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Multitask Scheduling on Cloud Additive Manufacturing Using NSGA-II

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Abstract:

Purpose: Cloud manufacturing (CM) represents a new manufacturing paradigm that integrates distributed resources to provide on-demand services. The high consumer demand from various locations, coupled with the customizability and complexity of manufacturing, complicates task scheduling. In this context, 3D printers are crucial as innovative manufacturing technologies with significant potential in producing complex and custom products. Scheduling in CM falls under the non-deterministic polynomial time-hard category, where tasks must be scheduled and distributed rapidly. Considerations of distance, minimization of delays, and makespan become critical variables that must be considered. This research aims to schedule and distribute tasks in CM using the non-dominated sorting genetic algorithm II (NSGA-II) to minimize delays, reduce makespan, and decrease costs.

Design/methodology/approach: NSGA-II is employed to tackle the complexities of scheduling in CM. The strength of NSGA-II lies in its ability to determine optimal and efficient solutions for multiobjective problems. Tasks originating from requests at various locations are adjusted based on material parameters and dimensions and then distributed to providers while considering aspects such as delay minimization, makespan, and cost.

Findings: The optimization results using NSGA-II demonstrate effective and efficient task distribution to providers. Across the four tested task distribution scenarios, the average computational time required was 5.59 seconds. Pareto analysis indicates a trade-off between various objective functions. Solutions with short distances tend to have increased maximum time and delays.

Originality/value: NSGA-II is effective for task distribution with multiobjective considerations. Not all three objective functions can be optimized simultaneously, given the trade-offs between distance, maximum time, and lateness. The priority of the objective functions should be determined to achieve optimal results. If minimizing lateness is most important, the focus should be on points with low lateness values. Further development can be done by modifying the Pareto front to make data-driven decisions that consider these trade-offs.

Keywords: cloud manufacturing, additive manufacturing, 3D printer, scheduling, non-dominated sorting genetic algorithm II

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1. Introduction

Cloud manufacturing (CM) represents a collaborative concept involving geographically distributed resource owners, operators, and demanders connected through information technology (Baumann & Roller, 2017). CM is a new manufacturing paradigm driven by consumer needs, integrating distributed resources to provide on-demand services (Li, Zhang, Liao & Liu, 2019). The concept and framework introduced in 2009 by Li, Zhang, Wang, Tao, Cao Jiang et al. (2010) are anticipated to transform the future landscape of the manufacturing industry (Adamson, Wang, Holm & Moore, 2017). This concept has garnered substantial attention, resulting in numerous publications covering discussions on the concept, architecture, and implementation of CM (Ghomi, Rahmani & Qader, 2019; Lim, Xiong & Wang, 2021).

In practical terms, CM enhances a company's flexibility through information technology, fostering collaboration among network elements (Schumacher, Erol & Sihn, 2016). CM responds to rapidly changing market needs and creates broader opportunities for cooperation (Ren, Zhang, Wang, Tao & Chai, 2017). Geographically distributed elements connect through a cloud network, becoming shared resources tailored to demand throughout the product lifecycle (Ren, Zhang, Tao, Zhao, Chai & Zhao, 2015).

Manufacturing resources have become a vital element in CM. Additive manufacturing (AM), commonly known as 3D printing (3DP), is a promising manufacturing technology that aligns with CM's operational mode as a manufacturing resource (Ren et al., 2015). 3DP can produce highly complex and personalized products (Pereira, Kennedy & Potgieter, 2019). Its potential extends to creating products unattainable through conventional processes and expanding 3DP technology applications from manufacturing and aerospace to social, cultural, biomedical, and construction industries (Calignano, Manfredi, Ambrosio, Biamino, Lombardi, Atzeni et al., 2017; Ismianti & Herianto, 2018). These advantages position 3DP as a key player in CM (Dilberoglu, Gharehpapagh, Yaman & Dolen, 2017).

While technology has supported CM's development, challenges persist in advancing virtualization, servitization, and scheduling technologies (Lim, Xiong & Lei, 2020). Scheduling in the CM system is a crucial issue (Liu, Zhang, Wang, Xiao, Xu & Wang, 2019), directly affecting production efficiency and manufacturing system costs (Zhang, Ding, Zou, Qin & Fu, 2019). The scheduling process involves allocating resources/services for tasks, dispatching tasks to resources/services, monitoring, controlling, optimizing resource/service status, and executing tasks to meet individual demanders' needs.

CM scheduling exhibits the characteristics of complexity and non-deterministic polynomial time (NP)-hard categories (Lin & Chong, 2017). In computational complexity theory, decision problems fall into the NP class, indicating non-deterministic polynomial time. CM, supporting dynamic system growth through a pay-as-you-go approach, introduces scheduling complexity (Liu, Wang, Wang, Xu & Zhang, 2019). Complexity arises from specific individual needs and complex task structures in cloud-based manufacturing. In this context, the coordination and synchronization of complex activities becomes crucial, especially in grouping resources with high flexibility (Akbaripour, Houshmand, van Woensel & Mutlu, 2018).

Providers in CM, serving as resource service providers, receive tasks from both internal and external sources (cloud) (Wang, Lin, Zhong & Xu, 2019). Internal tasks are typically ongoing and predictable, unlike external orders from the cloud, which are often unpredictable. This condition poses a challenge in managing efficient scheduling, in which all tasks must be completed on time per deadlines set by demanders. Given these conditions, investigating and understanding scheduling issues in the CM environment is crucial.

This study aims to identify a scheduling system solution capable of effectively and efficiently managing multiple tasks, minimizing makespan delays, and considering nearest distance selection as a cost minimization solution. The multiobjective minimization of makespan, delay, and distance has yet to be explored. The anticipated results will enhance the efficiency and effectiveness of CM for academic publication purposes.

