



A comprehensive framework for sustainable closed-loop supply chain network design

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ABSTRACT

Many companies face challenges in reducing their supply chain costs while increasing sustainability and customer service levels. A comprehensive framework for a sustainable closed-loop supply chain (CLSC) network is a practical solution to these challenges. Hence, for the first time, this study considers an integrated multi-objective mixed-integer linear programming (MOMILP) model to design sustainable CLSC networks with cross-docking, location-inventory-routing, time window, supplier selection, order allocation, transportation modes with simultaneous pickup, and delivery under uncertainty. An intelligent simulation algorithm is proposed to produce CLSC network data with probabilistic distribution functions and feasible solution space. In addition, a fuzzy goal programming approach is proposed to solve the MOMILP model under uncertainty. Eight small and medium-size test problems are used to evaluate the performance of the proposed model with the simulated data in GAMS software. The results obtained from test problems and sensitivity analysis show the efficacy of the proposed model.

1. Introduction

Fossil-based fuels are the largest source of energy production in the world. The International Energy Agency (IEA) reports that the share of fossil-based fuels in the world energy market in 2019 was about 84% (www.iea.org), and the Environmental Protection Agency reports more than 80% of the energy produced in the United States is based on fossil fuels (www.epa.gov). Excessive consumption of fossil fuels and limited non-renewable energy sources lead to large volumes of greenhouse gases. Implementing a sustainable supply chain, applying reverse logistics techniques, and optimizing the transport fleet can significantly reduce fossil fuel consumption and carbon emissions (Allen et al., 2021; Shuang et al., 2019). Hence, the pressure to gain a competitive advantage and remain sustainable has forced companies to adopt reverse logistics strategies and design closed-loop supply chains (CLSCs)

(Govindan et al., 2019; Mardan et al., 2019; Mohtashami et al., 2020). Product recovery, remanufacturing, recycling, and reusing strategies are the constituents of reverse logistics commonly used to reduce the consumption of raw materials in the forward logistics systems (Govindan et al., 2020; Azadnia et al., 2021). The simultaneous consideration of the forward and reverse supply chains results in the conception of CLSC (Govindan et al., 2015; Marcos et al., 2021). Modern CLSCs implement many efficient strategies, including simultaneous pickup and delivery and cross-docking, to manage the flow of materials in the supply chain (Abad et al., 2018; Marcos et al., 2021). Implementing these strategies could potentially result in a great degree of flexibility, agility, and reliability in supply chains (Shahramfard and Vahdani, 2019; Abdi et al., 2020). In recent years, the successful integration of vehicle routing methods with simultaneous pickup and delivery has gained interest (Ai and Kachitvichyanukul, 2009; Michaud and Llerena, 2011). Strategic

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initiative (e.g., simultaneous pickup and delivery) can significantly reduce emissions from urban freight transport (Kancharla and Ramadurai, 2018).

Many organizations implement remanufacturing strategies to improve the efficiency of their reverse logistics. Remanufacturing of returned products reduces the consumption of resources and allows for the minimization of adverse environmental impacts (Zhang et al., 2021). Simultaneous pickup and delivery and green vehicle routing in reverse logistics can reduce production costs by reusing the product components (Soleimani et al., 2018).

The efficient and effective distribution of products within supply chains is considered a complex and challenging task (Dulebenets, 2019). Cross-docking is a distribution strategy commonly used to improve efficiency in supply chains by transferring goods brought from suppliers to the cross-dock and another vehicle for delivery. The integration of vehicle routing with cross-docking allows identifying an efficient set of routes that effectively satisfy the transportation needs between pickup and delivery points (Grangier et al., 2017). As a result, there are few inventory holding costs, and there is no need for extensive storage facilities at the cross-dock. Also, the consolidation process at the cross-dock reduces the distribution costs in the supply chain (Baniamerian et al., 2019; Abad et al., 2018).

