Scheduling Modeling and Optimization of 3D Print Task in Cloud Manufacturing Environment Based on Quantum Wolf Pack Algorithm

Pianpian Gao

{gaopian@qq.com}

School of Management Engineering, Shandong Jianzhu University, Jinan, Shandong; 250101, China

Abstract. The cloud manufacturing service model effectively solves the problem of uneven distribution of manufacturing resources in the entire manufacturing industry and realizes the efficient use of manufacturing resources. We fully consider the heterogeneity of user orders and 3D printing, and build a supply and demand matching and task scheduling model for distributed 3D printing tasks and 3D printing equipment resources under cloud manufacturing, aiming at the characteristics of equipment resources and diversified production target requirements in the cloud manufacturing environment. In order to effectively solve the above problems, we propose a hybrid optimization method based on quantum wolf swarm algorithm and discrete event simulation. Among them, the design of local search improves the search process, and adopts Grover quantum algorithm to make the search more efficient. Numerical experiments show that the algorithm has good convergence and can find a satisfactory solution to the problem within a rational quantity of iterations.

Keywords: cloud manufacturing; 3D printing; production scheduling; resource matching; quantum wolf pack algorithm; discrete event simulation

1 Introduction

3D printing technology through computer-aided design layering method, can utilize digital data to produce actual objects, mainly through 3D printing for production, also known as additive manufacturing, it possesses the attributes of both digital and dispersed production, making it appropriate for intricate shapes, tiny quantities, and customized order tasks [1], is extensively utilized in a variety of areas, including industrial manufacture, aircraft, cuisine, and sports. Due to the dynamic and unpredictable market environment, the requirements for personalized product customization are getting higher and higher, and enterprises have to seek external resources to respond quickly to the market. Academician Li Bohu proposed the concept of "cloud manufacturing" in 2009 [2]. It offers a transparent setting for the effective integration and exchange of resources for 3D printing equipment [3]. However, with the advent of the era of personalization, the needs of users are becoming more and more complex and diversified, although the development of 3D printing equipment resources is still in its early stages, it is now vital to find a solution for how to match dispersed 3D printing jobs with 3D printing equipment resources for production in order to maximize user benefits in terms of cost and time. Jiang et al. [4] considered resources, capabilities, service quality and cost, and constructed a 3D printing

ICEMME 2023, November 17-19, Beijing, People's Republic of China

DOI 10.4108/eai.17-11-2023.2342663

order service matching optimization model in the networked distribution mode. Zhou et al. [5] studied the scheduling issue of 3D printing tasks considering personalized services in the cloud manufacturing environment, and established a 3D printing service scheduling model with the goal of minimizing processing time. Li et al. [6] established a cloud framework for distributed manufacturing, aiming at the minimum comprehensive consumption of resources in printing cost and printing time, and using genetic algorithms to find the optimal scheduling scheme, but the current research on 3D printing services ignores the heterogeneity of space and the diverse characteristics of production target requirements. In addition, the Wolf Pack Algorithm (WPA) is a novel model for swarm intelligence exhibiting robust global convergence and computational robustness, but it has the problem of slow convergence [7].

Therefore, this paper studies the matching of 3D printing tasks and manufacturing resources and the scheduling of 3D printing tasks in the context of cloud manufacturing, and constructs a 3D printing task service matching and scheduling model. We propose a hybrid optimization method ground on quantum wolf pack algorithm and discrete event simulation, in which variable neighborhood search is used to further improve the search process, effectively improve the optimization ability of the algorithm, and use Grover quantum algorithm to make the search more efficient.

2 Optimization model

2.1 Problem description

The cloud manufacturing platform of 3D printing is mainly composed of service providers (3D printing resource owners), service demanders (that is, individual users or enterprise users who have demand for 3D printing) and cloud manufacturing platforms. The service demander submits its own demand orders to the cloud manufacturing platform, and the cloud manufacturing platform allocates all orders in a unified manner, allocates appropriate 3D printing resources to the service provider according to its order needs, and calls the corresponding manufacturing resources of the service provider for manufacturing. In a cloud manufacturing environment, consider having N 3D printing resource providers located in different geographic regions. Alternative service paths exist in cloud manufacturing systems. Each 3D printing resource provider can provide a variety of service types, but its resource capacity is limited. The customer in the cloud manufacturing system submits T tasks to the center of the cloud manufacturing platform, and the cloud manufacturing platform splits each cloud manufacturing order into multiple cloud manufacturing sub-tasks according to experience, in which each cloud manufacturing sub-task has its own service type and service type matching candidate cloud manufacturing service provider collection, we only consider the linear cloud manufacturing sub-task splitting method. Every order submitted by a customer has a deadline and needs to be completed by the deadline. We assume that all orders are not interrupted in the process of processing products, the platform has several printing devices of various types, scattered in different positions in the space, and each printing equipment can process different amounts of work per unit time. Therefore, when the same task is arranged on different 3D printing equipment, the working time will be different, and the actual working time is determined by the workload of the task and the work efficiency of the corresponding 3D printing equipment.