2. Related Work

Cloud AM (CAM) is a concept in which manufacturing resources, primarily AM machines, are integrated into a cloud-based manufacturing system. CAM frameworks typically involve interactions between requesters, operators, and providers. Scheduling in a CAM system is an essential issue so that the system can run effectively and efficiently (Halty, Sánchez, Vázquez, Viana, Piñeyro & Rossit, 2020). In the scheduling process, task resource allocation is carried out, followed by monitoring, controlling, and optimizing the status of resources and task execution to meet demand requirements. Figure 1 provides a comprehensive overview of the scheduling process in a CAM system.

Various scheduling optimization efforts have been developed, as described by Rashidifar, Bouzary and Chen (2022), and Rad and Behnamian, (2022) use diverse approaches, including metaheuristics (53%), artificial intelligence and machine learning (14%), game theory (13%), exact methods (10%), and other approaches (10%). Furthermore, Rashidifar et al. (2022) mentioned the utilization of metaheuristic algorithms as follows: genetic algorithm (GA) (44%), particle swarm optimization (PSO) (11%), ant colony optimization (ACO) (11%), bat algorithm (6%), and others (28%).

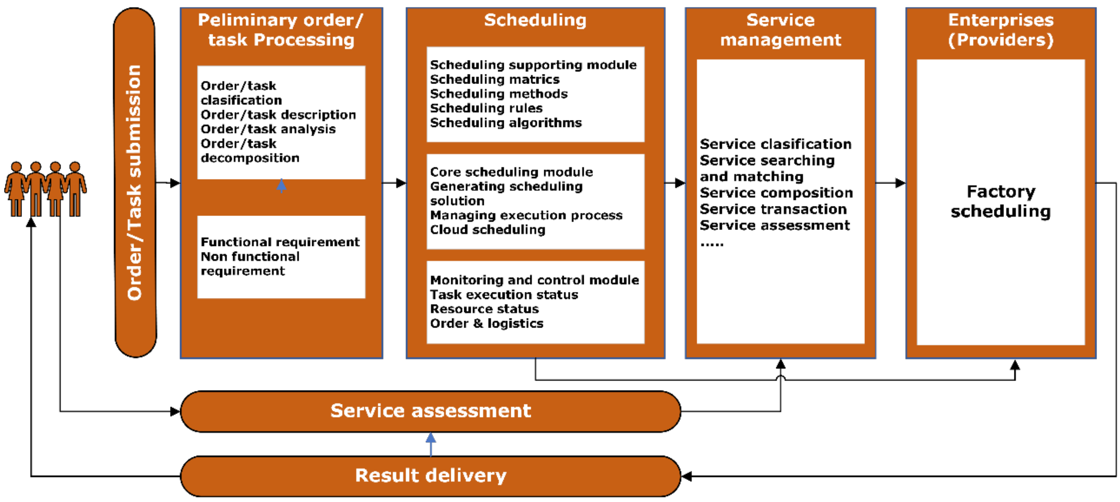

Figure 1. Procedure for scheduling cloud manufacturing reproducing (Liu, Wang, et al., 2019)

In general, the primary objectives of scheduling are minimizing makespan, minimizing costs, and increasing utilization and total flow time (Rad & Behnamian, 2022). Rad and Behnamian, (2022) classified their studies, with approximately 75% opting for single objectives, whereas the remaining discussed multiple objective functions. Research with multi-objective functions is carried out to optimize solutions for the main scheduling objectives. Table 1 provides a comprehensive overview of job scheduling optimization models in CAM, documented from various scientific sources. Various optimization designs have been developed to schedule machines and distribute tasks according to predetermined cost objectives, load balancing between printers, total delay, and number of components required. unprinted, using multiple identical fused deposition modeling, including computational time and modifying tabu search for scheduling optimization to minimize turnaround time and order costs.

A comprehensive review of NSGA-II for multi-objective combinatorial optimization problems was conducted by Verma, Pant and Snasel (2021), highlighting its suitability for finding efficient or near-optimal solutions. Its robustness and effectiveness have made NSGA-II a widely applied multi-objective evolutionary algorithm across various scheduling problems. Multi-objective evolutionary algorithms face challenges such as computational complexity, non-elitist approaches, and the need to define sharing parameters; however, NSGA-II can effectively overcome these issues (Deb, Pratap, Agarwal & Meyarivan, 2002). NSGA-II has been effectively applied to solve scheduling problems in flexible multi-objective job-shop models. The NSGA-II algorithm with an adaptive design optimizes scheduling settings for aerial materials. This adaptive design enhances the resolution of optimal solutions and ensures more accurate scheduling (Shang, 2022). An independent population elitism retention strategy is adopted to prevent the loss of optimal solutions (Zhang, 2022), distinguishing NSGA-II from other similar algorithms. NSGA-II emphasizes its effectiveness in solving bi-objective and tri-objective problems relevant to multi-task scheduling (Rahimi, Gandomi, Deb, Chen & Nikoo, 2022) and is even suitable for complex scheduling scenarios (Zhang, 2022).