In general, supply chain network design involves a large number of strategic and operational decisions. Supplier selection and order allocation are among the most common problems in supply chain networks, significantly impacting delivery time and costs (Lo et al., 2018). The location-inventory-routing (LIR) problem is another critical problem that significantly affects the overall emissions and inventory expenses in supply chain networks (Saragih et al., 2019). Similarly, simultaneous pickup and delivery strategies and cross-docking operations can directly reduce emissions and transportation costs (Abad et al., 2018). In addition, forward and reverse flow is another commonly adopted strategy for reducing waste and increasing supply chain sustainability. Effective time window decisions in supply chain management can also lead to customer prioritization and satisfaction (Shi et al., 2020). We present a comprehensive literature review and show various combinations of these strategies adopted by supply chain researchers and practitioners (Biuki et al., 2020; Nasr et al., 2021; Parast et al., 2021). We also highlight the existing research gaps in the supply chain network design literature and formulate three research questions. The first research question involves *designing and developing a general mathematical model for sustainable reverse supply chain networks*. Models proposed for supply chain network design are complex and include a large number of parameters. One of the common modeling problems is the lack of access to real-world data for validation. Most supply chain designers use simulated data to address this problem. The difficulty with simulation data is feasibility. The second research question involves *developing an intelligent algorithm to generate relevant data for producing a feasible solution space*. Finally, researchers often struggle with selecting an appropriate multi-objective solution approach for solving complex supply chain network design problems. The third research question involves *choosing a suitable multi-objective model and solution method for solving complex network design problems under uncertainty*.

Therefore, for the first time, in this study, a comprehensive multi-objective mixed-integer linear programming (MOMILP) model is developed to design sustainable CLSC networks by considering LIR problem, split-delivery, time window, cross-docking operations, supplier selection and order allocation, storage capability, backorder shortage, uncertain demand, and simultaneous pickup, and delivery. The proposed comprehensive CLSC network can handle multi-product, multi-period, multi-echelon problems that involve economic, environmental, and social sustainability under uncertainty. The contributions of this study are threefold. We develop: (1) a comprehensive MOMILP model for designing and optimizing a sustainable CLSC network; (2) an intelligent simulation approach for generating the supply chain network data using probabilistic distribution functions with feasible solution

space; and (3) a fuzzy multi-objective solution approach for solving the proposed MOMILP model under uncertainty.

The remainder of this paper is organized as follows. We present a review of CLSC and LIR literature in Section 2. In Section 3, we formulate our problem and present our proposed model. Section 4 presents our experimental results, followed by a sensitivity analysis in Section 5. Section 6 discusses our managerial implications, and Section 7 offers our conclusion and future research directions.

2. Literature review

In this section, we present an overview of CLSCs and LIR literature.

2.1. Closed-loop supply chain

The increasing number of end-of-use (EOU) and end-of-life (EOL) products are some of the most harmful effects of the forward supply chain systems. The CLSC is an effective solution to the dangerous EOU/EOL products by collecting them in reverse logistics and reusing them in the forward logistics again (Taleizadeh et al., 2019; Sommerville et al., 2021). The CLSC networks are designed to collect, sort, repair, refurbish, or remanufacture EOU/EOL products and appropriately dispose of them (Shaharudin et al., 2019; Zarbakhshnia et al., 2020). Readers should refer to Govindan et al. (2015), Govindan and Soleimani (2017), and Peng et al. (2020) for a detailed review of the CLSC networks.

Soysal (2016) considered a pickup and delivery inventory-routing problem within time windows over a planning horizon and proposed a MILP to solve this problem in a CLSC. Similarly, Iassinovskaia et al. (2017) examined the inventory-routing problem with an emphasis on the returnable items at time windows in a CLSC and proposed a meta-heuristic model to solve the problem. Soleimani et al. (2017) studied a CLSC network and developed a comprehensive genetic algorithm model with manufacturers, customers, suppliers, warehouses, distribution centers, and return and recycle centers. Likewise, Chen et al. (2017) proposed a multi-objective model for total cost and carbon emission optimization of CLSCs in the solar energy industry. Jiao et al. (2018) studied a CLSC design under uncertainty and proposed an adaptive data-driven robust approach for carbon emission optimization.

