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ORIGINAL RESEARCH PAPER

A Multi-product Sustainable Scheduling Model Focusing on Logistic Service Sharing in Cloud Manufacturing Systems

Masoumeh Akhavan Hariri[1] · Shokraneh Khashkhashimoghadam[2] · Omid Fatahi Valilai[3]

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Abstract

Cloud computing as a service-driven business approach connects the distributed resources over the globe and allows multiple service demanders to submit their requests simultaneously to cloud-based application platforms. Cloud manufacturing has been inspired by the same idea to enable the sharing of manufacturing and production resources over the globe through an Everything-as-a-Service model. Despite providing enormous benefits to production and manufacturing business models for globalized models, it faces challenges for efficiently matching the services and demands due to the requirements of logistics among operation service providers. Moreover, the utility optimization for matching production services should address environmental factors as increasing demanders look for fulfilling ethical practices. This paper has aimed to develop a multi-objective mathematical model to reduce operation and logistic costs as well as gas emissions from operation centers and logistic services. This model has resulted in a sustainable cloud manufacturing system that will lessen environmental degradation besides the shared operational costs optimization.

Keywords Sustainable supply chain network design · Sustainability · Multi-objective optimization · Cloud manufacturing

Article Highlights

- Cloud manufacturing connects global resources using an Everything-as-a-Service model.
- Multi-objective model balances cost, fuel use, and carbon emissions accurately and achieves a better supply fill rate.
- Optimized operations lessen environmental impact and shared costs.
- NSGA-II provides Pareto-efficient solutions for production and logistics routing.

✉ Omid Fatahi Valilai
OFatahiValilai@Constructor.University

Masoumeh Akhavan Hariri
M.Akhavan1992@gmail.com

Shokraneh Khashkhashimoghadam
S.Khashkhashimoghadam@Herts.ac.uk

1 Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran

2 School of Physics, Engineering & Computer Science, Department of Engineering and Technology, University of Hertfordshire, Hatfield, UK

3 School of Business, Social & Decision Sciences, Constructor University Bremen, Campu Ring 1, 28759 Bremen, Germany

Introduction

Cloud manufacturing, as a "Everything-as-a-Service" model, enables service demanders to access manufacturing and logistics services dynamically through cloud-based platforms. This paradigm facilities optimized service composition, task allocation, and cost reduction, which aligns closely with sustainability objectives (Rezapour Niari et al. 2021). Sustainable supply chain management (SSCM) integrates three key dimensions: economic, social, and environmental sustainability. With the growing emphasis on sustainability, the manufacturing function must be strategically aligned with the company's sustainability vision and goals (Delaram et al. 2021). Green supply chain networks not only enhance customer satisfaction and profitability but also contribute to environmental conservation and community well-being (Wang et al. 2022). Several internal and external factors drive green behavior within supply chains. Internal factors include corporate environmental awareness, resource capabilities, technical advancements, employee perceptions of social responsibility, and green production initiatives (Fatahi Valilai and Sodachi 2020). External factors encompass government regulations, environmental policies, profit expectations, pressures from supply chain partners, and consumer awareness

(Hariyani et al. 2024). As supply chains increasingly integrate digital technologies, cloud-based manufacturing systems have emerged as a transformative approach to managing distributed production and logistics. These systems require efficient strategies to balance economic and environmental costs while optimizing service sharing and resource utilization (Niari et al. 2022).

Despite these advancements, gaps remain in effectively incorporating shared logistics services and sustainability goals into cloud manufacturing systems. Many existing studies emphasize operational cost reduction but fail to adequately address the integration of logistics service sharing mechanisms or their environmental impact. For instance, while Golmohammadi et al. (2024) and Ito et al. (2021) propose optimization models for resource sharing and logistics networks, gaps persist in addressing real-world dynamics such as greenhouse gas emissions and multi-product routing challenges. Moreover, current approaches often overlook direct cost-sharing models and the synergy between logistics and production service sharing.

This study contributes to the field by proposing a multi-objective mathematical model that optimizes production routing while incorporating logistics sharing to minimize costs and environmental impact. Unlike existing models, our approach explicitly accounts for the economic and ecological trade-offs in cloud manufacturing. The model assigns subtasks to production sources while enabling service sharing, reducing operating costs, logistics costs, and overall cloud manufacturing expenses. By sharing logistic costs, the proposed model enhances customer satisfaction and promotes sustainability. Our research also provides decision-makers with an analytical framework to balance economic efficiency with environmental responsibility in cloud manufacturing networks.

The remainder of this paper is structured as follows: the "Literature Review" section presents a literature review, identifying research gaps and our contributions. The "The Proposed Cloud Service Composition Model" section details the problem formulation, including key assumptions and mathematical modeling. The "Solution Methodology" section describes the computational framework to solve the problem. In the "Results" section, we conduct numerical experiments and sensitivity analyses to validate the model. Finally, the "Conclusion" section summarizes our findings, discusses study limitations, and outlines potential directions for future research.

Literature Review

Our work investigates matching and production and logistic service allocation while considering sustainability in the cloud manufacturing platform. In what follows, we position our work relative to two main streams of literature: service scheduling in cloud manufacturing, sharing manufacturing, and sustainability.

Service Scheduling in Cloud Manufacturing (CMfg)

Cloud manufacturing (CMfg-SCOS) consists of three primary user groups: service demanders, resource providers, and cloud platform operators. To address the complexities of service composition and optimal selection, various approaches have been developed to improve efficiency and adaptability in these cloud-based systems. One significant approach is the three-tier programming service composition model proposed by Lim et al. (2022), which simultaneously considers all three user groups to enhance overall efficiency. This model facilitates better interaction and collaboration between service demanders, resource providers, and platform operators. Similarly, Aghamohammadzadeh et al. (2020) present a mathematical model for optimally combining manufacturing and logistics services to minimize operational and logistics costs while introducing the concept of configured cloud entropy. This concept supports operational and logistics suppliers in improving resource allocation decisions.

Service allocation complexities in multi-composite tasks have been addressed by Wan et al. (2023), who developed a hierarchical scheduling model. This model consists of user-level scheduling, which ensures a functional match between service demanders and providers, and sublevel scheduling, which employs an improved firefly genetic algorithm to optimize sub-task allocation. Enhancements in task scheduling within dynamic cloud-based Software as a Service (SaaS) platforms have been achieved through the use of Adaptive Priority Experience Replay (APER). This task scheduling algorithm, proposed by Zhu et al. (2022), dynamically adjusts task priorities based on real-time performance metrics, improving resource utilization and reducing task completion times. Additionally, dynamic data-driven simulations introduced by Shahab et al. (2022) further enhance scheduling efficiency and system robustness by allowing for real-time adjustments to fluctuating production demands.