2.2 Model

The notations utilized in this article are summarized in table 1.

Table 1. Variables and parameters of the 3D print order scheduling model.

Symbol	Description	Symbol	Description
n	The number of cloud manufacturing tasks	T_{ji}	The set of cloud manufacturing subtasks of the path j of cloud manufacturing task i
m	The number of cloud manufacturing task paths	K_{tji}	The set of service providers for the t cloud manufacturing subtask of the path j of cloud manufacturing task i
l	The number of cloud manufacturing subtasks	$\tilde{p}_{ktji}$	The service time for the cloud manufacturing subtask t of the path j of cloud manufacturing task i is provided by cloud manufacturing service provider k.
h	The number of cloud manufacturing service providers	$O_{kk'}$	The distance between Service Provider k and Service Provider k'
I	The set of cloud manufacturing tasks $i \in I, I = \{1, 2, \cdots, n\}$	d_i	The latest delivery date for the task i.
J	The set of cloud manufacturing task paths $j \in J, J = \{1, 2, \cdots, m\}$	S_{tji}	The start time of the processing of the subtask t of the path j of the task i.
T	The set of cloud manufacturing subtasks $t \in T, T = \{1, 2, \cdots, l\}$	C_{tji}	The end time of the processing of the subtask t of the path j of the task i.
K	The set of cloud manufacturing service providers $k \in K, K = \{1, 2, \cdots, h\}$	x_{ktji}	1 if the subtask t of the path j of task i is processed by service provider k, otherwise 0
J_i	The set of cloud manufacturing task paths of cloud manufacturing task i.	y_{ji}	1 if the task i is processed by the path j, otherwise 0

The objective function of the model is to minimize the makespan and reduce the load on the cloud manufacturing service, as shown in Equation (1):

$$\min f = (1\text{-}\alpha)\left(\max C_{ijl}\right) + \alpha \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{t=1}^{l} \sum_{k=1}^{h} \tilde{P}_{\mathrm{ijtk}} \mathrm{X}_{\mathrm{ijtk}} \tag{1}$$

s.t.

$$\sum_{k\in h} x_{ktji} = 1 \quad \forall i \in I, j \in J, t \in T \tag{2}$$

$$S_{tji} - S_{(t-1)ji} \ge \sum_{k\in K} \tilde{P}_{k'(t-1)ji} x_{k'(t-1)ji} + \sum_{k,k'\in K} O_{\mathrm{kk'}} \mathrm{X}_{\mathrm{ij(t-1)k'}} X_{ijtk} \tag{3}$$
$$\forall j \in J, \forall t \in T$$

$$\left| S_{tji} - S_{t'j'i'} \right| \ge x_{ktji} x_{kt'j'i'} \theta, \tag{4}$$
$$\text{where } \theta = \begin{cases} p_{kt'j'i'}, \text{ if } & S_{tji} - S_{t'j'i'} \ge 0 \\ p_{ktji}, \text{otherwise} & \end{cases}, \forall i \in I, \forall k \in K$$

$$\sum_{j\le J_i} y_{ji} = 1 \quad \forall i \tag{5}$$

$$S_{ktji} \le d_i \quad \forall i, j \in J_i, t \in T_{ji}, k \in K_{tji} \tag{6}$$

$$C_{tij} = s_{tij} + \sum_{k\in K} \tilde{P}_{ktij} x_{ktij}, \quad \forall i \in I, \forall j \in J, \quad \forall t \in T \tag{7}$$

$$s_{(t+1)ij} - C_{tij} \ge O_{kk'} x_{k'(t+1)ij} x_{ktij} \quad \forall i \in I, \forall j \in J, \quad \forall t \in T, \forall k \in K \tag{8}$$

Equation (2) restricts each cloud manufacturing task to only one candidate cloud manufacturing service provider. Equation (3) indicates that each cloud manufacturing task needs to be served by the cloud manufacturing service provider in the order of subtasks. Constraint (4) restricts cloud manufacturing service providers to only one subtask at a time. Constraint (5) restricts each cloud manufacturing order to only one service path. Constraint (6) limits the deadline for each cloud manufacturing order to be completed. Constraint (7) represents the completion time of the cloud manufacturing subtask. Constraint (8) limits the need to consider transit time when adjacent subtasks of the same cloud manufacturing order are assigned to different cloud manufacturing service providers.

