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Circular closed-loop supply chain network design considering 3D printing and PET bottle waste

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Abstract
One of the most critical pillars of Industry 4.0 (I4.0) is Additive Manufacturing (AM) or 3D Printing technology. This transformative technology has garnered substantial attention due to its capacity to streamline processes, save time, and enhance product quality. Simultaneously, environmental concerns are mounting, with the growing accumulation of plastic bottle waste, offering a potential source of recycled material for 3D printing. To thoroughly harness the potential of AM and address the challenge of plastic bottle waste, a robust supply chain network is essential. Such a network not only facilitates the reintegration of plastic bottle waste and 3D printing byproducts into the value chain but also delivers significant environmental, social, and economic benefits, aligning with the tenets of sustainable development and circular economy. To tackle this complex challenge, a Mixed-Integer Linear Programming (MILP) mathematical model is offered to configure a Closed-Loop Supply Chain (CLSC) network with a strong emphasis on circularity. Environmental considerations are integral, and the primary objective is to minimize the overall cost of the network. Three well-known metaheuristics of Simulated Annealing (SA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are employed to treat the problem which are also efficiently adjusted by the Taguchi design technique. The efficacy of our solution methods is appraised across various problem instances. The findings reveal that the developed model, in conjunction with the fine-tuned metaheuristics, successfully optimizes the configuration of the desired circular CLSC network. In conclusion, this research represents a significant step toward the establishment of a circular supply chain that combines the strengths of 3D printing technology and the repurposing of plastic bottle waste. This innovative approach holds promise for not only reducing waste and enhancing sustainability but also fostering economic and social well-being.

Keywords Closed-loop supply chain network · Sustainable development · Circular economy · Additive manufacturing · PET bottle · Metaheuristic

1 Introduction

In the highly competitive environment of the industry and the rapid growth of technology, the use of Additive Manufacturing (AM) can provide many competitive advantages as one of the critical factors in Industry 4.0 (I4.0). Some of these advantages include

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enhanced production speed, ability to generate complicated structural models, reduced work in process (WIP), reduced waste, no need for mold, no need to store materials, shortened supply chain (make-to-order production), increased flexibility to adapt to customer needs (customized demand) and reduce uncertainty (Ford & Despeisse, 2016; Khorram Niaki & Nonino, 2017; Kleer & Piller, 2019; Majeed et al., 2021). Therefore, AM not only provides lean manufacturing frameworks to the companies but also significantly impacts the supply chain (Chan et al., 2018).

AM has received considerable critical attention. More than 200 companies in various eras applied 3D printing technologies, such as Lima Corporate (medical), Launcher, ESA's ArianeGroup (space), BMW, Audi, Volkswagen (automotive), Norsk Titanium, Boeing, Rolls Royce, and Boom Supersonic (aerospace), Specialized and Fizik (sports), UK trains and Mobility goes Additive (railway), US Army, the US Navy, the US Air Force, the Russian Army, and the Spanish Navy (defense), Wilhelmsen, Thyssenkrupp and Navantia (maritime). Hence, AM holds significant promise for application across diverse industries, including both military and humanitarian missions (den Boer et al., 2020), foundry industries (Ngo et al., 2018), buildings (Li et al., 2020), electrochemical industry (Hashemi et al., 2020), healthcare (Bose et al., 2018; Ghomi et al., 2021), fashion (McCormick et al., 2020), aerospace (Fasel et al., 2020), education (Assante et al., 2020), jewelry (Martinelli, 2018).

According to the Senvol database, in 2020, 2246 different materials could be used in AM, and this number is growing. Among all types of materials, polymers have the largest share of use (cf. Table 1). According to the Additive Manufacturing Landscape 2020 report, over 80 percent of companies use polymers in 3D printing (Akinsowon & Nahirna, 2020). Therefore, the supply process and cost of raw materials must be investigated. For example, the US military uses plastic waste and PET bottles as raw materials to diminish cost and environmental impact (Fey, 2017).

Global production rates of plastic waste are rising sharply. In 2018, the total generated plastic waste in the US was 35.68 million tons. Figure 1 represents that in managing collected plastic waste in the US in 2018, among three common waste disposal methods, recycling, combusting with energy recovery, and landfilling, landfilled waste has the largest share, while we face the problem of limited land (U.S. Environmental Protection Agency, 2020).

The global plastic waste crisis is dire, with 400 million metric tons produced annually. 10 million tons end up in the oceans. Figure 2 shows the magnitude of global plastic production, while Fig. 3 illustrates the extent of plastic waste generation on a global scale. China leads in plastic production, but the U.S. tops in annual plastic waste at 42 million tons. Shockingly, 50 billion plastic water bottles are sold in the U.S. each year, and only 18% of plastic is recycled on average. India has the highest plastic recycling rate at 60%.

Table 1 Different types of materials used for AM (Wohlers et al., 2020)

Material	2017	2018	2019	2020
Wax	20	16	16	17
Sand	9	5	5	5
Polymer	385	524	802	1095
Metal	392	523	796	904
Composite	64	112	144	191
Ceramic	14	24	29	34
Total	884	1204	1792	2246

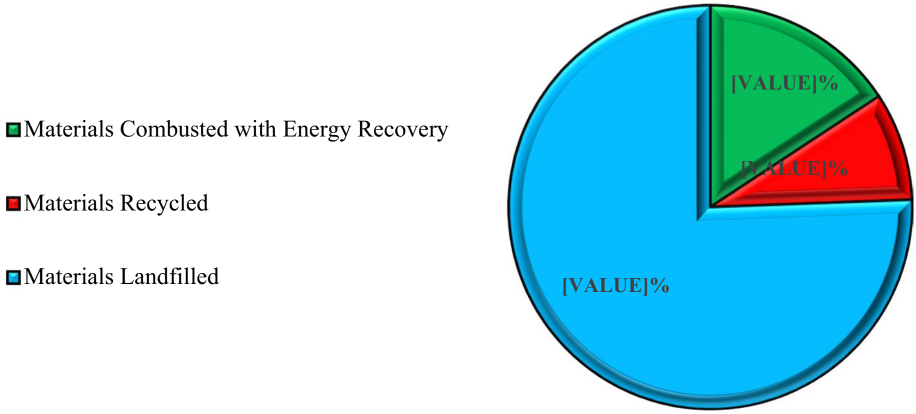

Fig. 1 Waste management in the US in 2018

Our oceans currently hold 5.25 trillion pieces of plastic. A 2016 assessment ranked the U.S., India, and China as the top three global plastic waste producers. Per capita, the U.S. remains a significant contributor, although some studies rate China as the largest overall producer. Other countries in the top ten include Brazil, Indonesia, Russia, Germany, and the UK. Individual lifestyle changes worldwide can help combat this pollution crisis. In 2018, the U.S. generated 130 kg of plastic waste per person, showing a slowing increase in the past three years. The challenge is to shift from slowing waste growth to reducing it.

Figure 4 represents the plastic recycling rate. India leads the world with an impressive 60% plastic recycling rate, demonstrating a significant commitment to sustainable waste

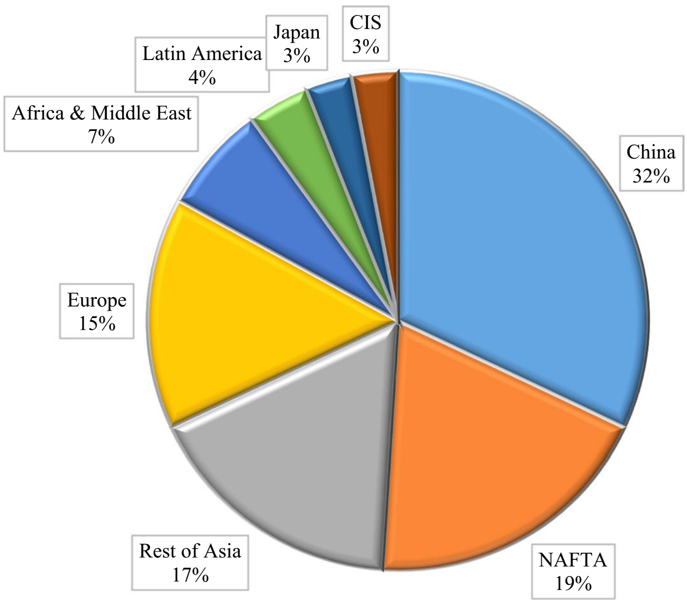

Fig. 2 Plastic production (https://theroundup.org/)

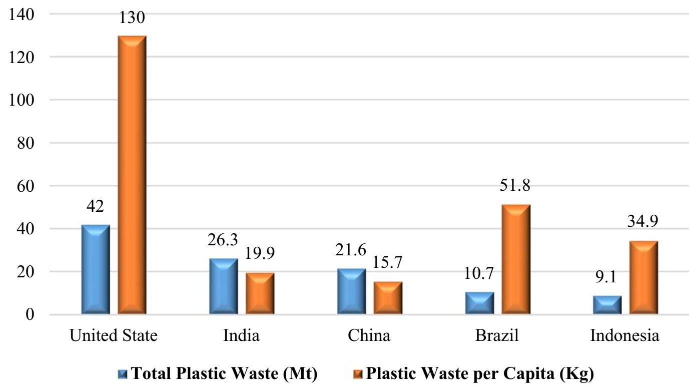

Fig. 3 Plastic waste generation (https://theroundup.org/)

management. Following closely behind are South Africa, the Netherlands, South Korea, Norway, and Spain, each making commendable efforts in plastic recycling. South Korea, in particular, is working towards raising its rate to 70% by 2030, further exemplifying dedication to the cause. In stark contrast, the global average plastic recycling rate lags significantly at a mere 18%, underscoring the importance of widespread improvement in recycling practices worldwide.