Deep reinforcement learning (DRL) has emerged as a transformative approach in cloud manufacturing. For environments characterized by constantly changing production demands, Wang et al. (2024) proposed a DRL-based scheduling method that enables service providers to learn adaptive policies suited to dynamic requirements. Coordination between manufacturing and logistics services has been integrated into a unified scheduling framework by Liu et al. (2024), improving efficiency while minimizing operational costs. This model considers factors such as task arrival times, setup times, and transportation logistics to optimize task completion rates and service quality. Furthermore, logistics decisions often made independently can lead to idle resources and excessive costs, as noted by Liu et al. (2024), whereas this paper works more holistically integrates logistic and production cost reduction to avoid such inefficiencies. In systems enhanced by blockchain technology, unique scheduling challenges arise that require innovative approaches. For instance, Zhang et al. (2022) addressed these challenges by introducing the dynamic selection evolutionary algorithm (DSEA), which optimizes manufacturing processes in blockchain-enabled environments. Meanwhile, reinforcement learning continues to gain traction as a powerful AI-driven tool for intelligent manufacturing. Li et al. (2023) emphasized its significance in sequential decision-making processes, and Wang et al. (2022) leveraged multi-agent reinforcement learning combined with advanced neural network architectures to improve real-time responsiveness and manage complex scheduling tasks. Expanding further, Moein Fazeli et al. (2024) developed a customized DRL environment tailored specifically to cloud manufacturing, introducing a novel DRL-based algorithm for service composition optimization. By exploring weight variations and service failure probabilities, their work provides valuable insights into adaptive and resilient scheduling strategies.

Collectively, these studies highlight the central role of task decomposition and scheduling in cloud manufacturing environments, where complex tasks are systematically divided and assigned efficiently to available resources. By integrating hierarchical scheduling models, evolutionary algorithms, data-driven simulations, and reinforcement learning techniques, researchers have greatly advanced the capabilities of cloud manufacturing. These approaches address key challenges, such as dynamic task arrival, real-time responsiveness, and uncertainty in resource availability, enabling the creation of flexible, scalable, and intelligent systems. The integration of manufacturing and logistics processes, combined with sophisticated scheduling algorithms, ensures optimal resource utilization and minimizes costs, ultimately advancing the efficiency and adaptability of cloud manufacturing platforms.

Shared Manufacturing

Over the past two decades, economic and social crises have led to a significant shift from traditional, independent manufacturing to shared manufacturing (SharedMfg) (Delaram et al. 2023). This new paradigm is driven by a combination of economic, environmental, and social motivations, as well as the appeal of innovation and financial benefits (Duran et al. 2024). At its core, shared manufacturing is based on the principles of value and resource sharing in production, where stakeholders share both costs and generated value. These platforms are typically more cost-effective than traditional business models (Reuschl et al. 2022). The SharedMfg model requires not only a shift in perspective for individual companies but also the development of collaborative infrastructure at the regional level. It seeks to promote a customer-centric approach that emphasizes cost-sharing efficiency while supporting sustainable manufacturing practices. However, the model comes with inherent challenges, such as operational complexities, difficulties in resource allocation, uncertainty in demand forecasts, conflicts over the use of shared resources, and the need for robust coordination mechanisms (Ghomi et al. 2019).

Despite its focus on sustainability, the importance of economic factors—specifically cost reduction—remains central to the evolution of the manufacturing sector. For example, research has proposed a game-theoretical framework to address competition among multiple vehicle-sharing companies, optimizing pricing and fleet management decisions (Liu et al. 2024). Similarly, capacity-planning problems have been modeled as Markov decision processes, allowing the development of efficient, real-time algorithms to minimize the need for safety capacity while adhering to resilience constraints. These models often center on operational costs, focusing specifically on capacity planning and resilience strategies (Li and White 2023). Logistics service sharing also plays a crucial role in supporting collective efficiency in manufacturing. Studies have investigated the use of logistical service sharing (LSS) between manufacturers and e-tailers in dual-channel supply chains, determining that such arrangements yield mutually beneficial outcomes only under specific conditions, such as when the manufacturer faces limited logistical disadvantages or when there is a significant cost difference in available logistics services (Guo et al. 2024). Additional models, such as those designed to optimize logistics networks using shared transportation resources, demonstrate the potential to improve supply chain performance by minimizing truck numbers under uncertain demand conditions (Ito et al. 2021). Efforts to address sustainability at a broader level have also led to new optimization methods for supply chains. One notable approach is the integration of the multi-objective dragonfly algorithm (MDA) into sustainable supply chain management. This approach optimizes multiple aspects of supply chains, including production, inventory, location planning, routing, and resource-sharing efficiency (Golmohammadi et al. 2024).

Our work differs from the studies above in several key ways. While these papers address broader sustainability goals such as waste reduction, they do not detail operational considerations like greenhouse gas emissions as they relate to distance, load, and service factors. Furthermore, although existing research explores resource allocation optimization, it lacks explicit focus on logistics-sharing scenarios and direct cost-sharing models for manufacturers operating in distributed environments. By addressing these gaps, our research provides a more refined perspective on the economic and environmental efficiency of shared manufacturing systems.

Sustainability

The concept of sustainability has gained increasing attention in recent years due to rising socio-environmental challenges such as climate change and air pollution (Elfarouk et al. 2022). In response, organizations are incorporating green practices into their supply chain operations to enhance environmental and social performance (Khan et al. 2021). Sustainable supply chain management (SSCM) establishes sustainability-focused objectives that align with stakeholder expectations, and its effectiveness is assessed through performance evaluations that measure environmental, social, and economic impacts (Zhao et al. 2022). Energy consumption, a key aspect of sustainability, significantly influences the environmental footprint of industrial activities (Song et al. 2023). Efficient energy management is essential to mitigate greenhouse gas emissions, reduce dependence on fossil fuels, and promote long-term ecological and economic stability (Radmanesh et al. 2023).

To address these concerns, Zhang et al. (2021) developed a two-layer planning model integrating a carbon emission trading policy to optimize location decisions in cold chain logistics. This model enhances operational efficiency while minimizing emissions, supporting sustainable decision-making in logistics management. In Bai et al. (2022), the authors examined the vehicle routing problem (VRP) for cold chain logistics, incorporating real-time traffic conditions to minimize carbon emissions and distribution costs. It offers guidance for logistics companies on distribution strategies and informs government policy on carbon taxation. The paper of Wei et al. (2021) evaluated manufacturing cloud services with a focus on environmental benefits within the supply chain. It discusses how cloud manufacturing can enhance resource sharing and efficiency, leading to reduced logistics costs and lower carbon emissions. Xie et al. (2024) developed a multi-objective optimization model to manage the green supply chain concerning both economic and environmental goals. It couples renewable energy, inventory, and transportation decisions within a green industrial park for fresh goods requiring low-temperature storage. The study demonstrates that adopting renewable energy microgrids and electric vehicles can reduce carbon emissions by 13.6 percent in the supply chain. A multi-objective optimization approach has been developed by Kumar and Kumar (2024) for designing a sustainable supply chain that aims to minimize carbon emissions while balancing other goals such as cost and operational efficiency. In this paper, transportation-related carbon emissions include distance traveled, mode of transportation, and Quantity of goods transported. Pahlevan et al. (2021) outlined a mathematical model to design a closed-loop supply chain network that incorporates economic, social, and environmental goals at the same time. Aside from deployment, production, distribution, reverse logistics, transportation costs, the emission rate emitted during manufacturing and assembly, recycling, and transportation are also considered. The reviewed literature primarily focused on energy consumption, while a smaller portion addressed various environmental concerns, such as reducing water usage and carbon footprints (Yang et al. 2020).