References	Objective Function	Machine	Algorithm
Ransikarbum, Ha, Ma & Kim, 2017	Min. latency and cost	Multiple identical	CPLEX
Kim, Park & Kim, 2017	Min. makespan	Multiple identical	GA
Li, Kucukkoc & Zhang, 2017	Min. Production cost	Multiple identical	CPLEX
Fera, Fruggiero, Lambiase, Macchiaroli & Todisco, 2018	Min. adv./late. & cost	Multiple identical	GA
Chergui, Hadj-Hamou & Vignat, 2018	Min. total tardiness	Multiple identical	Heuristic
Zhou, Zhang, Laili, Zhao & Xiao, 2018	Opt. supply-demand and delivery times	Multiple non-identical	Simulation
Dvorak, Micali & Mathieu, 2018	Min. Tardiness, min makespan	Multiple non-identical	Local search
Wang, Zheng, Xu, Yang & Zou, 2019	Max. utilization rate	Multiple identical	Computer vision
Li, Zhang, Wang & Kucukkoc, 2019	Max. profit	Multiple identical	Heuristic
Kapadia, Starly, Thomas, Uzsoy & Warsing, 2019	Mini. makespan	Multiple identical	GA
Zhou, Zhang, Ren & Wang, 2019	Min. Delivery time	Multiple identical	GA
Altekin & Bukchin, 2022	Min. makesspan and cost	Multiple non-identical	MILP
Kucukkoc, 2019	Min-max lateness	Multiple non-identical	GA
Oh, Zhou & Behdad, 2020	Min. cycle time	Multiple non-identical	Heuristic
Fera, Macchiaroli, Fruggiero & Lambiase, 2020	Min. cost, earliness & tardiness	Single	Tabu search
Ransikarbum, Pitakaso & Kim, 2020	Min. cost, Max load balance, min total tardiness	Multiple non-identical	MILP & AHP
Aloui & Hadj-Hamou, 2021	Min. makespan	Multiple non-identical	MILP
Ying, Fruggiero, Pourhejazy & Lee, 2022	Min. time/cost	Multiple identical	AIG
Hu, Che & Zhang, 2022	Min. makespan	Multiple non-identical	MILP
Rohaninejad, Tavakkoli-Moghaddam, Vahedi-Nouri, Hanzálek & Shirazian, 2022	Min. makespan and the total tardiness penalty	Multiple non-identical	NSGA II – K-Means – ANN
This research	Min. delays, makespan, and cost.	Multiple identical	NSGA-II

Table 1. Summary of 3D printing scheduling research based on the algorithm and objective function

NSGA-II has been employed in various scheduling contexts, including distributed computing systems (Ambekai, 2022), just-in-time single-machine scheduling (Kurniawan, Irman, Febianti, Kulsum, Herlina, Ilhami et al., 2021), and low-carbon, flexible job-shop scheduling (Seng, Li, Fang, Zhang & Chen, 2018). These applications demonstrate the versatility and effectiveness of the algorithm in various scheduling domains. Wang, Zhang, Liu and Gao (2022) applied NSGA-II to schedule machines with varying numbers of jobs using non-3DP machines. However, one limitation of the method proposed in this research is that it does not account for varying user preferences, such as matching quality in multi-user-oriented SPM models, potentially restricting its ability to meet the needs of diverse users. Rohaninejad et al. (2022) investigation of scheduling problems in parallel but not-identical clustered 3DP systems and the overall delay penalties. NSGA-II combined with a novel learning-based local search methodology that integrates a K-means clustering algorithm and artificial neural networks. NSGA-II hybrid effectively solving the scheduling optimization problem with two objective functions.

This research aims to develop a scheduling system using NSGA-II, focusing on three objective functions: minimizing makespan, costs, and delivery delays by selecting the shortest path between requester and provider. The prevailing rule is that printing costs are calculated based on the weight or length of the resin used, thereby employing cost minimization in this research to achieve the shortest shipping costs.

In enhancing the functionality of a CAM system, it is crucial to consider technical design support to ensure effective and efficient machine scheduling and distribution. The connectivity between the cloud platform and the device is significant. Static information provides data regarding the 3DP machine's status, including printing accuracy, available print space, supported document types, material types, and colors of the printer type. Dynamic information includes data about the printer's operational status (online/offline), error rates, and error types (Luo, Zhang, Ren & Lali, 2020). Moreover, collaboration between edge cloud and the Industrial Internet of Things enhances system effectiveness by reducing data transmission latency and leveraging artificial intelligence for the further development of CAM systems (Zhang, 2022).

3. Problem Definition

The system under study involves two main actors: the demander (D_i) and the provider (Pr_i). The demander, as an entity requiring 3DP services, is responsible for uploading G-code files into the system. The uploaded information encompasses the product's material, dimensions, the demander's location, and the desired deadline. In contrast, the provider is a service provider offering 3DP manufacturing resources. The necessary data from the provider include the location of the manufacturing resource, the type of 3DP machine used, available materials, dimensions of the 3DP bed, and the machine's precision level. In this study, we assume the following: All operational parameters, including setup time, processing time, and demand, are deterministic. During the printing process, no interruptions, including maintenance and/or downtime, are considered. The processing time and completion time of parts depend on their specifications, but the choice of machine does not affect the completion time. The settings of the 3D printing machine parameters are assumed to be identical

The selected data will undergo processing using the NSGA-II, after which the system will distribute tasks to providers (Figure 2). It illustrates the stages of task distribution from the demander to the provider. Incoming tasks are matched with the materials provided by the provider and adjusted according to the product dimensions and the dimensions of the 3D printer. Then, the system schedules the tasks by considering three objective functions: distance minimization, lateness, and makespan. Afterwards, the tasks are distributed to the providers based on the optimization results.

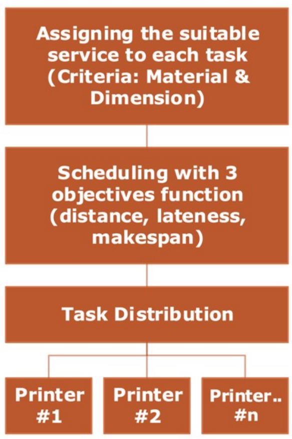

Figure 2. Matching rules, scheduling, and task distribution

D_i uploads several tasks, which will be matched with the 3DP type offered by Pr_i depending on the material type (M) and product parameters. The scheduling of a set of activities that have been matched will be done on a 3DP system by considering the minimizing of distance, latency, and makespan. D_i can upload multiple tasks ($T_{i,j}$) simultaneously. Meanwhile, a Pr_i may have more than one 3D printer ($S_{i,j}$) to offer its services. In situations with multiple simultaneous tasks (Zt_{ij}), the system will schedule and distribute these tasks to printers ($Pr_{i,j}$) that are not currently used. Each actor in this system has a specific location point determined by latitude and longitude coordinates. The demander's location is marked as (l_a, l_o), whereas the provider's location is also denoted by (L_a, L_o). The distance estimation depends on the proximity of the given coordinates. Table 2 shows more detailed information regarding this system.