Zeballos et al. (2018) considered a multi-product, multi-echelon, and multi-period network design problem in a CLSC and proposed a two-stage stochastic MILP model with uncertain quality and quantity of the returned products. Their model considers network design with manufacturing or remanufacturing products and new or recovered raw materials. Their network further considers first and second market customer demand, disposal and re-distribution centers, suppliers of raw materials, factories and distribution centers, recovery, and recycling centers. Noh and Kim (2019) studied a cooperative green supply chain composed of a manufacturer with multiple products and multiple retailers with limited resources under emission control regulations. They formulated the problem and compared a genetic algorithm model and a hybrid genetic algorithm-pattern search to solve the problem. Zhen et al. (2019) proposed a bi-objective optimization model for a green sustainable CLSC network under uncertain conditions. Mardan et al. (2019) developed a multi-period, multi-product, and multi-modal green CLSC network with two objectives. They proposed an accelerated benders decomposition algorithm and a mathematical model to solve the problem. They applied their proposed models in the wire-and-cable industry and conducted a sensitivity analysis to validate their models. Yavari and Geraeli (2019) focused on developing a green CLSC network under uncertainty and proposed a MILP model and a novel heuristic for solving large-scale problems. De and Giri (2020) formulated a mixed-integer nonlinear programming (MINLP) model in a CLSC network by considering carbon emissions and heterogeneous fleet. Their model simultaneously embarks on the minimization of the total network cost and carbon emissions. Parast et al. (2021) proposed a bi-objective MILP model for designing a green reverse supply chain for the perishable

products by considering simultaneous pickup and delivery, shortage, LIR problem, and vehicle scheduling. They applied a multi-objective fuzzy solution approach to solve their proposed model under uncertainty and assessed the performance of the proposed model in the bread distribution industry. Poursoltan et al. (2021) suggested a MINLP model for a two-level CLSC network under learning effect and vendor-managed inventory contract. They developed an efficient meta-heuristic algorithm for solving the proposed problem. Sadeghi Ahangar et al. (2021) designed a sustainable CLSC network to manage municipal solid waste using a MILP model based on a fuzzy programming approach. Their model was designed to optimize total cost, the workforce, and the emission level. The literature in reverse logistics and CLSC is rich and presents studies in waste management (Safaei et al., 2017; Liao et al., 2020), recycling (Saragih et al., 2019; Govindan et al., 2020), remanufacturing (Reimann et al., 2019; Taleizadeh et al., 2020; Zhang et al., 2020), disassembling (Yolmeh and Saif, 2020), reuse (Gu et al., 2018; Shimada and Van Wassenhove, 2019), and recovery (Ma et al., 2019; Wang et al., 2019), among others.

A literature review shows that many multi-objective solution approaches have been used to solve multi-objective mathematical models in the design of reverse supply chain/CLSC networks. Goal programming is one of the most popular methods used by researchers to solve complex models with more than two objective functions (Zandkarimkhani et al., 2020). Bal and Satoglu (2018) presented a goal programming model for managing electric and electronic waste in a sustainable reverse supply chain. Asim et al. (2019) proposed a multi-objective model to minimize total cost, total defective products, and total delivery time in a CLSC network under uncertainty. They applied a fuzzy goal programming approach to solve the multi-objective model under uncertainty. Nayeri et al. (2020) designed a multi-objective mathematical model under uncertainty with a robust fuzzy component to cope with the uncertainty in sustainable CLSC networks. Nasr et al. (2021) presented a novel integrated approach based on the best-worst method and MOMILP for designing a sustainable CLSC network with LIR problem, supplier selection, order allocation, vehicle scheduling, cross-docking, and shortage under uncertainty. They applied a fuzzy multi-objective solution approach for solving their MOMILP model using goal programming.