The reviewed literature primarily focused on energy consumption, while a smaller portion addressed various environmental concerns, such as reducing water usage and carbon footprints. In light of growing concerns about global warming, many countries have taken action, emphasizing the urgent need for sustainable and responsible use of the world's increasingly limited resources. As a result, companies are implementing strategies to enhance the sustainability of their manufacturing operations. In contrast to existing literature, our work, to the best of our knowledge, is the first to specifically emphasize the integration of cloud manufacturing systems with sustainability goals through logistic service sharing. While previous studies have focused on individual aspects of sustainability in supply chains or manufacturing systems, our research highlights the innovative potential of cloud manufacturing as a platform to enhance resource efficiency and reduce environmental impact. By leveraging shared logistics services within a cloud-based framework, our approach seeks to optimize both operational performance and sustainability outcomes. It offers a novel perspective on how digital technologies can contribute to greener and more cost-effective supply chain operations. A summary of the literature, their solution methods, strengths, and limitations and open issues is provided in Table 1.

The Proposed Cloud Service Composition Model

Manufacturing companies use cloud platforms to provide their resources and production capacity. Using this platform, customers of these services can finally request personal needs and have those needs met based on their cost and other parameters. In a logistics allocation model, tasks are required to be transferred if they are to be performed at two different sites. Each applicant who uses the logistics service pays for the service alone, and there is no way to determine how many people have used it. In this paper, however, the focus is on cost sharing among applicants for shared logistics services with the aim of cost sharing. In addition to logistics costs, operational costs as well as carbon emissions are also examined.

Table 1 Summary of the reviewed literature

Research	Service composition	Logistic sharing	Sustainability	Operational cost	Logistic cost	Proposed algorithm	Strengths	Limitations/open challenge
Lim et al. (2022)	Yes	Yes	No	Yes	No	Three-tier programming model	QoS-based service matching	Simplified assumptions/Limited scalability
Aghamohammadzadeh et al. (2020)	Yes	No	No	Yes	No	Cloud-entropy analysis	Dynamic adaptability/handling uncertainty and variability	Scalability challenges
Wan et al. (2023)	Yes	No	No	Yes	Yes	Hierarchical scheduling model	Multi-task scheduling/resource utilization	Uncertainty and scalability
Liu et al. (2024)	Yes	Yes	No	Yes	Yes	Dual-service integrated scheduling	Efficiency improvement	Adaptability in real-world environments
Liu et al. (2024)	No	Yes	Yes	Yes	Yes	Two-stage game-theoretical framework	Pricing management	Multi-stakeholder environments
Guo et al. (2024)	No	Yes	No	Yes	Yes	Game-theoretical modeling	Dual-channel supply chains	Dynamic and uncertain market conditions
Golmohammadi et al. (2024)	No	Yes	Yes	Yes	Yes	Multi-objective dragonfly algorithm (MODA)	Appropriate in complex decision-making	Limited adaptability to highly volatile market dynamics
Wei et al. (2021)	No	No	Yes	No	Yes	Real-time monitoring tools	Enhanced resource efficiency	Real-world scalability and adaptability
Bai et al. (2022)	No	No	Yes	Yes	Yes	Low-carbon vehicle routing problem (VRP)	Real-time traffic conditions	Scalability issues for large and highly dynamic road networks
Pahlevan et al. (2021)	No	No	Yes	Yes	Yes	Three-objective mixed-integer linear mathematical model	Life cycle-based sustainability strategies	High energy consumption in aluminum industry
Kumar and Kumar (2024)	No	No	Yes	Yes	Yes	Multi-objective mixed-integer linear programming (MILP)	Holistic approach to sustainable supply chain design	High computational complexity
Yang and Zhen (2025)	Yes	No	Yes	Yes	Yes	IoT and advanced analytics integration	Integration of IoT and machine learning for optimized manufacturing operations	High cost of implementation
This research	Yes	Yes	Yes	Yes	Yes	Multi-objective mathematical model/NSGA-II algorithm	Resource efficiency/balancing economic and ecological trade-offs	Dynamic cloud environments

The simultaneous reduction of these two costs (economic and environmental costs) is considered in this study.

Assumptions

- Tasks have direct structure.
- The cost of logistics is independent of the type of tasks and depends only on the distance between production resources.
- Transmission is direct and without considering the hub.

Mathematical Model

There are m companies on the cloud platform, each of which has different capabilities in terms of time and cost for each operation. Each production source in each city can provide i number of operations, $i \in \{1, 2, 3, \ldots, I\}$. The number of tasks k, $TK \in \{T_1, T_2, \ldots, T_k\}$, has reached the cloud platform at one time. Each of these tasks has a set of sub-tasks that are specified in the task breakdown phase, and each of these sub-tasks is executable by operations on the cloud generation platform. In cloud manufacturing, when two consecutive operations are different from one task in two manufacturing companies, to transfer a semi-finished product, a service is needed for transfer between companies, in which case a logistics service will be called. Table 2 introduces the indicators, parameters, and decision variables of the problem.

The optimization model aims to minimize operations costs as well as environmental cost , as its objective function in Eq. 1.

The function F_1 optimizes production and logistics costs. Production costs are based on the cost per hour required to perform operations, and logistics costs between companies are based on the distance between production points (in kilometers). In this model, the logistics cost is divided between the consumers who use the common logistics services between the two sources of production; this number is in the objective function with $Ts_j(m, m')$ as shown. The function F_2 minimizes the carbon emission, which typically means that it is an objective function in an optimization model designed to reduce the total amount of carbon dioxide (CO2) or other greenhouse gas (GHG) emissions associated with a particular system or process. The amount of greenhouse gas production is checked in order to determine the sustainability of the supply chain from an environmental perspective. Every logistics service emits greenhouse gases (CO2) with a certain coefficient. This coefficient is directly proportional to the distance traveled between cities and inversely proportional to the average number of products transported. In addition, each

Table 2 Indices, parameters, and decision variables

Parameters	Description
I	Number of operations/sub-tasks i
J	Number of logistics services j
K	Number of tasks k
M	Number of cities m
$LC_j(m, m')$	Cost of logistics service j between two cities m and m'
OC_{ikm}	Cost of performing o_{ik} operations in the city m
LC_j	Cost of the first logistics service (per kilometer)
oc_{ikm}	Cost of production source operations in the city m (per hour)
$d_{m,m'}$	Distance between cities m and m' (in kilometers)
t_{ikm}	Time of o_{ik} operation in the city m (hours)
p_m	Productivity rate of production source in the city m (%)
o_{ik}	Operations i for task k
U_{ik}	Cost of logistics service j between two cities m and m', $lc_j \times d_{m,m'}$
P	Cost of performing o_{ik} operations in the city m
$TR_j(m, m')$	Cost of the first logistics service (per kilometer)
EM_j	The GHG emission factor by using logistic service j-th
EM_m	The GHG emission factor in production unit m
LD_{sp}	The average load of transport product between m and m'
Decision Variables	Description
γ_{ikm}	Binary variable, If operation i is performed from task k in city m, 1, otherwise 0
$\delta_j(m, m')k(i, i')$	If logistic service j is used between city m and m' to transfer operations i to i', 1, otherwise 0

Table 3 Sub-tasks and operations related to each task

Task	Sub-task1	Sub-task2	Sub-task3	Sub-task4	Sub-task5
Task 1	1	1	1	1	1
Task 2	1	1	0	0	1
Task 3	1	0	1	1	0

production unit (located in different cities) emits greenhouse gases, the amount of which is determined at the time of production for all the products produced in any production unit.