Some of these materials, such as polymers, can be recycled or reused if collected and delivered to reclaimers. As shown in Fig. 5, the collected PET bottles in the US waste is less than half of the total generated plastic waste, and the rest is released into the environment and ocean (Aslani et al., 2021). Furthermore, These material is made of fossil fuels that emit greenhouse gases when exposed to sunlight, so they have many destructive effects on ocean ecosystems, marine species, and the environment. By 2030, the emitted CO2 from these materials will be approximately over 296 five-hundred-megawatt coal plants (1.34 gigatons per year). In this regard, It is vital to improve ongoing waste management methods (Hamilton et al., 2019).

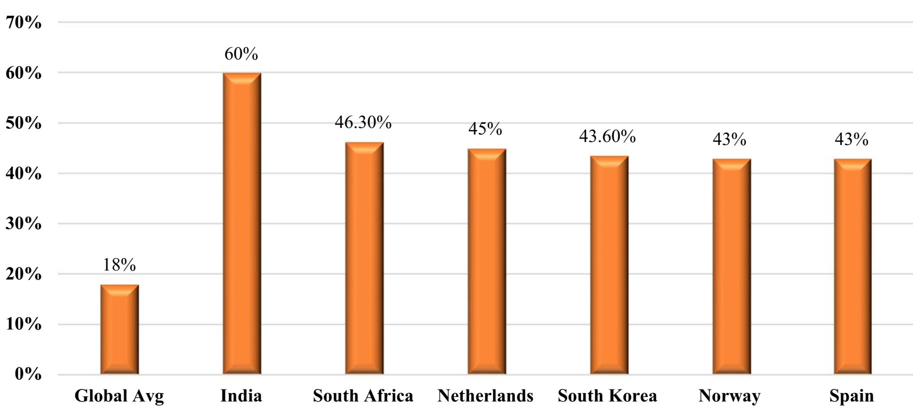

Fig. 4 Plastic recycling rate (https://theroundup.org/)

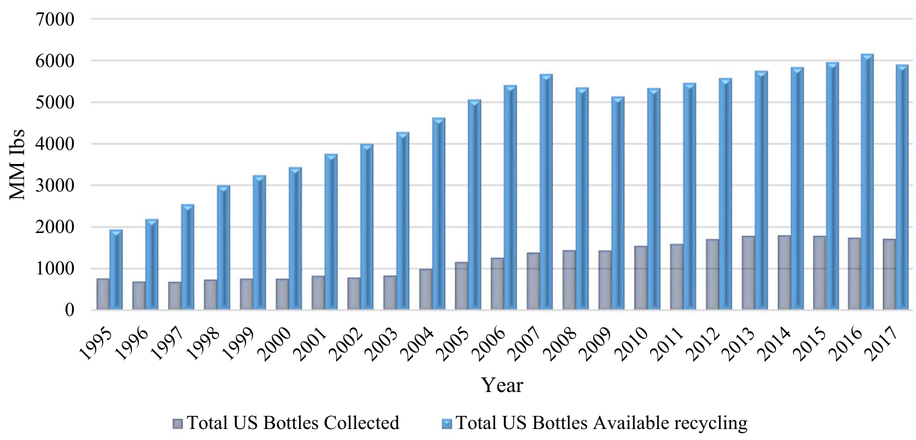

Fig. 5 Generated and collected Pet bottles in the US (1995–2017)

The key elements, emphasizing the urgency and global impact of the challenges are given as follows:

I. *Rising Global Adoption of AM*

The global adoption of AM has witnessed an unprecedented surge, with more than 200 companies across diverse industries integrating 3D printing technologies into their operations. In 2020 alone, 1095 different polymers were utilized in AM processes, accounting for a substantial portion of the total materials used (Wohlers et al., 2020). This widespread acceptance reflects the transformative impact of AM on manufacturing processes.

II. *Environmental Impact of Plastic Waste*

The plastic waste crisis has reached alarming proportions, with an annual production of 400 million metric tons globally. This crisis is vividly illustrated in Fig. 2, showcasing the magnitude of plastic production. Despite the staggering numbers, only 18% of plastic is recycled on average, contributing to environmental pollution and degradation. The severity of the issue is further highlighted by the fact that oceans currently hold 5.25 trillion pieces of plastic (see Fig. 3).

III. *Recycling Rates and Sustainability Efforts*

Figure 4 presents a snapshot of global plastic recycling rates, emphasizing India's remarkable leadership with a 60% recycling rate. Countries such as South Africa, the Netherlands, South Korea, Norway, and Spain are making commendable efforts to enhance plastic recycling. However, the global average recycling rate remains low at 18%, underscoring the need for substantial improvements in recycling practices worldwide.

IV. *PET Bottle Waste and Environmental Impact*

The environmental impact of PET bottle waste is substantial, with Fig. 5 revealing that collected PET bottles in the US represent less than half of the total generated plastic waste. This incomplete collection leads to adverse effects on ocean ecosystems, marine species, and the environment. The projected CO_2 emissions from these materials by 2030 further highlight the urgency to improve waste management practices.

There has been a growing concentration on configuring a Closed-Loop Supply Chain (CLSC) in recent years. Using reverse flows, recyclable, repairable, or reusable materials can return to the value cycle at the end of their life. In addition, designing a CLSC provides sustainable advantages and creates a circular environment (Ali et al., 2023; Sazvar et al., 2022). This network can be designed for plastic waste such as PET bottles or 3D printing waste. Consequently, it reduces the environmental impact and creates job opportunities and economic benefits. According to the American Chemistry Council report in 2019, 600 advanced recycling facilities provide 38,500 jobs (American Chemistry Council Economics and Statistics, 2019). Besides these social benefits, some polymeric materials, such as PET bottles, can be used instead of raw polymeric materials. Due to the high price of these polymers, recycled PET bottles could provide economic benefits (Mikula et al., 2021). In this regard, designing an appropriate CLSC positively impacts waste management. Ottosson and Oweini (2023) contributed to the circular economy discourse by proposing a CLSC for reusable plastic products. Aligned with EU directives on phasing out single-use plastics, their study provided a circular business model (CBM) involving collaboration, reusable product design, and implementation calculations. This research finally offered practical insights for businesses seeking sustainable alternatives to single-use plastics. Chowdary and Rayside (2024) explored circular economy strategies in beverage manufacturing, using discrete event simulation modeling. Their research pinpointed recycling PET bottles into 3D printing filament as the most economically efficient method, making a meaningful contribution to reducing plastic waste and fostering environmental sustainability.

The lack of an efficient supply chain for PET bottles and waste from 3D printing centers (waste of post-processing) and customers (prototyping, R and D processes, education, etc.) led us to develop a circular CLSC which is used to collect, sell and recycle these wastes as an important part of the circular economy. Accordingly, a novel optimization model is built up to formulate the problem which is then evaluated in terms of applicability and validity using metaheuristic solution algorithms.

The rest of this work is structured in the following way. The literature review of related works in this area is provided in Sect. 2. Moreover, Sect. 3, explains the problem statement and the proposed mathematical model. Section 4 is concerned with the optimization methods used for this study. Furthermore, to evaluate proposed solution approaches, computational results are analyzed in Sect. 5, and at the end, Sect. 6 summarizes the research and offers directions for further study.

2 Literature survey

In this section, the literature concerning CLSCs and sustainable supply chains is evaluated, especially those examining the possibility of converting PET bottles and plastic waste to 3D printing filament.

2.1 CLSC network design

There is a reverse follow in the CLSC for recycling, disassembling, reusing, and integrating environmental remarks into the conventional design of supply chains (Ghayebloo et al., 2015). Therefore, it can be applied to many products, such as gold, to collect and use again, which was investigated by Zohal and Soleimani (2016). They designed a CLSC and paid attention to CO_2 emissions as an environmental impact. Shokouhyar and Aalirezaei (2017) considered social, environmental, and economic effects. They proposed a reverse logistic network for waste electrical material. Therefore, they offered a MILP to control the influence of hazardous materials on both human health and environment. In their work, Metaheuristics are employed as a solution approach. In the same way, Rentizelas et al. (2018) introduced a supply chain network that minimizes the total cost of recycling plastic waste. Their proposed model was validated with a confirmed case of agricultural plastic waste in Scotland.

As mentioned, a substantial and expanding body of literature has explored recycling networks. Arampantzi and Minis (2017) investigated a sustainable supply chain design problem to minimize the cost (investment, operational, and emissions costs) and the environmental effects (greenhouse gas emissions and waste generation) along with the public consequences (employment situations and social community progress). Overall, these studies highlight the need for designing an appropriate supply chain to add social and environmental aspects to traditional models. Likewise, Sahebjamnia et al. (2018) suggested a supply chain for plastic waste but with different aspects and cases. They consider the sustainable part and design a sustainable tire CLSC. To solve their offered model they applied metaheuristics and hybrid metaheuristics models. According to Paydar and Olfati (2018), a reverse logistic (RL) can be designed to decrease recycling PET bottles costs. The four-level RL is solved by two metaheuristics and validated considering a real case.

Similarly, Accorsi et al. (2020) configured a CLSC network paying attention to reusable containers in the food industry and proposed a MILP model. Rezaei and Maihami (2020) explored a CLSC involving a manufacturer, retailer/remanufacturer, and a government-run collection center operating in primary and secondary markets. They focused on sustainability and emissions reduction in manufacturing, remanufacturing, and delivery. Game theory was used to address low-carbon customer preferences. Numerical analysis showed that reducing emissions positively affects profitability, particularly in remanufacturing. There are also many other similar studies in the literature addressing the CLSC design using different types of models and solution methods such as Abdolazimi et al. (2022), Sajadiyan et al. (2022), and Rajabi-Kafshgar et al. (2023).

