M}\sum_{i=1}^{M} P_i(t) = \left(\frac{1}{M}\sum_{i=1}^{M} P_{i,1}(t), \frac{1}{M}\sum_{i=1}^{M} P_{i,2}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{i,n}(t)\right) \tag{16}$$

Then there

$$L(t+1) = \beta\left|mbest - x(t)\right| \tag{17}$$

Then the position equation is:

$$x_{i,j}(t+1) = P_{i,j}(t) \pm \frac{\beta}{2}\left|mbest_j(t) - x_{i,j}(t)\right| \ln\left(\frac{1}{u_{i,j}(t)}\right) \tag{18}$$

Among them, β is the contraction expansion factor, and the dynamically changing β can adjust the particle search area and improve the performance of the algorithm. Among them, formula (18) is called the position iteration formula of quantum PSO algorithm.

In the process of applying the adaptive quantum PSO algorithm to nanocomposites 3D printing parameter optimisation, the specific design steps are as follows:

Step 1: Input corresponding information, i.e., system node information and branch information. According to the input control variables, the population size is m, dimension D, learning factors c_1 and c_2, and the amplitude of position.

Step 2: Initialise particle parameters.

Step 3: Substitute the control variables into the 3D printing parameters of nanocomposites to optimise the objective function. The optimisation objective function is as follows:

$$E = \{d_i, k_i, t_i, r_i\}, i = 1, 2, ..., n \tag{19}$$

Step 4: Calculate the average and individual fitness of particles, and compare their sizes. The particle state can be accurately analysed according to their size.

Step 5: If the population is too concentrated, it is necessary to increase the shrinkage and expansion factor, otherwise reduce the shrinkage and expansion factor, so as to improve the particle optimisation ability and the optimisation effect of 3D printing parameters of nanocomposites.

Step 6: Re determine the p_{Best} and g_{Best} of the particle. If $f(x) < p_{Best}$, then $p_{Best} = f(x)$; If $f(x) > p_{Best}$, then p_{Best} remains unchanged. If $f(x) < g_{Best}$, $g_{Best} = f(x)$; If $(x) > g_{Best}$, then g_{Best} remains unchanged;

Step 7: Judge whether the number of program runs reaches the threshold. If the conditions are met, the program runs and outputs the optimal solution, that is, the optimisation result of 3D printing parameters of nanocomposites. Otherwise, skip to step 3 and continue to run;

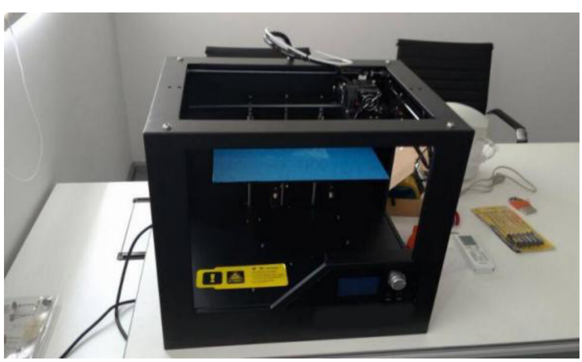
3 Simulation experiment design

3.1 Experimental scheme

The overall experimental scheme is as follows:

1 *Experimental environment*: Firstly, the model to be printed is designed in 123D design modelling software. In order to facilitate subsequent measurement and analysis, the print is designed into a block with a size of $20 \times 20 \times 3$ mm. The printing equipment selected in the experiment is shown in Figure 5.

Figure 5 3D printing device (see online version for colours)



2 *Experimental parameters*:

The FDM printer with the model of z-603s selected in this paper will have a certain impact on the printing quality. Therefore, the parameter range of the experiment is determined after taking different level values from multiple prints for verification. The details are described in Table 1.