Symbols	Keterangan	Symbols	Keterangan
C	Makespan	β	Cost factor shipping costs
S_i	Selected service	D_i	Demander (consumer)
Pr_i	Providers	lo	Longitude demander
L_o	Longitude provider	la	Latitude demander
L_a	Latitude provider	x_{ij}	Maximum product length
X_i	Maximum length of the printer table	y_{ij}	Maximum product width
Y_i	Maximum width of the printer table	z_{ij}	Maximum product height
Z_i	Maximum height of the Printer	m	Selected materials D_i
M	Materials provided Pr_i	$T_{i,j}$	Tasks
St	Warming up time	Zt_{ij}	Number of tasks
Sc	Cooling time	P_c	Printing costs
Pt	Printing time	w_i	Product weight of the slicer
pp	Post-processing time	c_i	Completion time
N_i	Number of 3D Prints	d_i	Due date
Q	The demander bears the costs	b_{ij}	Delivery time
α	The cost factor of printing costs	g_i	Delivery time
u	Handling fees	$G_{i,j}$	Distance between D_i dan Pr_i

Table 2. Notations and description

3.1. Model Size

The product size to be printed is a critical attribute in cloud-based 3DP services. The maximum size permissible for the selected service, denoted as S_i, must not be smaller than the model size of the task's 3DP, represented by $T_{i,j}$. This concept is articulated in Equations (1), (2), and (3). Additionally, before scheduling, material matching must be performed between providers (M_i) and demanders (m_i).

$$\min(x_i, y_i) \leq \min(X_i, Y_i) \tag{1}$$

$$\max(x_i, y_i) \leq \max(X_i, Y_i) \tag{2}$$

$$z_i \leq Z_i \tag{3}$$

3.2. Total Cost

Each service provider has the autonomy to set their own printing costs. To assist customers, operators may provide a general cost reference in line with industry standards. Typically, the cost of printing is determined based on the selected material type and the material's cost per unit weight, as outlined in Equation (4). The printing cost (P_c) is derived from the material weight, which is determined by slicer software. The calculation considers the specific material being used, followed by the associated cost factor. In addition, shipping costs are calculated based on the geographical distance between the customer and the provider. This distance is determined using the latitude (la) and longitude (lo) coordinates of both the customer and the provider, as detailed in Equation (6).

$$Q = P_c + G_{i,j} + \mathrm{u} \tag{4}$$

$$P_c = m.w_i.\alpha \tag{5}$$

$$G_{i,j} = \beta\sqrt{(l_o - L_o)^2 + (l_a - L_a)^2} \tag{6}$$

3.3. Optimization

The objective of this study is to minimize the makespan and reduce lateness by calculating the distance between the demanders and the providers. Minimizing makespan (minC) is achieved by minimizing the maximum makespan (C_{max}). Completion time (c_i) is the accumulation of the entire printing process time. The function for minimizing the makespan is presented in Equation 7. Equation 9 provides a mathematical formula for calculating the delay, considering the distance factor. Concurrently, the distance considered is the shortest between the claimant and the provider, as outlined in Equation 10.

$$minC_{max} = \min\left(max\sum_{i=1}^{n} c_i\right) \tag{7}$$

$$c_i = S_t + P_t + S_c + p_p \tag{8}$$

$$Lateness_{total} = \sum_{i=1}^{n} \max(0, (c_i - d_i) \tag{9}$$

$$J_{min} = \sum_{i=1}^{n} G_{i,j} \tag{10}$$

4. Methods

NSGA-II, which is widely recognized as a prominent GA for multiobjective optimization, excels in identifying numerous potential trade-off solutions, collectively referred to as the Pareto front, within a single run of the simulation. The core characteristics of NSGA-II encompass dominance-based sorting, crowd density assessment, selection, crossover, mutation, and a distinctive emphasis on elitism. A notable aspect of NSGA-II is its explicit preservation of the population's superior members across generations, ensuring the retention and continuity of high-quality solutions. This approach is instrumental in maintaining a robust parameter setting, as illustrated in Figure 3.

Figure 3 provides a comprehensive depiction of the NSGA-II algorithm's flow. The process begins by initializing a population randomly, which is subsequently assessed according to the objective function. Subsequently, the estimated population is organized according to non-sequential dominance, wherein Pareto ideal solutions are discerned from the rest. Subsequently, a calculation of crowd distance is executed in order to preserve genetic diversity. First, individual selection is carried out, and then crossover and mutation processes are applied to produce a new generation. The present population and its progeny are merged, and the procedure of non-sequential selection and crowd distance is iterated to choose the succeeding generation. This process continues until specific termination requirements are satisfied, such as achieving a predetermined number of generations or converging solutions. Ultimately, the algorithm produces a Pareto optimal solution, which is then designated as the output. The iteration continues until the specified stopping criterion is met, and the resulting output is the Pareto optimal solution.

