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RESEARCH ARTICLE

Modeling Approach of Cloud 4D Printing Service Composition Optimization Based on Non-Dominated Sorting Genetic Algorithm III

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ABSTRACT - The manufacturing industry is currently experiencing a paradigm shift from traditional centralized systems to distributed, personalized, and cloud-based intelligent manufacturing ecosystems. The advent of 4-dimensional (4D) printing technology introduces dynamic characteristics to manufacturing design and functionality, necessitating the effective management of these emergent 4D printing services. This study aims to bridge the gap between the static nature of existing cloud manufacturing services and the dynamic requirements imposed by 4D printing technology. We propose a comprehensive multiobjective optimization model for cloud-based 4D printing service portfolios, incorporating the intricate complexities of 4D printing services and assessing the efficacy of the Non-Dominated Sorting Genetic Algorithm III (NSGA III) in optimizing these service portfolios to meet dynamic demands. In this research, the NSGA III algorithm is employed to develop a multiobjective optimization framework for 4D printing service portfolios, addressing critical issues such as service cost, time, quality, adaptability, and overall service optimization amidst fluctuating demand and service availability. The findings indicate that the NSGA III algorithm demonstrates superior performance in terms of generational distance and inverted generational distance, particularly excelling in convergence and diversity for high-dimensional optimization problems when compared to the comparison algorithms. The study concludes that the NSGA III algorithm exhibits significant potential in optimizing the orchestration of cloud-based 4D printing service portfolios, underscoring its effectiveness in managing the complexities associated with these services. This research provides valuable insights for the advancement of intelligent cloud-based 4D printing systems, paving the way for future developments in this field.

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1. INTRODUCTION

In recent decades, an evolution has unfolded within the manufacturing sector, transitioning from traditional mass production methodologies towards bespoke manufacturing approaches and evolving from centralized production frameworks to distributed, cloud-based manufacturing ecosystems [1]. This transformation has been catalyzed by the advent of Service-Oriented Cloud Manufacturing (CMfg), a model that epitomizes the convergence of flexibility, resource sharing, and the delivery of manufacturing capabilities as services via the industrial internet [2]. Simultaneously, the emergence of 4D printing [3] technology, which extends beyond the capabilities of 3D printing by integrating the temporal dimension into the fabrication process, represents a significant advancement. This innovation enables materials to be designed with the inherent capacity to alter their configuration, properties, or functionality upon exposure to predetermined stimuli over time, thus facilitating the creation of objects equipped to adapt, self-organize, or transmute in response to external environmental variables.

The amalgamation of cloud manufacturing with 4D printing technologies marks a pivotal convergence within the realm of contemporary manufacturing, blending the digital with the tangible to foster the development of intelligent, versatile, and intricate products. This fusion harbors the potential to revolutionize our perceptions concerning product lifecycle management, supply chain dynamics, and the foundational principles of product design and functionality. This paper endeavors to scrutinize service portfolio optimization [4] within the domain of cloud manufacturing, with a particular focus on services allied to 4D printing. It presents a modeling approach that coordinates and optimizes the service composition of cloud-based 4D printing, achieving multiobjective optimization. It postulates that leveraging a multiobjective methodology facilitated by the Non-dominated Sorting Genetic Algorithm III (NSGA III) [5] could markedly augment the optimization of service portfolios associated with 4D printing. The objective transcends mere cost and quality considerations to include an assessment of the portfolio's adaptability and resilience in the face of demand volatility and resource availability fluctuations, thereby addressing the limitations inherent in extant procedural models.

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The research objectives are as follows:

a) To investigate the modeling approach for optimizing cloud-based 4D printing service composition:

   The primary goal of this study is to propose an optimization model based on the Nondominated Sorting Genetic Algorithm III (NSGA III) to address the multiobjective optimization problem in cloud-based 4D printing service composition.

b) To employ the NSGA III algorithm to solve the high-dimensional multiobjective optimization problem in cloud-based 4D printing service composition (C4DPS):

   This study compares the performance of the NSGA III algorithm with NSGA II, MOEA/D, and MOPSO algorithms in addressing the optimization of cloud-based 4D printing service composition, effectively handling the multiobjective optimization problem in C4DPS.

Abbreviations and Nomenclature in this paper are shown in Table 1.

Table 1. Abbreviations and nomenclature in this paper

Notations	Description
CMfg	Cloud Manufacturing
C3DP	Cloud 3D Printing
C4DP	Cloud 4D Printing
C4DPS	Cloud 4D Printing Services
C4DPSP	Cloud 4D Printing Services Platform
NSGA	Non-Dominated Sorting Genetic Algorithm
MOEA/D	Multiobjective Evolutionary Algorithm based on Decomposition
MOPSO	Multiobjective Particle Swarm Optimization

2. METHODOLOGY

2.1 C4DPS Metrics and Problem Description

To facilitate the advancement of C4DPS in a manner conducive to its sustainable development, careful consideration must be given not only to the interests of C4DPS stakeholders but also to those of cloud 4D printing service platforms and C4DP services suppliers. Consequently, this study undertakes the task of identifying evaluation metrics [6] from the perspectives of C4DPS stakeholders, cloud 4D printing platforms, and C4DP service providers. Subsequently, a multiobjective optimization model for the C4DPS service composition was developed.

C4DPS stakeholders are typically comprised of enterprises or individuals seeking to enhance their market competitiveness by optimizing production costs, elevating product quality, and improving responsiveness to market demands. Therefore, this study selects service cost, service time, and service quality as key evaluation metrics. The profitability of C4DPSP operators hinges on the compensation received from both C4DPS stakeholders and service providers. Consequently, it is imperative to consider the flexibility of C4DPS and assess its adaptability and comprehensive service offerings. C4DP service providers leverage idle printing services and capabilities by listing them on C4DPSP, aiming to maximize resource utilization and minimize wastage.

2.2 Description of the C4DP Service Composition Problem

The core issue addressed in this research is the proposition of an effective solution for high-dimensional multiobjective optimization specific to cloud-based 4D printing service composition. Within the C4DPS framework, stakeholders submit service requests to C4DPSP, initiating a process of printing service composition involving three distinct stages: task decomposition, subtask search and matching, and service composition optimization [7]. Figure 1 displays the decomposition of cloud 4D printing services into granular sub-services, each encapsulated by the resources and capabilities specific to cloud 4D printing.

During the task decomposition stage, service demands are uploaded to C4DPSP and systematically broken down according to predefined rules. Each resultant subtask is designed to be fulfillable by a single candidate resource set. Subsequently, in the subtask search and matching [8] stage, a specialized search matching tool is employed to pair each subtask with the corresponding candidate cloud 4D printing resource set, yielding a series of candidate resource sets. Figure 2 illustrates the schematic of C4DP service providers and task demanders globally engaging in C4DP service and task compositions on the C4DPSP.

Finally, in the service composition optimization stage, the platform selects an optimal candidate resource from within each candidate resource set, considering multiple objectives and constraints. This selection process results in a preferred C4DP service combination [9] tailored to execute the total task submitted by the service demander. Throughout this entire process, C4DPSP meticulously tracks and provides feedback on the service composition process.