Table 1 Parameters

Influence factor	*Range*	*Unit*
d_i	[0.06–0.2]	mm
k_i	[20–70]	mm/s
t_i	[190–220]	°C
r_i	[50–70]	°C

The experimental parameters are used to obtain the data during the operation of the 3D printing equipment, which is used as the experimental sample data, the sample data is de duplicated, the data de duplication results are input into the simulation software, the optimal operation parameters are obtained after many tests, and the parameters are used as the initial parameters, so as to improve the authenticity and reliability of the simulation experimental results.

3 *Evaluation index*:

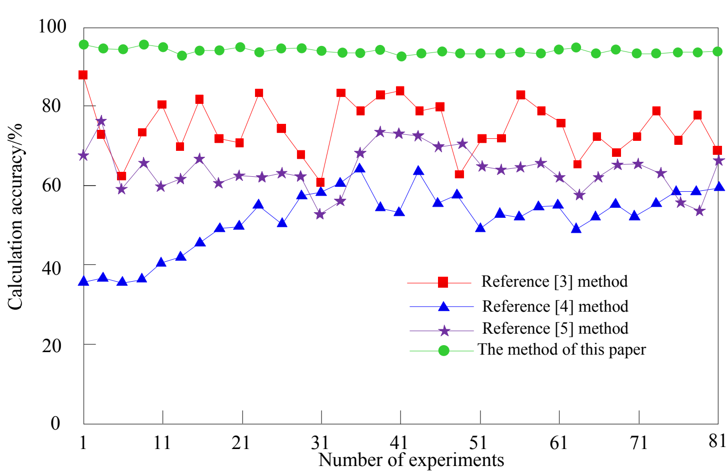
The application effects of different methods are verified by comparing the calculation accuracy of 3D printing parameters of nanocomposites and the optimisation time of 3D printing parameters of nanocomposites.

3.2 Experimental results

3.2.1 Calculation accuracy of 3D printing parameters of nanocomposites

The comparison results of the calculation accuracy of 3D printing parameters of nanocomposites by the four methods are described in Figure 6.

Figure 6 Comparison of calculation accuracy of 3D printing parameters of nanocomposites (see online version for colours)



The calculation accuracy of 3D printing parameters of nanocomposites in this method is always higher than 92%, while the calculation accuracy of 3D printing parameters of nanocomposites in Cui et al. (2021) method is between 60% and 80%, and the calculation accuracy of 3D printing parameters of nanocomposites in Ding and Wu (2019) method is between 35% and 65%, The calculation accuracy of 3D printing parameters of nanocomposites by Liu et al. (2019) method is between 52% and 77%, which shows that the calculation accuracy of 3D printing parameters of nanocomposites by this method is higher than that by experimental comparison method. The reason is that this method solves the kinematics of the model through the spatial three-dimensional mechanism model of the printer, and obtains the calculation results of printing parameters. Therefore, this method has high calculation accuracy.

3.2.2 Optimisation time of 3D printing parameters of nanocomposites

The comparison results of the optimisation time of 3D printing parameters of nanocomposites by the four methods are shown in Table 2.