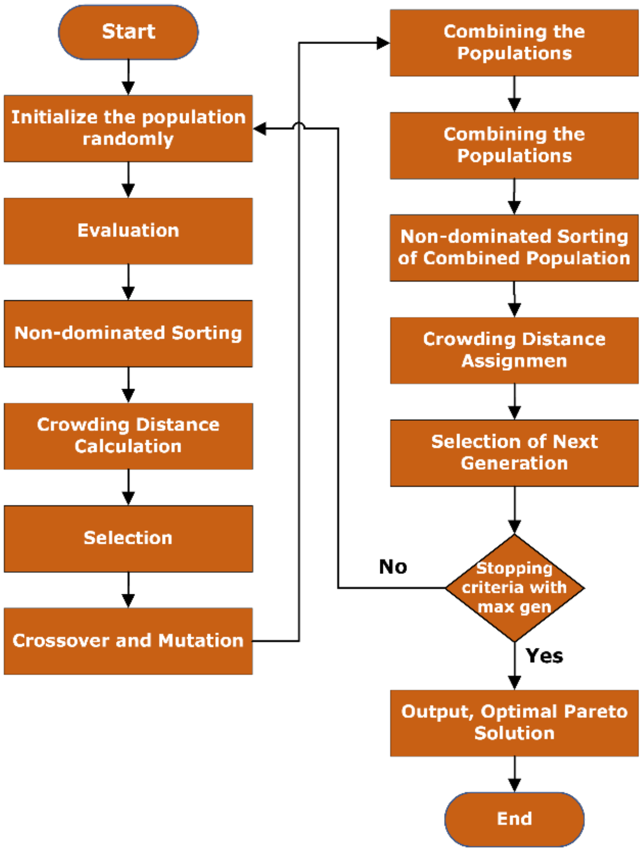

Figure 3. Flowchart of non-dominated sorting genetic algorithm II

5. Experiment

5.1. Scheduling

Scheduling involves planning and managing the time to complete a designated set of tasks or activities. In addition, management is responsible for allocating tasks to providers based on their objective functions. To facilitate this scheme, we presented a comprehensive CAM architecture in Figure 4. Efficient scheduling and the distribution of tasks are achievable with adequate technological support. As depicted in Figure 4, an adapter links the 3D printer and the cloud platform. A modified Raspberry Pi 4 was utilized as the adapter in this CAM system. This device can extract data from 3DP activities to gather static information, such as 3DP status, as well as dynamic information. This includes monitoring the printer's working mode (online/offline status) and recording any system failures.

5.2. Case Study

NSGA-II is an algorithm extensively utilized in multiobjective optimization. It introduces a highly efficient and effective sorting mechanism and the concept of crowding distance as a measure of solution density in objective space. This approach helps preserve diversity within the population. NSGA-II implements the principle of elitism, ensuring that the optimal solutions from the previous generation are automatically applied to subsequent generations, thereby enhancing the algorithm's capability to sustain high-quality solutions. The pseudocode for the NSGA-II algorithm is presented in Table 3.

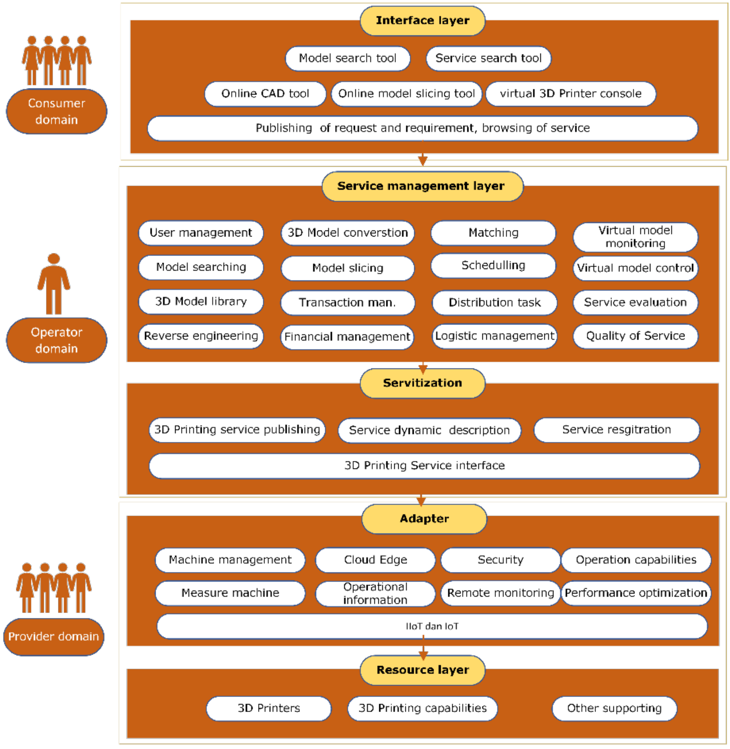

Figure 4. Cloud additive manufacturing architecture

: **input:** n/ POPULATION_SIZE
: **class item:** Name attribute, dimension, value, latitude, and longitude
: **printer Class:** Attribute name, capacity, latitude, longitude, time spent, item has, and time series
: **printerValue**(individual):
Calculating total distance, total lateness, and maximum time based on item assignments to printers using great_circle to measure the distance between item locations and printers
: **custom_cx**(ind1, ind2):
Applying crossover to two individuals by exchanging parts of their solutions
: **custom_mutation**(individual, indpb):
Applying mutation to an individual by randomly changing printer assignments
: Utilizing the NSGA-II algorithm for selection, crossover, and mutation
: Selection is based on non-dominated sorting and crowding distance
: For each generation up to MAX_GENERATIONS:
Evaluate each individual in the population
Apply selection, crossover, and mutation to form the next generation
Identify the Pareto front of the last population
: **near optimal_solution**
: **end**

Table 3. Pseudocode non-dominated sorting genetic algorithm II (NSGA-II)

The performances of meta-heuristic algorithms are significantly influenced by the values assigned to their parameters (Rohaninejad, Kheirkhah, Vahedi-Nouri & Fattahi, 2015). Hence, it is imperative to accurately establish these criteria. The parameters of the proposed meta-heuristics are determined through experimentation and are documented in Table 4. Based on the experimental results, the crossover probability (cxpb) was set at 0.6 and the mutation probability (mutpb) at 0.2, as detailed in Table 4. An experiment employing cxpb = 0.6 and mutpb = 0.8 was conducted, focusing on analyzing the population size and the highest fitness achieved. As depicted in Figure 5, a population size of 100 yielded significantly high best fitness. Utilizing the same parameter settings, additional trials were carried out to determine the optimal number of generations for NSGA-II. Figures 7 and 8 offer a comparative analysis of 200 and 100 generations. Considering the optimal computing time and convergence, 100 generations, with a specified number of datasets, should be the maximum limit for terminating the generational loop in NSGA-II.