Akbari-Kasgari et al. (2022) addressed the growing copper demand due to industrialization, emphasizing the need for sustainable copper supply chains. They suggested a unique network design that considers resilience, especially in earthquake-prone areas. Their research presented two models, one with backup suppliers and one without, aiming to optimize profit, minimize environmental impacts, and enhance social aspects. The results revealed that the model with backup suppliers improves supply chain responsiveness and economic and social performance but lags in environmental sustainability due to the environmental impact of backup suppliers. Momenitabar et al. (2022) investigated sustainable supply chains and offered a novel approach considering lateral transshipment along with backup suppliers in configuring a sustainable CLSC network. Their model aimed to minimize shortages, optimize costs, and enhance environmental performance while raising job opportunities. They tackled demand uncertainty and employed fuzzy robust optimization for efficient decision-making.

Shahidzadeh and Shokouhyar (2023) examined the role of reverse logistics in promoting the circular economy within supply chains, particularly focusing on consumer behavior's impact on sustainability. It expanded the concept of sustainability to include consumers, profitability, environmental concerns, and employee well-being. The research introduces an extended sustainability model and employs a unique linguistic interval-value hesitant fuzzy decision-making trial and evaluation laboratory (FDEMATEL) approach to examine the relationship between reverse logistics performance and sustainability.

Given all that has been mentioned so far, one gap is the lack of investigation at different levels after the treatment process. In these levels, industries with the potential of being reclaimers of these materials could be studied (see Tables 2 and 3).

2.2 Use of recycled PET bottles and plastic waste in 3D printing technology

In the last decades, 3D printing technology has attracted increasing attention, which is one of the critical factors in I4.0. As mentioned in the previous section, AM can benefit enterprises. Since most of the used materials in this technology are polymers, recycled plastic waste can be used, and consequently, costs and environmental impact will be reduced. Therefore, a number of research works have been performed to check the conditions of the required recycling process. These works are summarized in Table 4.

Lehrer and Scanlon (2017) examined the viability of extruding recyclable plastic into filament. to provide a sustainable and cost-effective method to satisfy the demand for 3D printing filament. They determined viscosity and melting temperature as vital influential factors. Since Polyethylene Terephthalate (PET) plastics have a high melting temperature, they do some modifications to access higher temperature extrusion. Moreover, the drying process influences shredded PET bottles. Moreover, viscosity is the most influential factor in the possibility of extruding filament. This study used a mix of cracked PET bottles with PETG pellets to improve viscosity. Exconde et al. (2019) stated that reusing and recycling plastic waste to produce filament could be an alternative to conserve energy and sustain the environment. Hence, they utilized a Multi-Criteria Decision-Making (MCDM) approach for materials selection. Recycled post-consumer plastics and virgin polymer resins for consumption in 3D printer filaments as possible choices.

From a logistics viewpoint, Santander et al. (2020) evaluated the economic and ecological feasibility of the distributed plastic recycling method. A Mixed-Integer Linear Programming (MILP) model was applied to assess a local CLSC network. The proposed model was elucidated through a case study involving a university aiming to execute a distributed recycling demonstrator. This initiative focused on recovering 3D printing wastes from secondary schools in France. According to the reviewed articles, there is a lack of an integrated supply chain that combines reverse logistics for collecting PET bottles and a CLSC of a 3D printing network.

PET polyethylene terephthalate, *PS* polystyrene, *P.P.* Polypropylene, *PLA* polylactic acid, *FPF* fused particle fabrication, *FDM* fused deposition modeling, *ABS* acrylonitrile butadiene styrene, *rPET* recycled polyethylene terephthalate

Table 2 Abbreviations

	Full names	Abbreviations
Solution technique	Ant Colony Optimization	ACO
	Benders Decomposition Algorithm	BDA
	Genetic Algorithm	GA
	Hybrid Genetic Algorithm	Pro-HGA
	ICA+TS	ICTS
	KA+GA	KAGA
	RDA+SA	H-RS
	RDA+WWO	H-RW
	WWO+GA	H-WG
	WWO+TS	H-WT
	Imperialist Competitive Algorithm	ICA
	Keshtel Algorithm	KA
	Multi-Objective Grey Wolf Optimization	MOGWO
	Multi-Objective Hybrid Harris Hawks Optimizer and Simulated Annealing	MOHHSA
	Non-dominated Sorting Genetic algorithm II	NSGA-II
	Particle Swarm Optimization	PSO
	Pareto Envelope-based Selection Algorithm II	PESA-II
	Red Deer Algorithm	RDA
	Simulated Annealing	SA
	Strength Pareto Evolutionary Algorithm II	SPEA-II
	Tabu Search	TS
	Water Wave Optimization	WWO
Decision-making technique	Fuzzy Decision-Making Trial and Evaluation Laboratory	DEMATEL
	Goal Programming	GP
Network	Closed-Loop Supply Chain	CLSC
	Reverse Logistic	RL
	Supply Chain	SC
Model	Integer Linear Programming	ILP
	Mixed-Integer Linear Programming	MILP
	Mixed-Integer Non-Linear Programming	MINLP
	Non-Linear Programming	NLP

2.3 Research gap

This research paper addresses the critical gap in the current body of literature by proposing a comprehensive and integrated MILP model to configure a circular CLSC network that optimally incorporates the recycling of plastic bottle waste and waste from 3D printing processes as 3D printing filament within an I4.0 context. This innovative model is designed to minimize overall costs while considering environmental, social, and economic objectives, reflecting the tenets of sustainable development and circular economy. Leveraging three prominent metaheuristics—SA, GA, and PSO—fine-tuned via the Taguchi design method, the study aims to provide practical solutions for configuring a CLSC that seamlessly

Table 3 Comparison between the most relevant SC and CLSC design studies and the current research

Model	Network	Case study	Objective		Solution method	Reference
			Multi/ Single	Description		
MILP	CLSC	–	Single	Total cost minimization	GAMS/CPLEX	Fareeduddin et al. (2015)
MILP	CLSC	–	Bi-	Total profit maximization, total greenness maximization	ε-constraint	Ghayebloo et al. (2015)
MILP	CLSC	Hospital equipment production	Single	Total benefit maximization	GA, PSO, hybrid PSO-GA, GAMS/CPLEX	Soleimani and Kannan, (2015)
ILP	CLSC	Gold industry	Multi-	Total benefit maximization, environmental impact minimization	ACO	Zohal and Soleimani (2016)
MILP	Sustainable RL	WEEE	Multi-	Total profit maximization, Social benefit maximization, environmental impact minimization	NSGA-II, Multi-objective GA	Shokouhyar and Aalirezaei (2017)
MILP	Sustainable SC	Refrigerator manufactures and supplies in Europe, Asia, and USA	Multi-	Economic cost minimization, Environmental cost minimization, social cost minimization	ε-constraint, GP	Arampantzi and Minis (2017)
MILP	CLSC	Oil refinement	Multi-	Total profit maximization, collection risk minimization	ε-constraint	Paydar et al., (2017)
MILP	SC	Recycling waste agricultural plastics	Single	Total cost minimziation	GAMS	Rentizelas et al. (2018)
MILP	CLSC	Tire	Multi-	Economic impact minimization, environmental impact minimization, social impact maximization	H-WG, H-RS, H-RW, H-WT, ε-constraint	Sahebjamnia et al. (2018)
MILP	RL	PET bottle RL network	Single	Total cost minimization	ICA, GA, LINGO	Paydar and Olfati (2018)
MINLP	Sustainable CLSC	Glass	Multi-	Total profit maximization, environmental impact minimization, social impact maximization	KA, RDA, GA, ICA, TS, SA, ICTS, H-RS, KAGA	Hajiaghaei-Keshteli and Fard (2019)

Table 3 (continued)

Model	Network	Case study	Objective		Solution method	Reference
			Multi/Single	Description		
MILP	CLSC	Wire and cable company	Multi-	Total cost minimization, environmental impact minimization	BDA, CPLEX	Mardan et al. (2019)
MILP	SSC	Cable supply chain	Bi-	Total profit maximization, social responsibility maximization	ε-constraint	Sherafati et al. (2019)
MILP	CLSC	–	Bi-	Total cost minimization, Responsiveness maximization	Augmented ε-constraint	Boronoos et al. (2019)
MILP	Sustainable CLSC	–	Multi-	Total cost minimization, Total CO_2 emission minimization, Social impact maximization	GA, HGA, Pro-HGA	Yun et al. (2020)
MILP	CLSC	Collecting end-of-life products	Single	Total amount of end-of-life products minimization	CPLEX	Medrano-Gómez et al. (2020)
MILP	CLSC	Retail food supply chain with reusable containers	Single	Total cost minimization	Branch and Bound	Accorsi et al. (2020)
MILP	CLSC	Manufacturer, retailer/remanufacturer, collection center	Single	Total profit maximization	Game theory-based approach	Rezaei and Maihami (2020)
NLP	CLSC	–	Bi-	Waiting time minimization, transportation time minimization	GA, CPLEX	Mohtashami et al. (2020)
MILP	CLSC	WEEE	Single	Total benefit maximization	CPLEX	Polat and Gungor (2021)
MILP	CLSC	Tire industry	Multi-	Total cost minimization, Total pollution minimization, Total job opportunity maximization	Fuzzy robust optimization approach	Momenitabar et al. (2022)
MILP	CLSC	Copper industry	Multi-	Total cost minimization, Total pollution minimization, Social utility maximization	Metaheuristics	Akbari-Kasgari et al. (2022)

Table 3 (continued)

Model	Network	Case study	Objective		Solution method	Reference
			Multi/ Single	Description		
MILP	CLSC	–	Single	Total cost minimization	SA, GA, ICA, KA, KASA, GASA, ICASA	Rajabi-Kafshgar et al. (2023)
MILP	CLSC	Electronics and automotive industry	Multi-	Total cost minimization, Total pollution minimization, Total job opportunity maximization	Fuzzy linguistic interval-value hesitant fuzzy DEMATEL	Shahidzadeh and Shokouhyar (2023)
MILP	CLSC	Soybean supply chain	Multi-	Total net profit maximization, Total CO_2 emission minimization, customer satisfaction maximization	MOGWO, MOHHSA	Gholian-Jouybari et al. (2023)
MILP	CLSC	Citrus supply chain	Multi-	Sustainability, Circularity Strategy	ε-constraint approach, SPEA-II, PESA-II	Goodarzian et al. (2023)
MILP	CLSC	–	Multi–	Environmental impact minimization, social equity maximization	New Indicators based on Gini Index	Battaïa et al. (2023)
MILP	Circular CLSC	–	Single	Total cost minimization	SA, GA, PSO	Our study