The challenge in these models is finding real-world data for validation purposes. As a result, researchers often use simulated data produced by probabilistic distribution functions where real-world data is unavailable. Sometimes researchers use independent parameters for simplicity, resulting in the infeasibility of the solution space (Govindan et al., 2014; Ahkamiraad and Wang, 2018; Ma et al., 2019). However, in intelligent simulation algorithms with dependent and interrelated parameters, the solution space is generally feasible (Zhalechian et al., 2016; Soleimani et al., 2018; Mardan et al., 2019; Tavana et al., 2021). For this reason, an intelligent simulation algorithm is used in this study to ensure the feasibility of the solution space.

2.2. Location-inventory-routing problem

There are three constituent LIR problems: location-allocation, inventory control, and vehicle routing (Zhang et al., 2014). From a historical perspective, although these three problems have been often investigated independently, the integration of the results has been instrumental in designing and developing efficient supply networks (Govindan et al., 2014; Hiassat et al., 2017; Zheng et al., 2019). A review of the related literature shows a large number of studies seeking to integrate two of the three problems mentioned above into one model, such as inventory-routing models (Cheng et al., 2017; Soysal et al., 2018), location-inventory models (Puga and Tancrez, 2017; Amiri-Aref et al., 2018), and location-routing models (Schiffer and Walther, 2017; Amiri et al., 2019). Recent findings show that effective integration of supply chain models can produce considerable savings in companies. In this regard, Liu and Lee (2003) introduced a single-product and multi-depot LIR model that considers inventory costs within an

integrated location and routing problem. Ahmadi-Javid and Seddighi (2012) proposed a mixed-integer programming (MIP) model by integrating inventory, routing, and location decisions in designing a multi-source distribution network and using a three-phase heuristic approach to solve the integrated problem. Zhalechian et al. (2016) developed a sustainable LIR model to integrate environmental damages from greenhouse gas emissions and energy consumption with employment and economic boom social advantages. Hiassat et al. (2017) developed an LIR model for perishable goods in which the inventory decisions were affected by perishability because of the existing variations in demand distribution. Rafie-Majd et al. (2018) also proposed a MINLP model to design a multi-echelon supply chain network for perishable products. The heterogeneity of vehicles, consideration of fuel consumption, demand uncertainty, and the use of LIR problem assumptions was among their model's fundamental assumptions.

Chao et al. (2019) proposed a two-stage MIP model to optimize a food distribution network by considering the LIR problem and time window. The first stage is related to optimizing the LIR problem by considering the time window, and the second stage pertains to the transportation problem with the capacity of vehicle constraint. Ghomi and Asgarian (2019) considered an LIR problem and formulated a MILP model to design perishable supply chain networks. They utilized a CPLEX solver to solve small and medium scale problems and a meta-heuristic algorithm to solve large-scale problems. Biuki et al. (2020) considered an LIR problem and proposed a MOMILP model to solve perishable products under uncertainty. Their model includes all three aspects of sustainability and makes use of a fuzzy approach to combat uncertainty. The LIR is a commonly encountered problem in sustainable supply chain networks (Zhalechian et al., 2016; Biuki et al., 2020), reverse logistics (Forouzanfar et al., 2018; Govindan et al., 2020), uncertain environments (Vahdani et al., 2018; Gholipour et al., 2020), and time window (Chao et al., 2019), among others. Table 1 presents a comprehensive review of the recent supply chain network design literature. This detailed and thorough review highlights the research gaps in the current supply chain network design literature for LIR models with cross-docking, pickup, and delivery. This is the first study to design a comprehensive sustainable CLSC for LIR problems with demand uncertainty, time window, cross-docking, and simultaneous pickup and delivery to the best of the authors' knowledge.