Item	Paramater NSGA-II
Number of demanders	6
Number of services (tasks)	20
Number of providers	9
Crossover probability (cxpb)	0.6
Mutation probability (mutpb)	0.2
Total population	100
Generation	100
Average computing time	5.59 s

Table 4. NSGA-II rules and parameters

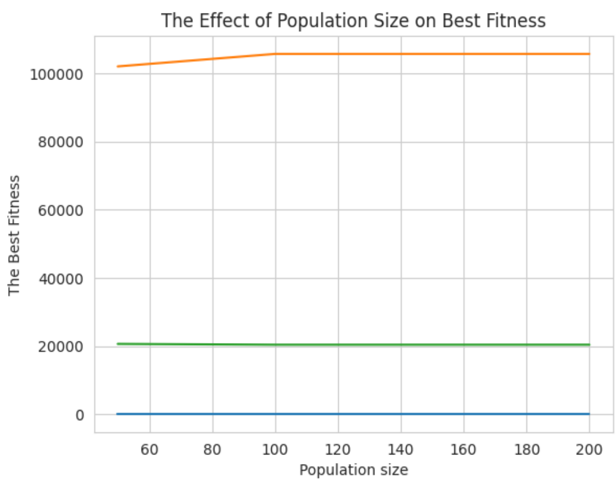

Figure 5. Population size versus best fitness

Based on the specified parameter settings, a trial was carried out with five iterations. Based on the results of this trial, the Pareto front will be analyzed. Figure 6 presents the results of the Pareto front three objective functions, which can be interpreted as follows:

1. Distance: Distance values show quite wide variations, indicating a considerable difference in the total distance covered by different solutions. Solutions closer to the makespan axis tend to have shorter total distances, which is desirable in most cases.

2. Lateness: The lateness metric reflects the delay in completion time relative to the predetermined deadline. Notably, a pronounced escalation exists in delays toward the right side of the plot, suggesting that these solutions are suboptimal in adhering to deadlines.
3. Makespan: The makespan axis represents the longest duration required to complete all tasks. Preferable solutions are those located at the lower end of this plot, as they demonstrate a reduced makespan.
4. Trade-off between Three Variables: The graph illustrates the interplay and compromise among distance, maximum time, and delay. Typically, solutions featuring shorter distances are associated with increased maximum times and delays. However, this correlation is not universally applicable and may vary depending on the specific distribution of the data points.
5. Point Clusters: These clusters indicate the groupings of efficient solutions regarding one or two variables but fall short on other variables.

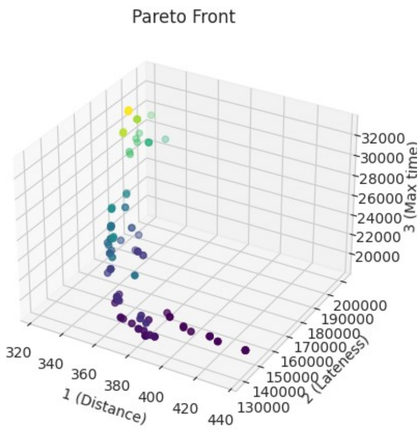

Figure 6. Pareto front analysis

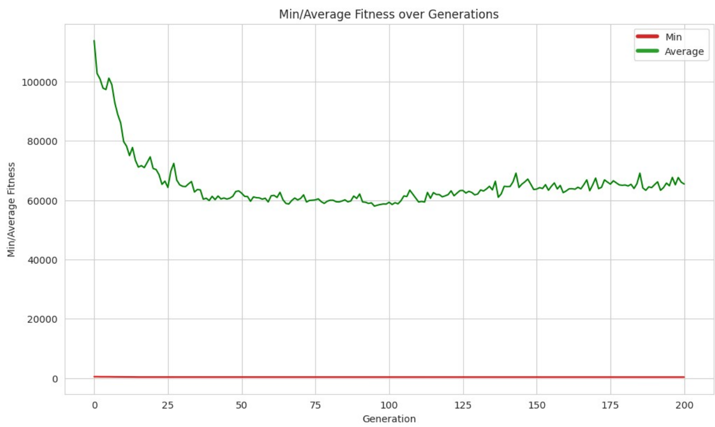

Figure 7. Generation versus fitness with the 200th generation

Figure 8. Generation versus fitness with the 100th generation

Scheduled tasks are optimized based on three objective functions. For clearer visualization, the number of tasks was adjusted to 20 and distributed among six demanders. Following established matching rules, the data are initially clustered by material similarity. Subsequent scheduling and task distribution are based on dimensional matching. Dimensions are categorized with codes: Code 1 is assigned to small products (dimensions between 10 × 10 × 10 mm and 50 × 50 × 100 mm), Code 2 to medium products (dimensions between 50 × 50 × 100 mm and 300 × 30 × 400 mm), and Code 3 to large products (dimensions between 300 × 300 × 400 mm and 500 × 500 × 700 mm).