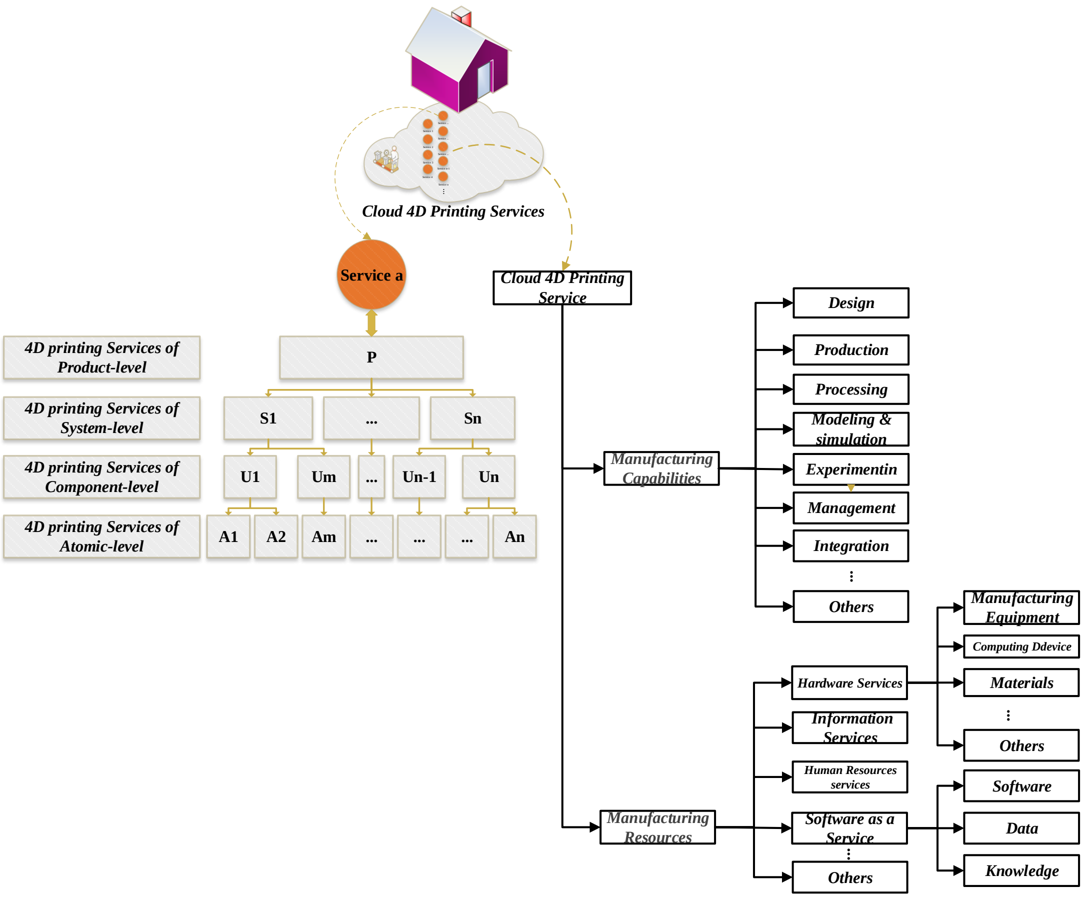

Figure 1. Cloud 4D printing services, resources and capabilities

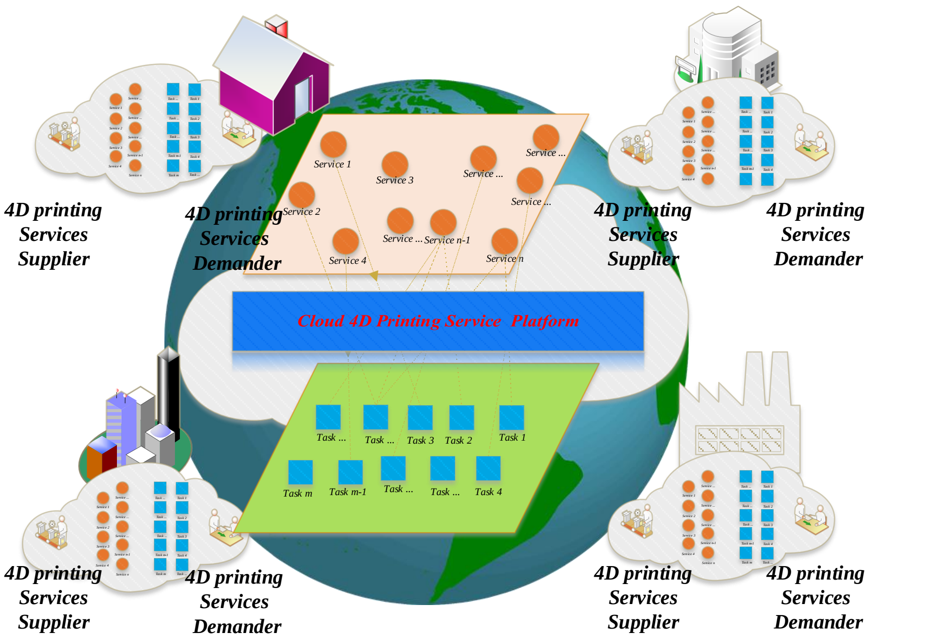

Figure 2. The Schematic diagram of the C4DP services and tasks compositions on the C4DPSP

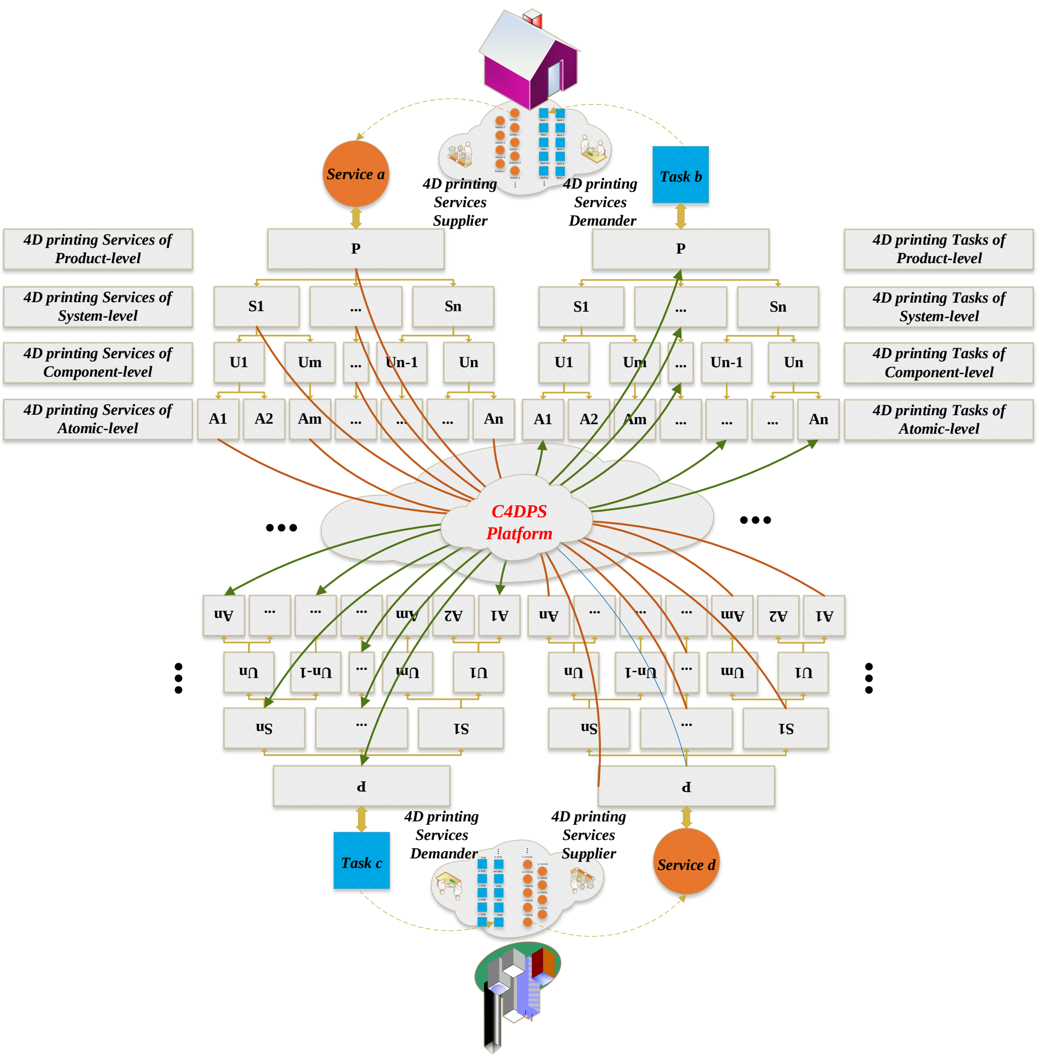

Figure 3. The granular 4D printing services and task composition at C4DPSP

The cloud-based manufacturing model for the C4DPS involves the demand side of printing services publishing C4DPS requirements to the C4DPSP. The C4DPSP allocates printing resources based on the characteristics of these requirements, ultimately leading to the provision of real 4D printing services by C4DP service providers to the service demanders. Figure 3 illustrates the schematic of service composition for multi-granular 4D printing services and required tasks within the C4DPSP.