3 Quantum Wolf Pack Algorithm(WPA-BGV)

The above model has a very complex structure and is difficult to optimize with traditional methods. In view of the characteristics of the problem, this paper proposes a hybrid algorithm structure, which uses the improved quantum wolf pack algorithm as the main optimization engine, and combines it with the simulation process to realize the processing of complex operations.

The basic Wolf Pack Algorithm (WPA) tackles the issue via imitating the natural process of wolves hunting. Individuals in the wolf pack are divided into head wolves, probe wolves, and fierce wolves, which together prey through three intelligent behaviors. After each generation of siege behavior, the wolf pack will be renewed by the survival of the fittest mechanism, eliminating the worst performing R wolves, while randomly generating R new wolves in the solution space to complete the population update. The standard wolf pack algorithm is inefficient to settle some problems due to its large number of iteration layers. When the wolf pack algorithm is applied to cloud manufacturing resource matching and order scheduling, it is prone to get stuck in local extremes and slow convergence speed. Given these issues, this paper proposes a hybrid optimization model ground on quantum wolf pack algorithm and discrete event simulation to address, which uses variable neighborhood search to further improve the search process, which adds the bacterial foraging algorithm (BFO) in the tendency behavior and migration behavior of bacteria exploration ability and other fields of transformation search method, thereby effectively improving the algorithm's optimization ability, using Grover quantum algorithm to make the search more efficient, which uses double qubit coding[8-9], based on the above improvements, as a result, the quantum wolf pack algorithm may successfully break out of local optimality.

The WPA-BGV algorithm optimizes the algorithm by altering the manner the update location is updated. As indicated in equation, let be the updated location of the wolf pack, N elements, after iterations of the G operator to obtain the target quantum state, is the initial uniform superposition state (9). Symmetrical projection ground on the initial in two-dimensional Hilbert space is available (10). Each G-transform can be rotated, after which the k-times G-transform is shown in Equation (11). Hence an updated formula for WPA-BGV can be acquired as demonstrated in Equation (12).

$$|\varphi\rangle = \frac{1}{\sqrt{N}}\sum_{x=0}^{N-1}|x\rangle \tag{9}$$

$$\mathrm{G} = \mathrm{H}^{\oplus \mathrm{n}}\left(2|0\rangle\langle 0| - \mathrm{I}\right)\mathrm{H}^{\oplus \mathrm{n}} = \left(2|\varphi\rangle\langle\varphi| - I\right)\mathrm{O} \tag{10}$$

$$G^{k}|\varphi\rangle = \sin\left(2k+1\right)\theta|\alpha\rangle + \cos\left(2k+1\right)\theta|\beta\rangle \tag{11}$$

$$\overline{QX}\left(t\right) = \sin\left(2\mathrm{k}+1\right)\theta\overrightarrow{X}\left(t\right) + \cos\left(2k+1\right)\theta\sqrt{1-\overrightarrow{X}\left(t\right)} \tag{12}$$

In addition, the coding of each bit of each individual is shown in Figure 1, WPA-BGV uses qubit coding to make chromosomal genes in a superposition of "0" and "1", αi is the probability of conversion to 0, βi is the probability of conversion to 1. Each qubit includes two part information, using candidate service machine and scheduling sequence. Figure 2 represents the solution converted to decimal, where '61' represents the first subtask of the sixth 3D printing order is arranged on the first 3D printer in the candidate set. Through the WPA-BGV algorithm process described above, the 3D printer in the candidate set used and the position in the encoding are changed.

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_d \\ \beta_1 & \beta_2 & \cdots & \beta_d \end{bmatrix}$$

Fig. 1. The structure of each bit of each individual

pop1	61	51	12	64	52	41	42	52	23	13

Fig. 2. The structure of the solution representation.

In summary, the WPA-BGV algorithm flow in this paper is shown in Figure 3.