The Pareto front is a key concept in multi-objective optimization, serving as a confirmation that individuals in the Pareto front indeed meet the criteria of non-domination. The steps involved include sorting the Pareto front using the sort non-dominated method, testing domination for each pair of individuals in the Pareto front to check if one individual dominates or is equivalent to another, and finally, validation. Solutions that are evenly distributed and encompass various trade-offs indicate that the algorithm effectively explores the solution space. The Pareto front also helps in assessing the diversity of solutions (Mendoza, Bernal-Agustin & Domínguez-Navarro, 2006). The more evenly the solutions are distributed in the Pareto front, the better the diversity of solutions generated by the algorithm. Figure 6 shows that the solutions are evenly distributed, indicating that the algorithm built with the specified parameters is capable of effectively exploring the solution space.

The Pareto analysis in Figure 6 illustrates a trade-off between distance, maximum time, and delay. A shorter distance tends to incur a greater delay, concurrently leading to an increase in the makespan. In this scenario, the system prioritizes assigning tasks to printers in closer proximity, consequently escalating the lateness and makespan values. However, opting for the shortest distance decreases logistics costs, thus offering advantages to demanders.

Id	Di,j	Dim	Pt	la	lo
1	D1.1	3	7200	−7.797957911	110.41786149494659)
2	D1.2	3	7200	−7.797957911	110.41786149494659)
3	D1.3	2	1144	−7.797957911	110.41786149494659)
4	D1.4	2	600	−7.797957911	110.41786149494659)
5	D2.1	2	3455	−7.771941787	110.30647808145225)
6	D2.2	3	1382	−7.771941787	110.30647808145225)
7	D3.1	2	4365	−7.742084599	110.43241716888542)
8	D3.2	3	1746	−7.742084599	110.43241716888542)
9	D4.1	1	770	−7.739099939	110.4001860526165)
10	D4.2	2	1525	−7.739099939	110.4001860526165)
11	D4.3	3	1438	−7.739099939	110.4001860526165)
12	D4.4	1	308	−7.739099939	110.4001860526165)
13	D4.5	2	610	−7.739099939	110.4001860526165)
14	D4.6	3	1438	−7.739099939	110.4001860526165)
15	D5.1	3	4530	−7.831553788	110.31778656611162)
16	D5.2	1	745	−7.831553788	110.31778656611162)
17	D5.3	3	1812	−7.831553788	110.31778656611162)
18	D5.4	1	298	−7.831553788	110.31778656611162)
19	D5.5	1	1855	−7.831553788	110.31778656611162)
20	D6.1	3	4955	−7.984251325	110.3054995397715)

Table 5. Demanders' data

Id	Pr1,j	Dim	La	Lo
1	Pr1.1	1	−7.765815728	110.37382632452378
2	Pr1.2	2	−7.765815728	110.37382632452378
3	Pr1.3	3	−7.765815728	110.37382632452378
4	Pr2.1	1	−7.811021919	110.32101165077016
5	Pr2.2	2	−7.811021919	110.32101165077016
6	Pr2.3	3	−7.811021919	110.32101165077016
7	Pr3.1	1	−7.686262259	110.4105695669599
8	Pr3.2	2	−7.686262259	110.4105695669599
9	Pr3.3	3	−7.686262259	110.4105695669599

Table 6. Providers' data

NSGA-II is specifically designed to optimize multiple objective functions. This research utilizes three functions: minimizing makespan, lateness, and distance. The outcomes of this research demonstrate that NSGA-II efficiently schedules and allocates tasks to online printers. Pareto analysis reveals a trade-off inherent in this optimization process. The Pareto front illustrates a set of non-dominant solutions. A solution is deemed non-dominant if it is not outperformed by any other solution across all evaluated objectives. In essence, no alternative solution can concurrently offer shortened distance, reduced lateness, and decreased maximum value. The overarching interpretation suggests that aiming for a lower makespan may necessitate compromising either latency or distance efficiency. The optimal decision depends on the specific priority assigned to each objective.

Utilizing these matching rules, the data are processed, resulting in a task distribution, as depicted in Figure 9. Figure 9 shows that the tasks are allocated to all online printers, resulting in consecutive makespans, which are presented in Table 7. Printers $Pr_{1.1}$, $Pr_{2.1}$, and $Pr_{3.1}$, characterized by dimension 1, are exclusively capable of handling the tasks of dimension 1. Printers $P_{2.1}$, $P_{2.2}$, and $P_{2.3}$, with dimension 2, can process tasks of both dimensions 1 and 2. Meanwhile, printers $P_{3.1}$, $P_{3.2}$, and $P_{3.3}$, which have dimension 3, are equipped to handle tasks of dimensions 1, 2, and 3. The highest recorded makespan is associated with $Pr_{1.3}$, amounting to 17,276, with four tasks assigned. $Pr_{1.3}$, with a dimension of 3, can print tasks across all dimensions. This printer is strategically located in the central position relative to the requesters who upload the tasks. In this instance, $Pr_{3.1}$ receives no tasks, resulting in a makespan value of 0. $Pr_{3.1}$, categorized under printers with dimension 1, is limited to the printing tasks of dimension 1 only. Its location is on the periphery relative to the demanders' uploading tasks.