3. Problem statement and proposed model

Environmental awareness and the new competitive markets have attracted policy planners, and decision-makers increased attention to sustainable business practices. The CLSC networks include practices such as recycling, refurbishing, reusing, repairing, remanufacturing, and reclaiming. This study presents a comprehensive optimization framework for CLSC networks by considering the sustainability dimensions (i. e., economic, environmental, and social). We formulate a forward/reverse closed-loop LIR supply chain network and propose a comprehensive MOMILP model in manufacturing capable of handling:

- location-inventory-routing,
- multi-product and multi-period,
- supplier selection,
- multiple transportation modes for shipping the raw materials from suppliers to plant,
- location of distribution, remanufacturing, and disposal centers,
- capacitated centers, suppliers, and vehicles,
- routing between the cross-docks and customers,
- multi-depot routing with the possibility of split-delivery in the demand points,
- simultaneous pickup and delivery,
- soft and hard time windows,
- heterogeneous vehicles,
- the possibility of storage in customers' warehouses,

Table 1
A comprehensive review of the recent supply chain network design literature.

Reference	Model type			Model structure			Inventory				Routing			
	LP	MILP	MINLP	Multi-product	Multi-period	Multi-objective	Continuous	Periodic	Storage	Shortage	Multi-depot	Capacitated	Heterogeneous vehicles	Split-delivery
Talaei et al. (2016)	-	✓	-	✓	-	✓	-	-	-	-	-	-	-	-
Zhalechian et al. (2016)	-	-	✓	✓	✓	✓	-	✓	✓	-	✓	✓	✓	-
Fang et al. (2017)	-	✓	-	-	✓	-	-	✓	✓	-	✓	✓	-	-
Iassinovskaia et al. (2017)	-	✓	-	-	✓	-	-	✓	✓	-	✓	✓	✓	-
Rezaei and Kheirkhah (2017)	-	✓	-	✓	-	-	-	-	-	-	-	-	-	-
Soleimani et al. (2017)	-	✓	-	✓	✓	✓	-	-	-	-	-	-	-	-
Abad et al. (2018)	-	-	✓	✓	-	✓	-	-	-	-	✓	✓	✓	-
Forouzanfar et al. (2018)	-	✓	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	-
Rad and Nahavandi (2018)	-	✓	-	✓	✓	✓	-	✓	✓	-	-	-	-	-
Rezaei and Kheirkhah (2018)	-	✓	-	✓	-	✓	-	-	-	-	-	-	-	-
Sahebjamnia et al. (2018)	-	✓	-	✓	-	✓	-	-	-	-	-	-	-	-
Soleimani (2018)	-	✓	-	✓	✓	✓	-	✓	✓	-	-	-	-	-
Soleimani et al. (2018)	-	✓	-	✓	✓	✓	-	-	-	-	✓	✓	✓	✓
Mardan et al. (2019)	-	✓	-	✓	✓	✓	-	✓	✓	-	-	-	-	-
Navazi et al. (2019)	-	✓	-	-	✓	✓	-	-	-	-	-	✓	-	-
Yavari and Geraeli (2019)	-	✓	-	✓	✓	✓	-	✓	✓	-	-	-	-	-
Zhen et al. (2019)	-	✓	-	✓	✓	✓	-	✓	✓	-	-	-	-	-
Biuki et al. (2020)	-	✓	-	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	-
Govindan et al. (2020)	-	✓	-	✓	-	✓	-	✓	✓	✓	✓	✓	✓	✓
Nayeri et al. (2020)	-	✓	-	✓	-	✓	-	-	-	-	-	-	-	-
Sadeghi et al. (2020)	-	✓	-	✓	✓	✓	-	✓	✓	-	✓	✓	✓	✓
This study	-	✓	-	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	✓

- backorder shortages,
- uncertain demand with a stochastic (scenario-based) approach, and
- collecting all returned products from customers.

Fig. 1 presents a comprehensive sustainable closed-loop supply chain network.