2.3 Optimization Model for Cloud 4D Printing Service Composition

a) Optimization Objectives and Constraints for C4DP Service Cost [10]

The total actual cost of C4DPS, *C*, is composed of the total production printing cost, *Cp*, and other costs of C4DPS, *Co*, with the optimization objective formulated as:

$$minC = min(C_p + C_o) \tag{1}$$

$$C_p = \sum_{i=1}^{m} \sum_{j=1}^{n} C(i,j)_p * \alpha(i,j) \tag{2}$$

$$C_o = \sum_{i=1}^{m} \sum_{j=1}^{n} C(i,j)_o * \alpha(i,j) \tag{3}$$

The total actual cost of C4DP must satisfy the following constraints:

$$C \leqslant C_{max} \tag{4}$$

In the equation, $C(i,j)_p$ denotes the production cost incurred by the C4DP sub-service *i* for completing sub-task *j* of the C4DP process; C_{max} represents the maximum total cost acceptable to the demand side for C4DP services; *n* and *m* respectively signify the number of C4DP sub-tasks and the corresponding candidate C4DP sub-services available; $\alpha(i,j)=1$ indicates that sub-task j is executed by sub-service i of the C4DP system.

b) Optimization Objectives and Constraints for C4DP Service Time [11]

The total actual time T is comprised of the total C4DP production time T_p and other transportation times T_o, with the optimization objective expressed as:

$$minT = min(T_p + T_o) \tag{5}$$

$$T_p = \sum_{i=1}^{m} \sum_{j=1}^{n} T(i,j)_p * \alpha(i,j) \tag{6}$$

$$T_o = \sum_{i=1}^{m} \sum_{j=1}^{n} T(i,j)_o * \alpha(i,j) \tag{7}$$

The total actual C4DP time must satisfy the following constraints:

$$T \leqslant T_{max} \tag{8}$$

where $T_{(i,j)p}$ represents the production time of C4DP sub-service i for completing C4DP sub-task j; T_{max} signifies the maximum total C4DP service time acceptable to the service demander.

c) Optimization Objectives and Constraints for C4DP Service Quality [12]

$$maxQ = max\left(\left(\sum_{i=1}^{m} \sum_{j=1}^{n} Q(i,j)^* \alpha(i,j)\right)/n\right) \tag{9}$$

The C4DP service quality must satisfy the following constraints:

$$Q \geqslant Q_{min} \tag{10}$$

where $Q(i,j)$ denotes the service quality of C4DP sub-service i for completing C4DP sub-task j; Q_{min} represents the minimum service quality acceptable by the C4DP service demander.

d) Optimization Objectives and Constraints for Adaptability to Changes [13] in C4DP Tasks

The capability to adapt to changes in C4DP tasks is the average of the adaptability to changes in each sub-task, defined as:

$$maxF_T = max\left(\left(\sum_{i=1}^{m} \sum_{j=1}^{n} F_T(i,j) * \alpha(i,j)\right)/n\right) \tag{11}$$

The ability to adapt to changes in C4DP manufacturing tasks must satisfy the following constraints:

$$F_T \geqslant F_{Tmin} \tag{12}$$

where $F_T(i, j)$ indicates the adaptability of C4DP sub-service i to changes in C4DP sub-task j; F_{Tmin} represents the minimum adaptability required by the operators of the C4DPSP platform for C4DPS service providers.

e) Optimization Objectives and Constraints for Comprehensive C4DP Service Evaluation [14]

The comprehensive service evaluation for C4DP is the mean of the composite service evaluations for each C4DP sub-task, represented as:

$$maxF_c = max\left(\left(\sum_{i=1}^{m} \sum_{j=1}^{n} F_c(i,j) * \alpha(i,j)\right)/n\right) \tag{13}$$

The comprehensive service evaluation must meet the following conditions:

$$F_c \geqslant F_{c\,min} \tag{14}$$

where $F_c(i,j)$ is the comprehensive service evaluation by the service demander for C4DP sub-service *i* completing C4DP sub-task *j*; $F_{c\,min}$ indicates the minimum service evaluation level required by the C4DPSP operators.

In summary, the optimization model for cloud manufacturing service composition considers the overall interests of the C4DPS demanders, the C4DPSP, and the C4DPS providers. The multiobjective optimization model is as follows:

$$min(C, T, 1-Q, 1-F_T, 1-F_c) \tag{15}$$

$$s.t.\begin{cases} C \leqslant C_{max} \\ T \leqslant T_{max} \\ Q \geqslant Q_{min} \\ \mathrm{F_T} \geqslant \mathrm{F_{Tmin}} \\ F_{\mathbf{c}} \geqslant F_{\mathbf{c}min} \end{cases} \tag{16}$$

The five constraints within the model respectively indicate that the total service cost *C* must not exceed the maximum cost C_{max} as stipulated by the service requester; the total service duration *T* must not surpass the longest allowable service time T_{max} defined by the service requester; the quality of the printing service *Q* must meet or exceed the minimum service quality Q_{min} specified by the service requester; the capability to accommodate changes in the printing tasks must not be less than the minimum capacity F_{Tmin} set by the printing service provider; and the overall service evaluation for the printing service by the service requester must not be lower than the minimum service evaluation F_{cmin} designated by the service requester.

2.4 The NSGA III Algorithm

The NSGA III [15] algorithm employs a selection mechanism based on uniform reference points, which offers improved convergence and diversity in solutions for multiobjective optimization problems of three or more dimensions. The model proposed in this article addresses a multiobjective combinatorial optimization problem for the C4DP. To resolve such issues, DEB et al. introduced the NSGA II [16] algorithm, which incorporates an elitist strategy to enhance population sampling and employs a crowding mechanism for the even distribution of solutions alongside a fast, non-dominated sorting approach to reduce computational complexity. However, in the context of high-dimensional (more than three objectives) optimization problems, the proportion of non-dominated solutions in the population increases exponentially, resulting in insufficient space for new solutions and, consequently, a slowdown in algorithm convergence and an overly concentrated optimal solution set. Additionally, as the number of objective functions increases, the computational cost of the algorithm's crowding distance operation becomes significantly high. The NSGA III algorithm, which incorporates a reference point-based method, maintains population diversity while effectively reducing the computational cost associated with high-dimensional objective functions, providing an efficient solution approach for the model constructed in this paper. The specific steps for solving the cloud 4D printing service optimization combination model using the NSGA III algorithm are depicted in Figure 4.

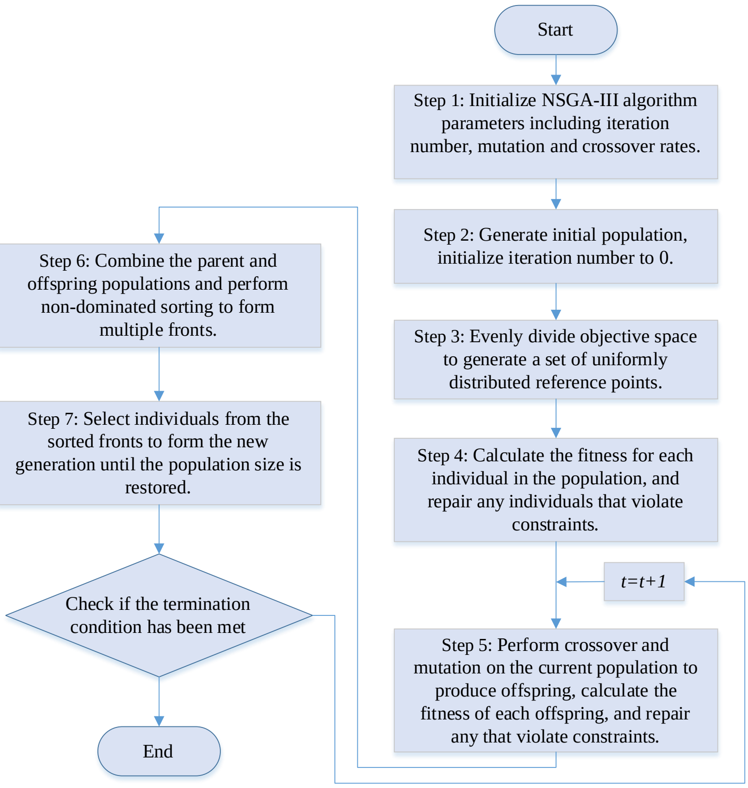

Figure 4. Flow chart of the NSGA III algorithm

Step 1: Initialize algorithm parameters, including the total number of iterations, mutation rate, and crossover rate.

Step 2: Determine the coding rules and initialize the population P_t, setting the initial iteration count to zero.

Step 3: Generate uniformly distributed reference points based on the equal division of each objective dimension and the number of objective functions.