The objective function represents a nonlinear integer classification problem, which, due to its high computational complexity, is best solved using innovative or meta-heuristic algorithms. The first part of constraint Eq. 2 captures the operational costs of production for each company, while the second part Eq. 3 contributes to the objective function by calculating the logistics cost, which is distributed among the users of logistics services for transferring semi-finished goods between production resources. Constraint Eq. 4 ensures that if a task requires operation i, this operation can only be assigned to a single company. Constraint Eq. 5 expresses an if-then condition in linear form: if two consecutive production points differ, a logistics service is required to transport goods between them. Constraint Eq. 6 defines the time capacity of each company, ensuring that the total operations performed within a company do not exceed its production time capacity. Equation 7 determines the number of shared logistics services between two production sources. Constraint Eq. 8 prevents the denominator from becoming zero; if there are no shared logistics services between two points m and m', the denominator remains non-zero. Similarly, constraint Eq. 9 ensures that the minimum value of $Ts_j(m, m')$ is one and does not reach zero. Finally, constraint Eq. 10 specifies that the decision variables are binary.

$$min(F_1 + F_2) \tag{1}$$

$$F_1 = \sum_{k\in K}\sum_{i\in I}\sum_{m\in M}\frac{\gamma_{ikm}\cdot OC_{ikm}\cdot t_{ikm}}{p_m} + \sum_{j\in J}\sum_{m,m'\in M}\left(\frac{\sum_{k\in K}\sum_{i,i'\in I_k} LC_{j(m,m')}\cdot d_{m,m'}\cdot \delta^{k(i,i')}_{j(m,m')}}{TS_{j(m,m')}}\right) \tag{2}$$

$$F_2 = \sum_{k\in K}\sum_{i\in I}\frac{EM_j\cdot d_{m,m'}\cdot \delta^{k(i,i')}_{j(m,m')}}{LD_{m,m'}} + \sum_{j}\sum_{i} EM_{p,m}\cdot t_{ikm}\cdot \gamma_{ikm} \tag{3}$$

S.t:

$$\sum \gamma_{ikm} = U_{ik} \qquad \forall i\in I, \forall k\in K, \forall j\in J \tag{4}$$

$$\gamma_{ikm}\cdot\gamma_{(i+1)km} - 1 \le \sum_{j\in J}\delta^{k(i,i')}_{j(m,m')} \qquad \forall i, i'\in I, \forall k\in K, \forall j\in J, \forall m, m'\in M \tag{5}$$

$$\sum_{k}\sum_{i} t_{ikm}\cdot\gamma_{ikm} \le cap_m \qquad \forall m\in M \tag{6}$$

$$Tr_{j(m,m'} = \sum_{k\in K}\sum_{i,i'\in I}\delta^{k(i,i')}_{j(m,m')} \qquad \forall j\in J, \forall m, m'\in M \tag{7}$$

$$TS_{j(m,m')} \ge Tr_{j(m,m')} \qquad \forall j\in J, \forall m, m'\in M \tag{8}$$

$$TS_{j(m,m')} > 1 \qquad \forall j\in J, \forall m, m'\in M \tag{9}$$

$$\delta^{k(i,i')}_{j(m,m')} * \gamma_i km = 0, 1 \qquad \forall i, i'\in I, \forall k\in K, \forall j\in J, \forall m, m'\in M \tag{10}$$

Solution Methodology

The genetic algorithm has only one optimal value, and the obtained answers can be sorted. Solutions that have a better objective function value will have more chances to reproduce and create a new generation. However, in the multi-objective genetic algorithm with non-dominated sorting, ranking the answers is not possible due to their multi-objective nature. The first version of the NSGA algorithm was presented in 1995, inspired by the single-objective genetic algorithm, but it had high computational complexity. If we assume that the number of objective functions is F and the population size is K, the complexity of NSGA is $O(FK^3)$. NSGA-II, a newer version, was introduced with a reduced complexity of $O(FK^2)$ and less execution time. This algorithm is based on the Pareto set of solutions, which may be optimal for several solutions at once, none of which is superior to the others. Thus, selecting the best answer from this set of optimal solutions is challenging. NSGA-II focuses on two concepts: better convergence and better solution distribution. According to this algorithm, the set of optimal solutions is available as Pareto solutions.

Fig. 1 Chromosome representation of a simple example

Production center(m)	1	2	1	1	3	3	2	1	3	3	1
Logistic service (j)	1	2	2	2	1	2	1	2	2	1	2

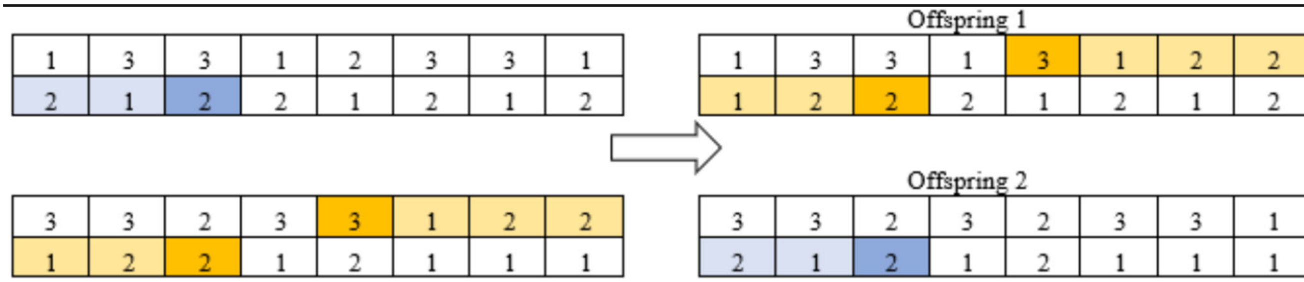

Fig. 2 Two-point crossover operator

Multi-objective optimization is an important class of techniques that has direct applications to solving many real-world problems. We use the epsilon constraint method to find different Pareto-optimal solutions on a small scale. Yet, for NP-hard problems in a manufacturing environment, we use a hybrid approach that combines genetic and NSGA-II algorithms. It has been found that a genetic algorithm can provide the optimal solution to objective 1, and another GA can provide the optimal solution to the second objective function. These two solutions are then introduced into the NSGA-II algorithm.

Chromosome Representation

The definition and utilization of chromosomes are crucial elements in the implementation of meta-heuristic algorithms. Properly coding the chromosome is essential to ensure the algorithm functions as intended and yields meaningful results. The correct representation of the solution vector enables the efficient application of crossover and mutation operators, allowing the solution space to be thoroughly explored and providing the potential to discover the optimal solution. Conversely, if the chromosome is inaccurately defined at the outset, the algorithm is likely to fail in producing acceptable results.

In this framework, a feasible solution vector is represented as a structure consisting of two rows. The first row specifies the city assigned to each operation, while the second row identifies the logistics service responsible for transporting goods between the selected cities.