3.1. Mathematical model

3.1.1. Indices

- c Raw material.
- p Product.
- d Cross-dock.
- r Remanufacturing center.
- n Disposal center.
- m, m' Customer.
- s Supplier.
- l Vehicle.
- a Transportation mode.
- t Time period.
- ξ Scenario.

3.1.2. Parameters

- CPV_l Maximum capacity of vehicle l .
- CPS_{cst} Maximum capacity of supplier s for supplying raw material c in time period t .
- $CPDS_{pd}$ Maximum capacity of cross-dock d for deliverable product p .
- $CPSD_{pd}$ Maximum capacity of cross-dock d for returned (pickup) product p .
- CPR_{pr} Maximum capacity of remanufacturing center r for product p .
- CPD_{pn} Maximum capacity of disposal center n for disposing of product p .
- TRS_{csat} Cost of shipping per unit of raw material c from the supplier s to plant by transportation mode a in time period t .
- $TRDS_{pdt}$ Cost of shipping per unit of product p from plant to cross-dock d in time period t .
- $TRDSR_{prt}$ Cost of shipping per unit of product p from cross-dock d to remanufacturing center r in time period t .

TRR_{prt} Cost of shipping per unit of product p from remanufacturing center r to plant in time period t .

$TRRD_{prnt}$ Cost of shipping per unit of product p from remanufacturing center r to disposal center n in time period t .

$FXDS_d$ Cost of opening cross-dock d .

FXR_r Cost of opening remanufacturing center r .

FXD_n Cost of opening disposal center n .

FXV_l Cost of purchasing vehicle l .

FXS_{st} Cost of ordering to supplier s in time period t .

PS_{cst} Price of per unit of raw material c purchased from supplier s in time period t .

$PRDS_{pdt}$ Cost of processing per unit of deliverable product p in cross-dock d in time period t .

$PRSD_{pdt}$ Cost of processing per unit of returned product p in cross-dock d in time period t .

PRR_{prt} Cost of remanufacturing per unit of product p in remanufacturing center r in time period t .

PRD_{pnt} Cost of disposing of per unit of product p in disposal center n in time period t .

$DMN_{pmt\xi}$ The demand of customer m for product p in time period t under scenario. $\xi CDS_{m'm}$ The geographical distance between customer m' and customer m .

DS_{dm} The geographical distance between cross-dock d and customer m .

$CT_{lm'm}$ The time required for vehicle l to move from customer m' to customer m .

CDT_{ldm} The time required for vehicle l to move from cross-dock d to customer m .

A_{pmt} Rate of returned product p from customer m in time period t .

B_{cp} Amount of raw material r required for producing per unit of product p .

E_{prt} Rate of remanufacturable product p shipped from cross-docks to remanufacturing center r in time period t .

θ_m The average time for loading and unloading products in location of customer m .

$JBDS_d$ The number of jobs created when the cross-dock d is opened.

JBR_r The number of jobs created when the remanufacturing center r is opened.

Routing			Supplier selection	Transportation mode	Location facilities	Facilities capacity	Cross-docking	Echelon		Closed-loop	Sustainable			Uncertainty		
Pickup and delivery	Time window							Forward	Reverse		Economic	Environmental	Social	Fuzzy	Stochastic	Robust
		Soft	Hard													
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	-	✓	✓	✓
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓	-
✓	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	-	-	-	-
✓	✓	✓	-	-	-	✓	-	✓	✓	✓	✓	-	-	-	-	-
-	-	-	-	-	✓	✓	✓	✓	✓	-	✓	-	-	-	-	-
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	-	-
✓	-	✓	✓	-	-	✓	✓	✓	-	-	✓	✓	-	-	-	-
-	-	-	✓	-	✓	✓	-	✓	✓	✓	✓	-	-	-	-	-
-	-	-	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	-	-	-	-
-	-	-	-	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	-	-
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	-	-
✓	-	-	-	-	✓	✓	-	✓	✓	-	✓	✓	-	✓	-	-
-	-	-	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	-	-	-
✓	-	-	-	-	✓	✓	-	✓	-	-	✓	✓	✓	-	-	-
-	-	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	-	-	-	✓
-	-	-	✓	-	✓	✓	-	✓	-	-	✓	✓	✓	✓	-	-
-	-	-	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	-	✓	-	-
✓	-	-	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	-	-	✓
✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-

JBD_n The number of jobs created when the disposal center n is opened.