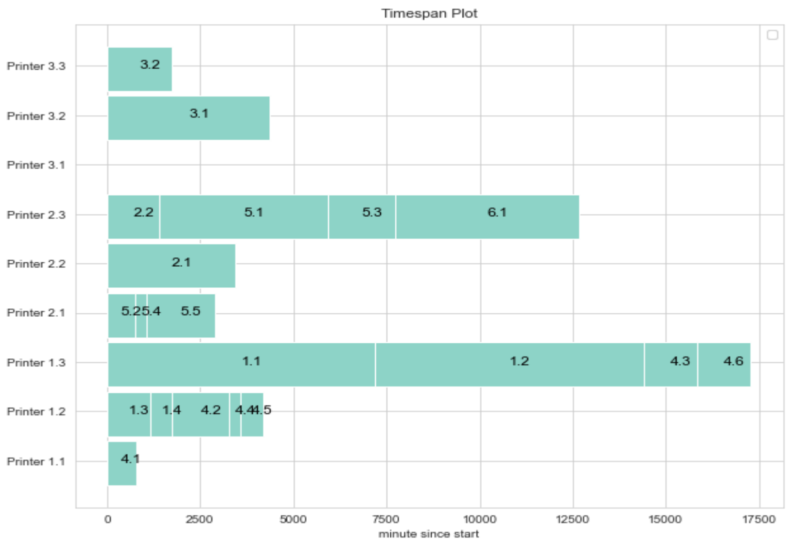

Figure 9. Scheduling and task distribution results

Pri,j	Ci	Number of tasks
Pr1.1	770	1
Pr1.2	1.2	5
Pr1.3	17276	4
Pr2.1	2898	3
Pr2.2	3455	1
Pr2.3	12679	4
Pr3.1	0	0
Pr3.2	4365	1
Pr3.3	1746	1
Total	43190.2	20

Table 7. Distribution task data

Figure 10 depicts the allocation of tasks to providers. Four tasks originating from the demand source D_1 are allocated to printer Pr_1. Printer Pr_2 is assigned two tasks from D_2, two tasks from D_3, six tasks from D_4, five tasks from D_5, and one task from D_6. A Pareto analysis reveals a trade-off between distance, maximum time, and delay.

Short distances tend to be associated with significant increases in delays, as well as an escalation in the makespan. In this scenario, the system prioritizes assigning tasks to the nearest printer, consequently resulting in heightened lateness and makespan values. However, selecting the shortest distance strategy effectively reduces logistics costs, thereby offering benefits to demand sources.

In determining the priority among distance, maximum time, and delay, the delay should be minimized, particularly by concentrating on points with low lateness values. A detailed analysis of specific clusters is necessary to understand the characteristics of their solutions and how they can be effectively applied in real-world contexts. Utilizing data from the Pareto front, informed decisions can be made considering the trade-offs between these three performance factors.

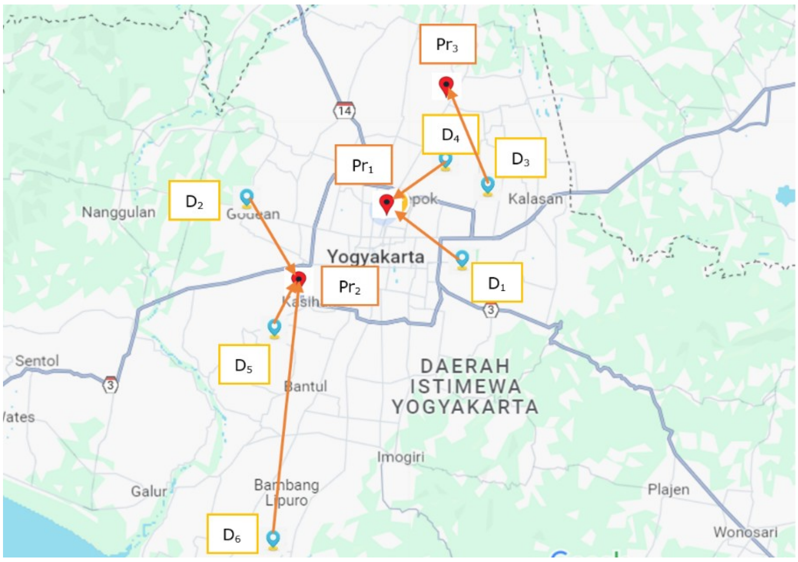

Figure 10. Distribution task

The research results indicate a significant variance in the distribution of tasks to online printers. However, tasks received by providers do not exclusively originate from the cloud; they can also emanate from offline systems, which are highly predictable. Such a situation can be accommodated to maximize resource functionality. Following this pattern, if a new task arrives subsequent to the scheduling of these tasks, it will be allocated to the printer with the shortest processing time or to a currently idle one.

NSGA-II has proven to be robust in various test scenarios, demonstrating its capability to handle complex multi-objective optimization problems, such as power distribution system design (Mendoza et al., 2006). NSGA-II has been successfully applied to a wide range of multi-objective optimization problems, showcasing its flexibility and effectiveness across various domains. The algorithm consistently produces high-quality non-dominated solutions, especially for large-scale problems. The computational efficiency of NSGA-II makes it well-suited for solving complex optimization problems within a reasonable time frame (Verma et al., 2021). In the case study conducted with various data size scenarios, the computation time was in the range of 5 seconds, demonstrating the computational efficiency of NSGA-II. The optimization results, with the specified parameter settings, produced optimal solutions according to the planned objective functions.

However, there is still potential for further optimization using NSGA-II. Studies have investigated hybridization between NSGA-II and other algorithms such as Tabu Search, Simulated Annealing, PSO, and ACO (Verma et al., 2021), as well as NSGA-II with k-means and local search (Wang et al., 2022) and NSGA-II with machine learning (Chen, Fang & Tang, 2019). These approaches aim to enhance the algorithm’s effectiveness and efficiency. This presents an opportunity for future research to combine NSGA-II with various algorithms to improve its effectiveness and efficiency in multi-objective functions.

6. Conclusion

The NSGA-II algorithm has been successfully employed to optimize the scheduling and distribution of tasks, adhering to the rules of matching materials and dimensions. This case study effectively scheduled and distributed 40 tasks among six demanders and nine printing service providers, with an average computational time of 5.59 seconds. Pareto analysis revealed a trade-off between objective functions. Solutions that minimized distance were associated with maximum time, which increased delays. Further research is necessary to understand consumer behavior and prioritize these aspects. If minimizing delay is paramount, emphasis should be placed on solutions with low latency values. A detailed analysis of specific clusters is recommended to comprehend the characteristics of their solutions and real-world applicability. Data from the Pareto front must be utilized to make informed decisions, considering the trade-offs among these three performance factors.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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