To illustrate this concept, consider a scenario with three primary tasks and five sub-tasks in total. Based on the configuration in Table 3, the first task requires all five sub-tasks to be completed. The second task relies on sub-tasks one, two, and five, while the third task depends on sub-tasks one, three, and four. This setup highlights how chromosomes encode not only task assignments but also logistical details, ensuring the optimization algorithm can efficiently process and solve the scheduling problem.

Now, let us assume the problem involves three cities and two logistics services. In this scenario, the chromosome is

Algorithm 1 Pseudo-code for Solution Calculation.

Require: $i, j, k, m, u, p, CapM, c, OC, t, EM, lc, d, LD, EMP$
Ensure: Solution (Eq-1)
for each $p \in P$ **do** ▷ Number/set of solutions in population P
  $S_p \leftarrow \emptyset$ ▷ A set of solutions dominated by p
  $N_p \leftarrow 0$ ▷ Number of solutions dominating p
  for each $q \in P$ **do**
    if $p < q$ **then** ▷ If p dominates q
      $S_p \leftarrow S_p \cup \{q\}$
    else if $p > q$ **then**
      $N_p \leftarrow N_p + 1$
    end if
  end for
  if $N_p = 0$ **then**
    $p.rank \leftarrow 1$
    $F_1 \leftarrow F_1 \cup \{p\}$ ▷ p belongs to the first front
  end if
end for
$i \leftarrow 1$ ▷ Initialize front counter
while $F_i \neq \emptyset$ **do**
  $Q \leftarrow \emptyset$ ▷ Store members of the next front
  for each $p \in F_i$ **do**
    for each $q \in S_p$ **do**
      $N_q \leftarrow N_q - 1$
      if $N_q = 0$ **then**
        $q.rank \leftarrow i + 1$
        $Q \leftarrow Q \cup \{q\}$
      end if
    end for
  end for
  $i \leftarrow i + 1$
  $F_i \leftarrow Q$
end while

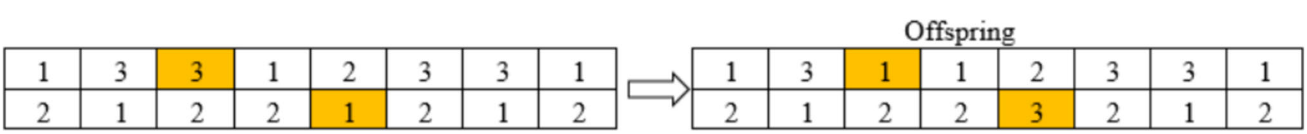

Fig. 3 The two-point mutation operator

Table 4 Parameters for genetic algorithm

Parameters	Value
Crossover probability (CP)	0.8
Mutation probability (MP)	0.2
Population size	200

designed to contain 11 columns, representing the total number of sub-tasks across all tasks. This encoding aggregates the sub-tasks into a single structure, enabling the representation of both city assignments and logistics services for each sub-task. The detailed breakdown of this chromosome structure is visually depicted in Fig. 1.

As evident from this solution vector, the first sub-task of Task 1 is completed in City 1, the second sub-task of Task 1 is completed in City 2, and similarly, the fourth sub-task of Task 3 is completed in City 1. Notably, since the first and second sub-tasks of Task 1 are carried out in different cities, Logistics Service 1 is utilized, as specified in the second row of the solution vector and indicated in the first column. This chromosome structure efficiently encodes all necessary information, enabling straightforward calculation of both the decision variables and the objective function.

Evaluation Function

In this study, we employed the penalty function technique to enforce solution limitations. This method ensures that answers failing to meet one or more categories of constraints are penalized, thereby encouraging the algorithm to prioritize feasible solutions. Specifically, when an answer violates the upper or lower limits of a constraint, a penalty is added to the objective function in minimization problems. This mechanism helps eliminate such solutions in subsequent iterations of the algorithm.

The penalty function technique utilizes both fixed and variable penalties to restrict solutions. Fixed penalties are applied uniformly, independent of the extent of constraint violation, while variable penalties are calculated based on the magnitude of the violation. If a solution vector cannot be found-irrespective of the degree of violation-both fixed and variable penalties are added to the objective function. Let PE represent the penalty for infeasible solutions, which can be

Table 5 Parameters for NSGA-II

Parameters	Value
Crossover probability (CP)	0.9
Mutation probability (MP)	0.2
Population size	100

Table 6 Task operation sequence

Operation	Task1	Task2	Task3	Task4	Task5	Sub-Task
1	✓		✓		✓	1
2	✓			✓		2
3		✓		✓		3
4	✓		✓	✓	✓	4
5	✓				✓	5
6	✓		✓			6
7		✓			✓	7
8	✓		✓	✓	✓	8
9	✓			✓	✓	9
10	✓		✓	✓	✓	10

calculated using Eq. 11:

$$PE = max(0, \sum_{m} \sum_{k} \sum_{i} t_{ikm} \cdot \gamma_{ikm} - cap_m) \qquad (11)$$

For a minimization objective function, the fitness value of the solution chromosomes is determined using Eq. 12:

$$B_i^j = \begin{cases} Z_i^j & \text{if } PE = 0 \\ Z_i^j + FixP + PE \cdot VarP & \text{if } PE > 0 \end{cases} \qquad (12)$$

where B_i^j is the fitting value of the i-th chromosome in the j-th objective function, Z_i^j is the objective value, and FixP and VarP are the fixed and variable penalties.

Selection

Selection is based on two elements:

- Populations are selected in lower ranks.
- Calculation of crowding distance: assuming p and q are members of the same rank, the member with a greater crowding distance is selected. It should be mentioned that the priority of selection is based first on rank and then on congestion distance. It uses the crowding distance to obtain a more uniform solution front than other algorithms and estimate the density of points around the solutions. It should be mentioned that the crowding distance is a factor that is used to better choose the answers

Table 7 GHG emission factor and logistic cost for each logistic service

Logistic service	GHG emission factor	Logistic cost
1	4	0.04
2	3	0.05
3	6	0.06

Table 8 Distance between cities

Distance	Berlin	Hamburg	Munich	Hannover	Frankfurt	Stuttgart	Dusseldorf	Dresden	Bremen	Erfurt
Berlin	0	28.9	58.4	28.6	54.5	63.2	57.2	19.3	39.4	30.1
Hamburg	28.9	0	79.1	15.9	49.2	65.4	40.1	47.6	12.6	39.2
Munich	58.4	79.1	0	65.9	39.2	23.2	61.2	46.1	76.7	39.6
Hannover	28.6	15.9	65.9	0	35.0	51.2	29.2	36.6	12.7	25.0
Frankfurt	54.5	49.2	39.2	35.0	0	21.0	23.2	46.6	47.4	26.2
Stuttgart	63.2	65.4	23.2	51.2	21.0	0	40.7	50.9	63.2	33.9
Dusseldorf	57.2	40.1	61.2	29.2	23.2	40.7	0	58.3	29.2	41.3
Dresden	19.3	47.6	46.1	36.6	46.6	50.9	58.3	0	47.3	21.5
Bremen	39.4	12.6	76.7	12.7	47.4	63.2	29.2	47.3	0	36.3
Erfurt	30.1	39.2	39.6	25.0	26.2	33.9	41.3	21.5	36.3	0