Table 4 Studies related to the feasibility of recycling PET plastic into filament

Reference	Recycled Material			Supply chain	Description
	PET	PLA and ABS	Others		
Lehrer and Scanlon (2017)	✓				Examining influential factors on the feasibility of extruding recyclable plastics into filaments were examined
Byiringiro and Mutiva (2018)	✓				Investigating recycled PET specification and extrusion parameters for 3D printing filament
Zander et al. (2019)	✓		✓		Studying bends of waste PET, PP, and PS as filaments for 3D printing
Exconde et al. (2019)	✓		✓		Using an MCDM approach for selecting plastic material for 3D printer filaments
Peeters et al. (2019)		✓			Offering academics and practitioners a more profound understanding of the challenges associated with recycling 3D printing waste in a decentralized manner
Little et al. (2020)	✓				Using an open-source toolchain to produce filament from PET bottle flake with FPF processing was evaluated
Oussai et al. (2020)	✓				Using the 'Next filament extruder' for the extrusion of shredded PET with three distinct diameters
Santander et al. (2020)		✓		✓	A CLSC to convert 3D printing waste to filament
Nur-A-Tomal et al. (2020)			✓		Carrying out an investigation into utilizing waste plastics such as plastic toys to produce filament
Mikula et al. (2021)	✓	✓	✓		A study on the possibility of reusing polymeric materials for 3D printing
Bakır et al. (2021)	✓				Studying the effect of FDM process parameters on the mechanical characteristics of 3D-printed parts made of rPET filaments

PET: Polyethylene terephthalate, PS: Polystyrene, P.P.: Polypropylene, PLA: Polylactic acid, FPF: Fused Particle Fabrication,FDM: Fused Deposition Modeling,ABS: Acrylonitrile butadiene styrene,rPET: Recycled polyethylene terephthalate integrates 3D printing technology with recycled materials. The gap addressed lies in the holistic approach to CLSC design within a circular economy, emphasizing both materials and industries while achieving optimal environmental, social, and economic outcomes.

3 Problem definition

Here, a 3D printing filaments CLSC network is configured in a circular environment. There has been an accumulative interest in employing 3D printing technologies in recent years that provide competitive advantages, such as time-saving, customizing, and satisfactory quality. Unfortunately, the high price of filament produced by raw material is an important issue and might affect this product's consumption. However, applying recycled filament or using recycled material to make filament can be employed to solve this problem. One of these materials can be PET bottles. If we use recycled materials, we convert them into valuable substances and reduce environmental impacts. Therefore, ecological problems and total costs can be efficiently diminished by location-allocation of recycling and designing a CLSC network, collection, and treatment hubs. In the following, we will describe the proposed CLSC.

The suggested network is presented in Fig. 6. This network is a combination of two sub-network and includes eight echelons: 3D printing center (DPC), treatment center (TC), recycling center (RC), filament customer (FC), processing center (PC), collection center (CC), markets (recycling companies), and end-user. In the first network, filaments are transported from recycling centers to DPCs. In addition, the waste of the printing process can be transformed into TCs. Next, 3D-printed objects are the products of DPCs that are shipped to customers. Afterward, in a reverse flow, a fraction of received products by 3D-printed customers are sent to treatment centers. PET bottles collected from end-users in another network are shipped to CCs. Then, after separating extra material from PET bottles, they are sent to PCs. In PCs, Pet bottles are sorted and pressed into the bales. After that, bales are transformed into reclaimers (i.e., markets and TCs).

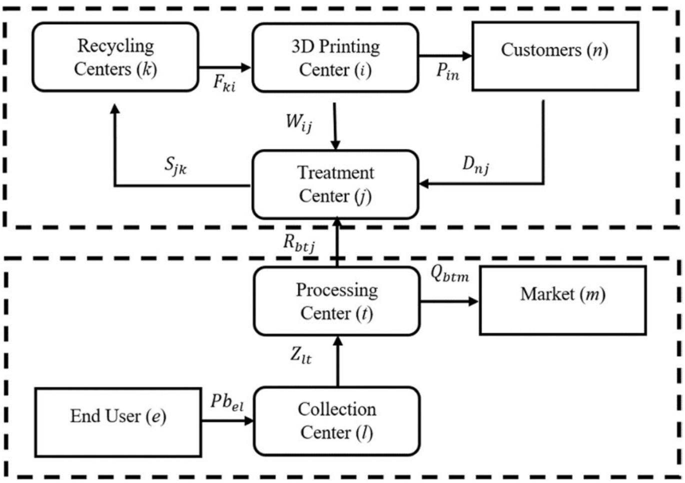

Fig. 6 Proposed 3D printing CLSC network

On the other hand, transformed bales to TCs connect two sub-networks. In TCs, all received material from PCs, DPCs, and FCs is crushed into flakes. After the treatment (crushing, washing, and drying), it can be sent to RCs. In these RCs, chips are combined with other raw materials to enhance filament quality. Then, they are converted to 3D printing filament.

Next, we introduce the assumptions underlying the offered model:

I. Capacity of all centers is limited,
II. Demand of customers must be satisfied,
III. Potential location of each echelon is predefined,
IV. Production capacity and customers' needs are determined,
V. Number of facilities and their potential sites are specified,
VI. Amount of 3D printed products sent to the treatment centers is a fraction of the received products,
VII. Color of all PET bottles is considered the same. In other words, color does not affect the demand for bales.

3.1 Model

The suggested mathematical model is developed based on Pishvaee et al. (2010). Table 5 represents the notations building up the model.

3.1.1 Objective functions

$$\text{minimize}\, Z = f_1 + f_2 + f_3 \tag{1}$$

$$f_1 = \sum_i Fu_i U_i + \sum_j Fy_j Y_j + \sum_k Fv_j V_i + \sum_t Fx_j X_i + \sum_l Fg_j G_i$$

$$f_2 = \sum_k \sum_i Cf_{ki} F_{ki} + \sum_i \sum_n Cp_{in} P_{in} + \sum_n \sum_j Cd_{nj} D_{nj} + \sum_i \sum_j Cw_{ij} W_{ij}$$

$$+ \sum_j \sum_k Cs_{jk} S_{jk} + \sum_b \sum_t \sum_j Cr_{btj} R_{btj} + \sum_t \sum_m Cq_{tm} Q_{tm} + \sum_l \sum_t Cz_{lt} Z_{lt}$$

$$+ \sum_e \sum_l Cpb_{el} Pb_{el}$$

$$f_3 = \sum_i Cu_i \left(\sum_n P_{in} + \sum_j W_{ij} \right) + \sum_k \sum_j Cy_j S_{jk} + \sum_i \sum_k Cv_k F_{ki} + \sum_t \sum_l Cg_l Z_{lt}$$

$$+ \sum_t Cx_t \left(\sum_j R_{tj} + \sum_m Q_{tm} \right)$$

Table 5 Notations used in the suggested mathematical model

Indices	
$i = 1, \dots, I$	Potential 3D printing center (DPC) locations,
$k = 1, \dots, K$	Potential recycling center (RC) locations,
$j = 1, \dots, J$	Potential treatment center (TC) locations,
$n = 1, \dots, N$	Filament customer (FC) locations,
$t = 1, \dots, T$	Potential processing center (PC) locations,
$m = 1, \dots, M$	Market locations,
$e = 1, \dots, E$	End-user locations,
$l = 1, \dots, L$	Potential collection center (CC) locations,
$b = 1, \dots, b$	Type of bales (TB) in processing centers
Parameters	
Fu_i	Fixed cost of DPC_i,
Fy_j	Fixed cost of TC_j,
Fv_k	Fixed cost of RC_k,
Fx_t	Fixed cost of PC_t,
Fg_l	Fixed cost of CC_l,
Cv_k	Recycling process cost for each item of filament for RC_k,
Cf_{ki}	Shipping cost for each item of filament shipped from RC_k to DPC_i,
Cu_i	Printing cost for each item of product for DPC_i,
Cw_{ij}	Shipping cost for each item of waste shipped from DPC_i to TC_j,
Cy_j	Treatment process cost for each item of product for TC_j,
Cs_{jk}	Shipping cost for each item of PET and waste flakes shipped from TC_j to RC_k,
Cx_t	Sorting and processing cost for each item of product for PC_t,
Cr_{btj}	Shipping cost for each item of TB_b shipped from PC_t to TC_j,
Cg_l	Collecting cost for each item of product for CC_l,
Cz_{lt}	Shipping cost for each item of separated PET bottle waste shipped from CC_l to PC_t,
Sc_k	Cost savings for each item of recycled filament shipped from RC_k to DPC_i,
Cp_{in}	Shipping cost for each item of printed object shipped from DPC_i to FC_n,
DM_m	Demand of TB_b by market m,
Cd_{nj}	Shipping cost for each item of waste shipped from FC_n to TC_j,
DC_n	Demand for 3D-printed objects by FC_n,
Cq_{tm}	Shipping cost for each item of TB_b shipped from PC_t to market m,
θ_b	Fraction of TB_b sorted in PC_t,
Cpb_{el}	Shipping cost per unit of PET bottle waste shipped from end-user e to CC_l,
γ_l	Waste percentage of collected PET bottles after separating process in CC_l,
α_n	Waste percentage collected from FC_n,
λ_i	Waste percentage in DPC_i,
β_t	Capacity percentage of PC_t For treatment PET bottles,
ρ_k	Production rate of filament in RC_k,
Cpu_i	Capacity of DPC_i,
Cpy_j	Capacity of TC_j,
Cpv_k	Capacity of RC_k,
Cpx_t	Capacity of PC_t,
Cpg_l	Capacity of CC_l,
Tp_e	Total PET bottle discarded by end-user e,

Table 5 (continued)

Decision variable	
F_{ki}	Number of filaments transferred from RC_k to DPC_i,
P_{in}	Number of printed objects transferred from DPC_i to FC_n,
D_{nj}	Number of waste transferred from FC_n to TC_j,
W_{ij}	Number of waste transferred from DPC_i to TC_j,
S_{jk}	Number of PET flakes transferred from TC_j to RC_k,
R_{tj}	Number of Bales transferred from PC_t to TC_j,
Q_{tm}	Number of Bales transferred from PC_t to market m,
Z_{lt}	Number of separated PET bottle waste transferred from CC_l to PC_t,
Pb_{el}	Number of PET bottles transferred from end-user e to CC_l,
U_i	1 If the 3D DPC_i opens at the location; 0 otherwise,
Y_j	1 If TC_j opens; 0 otherwise,
V_k	1 If RC_k opens; 0 otherwise,
X_t	1 If PC_t opens; 0 otherwise,
G_l	1 If CC_l opens; 0 otherwise.