Step 4: Calculate the fitness of each individual in the population and repair out-of-bounds individuals based on the model's constraint handling rules.

Step 5: Generate the offspring population Q_t through crossover and mutation operations, calculate the fitness of each individual in the offspring population, and repair out-of-bounds individuals based on constraint rules.

Step 6: Merge population P_t with offspring population Q_t, resulting in a combined population size of $2N$.

Step 7: Perform fast non-dominated sorting on the combined population to identify several non-dominated fronts F_1, F_2, F_3, …, F_L.

Step 8: Add higher priority non-dominated fronts to the next generation population until all individuals from the Lth front are selected. If the next generation population size equals N, proceed to Step 11; if greater than N, go to Step 9.

Step 9: Normalize the individuals from the first L fronts to fall within [0,1].

Step 10: Calculate the perpendicular distance of all individuals in the first L fronts to the reference points, identify the reference point associated with each individual based on the shortest perpendicular distance, calculate the niche of the jth reference point, and select K individuals from the Lth front to enter the next generation population, ensuring the population size equals N, and increase the iteration count by one.

Step 11: Check if the predefined number of iterations has been reached; if so, terminate the iteration; otherwise, repeat Steps 5 to 10.

In the practical scenario of Cloud 4D Printing (C4DP) service composition, a C4DP task, denoted as *C4DP_T,* is decomposed into 'i' subtasks, each represented as $C4DP\_T_i$. For each subtask, there are '*m*' corresponding Cloud 4D Printing Services (C4DPS). The '*i*'th chromosome's gene encoding as '*j*' signifies that the subtask $C4DP\_T_i$ is to be executed by the sub-service $C4DPS_j$. The integer encoding of the chromosome's genes is depicted in Figure 5, which visually represents the mapping relationship between the C4DP service portfolio and the chromosomal structure. This gene encoding scheme facilitates the genetic algorithm's process in identifying and orchestrating the optimal service composition, reflecting the multitiered architecture of C4DPS.

C4DP_Task	*C4DP_T*				
C4DP Subtask	$C4DP\_T_1$	$C4DP\_T_2$	$C4DP\_T_3$	…	$C4DP\_T_i$
Chromosome	2	1	1		2
C4DP Service	$C4DPS_1$	$C4DPS_2$	$C4DPS_3$	…	$C4DPS_i$
	$C4DPS_{11}$	$C4DPS_{12}$	$C4DPS_{13}$	…	$C4DPS_{1i}$
	$C4DPS_{21}$	$C4DPS_{22}$	$C4DPS_{23}$	…	$C4DPS_{2i}$
	…	…	…	…	…
	$C4DPS_{m1}$	$C4DPS_{m2}$	$C4DPS_{m3}$	…	$C4DPS_{mi}$

Figure 5. Mapping relationship diagram between C4DP Service Composition and Chromosome

Based on uniform reference points, the steps of the minimal niche selection mechanism are as follows:

Step 1: Normalizing the Objective Function

Define the Ideal Point: Let M represent the number of optimization objectives. Compute the minimum value z_j^{min} for each objective dimension j in the current population, $j \in \{1,2,\ldots, M\}$, and designate these as the ideal points for the current population.

Compute Adjusted Objective Values: For each individual, subtract the corresponding ideal point from the objective value $f_j(x)$ in each dimension to obtain the adjusted value:

$$f_j'(x) = f_j(x) - z_j^{min} \tag{17}$$

Calculate Additional Objective Vectors: Use the following formula to calculate the additional objective vector $z^{i,max}$:

$$ASF(x,w) = max_{i=1}^{M} f_i'(x)/w_i \tag{18}$$

$$z^{i,max} = x: argminASF(x, w_i), w_i = (\tau, \cdots, \tau), \tau = 10^{-6}, w_i^j = 1 \tag{19}$$

Determine Hyperplane Intercepts: The hyperplane formed by these *M* additional objective vectors intersects each objective dimension at a_j, *j=1,2,...,M*. If the hyperplane cannot be formed or the intercepts cannot be determined, set a_j to the maximum value for each objective dimension.

Normalize the Objective Function Values: Normalize the objective function values as follows: $f_j^n(x) = f_j'(x)/\left(a_j - z_j^{min}\right)$

Step 2: Associating Individuals with Reference Points

Calculate Distances: For each individual, compute the distance to all reference lines (lines connecting the origin in the *M*-dimensional space to the reference points). The reference point associated with the closest reference line to an individual is identified as the reference point for that individual.

Step 3: Individual Selection Based on Reference Points

Initialize Selection Parameters: Let *K* denote the number of individuals to be selected from the current layer *l* to form the next generation population. Set *k=1*.

Define Association Counts: Define ρ_j as the number of individuals associated with the *j*th reference point in the first *l*−1 layers. The set of reference points with the minimum association count is

$$J_{min} = \{j: argmin_{j \in Z^r} \rho_j\} \tag{20}$$

Choose any reference point *J* from the minimal niche set J_{min}, and define I_j as the set of individuals in layer *l* associated with reference point *j*.

Select Individuals: If $I_j = \emptyset$, exclude this reference point. Otherwise, consider two scenarios:

If $\rho_j = 0$, select the individual from I_j that is closest to reference point *j* to enter the next generation and increment ρ_j by 1.

If $\rho_j \neq 0$, select any individual from I_j to enter the next generation and increment ρ_j by 1.

Repeat Selection Process: Increment *k* by 1, and repeat steps 2-4 until *k*=*K*.

The inception of the optimization process is marked by the establishment of an initial population. The subsequent phase involves the critical generation of reference points. A priori stratified reference points act as beacons for the assurance of diversity within the solution space. The layered generation of these points is meticulously executed, ensuring a holistic exploration of the Pareto frontier. Furthermore, the normalization of objective functions is an imperative process for harmonizing the scales of objectives, allowing for an equitable evaluation and comparison. This normalization fosters uniformity across objectives, thereby facilitating a coherent selection mechanism. The quintessence of the NSGA III algorithm is the selection methodology based on the proximity of individuals to the pre-established reference points. This technique not only ensures the diversity of the resultant solutions but also propels the evolutionary trajectory towards an optimally diversified Pareto-optimal frontier. Such a comprehensive approach is critically consequential for the NSGA III algorithm's proficiency in navigating the high-dimensional objective space intrinsic to cloud 4D printing service compositions.

2.5 Evaluation Metrics for Multiobjective Algorithms

Two metrics are utilized to evaluate the performance of multiobjective optimization algorithms: Generational Distance (GD) [17] and Inverted Generational Distance (IGD) [18]. These metrics serve to assess algorithm performance comprehensively. Generational Distance (GD) is a metric used to quantify the distance between the set of non-dominated solutions generated by an evolutionary algorithm and the true Pareto front. Specifically, GD calculates the square root of the sum of the squared minimum Euclidean distances from each solution in the set to the true Pareto front. Generational Distance (GD) is a unary metric that measures the average minimum Euclidean distance from the non-dominated solution set obtained by the algorithm to the true Pareto front [19]. This metric evaluates the convergence of the solution set. A lower GD value indicates better convergence [20]. The calculation formula is as follows:

$$GD(P, P^*) = \frac{\sqrt{\sum_{X \in P} d(x^*, X)^2}}{|\, P \,|} \tag{21}$$

where $d(x^*, X)$ denotes the minimum Euclidean distance from solution x^* in $P*$ to *X*, and $|P|$ represents the number of solutions in *P*. GD is primarily used to evaluate the proximity of the solution set within the objective space, with smaller GD values indicating a closer approximation to the true Pareto front, thus reflecting the algorithm's superior approximation capabilities.

Inverted Generational Distance (IGD) is another metric used to assess the relationship between the set of non-dominated solutions generated by an evolutionary algorithm and the true Pareto front. Unlike GD, IGD calculates the average distance from points on the true Pareto front to the nearest points in the solution set. Inverted Generational Distance (IGD) is a binary metric [21] that calculates the average Euclidean distance from all solutions in the true Pareto front to the non-dominated solutions obtained by the algorithm. This metric assesses both the convergence and diversity of the solution set. A smaller IGD value indicates that the solution set is closer to the true Pareto front and more uniformly distributed [22], signifying better convergence and diversity. The formula is as follows:

$$IGD(X,P^*) = \frac{\sum_{x^* \in P^*} d(x^*, X)}{|\, P^* \,|} \tag{22}$$

where $d(x^*, X)$ signifies the minimum Euclidean distance from solution x^* in P^* to X, and $|P^*|$ denotes the number of solutions in P^*. IGD is primarily used to evaluate the coverage of the solution set within the objective space, with smaller IGD values indicating that the solution set more accurately represents the true Pareto front, thus demonstrating the algorithm's stronger coverage capabilities.