Table 9 Operation time in each city

Time	Berlin	Hamburg	Munich	Hannover	Frankfurt	Stuttgart	Dusseldorf	Dresden	Bremen	Erfurt
Operation 1	7.3	6.3	5.5	3.4	INF	6.2	INF	6.7	6.3	5.4
Operation 2	INF	5.6	6.9	5.6	5.3	7.8	7.5	3.2	INF	3.7
Operation 3	6.6	6.0	INF	5.9	5.3	6.4	6.0	3.7	6.8	7.2
Operation 4	7.9	INF	5.9	6.2	3.2	INF	7.6	7.8	8.0	5.6
Operation 5	7.1	3.4	5.5	INF	6.2	5.2	7.4	5.5	6.8	INF
Operation 6	2.9	INF	5.8	INF	6.8	6.2	7.3	5.4	6.1	7.1
Operation 7	5.0	7.6	INF	3.6	5.5	5.7	INF	6.7	INF	7.1
Operation 8	INF	7.7	3.3	5.9	INF	6.0	7.6	6.6	6.5	6.2
Operation 9	INF	7.1	6.0	INF	5.8	3.1	3.2	INF	6.8	5.7
Operation 10	5.1	INF	6.7	7.7	6.8	7.2	INF	7.9	2.9	5.3

Table 10 Operation cost in each city (per hour)

Cost	Berlin	Hamburg	Munich	Hannover	Frankfurt	Stuttgart	Dusseldorf	Dresden	Bremen	Erfurt
Operation 1	0.42	0.58	0.33	0.49	INF	0.69	INF	0.73	0.86	0.42
Operation 2	INF	0.39	0.80	0.52	0.72	0.54	0.37	0.30	INF	0.35
Operation 3	0.47	0.46	INF	0.55	0.64	0.82	0.88	0.32	0.45	0.48
Operation 4	0.53	INF	0.71	0.62	0.33	INF	0.73	0.66	0.32	0.80
Operation 5	0.39	0.33	0.58	INF	0.87	0.70	0.58	0.40	0.60	INF
Operation 6	0.31	INF	0.43	INF	0.59	0.65	0.75	0.69	0.61	0.32
Operation 7	0.53	0.39	INF	0.29	0.61	0.87	INF	0.65	INF	0.78
Operation 8	INF	0.40	0.28	0.69	INF	0.82	0.90	0.70	0.81	0.30
Operation 9	INF	0.45	0.37	INF	0.41	0.27	0.30	INF	0.44	0.32
Operation 10	0.69	INF	0.77	0.64	0.52	0.57	INF	0.60	0.33	0.75

in terms of spreading on one front and is defined as follows: For the beginning and end points of a front, its value is assumed to be infinite. For other points of the front, from 2 to 1-k is defined as the following relationship: $CD[i] = f_{i+1}^m - f_{i-1}^m / f_{max}^m - f_{min}^m$ where CD[i] is the distance from the solution i on the front F, and the value of the objective function of this solution in the front F is the minimum value and the maximum value of the objective function m in the front F, respectively. A better answer is the one that has a greater crowding distance.

NSGA-II Operators

Crossover

In NSGA-II, the crossover operator is the most critical search mechanism. To generate offspring, we employ a two-point crossover technique, wherein the middle section of two parent chromosomes is exchanged. The detailed process is illustrated in Fig. 2.

Mutation

The mutation operator is the second key operator utilized in the NSGA-II algorithm. Its primary role is to explore unexplored regions of the solution space and enhance the diversity of solutions. In this operator, a subset of parent chromosomes is randomly selected with equal probability, and some of their genes are modified. It is important to note that the mutation operator can sometimes improve the quality of a solution and, at other times, deteriorate it. Various methods for implementing mutation exist in the literature, each tailored to the specific problem at hand.

In this study, one or more elements of the chromosome are randomly chosen, and the values of the selected genes are replaced with new values from the allowed range. Figure 3 illustrates an example of how a mutation is applied to a chromosome.

It is widely recognized that the selection of algorithm parameters plays a critical role in determining its performance. The choice of these parameters directly influences the balance between exploration and exploitation within the algorithm, making it essential to select them empirically. The optimal parameters for the genetic algorithm and NSGA-II, as determined in this research, are presented in Tables 4 and 5.

Table 11 Carbon emission parameter in each production unit

Production units	GHG emission factor	Productivity rate	Production capacity
Berlin	4	1	100
Homburg	3	1	100
Munich	6	1	100
Hannover	3	1	100
Frankfurt	2	1	100
Stuttgart	6	1	100
Dusseldorf	2	1	100
Dresden	1	1	100
Bremen	5	1	100
Erfurt	9	1	100

Table 12 Pareto front solutions for simple example

Solution ID	Total operation cost	Total carbon emission (in Kg)
1	75.46	1631.50
2	80.05	1484.77
3	82.24	1413.28
4	85.20	1296.82
5	86.59	1224.32
6	88.54	1202.16
7	88.85	1169.07
8	90.49	1121.22
9	91.13	1059.24
10	94.58	1032.94
11	97.15	953.743
12	99.71	912.058
13	105.1	830.480
14	116.8	601.062
15	122.0	554.476

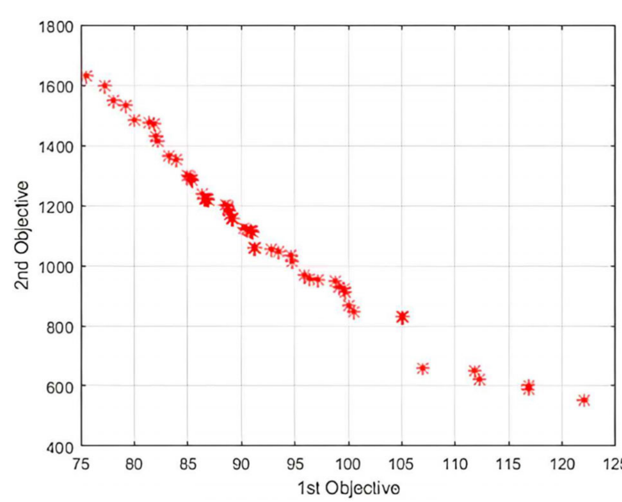

Fig. 4 True Pareto front for simple example after 52 optimization trials

Table 13 Logistics services used in Solution ID 1

k	1	2	3	4	5
i	2, 4, 5, 6, 8, 9	1, 4, 6, 7, 9	1, 4, 5, 6, 7, 8	1, 3, 4, 8, 9	1, 2, 4, 5, 6, 7, 8, 9
i'	4, 5, 6, 8, 9, 10	3, 6, 7, 9, 10	4, 5, 6, 7, 8, 10	2, 4, 8, 9, 10	2, 3, 5, 6, 7, 8, 9, 10
j	3, 2, 1, 2, 2, 3	1, 2, 2, 2, 1	1, 1, 1, 1, 1, 1	3, 2, 1, 2, 3	1, 1, 1, 1, 2, 1, 2, 3
m	10, 5, 2, 1, 10, 7	4, 9, 1, 4, 10	4, 9, 2, 1, 4, 10	10, 8, 5, 10, 7	4, 10, 9, 2, 1, 4, 10, 7
m'	5, 2, 1, 10, 7, 9	9, 1, 4, 10, 9	9, 2, 1, 4, 10, 9	8, 5, 10, 7, 9	10, 9, 2, 1, 4, 10, 7, 9

Results

Simple Example

In this section, the problem is solved using the model developed in the previous chapter, incorporating Eqs. 1 through 9 and the hybrid NSGA-II algorithm. The solution process is implemented in MATLAB on a machine equipped with an AMD A4-3300 CPU (1.9 GHz), Windows 10 64-bit operating system, integrated 1.9 GHz graphics, and 4 GB of RAM.