The object function minimizes the total cost, including fixed opening costs (f_1), production costs (f_2), and transportation costs (f_3).

3.1.2 Model constraints

The main constrainsts are the model are listed as follows:

$$\sum_{k} F_{ki} \leq Cpu_i \times U_i \quad \forall i \in I, \tag{2}$$

$$\sum_{b} \sum_{t} R_{tj} \leq \beta_j \times Cpy_j \times Y_j \quad \forall j \in J, \tag{3}$$

$$\sum_{n} D_{nj} + \sum_{i} W_{ij} \leq \left(1 - \beta_j\right) \times Cpy_j \times Y_j \quad \forall j \in J, \tag{4}$$

$$\sum_{j} S_{jk} \leq \frac{1}{\rho_k} \times Cpv_{k} \times V_k \quad \forall k \in K, \tag{5}$$

$$\sum_{l} Z_{lt} \leq Cpx_t \times X_t \quad \forall t \in T, \tag{6}$$

$$\sum_{e} Pb_{el} \leq Cpg_l \times G_l \quad \forall l \in L, \tag{7}$$

$$\sum_{l} Pb_{el} \leq Tp_e \quad \forall e \in E. \tag{8}$$

Constraints (2)–(7) consider the finite capacity of each center. Hence, these constraints guarantee that the delivered product quantities to DPC_i, TC_j, RC_k, PC_t and CC_l are limited by the capacity of each center, respectively. Furthermore, Constraint (8) ensures that the quantity of PET bottles shipped to CC_l does not violate the capacity of end-user e.

$$\sum_i F_{ki} \leq \rho_k \times \sum_j S_{jk} \quad \forall k \in K, \tag{9}$$

$$\sum_n P_{in} \times \frac{1}{(1-\lambda_i)} \leq \sum_i F_{ki} \quad \forall i \in I, \tag{10}$$

$$\sum_k S_{jk} \leq \sum_n D_{nj} + \sum_i W_{ij} + \sum_t R_{tj} \quad \forall j \in J, \tag{11}$$

$$\sum_j R_{tj} + \sum_m Q_{tm} \leq \sum_l Z_{lt} \quad \forall t \in T, \tag{12}$$

$$\sum_t Z_{lt} \leq (1-\gamma_l) \times \sum_e Pb_{el} \quad \forall l \in L, \tag{13}$$

$$\sum_j D_{nj} \leq \alpha_n \times \sum_i P_{in} \quad \forall n \in N, \tag{14}$$

$$\sum_j W_{ij} \leq \frac{\lambda_i}{\left(1-\lambda_i\right)} \times \sum_n P_{in} \quad \forall i \in I. \tag{15}$$

The number of sent products in a center should be less or equal to the received product quantity. Thus, Constraint (9) ensures that the amount of filament transported from RC_k should be fewer than or equal to the material quantity which was received from TC_j. Like Constraint (9), Constraints (10)–(13) control the flows in DPC_i, TC_j, RC_k, PC_t and CC_l. Moreover, Constraints (14)–(15) show the amount of waste transported from DPC_i and FC_n to TC_j.

$$\sum_t Q_{tm} \geq DM_m \forall b \in B, \quad \forall m \in M, \tag{16}$$

$$\sum_i P_{in} \geq DC_n \quad \forall n \in N. \tag{17}$$

Constraints (16)–(17) satisfy the demand of markets and 3D printed customers, respectively.

$$\begin{aligned} &U_i, Y_j, V_k, X_t, G_l \in \{0,1\} \quad \forall i,j,k,t,l, \\ &F_{ki}, P_{in}, D_{nj}, W_{ij}, S_{jk}, R_{btj}, Q_{btm}, Z_{lt}, Pb_{el} \geq 0 \quad \forall i,j,k,t,l,n,b,t,e. \end{aligned} \tag{18}$$

Constraint (18) presents positive and binary variables.

Segment 1					Segment 2			Segment 3				Segment 4		
E			*L*		*L*		*T*	*T*	*M* + *J*			*J*		*K*
0.81	0.91	0.12	0.91	0.63	0.97	0.28	0.55	0.95	0.96	0.15	0.23	0.95	0.97	0.48

Segment 5				Segment 6						Segment 7			
K	*I*			*I* + *N*				*J*		*I*			*N*
0.81	0.14	0.42	0.91	0.24	0.65	0.03	0.84	0.93	0.68	0.51	0.01	0.79	0.95

Fig. 7 Schematic design of the proposed chromosome

Segment 1					Segment 2			Segment 3				Segment 4		
E			*L*		*L*		*T*	*T*	*M* + *J*			*J*		*K*
3	1	2	2	1	2	1	1	1	2	3	1	1	2	1

Segment 5				Segment 6						Segment 7			
K	*I*			*I* + *N*				*J*		*I*			*N*
1	1	2	3	3	1	2	4	2	1	2	1	3	1

Fig. 8 Random key and priority-based chromosome of Segment 1

4 Solution algorithms

This section presents the encoding and decoding procedure and explains the metaheuristics used to treat the problem. The number of potential places (binary variables), especially in large-scale location problems, implies the complexity of the problem. It is known that the supply chain network design problems' complexity is NP-hard (Seyedi & Maleki-Daronkolaei, 2013). Despite the reliability of the exact methods, these methods are not very efficient in large-scale problems (Abdi et al., 2021). In that respect, three distinguished metaheuristics (i.e., PSO, GA, and SA) are employed to seek a satisfactory solution. In the following, the applied solution approaches and representation approaches are detailed.

4.1 Encoding and decoding

Various methods have been proposed for encoding and decoding the solutions. In the present research, the priority-based encoding approach (Gen et al., 2006; Michalewicz et al., 1991) is employed. A small-scale problem is used to explain that the constraints are met. The number of 3D printing centers, treatment centers, recycling centers, processing centers, filament customers, markets, and end-users are assumed as 3, 2, 1, 1, 1, 1, and 1, respectively. Figure 7 shows the proposed chromosome. It is divided into seven segments. First, random numbers between 0 and 1 are randomly generated to make the chromosome. Then, for each segment, the random numbers are sorted based on priority to achieve the allocation sequence. For instance, consider Segment 3. According to the priority in Fig. 8, Constraints (3), (12), and (16) can be satisfied in the procedures of allocation. The further constraints procedures are the same. The applied algorithms are explained in the following.

4.2 Particle swarm optimization

Kennedy and Eberhart (1995) introduced PSO algorithm, which is a population-based algorithm inspired by the social behavior of birds, bees, or fishes (Barzinpour et al., 2013). Several versions have been also developed to improve the efficiency of PSO. For instance, weighted PSO (WPSO) (Dhivya & Meenakshi, 2015), adaptive PSO (APSO) (Dashora & Awwal, 2016), Levy Flight PSO (LFPSO) (Gupta et al., 2016), multi-vector PSO (MVPSO) (Fakhouri et al., 2020), etc. The first population of particles is placed randomly, and the objective function is evaluated. Then, each particle moves to a new position on the basis of its own best position, global best-known position, and velocity. Afterward, the history of the best location and global location is updated, and new movements are conducted. This procedure continues till the swarm is likely to attain a satisfactory best-known solution (Poli et al., 2007). The pseudo-code of the suggested PSO is displayed in Fig. 9.

4.3 Genetic algorithm

GA was first introduced by (Holland, 1992). Various engineering problems applied this population-based technique to solve their problems (Gholizadeh & Fazlollahtabar, 2020; Midaoui et al., 2021; Seyedi et al., 2022a, 2022b).

In this method, the algorithm starts with an initial randomly generated population. Next, the fitness value is evaluated for each individual. In each iteration, new solutions are developed by biologically inspired operators (crossover and mutation). The selection, crossover, and mutation operator continue until a termination condition is met (Esmaeili & Barzinpour, 2014). The pseudo-code of the offered GA is displayed in Fig. 10.

PSO pseudo-code

Initialize initial randomly: $P(0)$,
Assess the fitness of all particles of $P(0)$, $pBest$, and $gBest$,
Initial Velocity: $V(0)$,
Select a maximum number of generations: t_max,
while the stopping criteria are not met and $t < t\_max$
    $t = t + 1$;
    Update Velocity using:
    Velocity= w×Velocity + $c1$×rand× $(pBest - P)$ + $c2$×rand× $(gbest - P)$;
    Do Velocity limitation
    Update Position using:
    P=P+Velosity;
    Do Velocity Mirror Effect
    Do Position limitation
    Evaluate $P(t)$,
    Update $Personal\ Best$,
    Update $Global\ Best$,
    Reduce w,
end while
return $Global\ Best$.