H_{pmt} The cost of holding per unit of product p in the warehouse of customer m in time period t .

SH_{pmt} The penalty for facing a shortage for product p in the location of customer m in time period t .

TW Maximum time allowed to return vehicles to cross-docks.

ET_{mt} The earliest time allowed to visit customer m in time period t .

FT_{mt} The latest time allowed without penalty to visit customer m in time period t .

FT'_{mt} The latest time allowed with a penalty to visit customer m in time period t .

ψ Penalty for per unit exceeding the time window.

F_l The amount of fuel consumed by the vehicle l per unit of distance.

ENS_{csat} CO₂ emissions resulted from shipping each unit of raw ma-

$$XDS_d \begin{cases} 1 & \text{If distribution center } d \text{ is opened} \\ 0 & \text{Otherwise} \end{cases}$$

$$XR_r \begin{cases} 1 & \text{If remanufacturing center } r \text{ is opened} \\ 0 & \text{Otherwise} \end{cases}$$

$$XD_n \begin{cases} 1 & \text{If disposal center } n \text{ is opened} \\ 0 & \text{Otherwise} \end{cases}$$

$$XV_l \begin{cases} 1 & \text{If vehicle } l \text{ is purchased} \\ 0 & \text{Otherwise} \end{cases}$$

$$X_{ld} \begin{cases} 1 & \text{If vehicle } l \text{ is allocated to distribution center } d \\ 0 & \text{Otherwise} \end{cases}$$

$$Y_{lm'mt\xi} \begin{cases} 1 & \text{If vehicle } l \text{ moves from customer } m' \text{ to customer } m \text{ in time period } t \text{ under scenario } \xi \\ 0 & \text{Otherwise} \end{cases}$$

terial c from supplier s to plant by transportation mode a in time period t .

ENF CO₂ emissions resulted from consumption of per unit of fuel.

ϖ_ξ Probability of scenario. ξM A big number.

3.1.3. Variables

$$XS_{csat\xi} \begin{cases} 1 & \text{If supplier } s \text{ is selected to purchase raw material } c \text{ in time period } t \text{ under scenario } \xi \\ 0 & \text{Otherwise} \end{cases}$$

$AVT_{lmt\xi}$ Arrival time of vehicle l to the location of customer m in time period t , under scenario. $\xi Q_{lmt\xi}$ Amount of exceeding time window allowed to service to customer l in time period t , under scenario. $\xi DL_{pldmt\xi}$ The amount of delivered product p to customer m from cross-dock d by vehicle l in time period t , under scenario. $\xi PC_{pldmt\xi}$ The amount of

product p returned from customer m to cross-dock d by vehicle l in time period t , under scenario. $\xi \gamma_{plmt\xi}$ Total deliverable product p in vehicle l

when it leaves the location of customer m in time period t , under scenario. $\xi \gamma'_{plmt\xi}$ Total returned product p in vehicle l when it enters the location of customer m in time period t , under scenario. $\xi \alpha_{pmt\xi}$ The amount of product p stored in the warehouse of customer m in time period t , under scenario. $\xi \beta_{pmt\xi}$ The amount of facing a shortage for product p in the location of customer m in time period t , under scenario. $\xi \eta_{pmt\xi}$ Inventory level of customer m for product p in time period t , under scenario. $\xi YS_{csat\xi}$ The amount of raw material c purchased from supplier s by transportation mode a in time period t , under scenario. $\xi YDS_{pdrt\xi}$ The amount of product p shipped from plant to cross-dock d in time period t , under scenario. $\xi YDSR_{pdrt\xi}$ The amount of product p shipped from cross-dock d to remanufacturing center r in time period t , under scenario. $\xi YR_{prt\xi}$ The amount of product p shipped from remanufacturing center r to plant in time period t , under scenario. $\xi YRD_{prnt\xi}$ The amount of product p shipped from remanufacturing center r to disposal center n in time period t , under scenario. ξ