4 Real-case experiment and results

An example is used to verify the proposed distributed 3D printing task scheduling model in the cloud manufacturing environment and the proposed WPA-BGV algorithm. The service provider of this example has 10 3D printing equipment resources. It is assumed that the service demander of the 3D printing service platform receives 6 distributed 3D printing tasks. The specific task information is shown in Table 2.

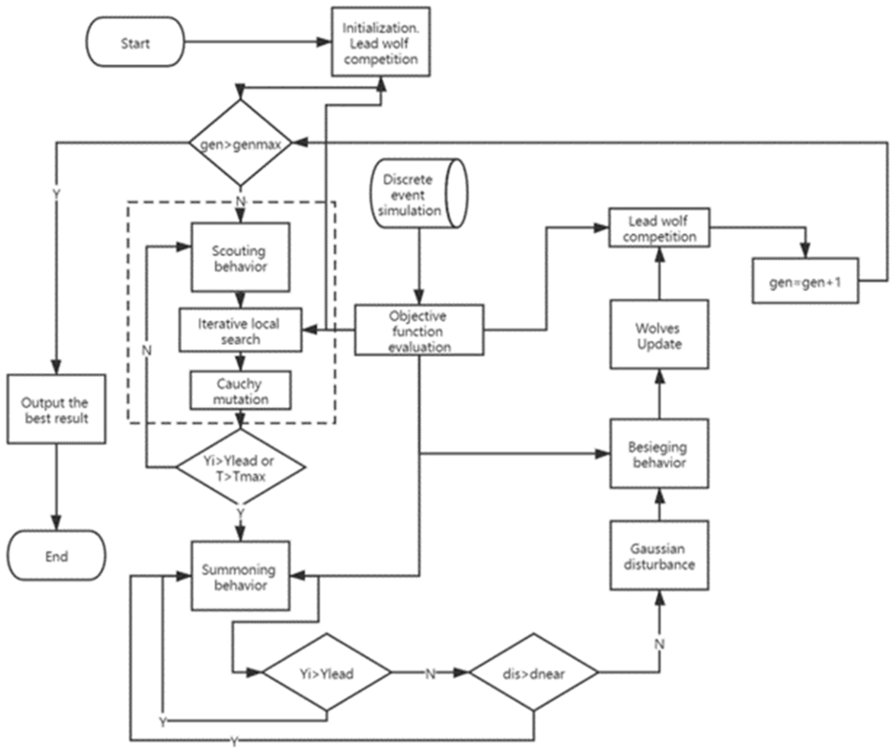

Fig. 3. Flow chart of WPA-BGV.

Table 2. Cloud manufacturing order .

Order	Suborder on alternative cloud manufacturing service [cloud manufacturing service1(service time1)/cloud manufacturing service2(service time2)/...]					
	1	2	3	4	5	6
1	[5(3)]	[6(10)]	[4(9)]	[2(5)/9(4)]	[3(3)/7(3)]	[5(10)]
2	[4(6)]	[2(8)/9(6)]	[8(4)]	[6(2)/7(6)]	[5(3)]	[1(3)/10(3)]
3	[3(4)]	[6(5)/8(7)]	[7(7)]	[2(5)/1(5)]	[4(9)/10(11)]	[5(1)]
4	[5(7)]	[2(3)]	[4(4)/7(6)]	[10(3)]	[9(1)/1(7)]	[3(3)/6(6)]
5	[4(6)/5(4)]	[1(10)]	[9(7)/10(9)]	[6(8)]	[2(5)]	[3(4)/8(7)]
6	[2(3)/1(7)]	[4(10)]	[6(8)/9(7)]	[7(9)]	[8(4)]	[3(9)/5(4)]

Figure 4 shows the change curve of the mean and optimal values of the objective function solved by the WPA-BGV algorithm. The optimal value of objective function is 118.5 in the iterative curve, which is obtained at the 20th iteration, showing a good convergence effect. and it can be seen from the example that the WPA-BGV algorithm with discrete event simulation performs well in the process of calculating the instance, and obtains good results in solving the cloud manufacturing allocation and scheduling problems.

To validate the optimization capability of the WPA-BGV algorithm in solving the unit scheduling problem stated in this paper, The experimental results are measured by CPU time and optimal cost index, which are 8.13s, 10.21s, 12.23s and 9.21s, respectively, and the optimal cost is 118.5, 122.3, 132.4 and 142.2, respectively, so the proposed algorithm is practical and effective in solving such problems.