3. RESULTS AND DISCUSSION

To verify the feasibility and effectiveness of the proposed model and methodology, both algorithmic tests and application examples have been designed and conducted. The experiments were executed using MATLAB R2023a software on a Windows 10 system with 8 GB of RAM. In this study, DTLZ [23] functions, namely DTLZ1, DTLZ2, DTLZ3, DTLZ4, DTLZ5, and DTLZ6, were selected as benchmark test functions for algorithm evaluation. The Non-dominated Sorting Genetic Algorithm II (NSGA II) was employed as the benchmark algorithm. The optimization problem involves a target dimensionality (M) of 5 and a decision variable dimensionality (D) of 8. The population size is set to 1000 individuals, evolving over 10,000 generations. The crossover probability is fixed at 0.9, while the mutation probability is set to 1/D. Additionally, the algorithm employs 200 reference points. This rigorous approach ensures a robust assessment of the algorithm's performance against established multiobjective optimization benchmarks.

In multiobjective optimization, the mean and standard deviation are the two primary statistical metrics used to evaluate algorithm performance. The mean reflects the average level of the objective function values achieved by the algorithm, while the standard deviation indicates the stability and consistency of the results. Ideally, a proficient optimization algorithm should excel in both metrics, achieving low objective function values (low mean) and high consistency (low standard deviation) across multiple runs.

Table 2. The mean value and the standard deviation of GD

	M	D	NSGAIII	NSGAII
DTLZ1	5	8	2.2966e+0 (3.99e-1) -	1.2556e+0 (3.50e-1)
DTLZ2	5	8	3.2205e-3 (1.35e-4) +	6.9837e-3 (5.95e-4)
DTLZ3	5	8	8.0367e-+0 (7.66e-1) -	6.0715e+0 (1.10e+0)
DTLZ4	5	8	2.9700e-3 (2.35e-4) +	5.0853e-3 (6.23e-4)
DTLZ5	5	8	1.9604e-2 (1.39e-3) +	2.1947e-2 (8.42e-4)
DTLZ6	5	8	1.1241e-1 (2.89e-3) +	1.2936e-1 (3.87e-3)

Table 3. The mean value and the standard deviation of IGD

	M	D	NSGAIII	NSGAII
DTLZ1	5	8	2.9911e+0 (1.00e+0) -	2.2473e+0 (7.53e-1)
DTLZ2	5	8	1.3203e-1 (1.80e-3) +	1.7500e-1 (4.61e-3)
DTLZ3	5	8	9.4268e+0 (3.06e+0) =	9.5787e+0 (2.81e+0)
DTLZ4	5	8	1.8606e-1 (1.01e-2) -	1.6724e-1 (5.84e-3)
DTLZ5	5	8	3.7003e-2 (6.97e-3) -	2.1752e-2 (3.53e-3)
DTLZ6	5	8	1.0611e+0 (2.13e-1) +	1.6590e+0 (2.28e-1)

To evaluate the relative performance of NSGA II and NSGA III based on the mean and standard deviation of GD (Generational Distance) and IGD (Inverted Generational Distance) metrics, the following considerations are made:

Priority to Mean: The mean is considered first. A lower mean suggests that the algorithm achieves better average performance across multiple runs. Thus, we compare the mean values of the two algorithms. If one algorithm significantly outperforms the other in terms of the mean, it is deemed superior, even if its standard deviation is slightly higher.

Standard Deviation as a Secondary Metric: When the mean difference is minimal, the standard deviation serves as an auxiliary criterion. If the mean values of the two algorithms differ by a small margin (e.g., within a 5% relative difference), the algorithm with the lower standard deviation is preferred. A lower standard deviation implies higher robustness and stability in the algorithm's performance across different runs.

In most DTLZ test functions based on GD and IGD metrics, NSGA III demonstrates superior performance compared to NSGA II, especially in terms of the mean. Table 2 presents the mean value and the standard deviation of GD, while Table 3 illustrates the mean value and the standard deviation of IGD, which indicates that NSGA III is more effective in finding solutions closer to the Pareto front with higher consistency. However, in certain cases (e.g., DTLZ1), NSGA II may still outperform NSGA III. The data presented in both tables illustrate that the NSGA III algorithm yields lower values for Generational Distance (GD) and Inverted Generational Distance (IGD) metrics compared to NSGA II. This indicates that NSGA III is more effective in generating solutions that are both closer to the true Pareto front and more diverse [24, 25]. Such performance demonstrates the superiority of NSGA III in handling multiobjective optimization problems in cloud 4D printing services with higher dimensions, outperforming NSGA II in this regard [26].

3.1 Case study

Drawing upon real-world scenarios and empirical evidence in Cloud 4D Printing Services (*C4DPS*), this study designs a plausible range and constraints for each evaluative index. Utilizing functions provided by MATLAB, the data for each metric is randomly generated to circumvent biases inherent in manually curated datasets. The parameters set for this research include a maximum total cost (C_{max}) of 15,000 RMB, a total time (T_{max}) of 30 hours, and a minimum overall quality (Q_{min}) of 0.6, as detailed in Table 4. The optimization objectives and constraints for adaptability to changes in 4D printing tasks (F_T) and for comprehensive C4DP service evaluation (F_c) are both set at 0.6. The NSGA III and NSGA II algorithms are employed to resolve the service composition optimization model for C4DPS, with a population size of 1,000 and a maximum number of function evaluations set at 10,000.

Table 4. Value range of related evaluation indicators

Parameters	Unit	Range of Values
$C(i,j)_p$	Ten Thousand YUAN(RMB)	[0.3,1.2]
$C(i,j)_o$	Ten Thousand YUAN(RMB)	[0.1,0.3]
$T(i,j)_p$	Hour	[14,20]
T(i,j)_o	Hour	[7， 10]
Q(i,j)	-	[0,1]
$F_T(i,j)$	-	[0,1]
$F_c(i,j)$	-	[0,1]

Figure 6 and Figure 7 illustrate that NSGA III maintains extremely low GD values across all evaluation functions, demonstrating excellent convergence. In terms of stability, the GD curve for NSGA III remains remarkably steady throughout the process, indicating high stability. Compared to MOEA/D, MOPSO, and NSGA II, NSGA III consistently shows better performance in GD metrics. Therefore, NSGA III exhibits superior convergence and stability in multiobjective optimization problems, particularly in terms of the GD metric, highlighting its advantages in solving multiobjective optimization issues in cloud 4D printing services.

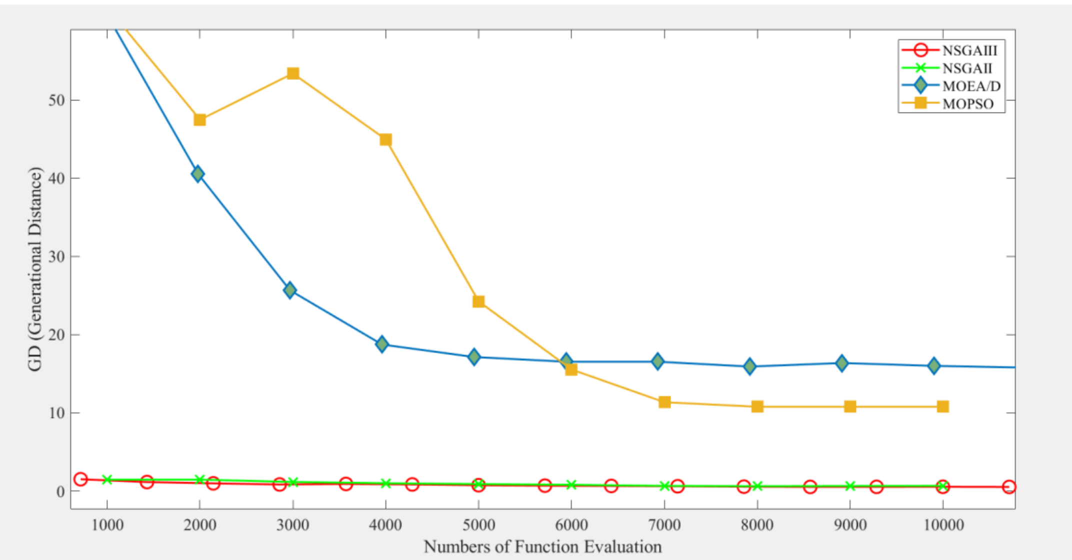

Figure 6. The curves of the GD value of NSGA III and other algorithms on the number of function evaluations