Table 2 Optimisation time of 3D printing parameters of nanocomposites

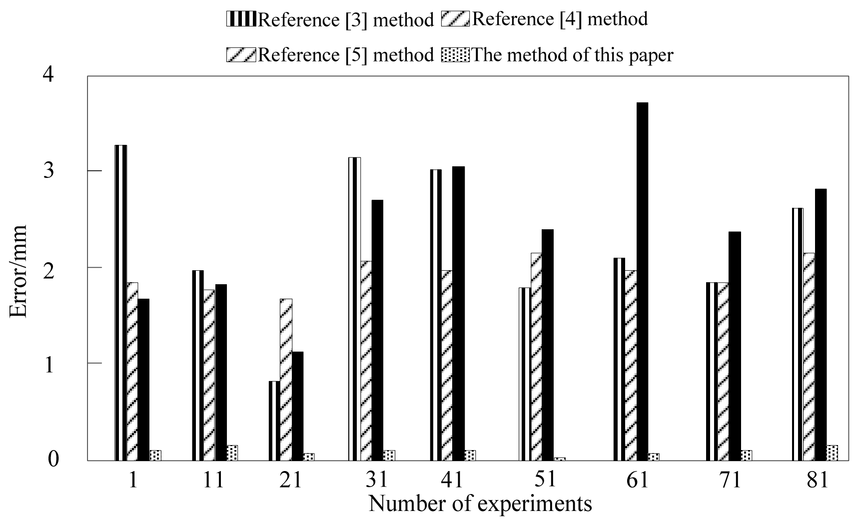
Number of experiments	*Parameter optimisation time/s*			
	The method of this paper	*Cui et al. (2021) method*	*Ding and Wu (2019) method*	*Liu et al. (2019) method*
1	0.58	1.52	1.05	0.98
11	0.69	1.36	1.22	1.25
21	0.75	1.47	1.36	1.36
31	0.84	1.55	1.54	1.44
41	0.63	1.28	1.62	1.51
51	0.57	1.96	1.33	1.32
61	0.99	1.35	1.25	1.47
71	0.68	1.24	0.96	0.96
81	0.75	1.47	0.89	1.74
Average value	0.72	1.47	1.25	1.34

The average optimisation time of 3D printing parameters of nanocomposites in this method is 0.72 s, which is the lowest among the four methods, while the average optimisation time of 3D printing parameters of nanocomposites in Cui et al. (2021) method is 1.47 s, which is the highest among the four methods. The average optimisation time of 3D printing parameters of nanocomposites in Ding and Wu (2019) method is 1.25 s. The average optimisation time of 3D printing parameters of nanocomposites in Liu et al. (2019) method is 1.34 s. The optimisation time of 3D printing parameters of nanocomposites is shorter and the efficiency is higher. The reason is that this method constructs the objective function of 3D printing parameter optimisation of nanocomposites, and uses the improved PSO algorithm to solve the function to realise the optimisation of 3D printing parameters, so it shortens the optimisation time and improves the optimisation efficiency.

3.2.3 3D printing error of nanocomposites

The 3D printing errors of nanocomposites optimised by four methods are compared, and the specific results are described in Figure 7.

Figure 7 3D printing error of nanocomposites



According to the data in Figure 7, the maximum 3D printing error of nanocomposites in this method is 0.2 mm, the maximum 3D printing error of nanocomposites in Cui et al. (2021) method is 3.3 mm, the maximum 3D printing error of nanocomposites in Ding and Wu (2019) method is 2.2 mm, and the maximum 3D printing error of nanocomposites in Liu et al. (2019) method is 4.6 mm. The 3D printing error of nanocomposites material in this paper is lower, indicating that the 3D printing parameter optimisation effect of nanocomposites material in this method is better. The reason is that this method calculates the 3D printing parameters of nanocomposites and uses the improved PSO algorithm to solve the function, so the 3D printing error of nanocomposites is greatly reduced.

4 Conclusion

1 3D printing technology has been applied to various fields. However, due to the limitation of materials, it is difficult to further study 3D printing technology. Therefore, nanocomposites materials can be used as 3D printing materials to reduce costs and improve the success rate of printing.

2 However, it is difficult to determine the existing nanocomposites as 3D printing parameters, which leads to the deterioration of nanocomposites as 3D printing effect. Therefore, this paper designs an optimisation method of 3D printing parameters of nanocomposites based on improved PSO algorithm.

3 Experimental results show that the calculation accuracy of 3D printing parameters of nanocomposites materials is always higher than 92%, the average optimisation time of 3D printing parameters of nanocomposites materials is 0.72 s, and the maximum error of 3D printing nanocomposites materials is 0.2 mm. Therefore, it is proved that this method has the characteristics of high accuracy of 3D printing parameters of nanocomposites, short optimisation time of 3D printing parameters of nanocomposites and low 3D printing error of nanocomposites. It can be widely used in 3D printing to promote the further development of 3D printing technology.

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