In the example provided, the cloud production system is hosted in Germany, with each production company situated in a different city within the country. Completing the tasks submitted to the cloud production system involves various activities that need to be carefully planned and scheduled by the firms. The details of five jobs submitted to the system, along with the sequence of operations required to complete them, are outlined in Table 6.

It is also assumed that three logistics services are available for the transfer of semi-finished products between cities. Table 7 displays their carbon emission factor and transportation cost per kilometer.

The transportation cost between cities is calculated by multiplying the cost per kilometer for each logistical service unit by the distance between the cities. Table 8 provides detailed information on the distances between the cities.

The production cost is determined by multiplying the time required to complete an operation by the cost per unit of time. Tables 9 and 10 respectively present the time required for each procedure and the cost associated with performing each operation in each city.

The greenhouse gas (GHG) emission rate for each production unit per load is assumed to correspond to the values provided in Table 11.

Table 12 presents a trade-off analysis between the two objectives for a small-scale problem instance consisting of five tasks, ten sub-tasks, and ten cities. Each solution reflects unique vehicle routing configurations, leading to varying total operational costs and total fuel consumption, which in turn result in different levels of total emissions.

Figure 4 shows the true Pareto front for this simple example after 52 optimization trials.

Table 13 details the logistics services used in Solution ID 1, providing insight into the timetable of vehicle routes across the periods. In this scenario, economic cost is prioritized, and tasks are distributed to production centers in a manner that minimizes production and logistics costs. Since the logistics costs of the first service are lower than those of the other two services, fifteen tasks utilize the first service, ten use the second service, and five rely on the third logistics service.

Logistics Services in Solution ID 15: In Solution ID 15, the focus shifts to minimizing environmental costs, reflecting the decision-maker's priority in this scenario. To reduce carbon emissions, fewer logistics services are utilized across the supply chain network. Specifically, the second logistics service is used nine times, the first service is employed to transport semi-finished products to two destinations, and the third service is only used once. The optimal allocation of operations to production resources and their corresponding logistics services for Solution ID 15 is presented in Table 14.

Table 14 Logistics services used in Solution ID 15

k	1	2	3	4	5
i	1, 4, 8, 9	1, 4, 6, 8	8, 9, 6, 8	1, 4, 6	8, 9
i'	2, 5, 9, 10	3, 5, 7, 10	9, 10, 7, 9	3, 5, 7	9, 10
j	2, 2, 2, 2	1, 2, 1, 2	2, 3, 2, 2	1, 1, 1, 1	2, 2, 3, 1
m	4, 5, 8, 7	4, 4, 9, 4	8, 7, 8, 4	9, 4, 10, 7	9, 7, 4, 8
m'	5, 8, 7, 5	5, 9, 4, 9	7, 9, 7, 5	4, 10, 9, 7	5, 9, 10, 4

Simple Example: Sensitivity Analysis

To evaluate the efficacy of the proposed NSGA-II algorithm, the results of the first example are compared with those of a second example. In the second example, the production rate, production capacity (Table 15), and carbon emission factors for each logistics service (Table 16) are varied. This compar-

Table 15 GHG emission factor and logistic cost for each logistic service

Logistic service	GHG emission factor	Logistic cost
1	4	0.04
2	6	0.05
3	2	0.06

ison highlights the algorithm's effectiveness in adapting to different problem scenarios and constraints.

Each manufacturing center's productivity rate and output capacity are determined using random numbers within specified ranges: productivity rates are randomly generated between 0 and 1, while output capacities are randomly generated between 70 and 100.

To generate the Pareto front, a total of 63 test trials were conducted for each scenario. The results of these trials are summarized in Table 17 and visually represented in Fig. 5, demonstrating the trade-offs between the objectives under different parameter configurations.

Figure 5 shows the true Pareto front after 63 optimization trials.

In each example, the number of logistical services can be analyzed and compared. In Solution ID 1 (Table 18), where production and logistic costs are prioritized over environmental concerns, sub-tasks are assigned to the production centers and logistics services that are the most cost-effective and efficient. Conversely, in Solution ID 12 (Table 19), tasks are allocated to minimize environmental impact. As a result, the third logistics service, which produces the least pollution, is utilized more frequently.

In Solution ID 1, the focus is on minimizing operation and logistics costs. Tasks are allocated in a way that prioritizes economic efficiency, with no restrictions on the number of logistical services used. In contrast, Solution ID 12 emphasizes reducing carbon emissions. To achieve this, the third logistics service, which has the lowest greenhouse gas emission rate, is utilized more frequently than the others.

More Complex Example

In this implementation, the data used for the problem is consistent with the previous dataset presented in the "Simple Example" section. However, the primary distinction is that the number of tasks and sub-tasks has been significantly increased to provide a more complex and realistic problem instance. This adjustment allows for a deeper analysis of sequencing operations and the corresponding impact on overall efficiency.

Table 20 presents the structure of each task in this updated problem instance. Each row in the table represents a sub-task, while the columns indicate whether a particular sub-task is included in a specific task. The checkmarks in the table signify the presence of a sub-task within a task, illustrating the diverse nature of task structures and their dependencies. This expanded configuration leads to a more intricate decision-making process when optimizing the scheduling and sequencing of operations.

To evaluate the effectiveness of the proposed solution, a Pareto front analysis was conducted, considering two conflicting objectives: total operation cost and total carbon emissions. The results, summarized in Table 21, highlight a range

Table 16 Carbon emission parameter in each production unit

Production units	GHG emission factor	Productivity rate	Production capacity
Berlin	4	0.67	88
Homburg	3	0.81	67
Munich	6	0.71	55
Hannover	3	0.49	83
Frankfurt	2	0.41	69
Stuttgart	6	0.79	65
Dusseldorf	2	0.60	54
Dresden	1	0.55	72
Bremen	5	0.43	72
Erfurt	9	0.91	62

Table 17 Part of Pareto front solutions for simple example with different parameters

Solution ID	Total operation cost	Total carbon emission (in Kg)
1	178.3	965.603
2	188.0	902.903
3	205.1	865.155
4	213.1	808.090
5	220.1	766.805
6	230.3	720.380
7	235.1	690.995
8	238.4	681.962
9	244.1	670.375
10	247.4	600.595
11	256.9	594.473
12	265.3	588.650