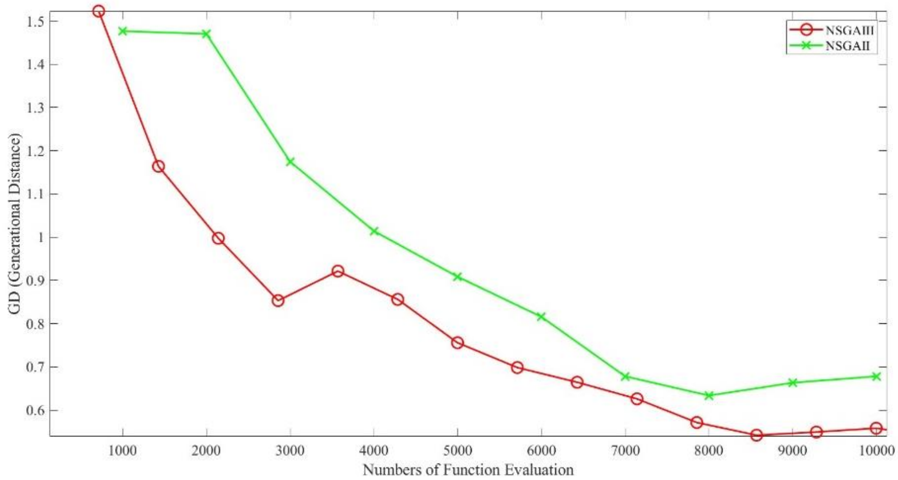

Figure 7. The curves of the GD value of NSGA III and NSGA II on the number of function evaluations

From Figure 8 and Figure 9, although NSGA III initially shows a slightly higher IGD than NSGA II, their performance converges over more extended evaluation periods, with NSGA III ultimately exhibiting significantly better performance. NSGA III achieves notably lower IGD values across all evaluation counts compared to MOEA/D and MOPSO, indicating a clear advantage in solution quality and convergence. In terms of stability, both NSGA III and NSGA II maintain very stable IGD values near zero throughout the evaluation. Conversely, MOEA/D and MOPSO exhibit IGD values around 400 and 100, respectively, indicating poor stability. Regarding convergence speed, despite NSGA III's slightly higher initial IGD, it converges rapidly, reaching levels similar to NSGA II, whereas MOEA/D and MOPSO converge more slowly. Overall, NSGA III excels in solution quality, convergence, and stability according to the IGD metric, demonstrating significant superiority in multiobjective optimization for cloud 4D printing services.

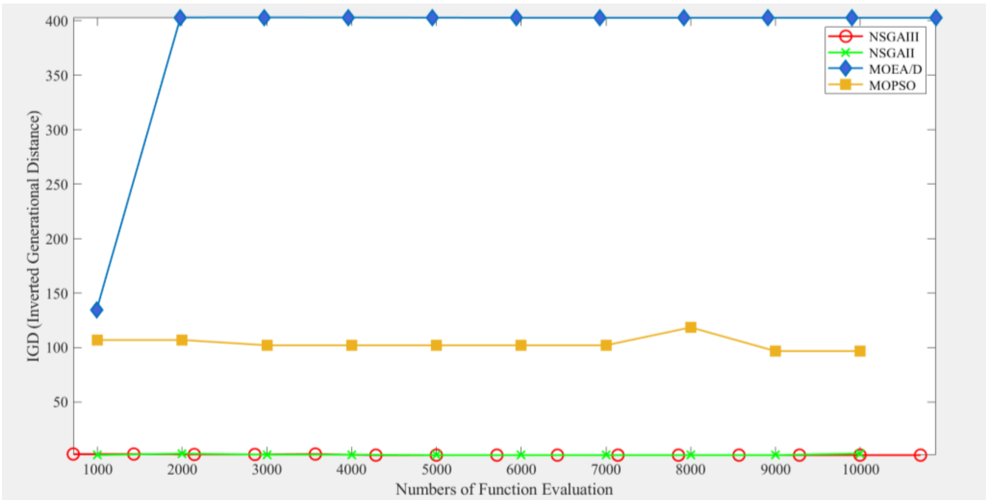

Figure 8. The curves of the IGD value of NSGA III and other algorithms on the number of function evaluations

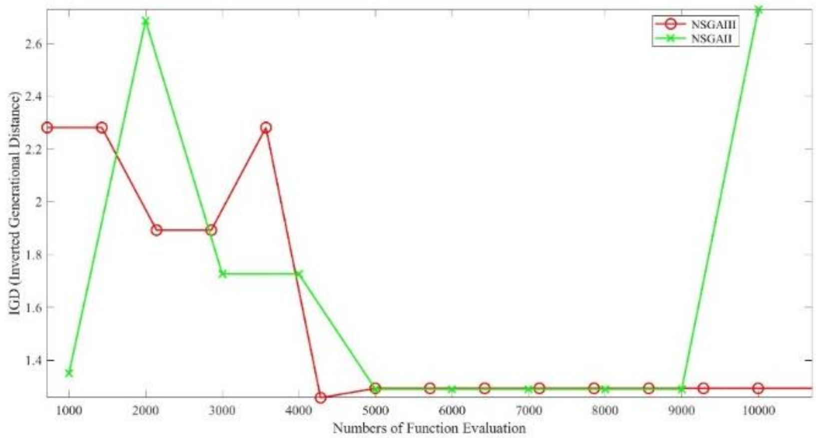

Figure 9. The curves of the IGD value of NSGA III and NSGA II on the number of function evaluations

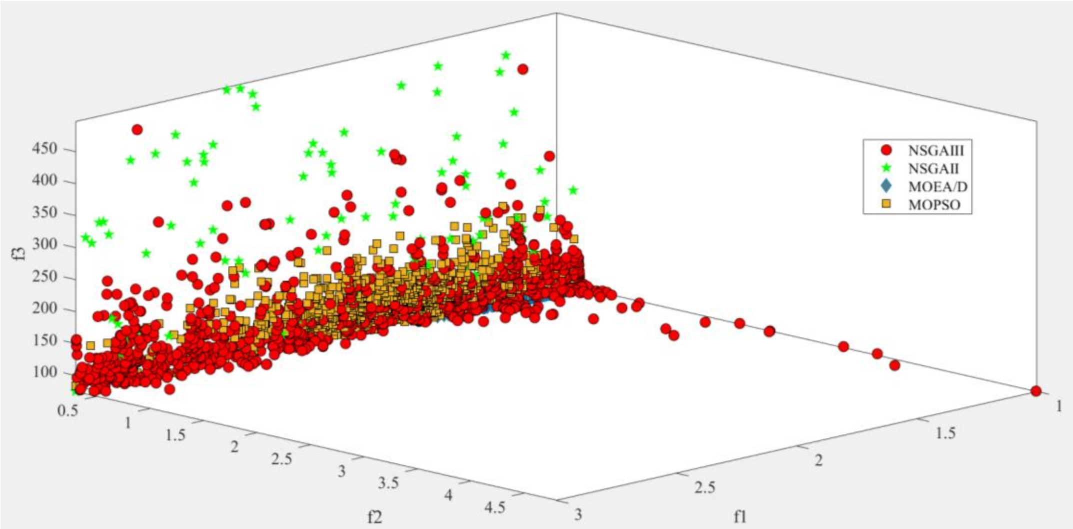

Figure 10. The value of the population(objectives)

As illustrated in Figure 10, the diversity of solutions generated by NSGA III is evidenced by the broad distribution along the f3 dimension, indicating its capability to explore a wider range of trade-offs among objectives. While NSGA II and MOPSO also exhibit some diversity, they are not as pronounced as NSGA III. MOEA/D, on the other hand, shows very limited diversity, indicating poor exploration capability. In terms of convergence, NSGA III exhibits a dense population within the lower bounds of f1 and f2, suggesting good convergence to the Pareto front. MOPSO also demonstrates good convergence but lacks diversity in the higher f3 range. NSGA II shows reasonable convergence but is less dense compared to NSGA III. MOEA/D struggles with both convergence and diversity. In exploring the objective space, NSGA III outperforms by extensively exploring higher ranges of f3. NSGA II shows greater extensibility than MOPSO, but MOEA/D performs the worst in exploration. In conclusion, NSGA III outperforms MOEA/D, MOPSO, and NSGA II in terms of diversity, convergence, and overall exploration of the objective space. The dense population and wide distribution along the f3 dimension in the scatter plot indicate that NSGA III provides a more comprehensive set of solutions, making it advantageous in multiobjective optimization problems.