Fig. 9 Proposed pseudo-code of the suggested PSO

GA pseudo-code
Initialize the population randomly: $P(0)$,
Assess the fitness of all individuals of $P(0)$,
Select a maximum number of generations: t_max,
while the stopping criteria are not met and $t < t\_max$
$t = t + 1$;
Choosing parents for offspring production,
for each $N\_crossover$
Do crossover
end for
for each $N\_mutation$
Do mutation
end for
Assess P(t),
Do survival selection (%20 Elitism + %80 Randomly)
Update the best individual if there is a superior solution,
end while
Return the best individual of $P(t)$.

Fig. 10 Proposed pseudo-code of the suggested GA

4.4 Simulated Annealing

For the first time, SA was presented by Kirkpatrick et al., (1983). This single-solution-based metaheuristic algorithm is a standard solution method. Furthermore, SA has been used for treating many supply chain and location-allocation problems, such as (Fakhrzad & Goodarzian, 2021; Jabalameli et al., 2012; Liu et al., 2020; Seyedi et al., 2022a, 2022b).

In this method, the algorithm begins with a primary feasible solution, and then, a specific cost function is calculated for each solution. A new solution is generated in each iteration by slightly modifying one or some variables. An unfavorable neighbor is acknowledged with a probability established by the Boltzmann probability $P = e^{-\Delta\theta/T}$, while an improving move is always accepted. In the Boltzmann probability, $\Delta\theta$ expresses the new and the best solutions difference, and T is the temperature (Garza-Santisteban et al., 2019). The procedure is repeated for a constant number of iterations. The pseudo-code of the proposed SA is given in Fig. 11.

5 Computational results

This section assess the model and the performance of applied methodologies. First, twenty-four small, medium, and large problems are randomly generated. Next, to tune the parameters of metaheuristics, the Taguchi design method is utilized.

Afterward, based on the results, solution approaches are compared. Finally, various criteria are used to select the best algorithm and solution.

SA pseudo-code

```
Initialize initial random solution generation,
Value: Solution evaluation;
Generate N neighborhoods and evaluate Δf,
T0 = |Δf_min + 0.1(Δf_max − Δf_min)|;
while the stopping criteria are not met
    for subIt = 1: Maximum sub iteration
        A new solution: Neighborhood solution generation,
        New Value: New solution evaluation;
        if New value < Value
            Solution=New solution;
            Value=New Value;
        else
            Δ=New value-Value;
        end if
    end for
reduce T,
if there is a better solution, update the Best solution,
end while
Return the best solution.
```

Fig. 11 Pseudo-code of the suggested SA

5.1 Data

The performance of the employed metaheuristics is assessed in this sub-section. In this regard, twenty-four random problems in three different levels are produced and compared. These test problems are classified based on 3D printing centers (I), treatment centers (J), recycling centers (K), processing centers (T), collection centers (L), filament customers (n), markets (M), and end-user (E). The various dimensions of generated problems are presented in Table 6 and Fig. 12. In each echelon, the problem complexity is shown by the number of binary variables (potential places). Furthermore, Table 7 provides the other parameters' values.

5.2 Parameter setting of the algorithms

The performance of metaheuristics is highly influenced by the identity of the algorithm's parameters. Therefore, the parameters of metaheuristics are tuned to improve the reliability of solution approaches. Many works have employed the complete factorial design to set the parameters. However, the more factors there are, the less effective this method is. In this respect, the experiments are designed by Taguchi Methods to decrease the test numbers and the examination complexity (Taguchi, 1986). First, each test problem is run ten times. Then, the number of objective functions is converted to relative percentage deviation (RPD) to

Table 6 Problems with different sizes

Problem size	Problem number	I	J	K	T	L	N	M	E	Total variable	Total binary variable
Small	1	2	2	2	2	2	3	2	10	60	10
	2	2	3	5	4	3	8	3	15	153	17
	3	3	3	6	5	3	12	4	18	205	20
	4	4	4	8	6	4	16	5	20	328	26
	5	5	4	10	7	5	19	6	25	447	31
	6	6	5	10	8	6	22	7	28	597	35
	7	8	5	12	9	7	28	8	30	767	41
	8	10	6	12	10	8	33	9	35	1006	46
Medium	9	12	10	18	13	10	50	14	50	2021	63
	10	14	11	20	14	12	55	15	55	2522	71
	11	16	12	20	15	14	60	16	60	3019	77
	12	18	13	22	17	15	65	17	65	3586	85
	13	20	14	22	19	17	70	18	70	4221	92
	14	22	15	24	20	18	75	19	75	4832	99
	15	25	16	24	22	19	79	20	80	5484	106
	16	30	17	26	25	20	83	21	85	6411	118
Large	17	35	20	34	30	25	103	27	100	9434	144
	18	38	21	35	32	28	107	28	110	10,808	154
	19	40	22	37	33	29	111	29	120	11,897	161
	20	45	24	39	35	30	115	30	130	13,544	173
	21	50	25	40	37	32	119	31	140	15,145	184
	22	53	28	42	40	33	123	32	150	17,196	196
	23	58	29	42	42	34	127	33	170	19,036	205
	24	60	30	43	43	35	131	34	200	21,068	211

balance the results' measure. Next, the mean of RPD is utilized to compute signal-to-noise (S/N) ratios. Eventually, the best level was chosen.

Table 8 presents preferred parameters (factors) and their levels. Moreover, the amount of initial temperature in simulated annealing is selected adaptively. First, some neighborhoods are generated. After evaluating Δf, Eq. (19) is used to calculate $T0$:

$$T0 = \left|\Delta f_{\min} + 0.1(\Delta f_{\max} - \Delta f_{\min})\right|. \tag{19}$$

Moreover, the temperature reduction ratio is done by Eqs. (20)–(22) (Hosseini Baboli et al., 2023; Liao et al., 2020).

$$T_i = T_0 - i \times \left(\frac{(T_0 - T_f)}{N}\right)(i = 1, \dots, N), \tag{20}$$

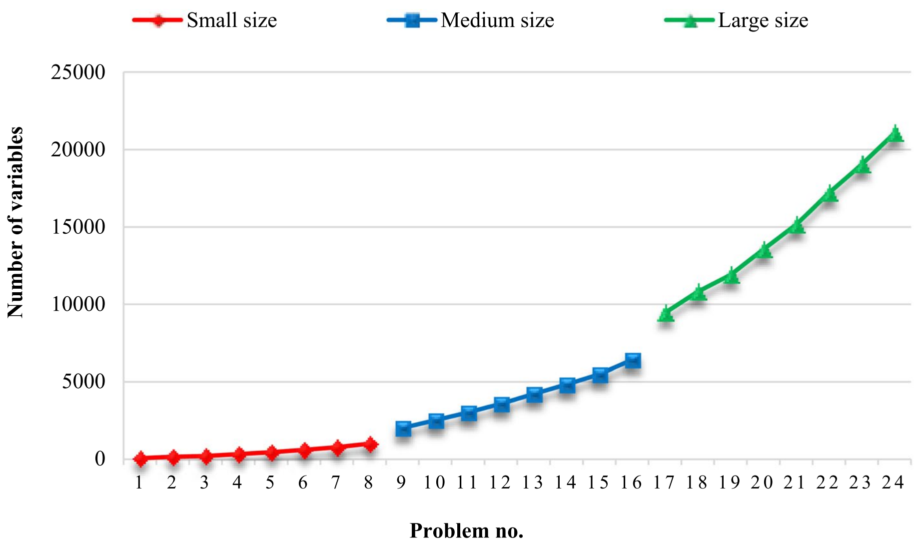

Fig. 12 Dispersion of problem size

Table 7 Parameter setting of the suggested model

Factors	Levels	Factors	Levels
Fy_j	$U(100, 400)$	Cpy_j	$U(400, 500)$
Fu_j	$U(500, 1000)$	Cpu_i	$U(400, 600)$
Fv_k	$U(200, 600)$	Cpv_k	$U(400, 800)$
Fx_t	$U(100, 200)$	DM_m	$U(150, 200)$
Fg_l	$U(100, 200)$	DC_n	$U(20, 50)$
Cu_i	$U(5, 15)$	γ_l	0.125
Cy_j	$U(2, 6)$	α_n	0.2
Cv_k	$U(5, 10)$	λ_i	0.1
Cx_t	$U(1, 5)$	β_t	0.5
Cg_l	$U(1, 6)$	ρ_k	2
$Cf_{ki}, Cp_{in}, Cd_{nj}, Cw_{ij}$ $Cz_{lt}, CPb_{el}, Cs_{jk}, Cr_{tj}, Cq_{tm}$	$U(1, 10)$		

$$T_i = T_0 - \left(\frac{(T_0 - T_f)(N+1)}{N}\right)\left(1 - \frac{1}{(i+1)}\right)(i = 1, \dots, N), \tag{21}$$

$$T_i = \frac{1 - tgh\left(\left(\frac{10i}{N}\right) - 5\right)}{2}\left(T_0 - T_f\right) + T_f(i = 1, \dots, N). \tag{22}$$

According to the parameters and their levels, L9, L18, and L18 orthogonal arrays in Taguchi methods are used for the SA, GA, and PSO, respectively. To assess the result of each experiment, the RPD with the below equation is utilized:

Table 8 Parameter levels of the algorithms

Factor	Level	Symbol	Type
PSO			
MaxIt(Maximum number of iterations)	3	A	A(1)-150 A(2)-200 A(3)-250
nParticle(Population size)	3	B	B(1)-10 B(2)-20 B(3)-40
w(Inertia weight)	3	C	C(1)-0.9 C(2)-1.2 C(3)-1.4
*c*1(Personal learning coefficient)	3	D	D(1)-1 D(2)-1.5 D(3)-2
*c*2(Global learning coefficient)	3	E	E(1)-1 E(2)-1.5 E(3)-2
SA			
MaxIt(Maximum number of iterations)	3	A	A(1)-150 A(2)-200 A(3)-250
Reduction ratio of temperature	3	B	B(1)-Linear (Eq. 20) B(2)-Exponential (Eq. 21) B(3)-Hyperbolic (Eq. 22)
Neighborhood search structure	3	C	D(1)-Swap D(2)-Reversion D(3)-Insertion
GA			
MaxIt(Maximum number of iterations)	3	A	A(1)-150 A(2)-200 A(3)-250
nPop(Population size)	3	B	B(1)-100 B(2)-150 B(3)-200
PC(Probability of crossover)	3	C	C(1)-0.2 C(2)-0.5 C(3)-0.8
PM(Probability of mutation)	3	D	D(1)-0.1 D(2)-0.2 D(3)-0.3
Type of crossover	3	E	E(1)-One-point crossover E(2)-Two-point crossover E(3)-Uniform crossover
Type of mutation	3	F	F(1)-Pairwise Mutation F(2)-Swap Mutation

Table 8 (continued)

Factor	Level	Symbol	Type
			F(3)-Inversion Mutation

$$RPD = \frac{\mathrm{alg}_{\mathrm{sol}} - \min_{\mathrm{sol}}}{\min_{\mathrm{sol}}}, \tag{23}$$

where $\min_{\mathrm{sol}}$ is the minimum value of the cost function and $\mathrm{alg}_{\mathrm{sol}}$ is the attained solution (Ruiz & Stutzle, 2007). Tables 9, 10 and 11 provide orthogonal arrays and the average RPD of 10 times run for all 24 problems and all test problems.

Taguchi design method seeks to maximize the controllable factor's effects and minimize the impact of the noise. The S/N ratio can be used for providing both targets. In addition, there are three classifications for the Taguchi method: the more significant, the better, the

Table 9 Orthogonal array L9 for SA

Trial	A	B	C	Mean of RPD	S/N
1	1	1	1	0.141	17.01
2	1	2	2	0.124	18.10
3	1	3	3	0.192	14.32
4	2	1	2	0.175	15.13
5	2	2	3	0.147	16.66
6	2	3	1	0.082	21.75
7	3	1	3	0.186	14.62
8	3	2	1	0.056	25.01
9	3	3	2	0.117	18.62

Table 10 Orthogonal array L18 for GA

Trial	A	B	C	D	E	F	Mean of RPD	S/N
1	1	1	1	1	1	1	0.190	14.44
2	1	2	2	2	2	2	0.131	17.67
3	1	3	3	3	3	3	0.086	21.27
4	2	1	1	2	2	3	0.121	18.34
5	2	2	2	3	3	1	0.075	22.55
6	2	3	3	1	1	2	0.129	17.75
7	3	1	2	1	3	2	0.131	17.65
8	3	2	3	2	1	3	0.092	20.75
9	3	3	1	3	2	1	0.054	25.38
10	1	1	3	3	2	2	0.097	20.22
11	1	2	1	1	3	3	0.155	16.17
12	1	3	2	2	1	1	0.139	17.13
13	2	1	2	3	1	3	0.084	21.49
14	2	2	3	1	2	1	0.149	16.51
15	2	3	1	2	3	2	0.095	20.44
16	3	1	3	2	3	1	0.099	20.11
17	3	2	1	3	1	2	0.032	29.81
18	3	3	2	1	2	3	0.111	19.06

Table 11 Orthogonal array L18 for PSO

Trial	A	B	C	D	E	Mean of RPD	S/N
1	1	1	1	1	1	0.208	13.65
2	1	2	2	2	2	0.146	16.69
3	1	3	3	3	3	0.084	21.47
4	2	1	1	2	2	0.181	14.85
5	2	2	2	3	3	0.106	19.46
6	2	3	3	1	1	0.145	16.77
7	3	1	2	1	3	0.189	14.48
8	3	2	3	2	1	0.152	16.36
9	3	3	1	3	2	0.090	20.95
10	1	1	3	3	2	0.154	16.24
11	1	2	1	1	3	0.147	16.67
12	1	3	2	2	1	0.127	17.90
13	2	1	2	3	1	0.170	15.38
14	2	2	3	1	2	0.167	15.53
15	2	3	1	2	3	0.066	23.59
16	3	1	3	2	3	0.151	16.42
17	3	2	1	3	1	0.131	17.68
18	3	3	2	1	2	0.076	22.37

smaller is better, and the nominal is better. In this work, RPD will be used as a response. Hence, "the smaller is better" is applied to adjust parameters, and Eq. (24) is utilized to calculate the value of the S/N ratio:

$$S/N = -10\log_{10}\left(\sum\left(Y^2\right)/n\right), \tag{24}$$

where Y is the response of each test problem and n is the number of orthogonal arrays. Minitab was employed to analyze the response (RPD) of designed experiments. Figures 13, 14 and 15 illustrate the mean of S/N. As a result, the level of SA's parameters is 3,2, and 1. Moreover, the best levels for PSO and GA are 3, 3, 1, 3, and 3 and 3, 2, 1, 3, 1, and 2, respectively. Table 12 provides The best value of each factor.

5.3 Experimental results

When the appropriate value for the parameters of the algorithms is chosen, all twenty-four test problems are executed thirty times. RPD and hitting time are two metrics that are employed to appraise the performance of the algorithms. Hitting time lasts until the algorithm finds the minimum solution for the first time. The averages of these criteria are summarized in Table 13. Moreover, to clarify differences, the results are illustrated in Figs. 16 and 17.

In conclusion, for small and medium size problems, GA provides a better, best-known solution. However, SA has less than 10% deviations from GA's solutions. On the other hand, GA needs more time than SA to find this solution. Thus, from the point of view of time or quality, SA or GA, i.e., selected respectively. For large-scale problems, SA and GA

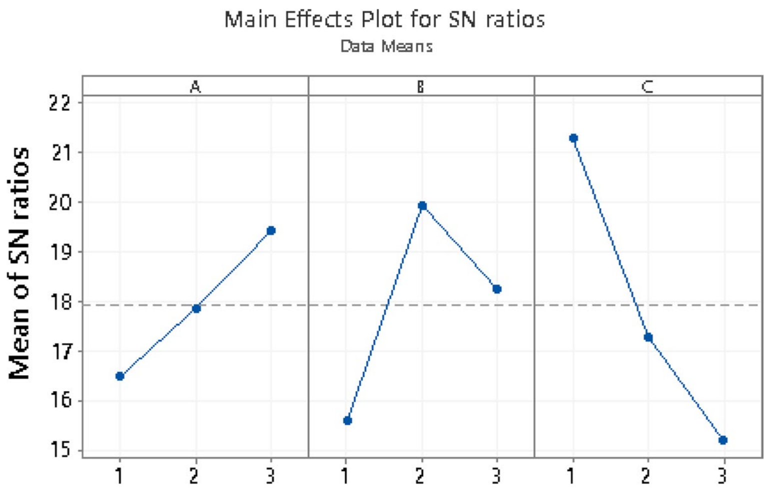

Fig. 13 Mean SN plot for levels of the factors in SA

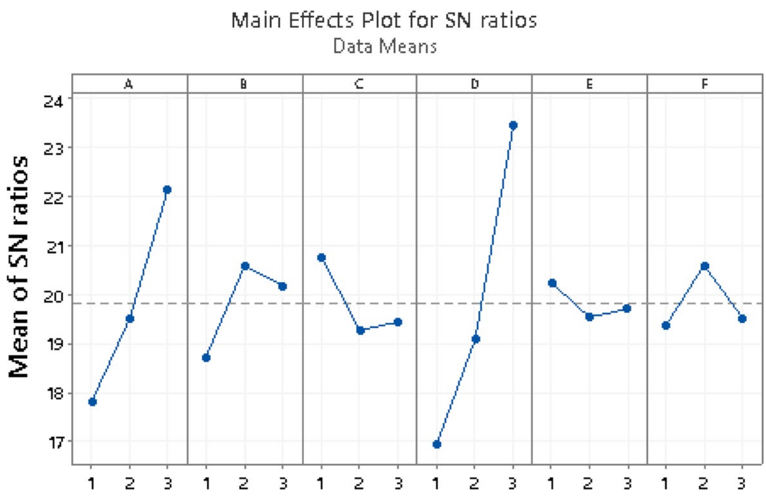

Fig. 14 GA factors mean SN plot

have almost the same function. Since SA significantly needs less time, this algorithm is chosen to treat large-scale problems.