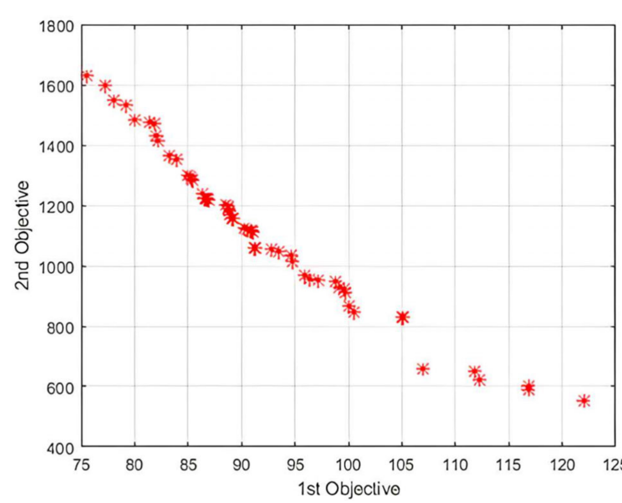

Fig. 5 True Pareto front after 63 optimization trials

Table 18 Logistics services used in Solution ID 1

k	1	2	3	4	5
i	2, 4, 5, 6, 8, 9	1, 4, 7, 9	4, 5, 6, 8	1, 2, 3, 4, 9	1, 4, 5, 7, 8, 9
i'	4, 5, 6, 8, 9, 10	3, 6, 9, 10	5, 6, 7, 10	2, 3, 4, 8, 10	2, 5, 6, 8, 9, 10
j	2, 2, 3	1, 2, 3	3, 3, 3	3, 3, 3	3, 3, 3
m	8, 5, 2, 1, 10, 6	4, 5, 8	7, 8, 2, 1	4, 4, 10, 8	5, 6, 4, 5, 2, 1, 3, 6
m'	5, 2, 1, 10, 6, 9	5, 8, 7, 9	2, 1, 4, 9	10, 8, 5, 6, 9	5, 2, 1, 3, 6, 5

Table 19 Logistics services used in Solution ID 12

k	1	2	3	4	5
i	4, 9, 1, 4, 7, 9	4, 5, 6, 8	1, 3, 8	1, 7, 8, 9	
i'	5, 10, 3, 6, 9, 10	5, 6, 7, 10	2, 4, 9	2, 8, 9, 10	
j	3, 3, 3	3, 3, 3	3, 3, 3	3, 3, 3	
m	8, 7, 4, 5, 8, 7	8, 2, 1	4, 8, 2	4, 4, 5, 8, 7	
m'	7, 8, 5, 8, 7, 5	2, 1, 4	9, 2, 4, 5	5, 8, 7, 5	

Table 20 Sequencing tasks operations with increasing number of tasks and sub-tasks

Sub-task	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10
1	✓	✓	✓	✓	✓	✓	✓			
2	✓		✓	✓	✓		✓	✓	✓	✓
3		✓	✓	✓	✓	✓		✓	✓	
4	✓	✓		✓	✓	✓		✓	✓	✓
5	✓		✓	✓	✓		✓	✓	✓	
6	✓	✓	✓		✓	✓	✓		✓	✓
7		✓		✓		✓	✓	✓		
8	✓		✓	✓	✓	✓	✓	✓	✓	✓
9	✓	✓		✓	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓			✓	✓
11	✓	✓	✓	✓		✓	✓	✓	✓	✓
12		✓		✓	✓		✓		✓	
13	✓		✓		✓	✓		✓	✓	
14		✓				✓				
15		✓	✓	✓			✓	✓		

of solutions that balance these two criteria. The first few solutions exhibit lower operational costs but higher emissions, while the later solutions prioritize environmental sustainability at the expense of increased costs. These trade-offs provide insights into potential strategies for decision-makers based on their preferences and constraints.

As it is clear from Table 22, with the increase in the number of operations, the policy of sharing logistics services as well as selecting the greener logistic service has been maintained.

Furthermore, Table 22 compares the number of logistic services used in two extreme solutions-Solution ID 1 (low-cost oriented) and Solution ID 14 (environmentally friendly). As observed, Solution ID 14 employs a smaller number of logistics services, reflecting an emphasis on sustainability through the consolidation of operations and the selection of greener transportation options. This comparison demonstrates that even as the complexity of the problem increases, the policy of optimizing logistics services remains crucial in achieving a balanced trade-off between cost and environmental impact.

By incorporating a larger set of tasks and sub-tasks, this implementation provides a more comprehensive scenario for analyzing sequencing operations and logistics optimization, contributing to more effective and sustainable decision-making strategies in real-world applications.

Conclusion

Cloud manufacturing connects distant resources and enables multiple service seekers to submit requests to a cloud platform simultaneously via the Internet. Its customers, suppliers, manufacturers, distributors, and retailers benefit from enhanced collaboration and resource sharing; however, effective service composition remains a challenge. Increasing ethical awareness has also led consumers to favor companies that actively regulate their supply chain's environmental and social impacts.

Table 21 Pareto front solutions for complex example

Solution ID	Total operation cost	Total carbon emission (in Kg)
1	378.5	4731.26
2	409.3	4115.61
3	437.6	3908.11
4	449.9	3839.67
5	462.5	3734.12
6	481.5	3704.00
7	494.7	3497.50
8	522.6	3356.34
9	22836	3196.85
10	45622	3103.65
11	69319	2930.00
12	13858	2845.29
13	28974	2782.54
14	41641	2755.35

Table 22 Comparison of the number of logistic services in two solutions

	Solution ID 1	Solution ID 14
Total number of j_1	28	19
Total number of j_2	21	11
Total number of j_3	24	24
Total number of logistic services	73	55

This paper integrates two critical problems in manufacturing: production routing and pollution routing. A multi-objective approach has been developed to balance conflicting goals—minimizing overall operational costs (including production and logistics) and minimizing fuel consumption, which directly impacts total carbon emissions. Due to the combinatorial complexity of the problem, the NSGA-II algorithm has been employed to generate a set of Pareto-efficient solutions.

Extensive numerical experiments were conducted on instances of varying sizes, ranging from five tasks with ten sub-tasks to ten tasks with fifteen sub-tasks, each following distinct sequencing orders and distributed across multiple locations in Germany. The results demonstrate that the proposed approach effectively identifies trade-offs between operational costs and carbon emissions, enabling decision-makers to adopt solutions that align with their strategic priorities. The Pareto front obtained from the NSGA-II method highlights the diverse range of feasible solutions, providing valuable insights for decision-making in cloud manufacturing.

An interesting direction for future research is the validation of the proposed model using real-world data from industrial applications. While the current study relies on synthetic data to analyze trade-offs between cost and emissions, future studies could leverage actual production and logistics data to assess the model's practicality. Furthermore, integrating dynamic demand patterns, uncertainty factors, or real-time optimization techniques could enhance the adaptability of the model. The incorporation of machine learning techniques for predictive decision-making and adaptive strategies in cloud manufacturing environments also presents a promising avenue for further exploration.

Author Contribution **Masoumeh Akhavan Hariri:** investigation, data curation, writing—original draft, editing, visualization.
Shokraneh Khashkhashimoghadam: review and editing, methodology, formal analysis, supervision.
Omid Fatahi Valilai: review and editing, methodology, formal analysis, conceptualization, supervision, project administration.

Availability of Data and Material The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of Interest The authors declare no competing interests.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process The authors confirm that they have not used generative AI or AI-assisted technology.

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