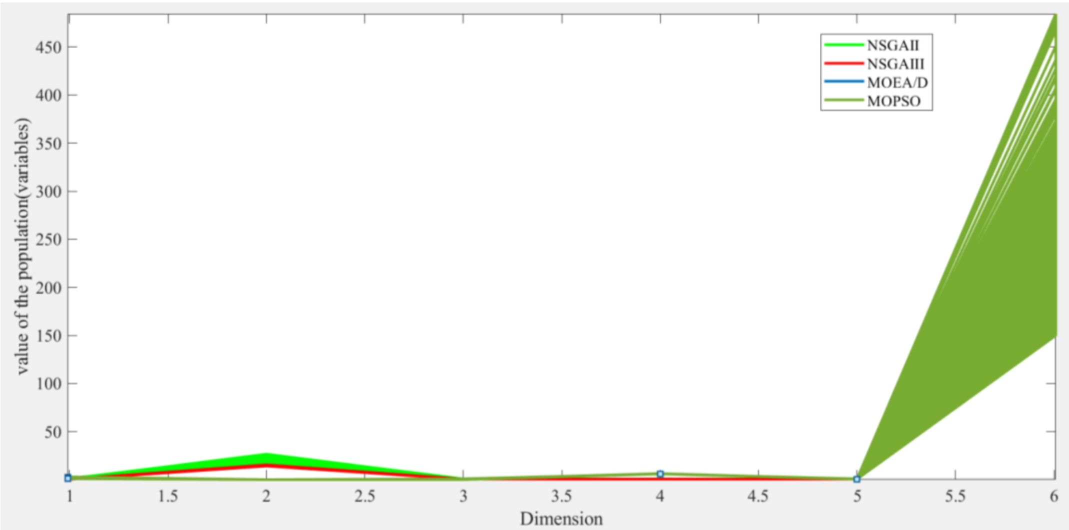

Figure 11. The value of the population(variables)

Based on the analysis of the figures as depicted in Figure 11, the value of the population(variables), NSGA III demonstrates a stable distribution across all dimensions, indicating a controlled and balanced approach to population value allocation. NSGA II and MOEA/D also exhibit stability, albeit with minor deviations in specific dimensions. In contrast, MOPSO displays a lack of control, with significant surges in population values, particularly in the final dimension. Regarding cross-dimensional consistency, NSGA III maintains uniformity, ensuring that no single dimension dominates or distorts the overall population value. NSGA II and MOEA/D similarly exhibit consistency, though perhaps not as robust as NSGA III. MOPSO, however, fails to maintain this consistency, indicating potential issues in convergence and diversity control. In terms of controlling population values, NSGA III effectively maintains low and stable values across all dimensions, suggesting superior control mechanisms. While NSGA II and MOEA/D show reasonable control, they may not be as precise as NSGA III. MOPSO exhibits poor control with significant variability, especially in higher dimensions.

In summary, NSGA III outperforms MOEA/D, MOPSO, and NSGA II in maintaining stable, consistent, and controllable population value distributions across all dimensions. The absence of significant peaks and the adoption of a balanced approach indicate that NSGA III possesses superior population management mechanisms, resulting in better overall performance in multiobjective optimization scenarios.

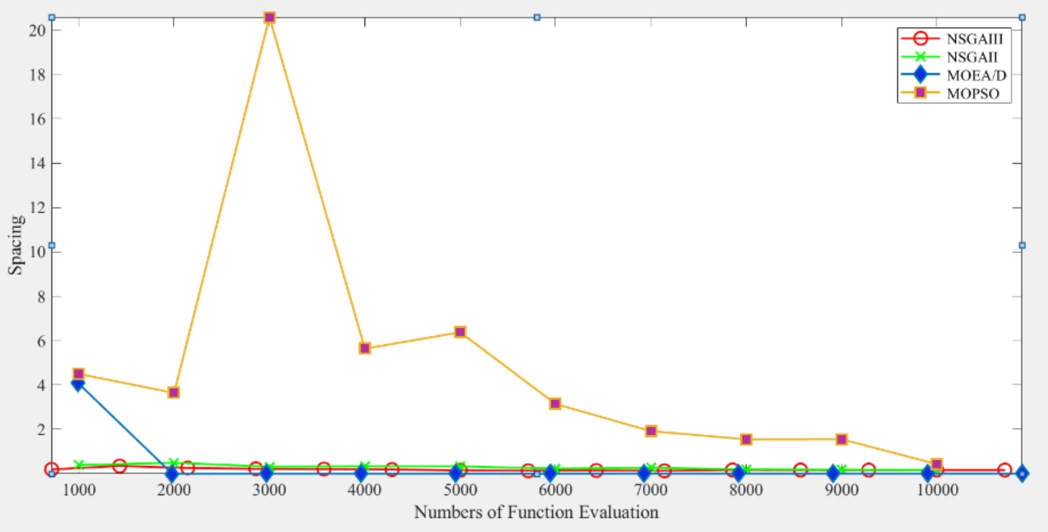

Figure 12. The curves of the Spacing value of NSGA III and other algorithms on the number of function evaluations

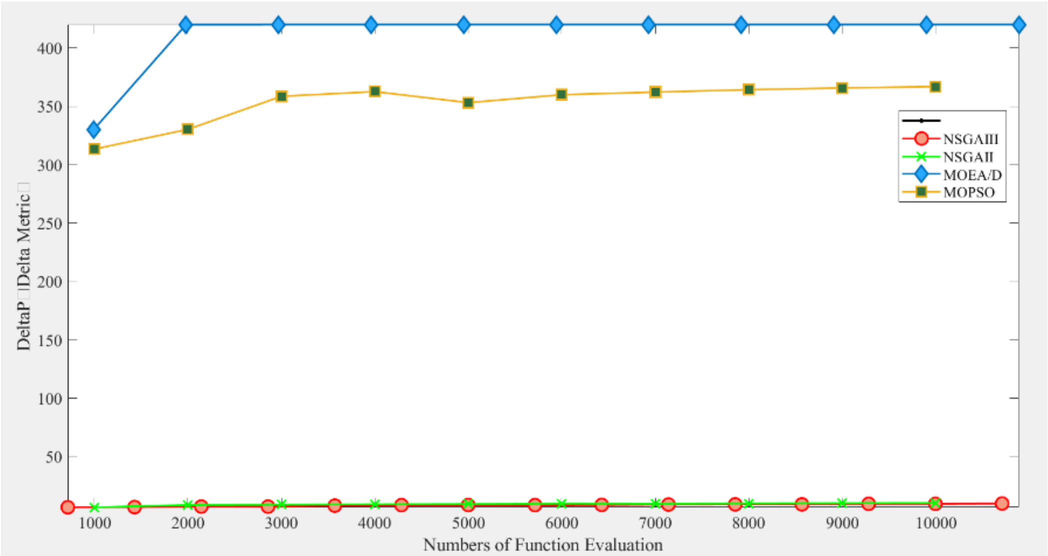

Figure 13. The curves of the DeltaP value of NSGA III and other algorithms on the number of function evaluations

In the multiobjective optimization domain of Cloud 4D Printing Services, the effectiveness of algorithms is intricately assessed through a spectrum of metrics, each elucidating distinct facets of the solution set. Central to these metrics is Generational Distance (GD), where a trend toward diminishing GD values underscores an algorithm's refined capacity to generate solutions that closely align with the true Pareto front. It is observed that NSGA III manifests a downward trajectory in GD values when juxtaposed with NSGA II, signifying enhanced performance. Complementing GD, the Inverted Generational Distance (IGD) grants a dual perspective of proximity and diversity of solutions. NSGA III stands out with its robustness, evidenced by lower IGD values, which signifies not only a closer approximation to the Pareto front but also a more diverse representation of solutions.