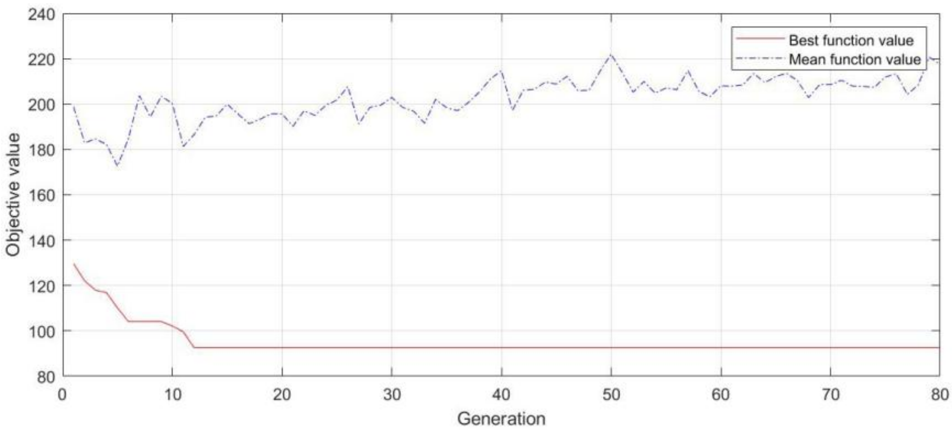

Fig. 4. The mean value and optimal value of the objective function solved by WPA-BGV.

5 Conclusions

Aiming at the problem of matching the supply and demand of distributed 3D printing tasks and 3D printing equipment resources in the cloud manufacturing environment, we propose a cloud manufacturing 3D printing service platform, and build a distributed 3D printing task scheduling model in the cloud manufacturing environment with the total task cost and task time of distributed 3D printing, in addition, an algorithm for hybrid solution is suggested, with the quantum wolf pack algorithm as the main optimization engine, the bacterial foraging search operator is introduced to elevate its optimization ability, and the Grover quantum algorithm is used to make the search more efficient. Considering the complexity of the decoding process and the future expansion of model randomness, the algorithm employs a discrete event simulation process to find the objective function value. Simulation experiments reveal that the proposed method can provide an effective scheduling scheme for the matching of production orders and manufacturing resources and production order scheduling in the cloud manufacturing environment, and optimize the completion time of all workpieces by determining the allocation of each subtask. Each order is on a different plant and machine. In addition, the calculation results also show that the algorithm proposed in this paper has good convergence and can find a satisfactory solution to the problem within a rational quantity of iterations.

References

[1] Wu Q , Xie N , Zheng S ,et al.Online order scheduling of multi 3D printing tasks based on the additive manufacturing cloud platform[J].Journal of Manufacturing Systems, 2022(63-):63.

[2] Bo-Hu L I , Lin Z , Lei R ,et al.Further discussion on cloud manufacturing[J].Computer Integrated Manufacturing Systems, 2011, 17(03):449-457.

[3] Grassi A , Guizzi G , Santillo L C ,et al.Assessing the performances of a novel decentralised scheduling approach in Industry 4.0 and cloud manufacturing contexts[J].International Journal of Production Research, 2020(2017):1-20.

[4] Jiang Yue-juan，Lu Bing-heng，Fang Xue-wei，et al.3D printing-based Internet collect-manufacturing mode［J］.Computer Integrated Manufacturing Systems，2016，22（6）：1424-1433.

[5] Zhou L，Zhang L，Zhao C，et al.Diverse task scheduling for individualized requirements in cloud manufacturing［J］. Enterprise Information Systems，2018，12（3）：300-318.

[6] Li Tian-qun，Tong Jing，Huang Si-yu，et al.Research of model repair algorithm and task scheduling algorithm in cloud manufacturing platform［J］.Application research of Computers，2018，35（8）：2342-2346.

[7] Hu J , Wu H , Zhan R ,et al.Hybrid integer-coded Wolf Pack Algorithm for multiple-type flatcars loading problem - ScienceDirect[J].Journal of Rail Transport Planning & Management, 2020, 16.

[8] Ghosh, M., et al.: A novel quantum algorithm for ant colony optimization[J]. IET Quant. Comm. 2022 3(1): 13–29.

[9] Lamata L. Quantum reinforcement learning with quantum photonics[J]. Photonics. MDPI, 2021, 8(2): 33.