6 Conclusion and further studies

In this study, we delved into the intricate design and configuration of a circular CLSC network for an AM process. This network encompasses two vital sub-networks. In the first sub-network, we focused on the collection and baling of PET bottles, which cater to market demand and the needs of the second sub-network. The second sub-network

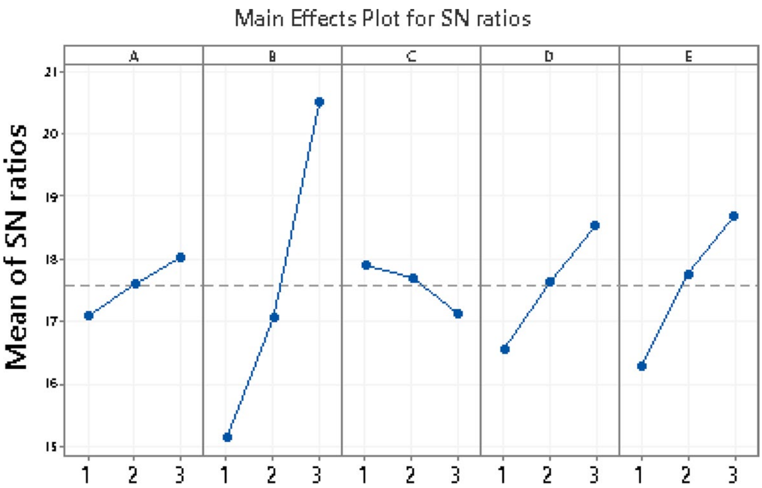

Fig. 15 PSO factors mean SN plot

Table 12 Best level for the parameters of the suggested metaheuristic algorithms

Method	Parameters	Best level
GA	nPop (Population size)	150
	MaxIt (Maximum number of iterations)	250
	PM (Probability of mutation)	30%
	PC (Probability of crossover)	20%
	Type of mutation	Swap Mutation
	Type of crossover	One-point crossover
SA	The reduction ratio of temperature	Exponential
	MaxIt (Maximum number of iterations)	250
	Neighborhood search structure	Reversion
PSO	nParticle (Population size)	40
	MaxIt (Maximum number of iterations)	250
	C1 (Personal learning coefficient)	2
	C2 (Global learning coefficient)	2
	W (Inertia weight)	0.9

involves the collection of waste from 3D printing processes, consumer waste, and bales, which are then processed in treatment centers to produce flakes. These flakes are further transformed into 3D printing filaments in recycling centers. To optimize this complex network, we introduced a novel MILP model, with the primary objective of minimizing total costs, encompassing location costs, transportation costs, and processing costs, all while addressing specific environmental and economic targets. We harnessed the power of three well-known metaheuristics as solution methods in our quest for efficient optimization. Prior to comparing the algorithm results, we employed the Taguchi design method to fine-tune their parameters. Based on the outcomes, we tailored our selection of either SA or GA, depending on factors such as time and quality. For large-scale

Table 13 Computation results obtained by the algorithms

Problem no	SA			GA			PSO		
	Best cost	RPD	Time	Best cost	RPD	Time	Best cost	RPD	Time
1	11,240.73	0.30	0.26	11,207.50	0.00	0.50	11,317.68	0.98	0.21
2	22,089.61	1.88	0.31	21,682.51	0.00	1.96	22,310.55	2.90	0.56
3	25,899.57	2.89	1.29	25,171.89	0.00	9.47	26,893.40	6.84	1.84
4	35,432.98	5.79	1.56	33,494.31	0.00	12.17	36,536.74	9.08	2.19
5	38,414.62	7.16	2.24	35,847.26	0.00	14.51	40,890.28	14.07	2.67
6	43,395.00	6.35	2.18	40,802.60	0.00	14.50	45,939.37	12.59	3.32
7	55,151.81	8.31	2.52	50,921.14	0.00	16.59	57,907.80	13.72	6.29
8	64,816.20	3.80	2.75	62,443.25	0.00	18.17	68,465.83	9.64	7.11
9	91,510.49	4.36	4.17	87,687.25	0.00	23.76	99,276.35	13.22	9.16
10	104,895.18	4.37	4.38	100,506.87	0.00	25.69	111,296.97	10.74	9.43
11	112,258.49	2.81	5.41	109,194.82	0.00	27.09	123,844.50	13.42	9.71
12	121,087.47	2.52	5.07	118,109.46	0.00	28.68	131,035.62	10.94	10.65
13	134,858.62	3.04	5.04	130,875.29	0.00	30.46	148,931.61	13.80	11.33
14	141,699.07	0.67	5.37	140,759.42	0.00	33.35	154,105.20	9.48	11.77
15	151,036.86	0.54	5.80	150,220.71	0.00	35.29	161,548.55	7.54	13.05
16	159,253.55	0.00	6.71	159,683.75	0.27	38.33	176,873.08	11.06	13.45
17	204,244.87	0.00	8.02	206,023.89	0.87	50.96	220,472.74	7.95	18.24
18	218,680.65	0.00	8.88	223,238.38	2.08	54.85	238,126.61	8.89	20.08
19	220,182.89	0.00	9.20	223,212.42	1.38	54.22	240,432.58	9.20	19.29
20	232,991.28	3.22	9.19	225,713.43	0.00	60.73	251,305.37	11.34	20.46
21	250,469.02	0.00	9.61	251,201.22	0.29	65.44	270,525.98	8.01	22.03
22	261,592.05	0.00	10.64	263,621.87	0.78	67.95	277,242.02	5.98	22.36
23	263,939.01	0.00	10.84	270,017.35	2.30	68.36	283,769.94	7.51	23.40
24	270,059.30	0.00	11.67	270,137.74	0.03	68.34	287,399.11	6.42	24.52

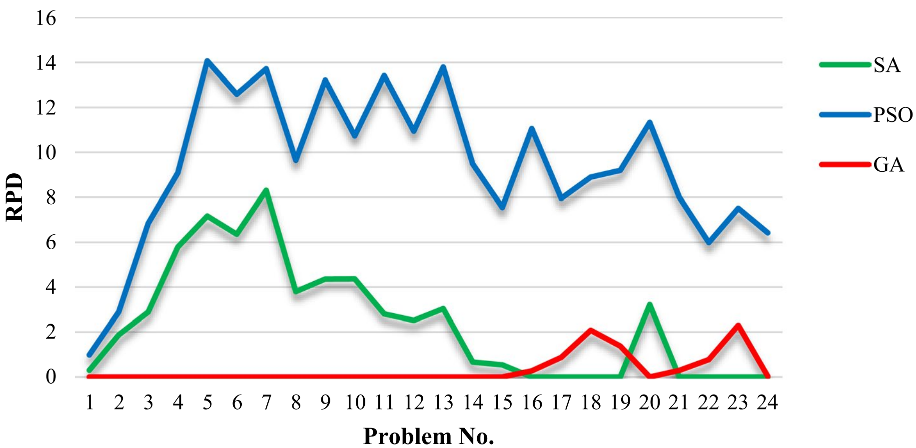

Fig. 16 RPD values

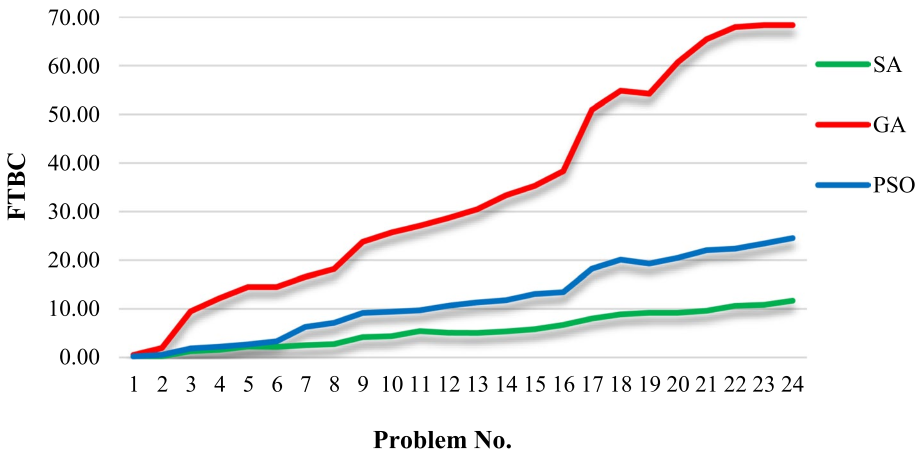

Fig. 17 First time find the best cost (FTBC)

problems, SA and GA exhibited similar performance, but the former was notably faster, leading to our choice for large-scale scenarios. The results obtained through this rigorous approach offer valuable insights into the feasibility of utilizing plastic waste in filament production. Our proposed CLSC model not only aims to reduce network expenses but also implicitly addresses other crucial objectives, including mitigating environmental impacts and cutting the costs associated with sourcing filament from raw materials. The summary of findings can be classified into the following items.

- **Algorithm Performance:** For small and medium-sized problems, GA consistently provided better-known solutions compared to SA and PSO. Moreover, SA exhibited less than a 10% deviation from GA's solutions, making it a competitive alternative. On the other hand, GA achieved better solutions but required more time, leading to a trade-off between time and solution quality.
- **Large-Scale Problem Solution:** SA and GA demonstrated similar performance for large-scale problems. Notably, SA exhibited significantly faster convergence, making it the preferred choice for large-scale scenarios.
- **Optimal Algorithm Selection:** The choice between SA and GA depended on the specific requirements of the problem, with SA being more time-efficient and GA offering potentially superior solutions.
- **Implications for CLSC Networks:** This study emphasized the importance of considering both time efficiency and solution quality in choosing metaheuristic algorithms for optimizing CLSC networks. The proposed model and optimization strategies contributed to reducing network expenses and address environmental concerns associated with filament production.

Of course, there are various gaps which could be considered for future work:

(i) **Environmental Footprint:** Delving deeper into the environmental impact of CLSC networks by conducting comprehensive carbon emissions assessments, especially in collection and transportation phases,

(ii) **Socioeconomic Impacts:** Exploring the social and economic implications, focusing on job creation, local community benefits, and cost-effectiveness of using recycled materials in filament production,
(iii) **Uncertainty Management:** Applying uncertainty-handing techniques to enhance the network's adaptability to real-world uncertainties and unexpected events (Baltas et al., 2022; Kara et al., 2019; Özcan et al., 2023; Özmen et al., 2017; Palancı et al., 2016; Savku & Weber, 2018, 2022; Üstünkar et al., 2012),
(iv) **Technology-Specific Networks:** Investigating the enhancement of CLSC networks through establishing different 3D printing technologies and processes, acknowledging their unique requirements,
(v) **Bale Differentiation:** Examining how differentiating bales, such as by color or other characteristics, impacts network efficiency and performance,
(vi) **Real-Case Implementation:** Validating the proposed models and strategies through real-case studies, collaborating with industries to apply them in diverse contexts.

These research directions will contribute to the ongoing development and optimization of CLSC networks, aligning them with sustainability, efficiency, and environmental responsibility in supply chain management.

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Declarations

Conflict of interest There is no conflict of interest to declare.

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Consent for publication N/A

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