In parallel, the Spacing and Spread metrics evaluate the uniformity and extent of coverage across the Pareto front [27]. A smaller Spacing value for NSGA III indicates a more homogeneous distribution of solutions with minimal variance, implying a methodical spanning of the Pareto front, as illustrated in Figure 12. This uniform distribution is also mirrored in the DeltaP metric, as presented in Figure 13, where NSGA III's lower values typically reflect a more uniform dispersal of solutions along the Pareto front—a hallmark of optimization superiority. These insights collectively point towards NSGA III’s capability in exploring and exploiting the solution space efficiently, making it a preferred choice for solving C4DPS multiobjective problems. Figure 14 illustrates the curves of the CPF value of NSGA III and other algorithms on the number of function evaluations [28]. In the meantime, Figure 15 depicts the curves of the Spread value of NSGA III and other algorithms on the number of function evaluations [29].

However, the NSGA III algorithm encounters several limitations and challenges during its implementation. Primarily, NSGA III exhibits considerable computational complexity, particularly when confronted with high-dimensional optimization tasks, necessitating substantial computational resources. Furthermore, the algorithm's efficacy is heavily contingent upon the judicious selection of reference points; erroneous choices can lead to suboptimal convergence and diminished diversity. Moreover, while NSGA III proves adept at addressing multiobjective optimization challenges, its performance notably deteriorates beyond ten objectives, highlighting issues related to scalability. The sensitivity of algorithmic parameters also necessitates careful consideration, demanding extensive experimental validation and specialized knowledge in the domain of cloud 4D printing. Additionally, NSGA III demonstrates deficiencies in effectively managing constraint optimization problems; current constraint handling mechanisms may not offer adequate efficiency, thereby impacting solution quality. Finally, the practical deployment of NSGA III introduces inherent complexities, requiring substantial computational resources, domain-specific expertise, and sensitivity to initial conditions and parameter configurations. To address these challenges, future research endeavors will concentrate on hybrid algorithm development, enhancing algorithm scalability, and advancing sophisticated constraint handling mechanisms, thereby augmenting the performance and applicability of NSGA III.

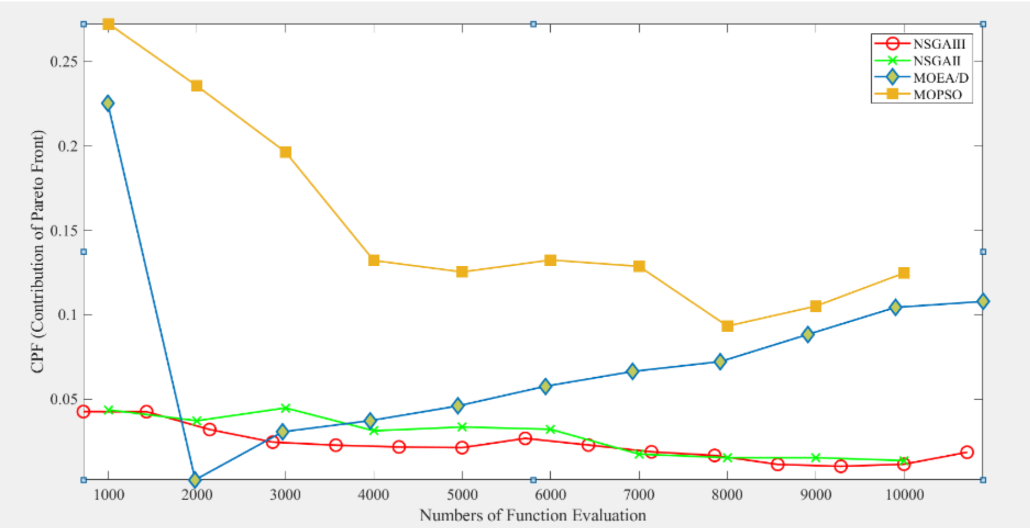

Figure 14. The curves of the CPF value of NSGA III and other algorithms on the number of function evaluations

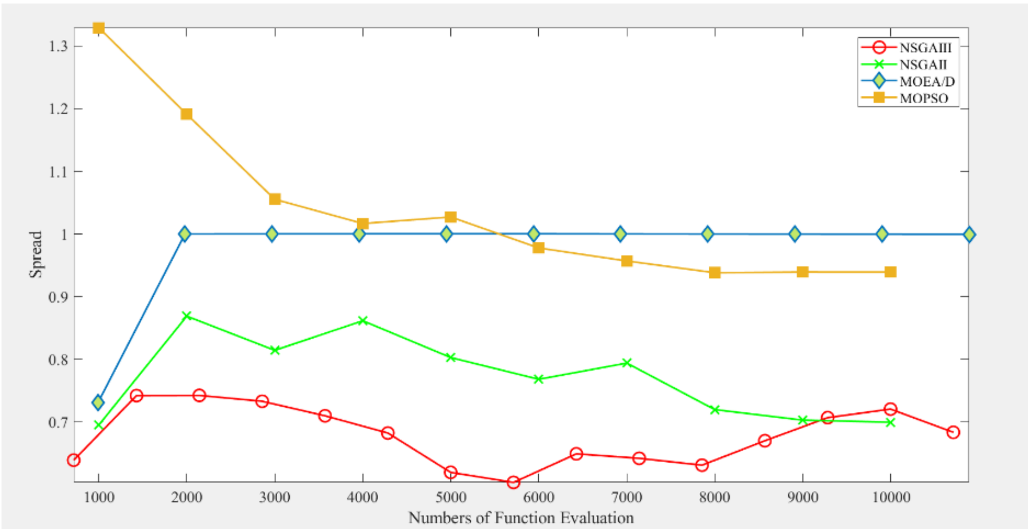

Figure 15. The curves of the Spread value of NSGA III and other algorithms on the number of function evaluations

4. CONCLUSIONS

This paper addresses the optimization of composite services in cloud 4D printing, which involves conflicting objectives such as cost minimization, time reduction, quality maximization, and adaptability enhancement. A multiobjective optimization framework employing the Non-dominated Sorting Genetic Algorithm III (NSGA III) is proposed for this purpose. NSGA III is specifically designed to tackle the high-dimensional and multiobjective nature of cloud-enabled 4D printing service composition. Comparative analyses against NSGA II, MOEA/D, and MOPSO algorithms demonstrate that NSGA III excels in achieving superior convergence and solution diversity. Results indicate that NSGA III significantly outperforms other algorithms in terms of Generational Distance (GD) and Inverted

Generational Distance (IGD) metrics, indicating closer approximation to the true Pareto frontier and better solution diversity. The algorithm also exhibits higher stability and faster convergence rates, rendering it highly effective in optimizing cloud 4D printing services. The study confirms NSGA III's capability to enhance the adaptability and resilience of service compositions amidst demand fluctuations and resource variability. In summary, this paper presents a robust and efficient multiobjective optimization model utilizing NSGA III for cloud-based 4D printing services. The algorithm effectively balances multiple objectives and addresses challenges posed by high-dimensional optimization problems, thereby validating its efficacy in manufacturing optimization. The application of NSGA III in cloud 4D printing services signifies advancements in manufacturing optimization, ensuring resilient and adaptable manufacturing systems conducive to smarter and more efficient production processes.

4.1 Future Research

Future research endeavors should explore hybrid optimization methodologies integrating NSGA III with complementary algorithms to further enhance performance and scalability. Additionally, developing advanced constraint-handling techniques is pivotal for addressing complex optimization scenarios. Extending the application of NSGA III to diverse domains and real-world industrial applications will yield valuable insights and broaden the validation of its effectiveness. This research holds significance for advancing smart cloud manufacturing, particularly in optimizing the efficiency, adaptability, and sustainability of composite cloud manufacturing services, including 4D printing. Optimization of 4D printing services can yield substantial cost reductions, enhanced product quality, and improved responsiveness to market demands, thereby fostering more sustainable and competitive practices in smart manufacturing and Industry 4.0. Future investigations will focus on integrating machine learning techniques to refine the NSGA III algorithm by dynamically forecasting demand patterns and optimizing resource allocation. Moreover, efforts will be directed toward enhancing algorithmic scalability and performance in practical industrial settings to ensure broader applicability.

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CONFLICT OF INTEREST

The article has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission, and declare no conflict of interest in the article.

AUTHORS CONTRIBUTION

Jiajia Liu: Conceptualization, Methodology, Software, Writing- Original Draft Preparation

Edi Syams: Data Curation, Validation, Supervision

Azizan; Mohd Idris Shah: Software, Validation, Writing-Reviewing and Editing

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