3.1.4. Objective functions

$$\sum_{m'} Y_{lm'mt\xi} \leq 1 \forall l, m, t, \xi \tag{9}$$

$$\gamma_{plm't\xi} + M \times (1 - Y_{lm'mt\xi}) \geq \gamma_{plmt\xi} + DL_{pldmt\xi} \forall p, l, m', m > 1, t, \xi \tag{10}$$

$$\gamma_{pl1t\xi} \geq \sum_m DL_{pldmt\xi} \forall p, l, d, t, \xi \tag{11}$$

$$\gamma'_{plmt\xi} + M \times (1 - Y_{lm'mt\xi}) \geq \gamma'_{plm't\xi} + PC_{pldmt\xi} \forall p, l, m', m > 1, t, \xi \tag{12}$$

$$\gamma'_{pl1t\xi} \geq \sum_m PC_{pldmt\xi} \forall p, l, d, t, \xi \tag{13}$$

$$\sum_{l,m} DL_{pldmt\xi} \leq CPDS_{pd} \forall p, d, t, \xi \tag{14}$$

$$\sum_{l,m} PC_{pldmt\xi} \leq CPSP_{pd} \forall p, d, t, \xi \tag{15}$$

$$\begin{aligned} Min Z_1 = & \sum_{c,s,t,\xi} \varpi_\xi \times FXS_{st} \times XS_{cst\xi} + \sum_d FXDS_d \times XDS_d + \sum_r FXR_r \times XR_r + \sum_n FXD_n \times XD_n + \sum_l FXV_l \times XV_l + \sum_{c,s,a,t,\xi} \varpi_\xi \times PS_{cst} \times YS_{csat\xi} \\ & + \sum_{p,l,d,m,t,\xi} \varpi_\xi \times PRDS_{pdt} \times DL_{pldmt\xi} + \sum_{p,l,d,m,t,\xi} \varpi_\xi \times PRSD_{pdt} \times PC_{pldmt\xi} + \sum_{p,d,r,t,\xi} \varpi_\xi \times PRR_{prt} \times YDSR_{pdrt\xi} + \sum_{p,r,n,t,\xi} \varpi_\xi \times PRD_{prnt} \times YRD_{prnt\xi} + \sum_{c,s,a,t,\xi} \varpi_\xi \times TRS_{csat} \times YS_{csat\xi} \\ & + \sum_{p,d,t,\xi} \varpi_\xi \times TRDS_{pdt} \times YDS_{pdt\xi} + \sum_{p,d,r,t,\xi} \varpi_\xi \times TRDSR_{pdrt} \times YDSR_{pdrt\xi} + \sum_{p,r,t,\xi} \varpi_\xi \times TRR_{prt} \times YR_{prt\xi} + \sum_{p,r,n,t,\xi} \varpi_\xi \times TRRD_{prnt} \times YRD_{prnt\xi} + \sum_{p,m,t,\xi} \varpi_\xi \times H_{pmt} \times \alpha_{pmt\xi} + \sum_{p,r,n,t,\xi} \varpi_\xi \\ & \times TRRD_{prnt} \times YRD_{prnt\xi} + \sum_{p,m,t,\xi} \varpi_\xi \times H_{pmt} \times \alpha_{pmt\xi} \end{aligned} \tag{1}$$

$$Min Z_2 = \sum_{c,s,a,t,\xi} \varpi_\xi \times ENS_{csat} \times YS_{csat\xi} + ENF \times \sum_{l,m' > 1, m > 1, t, \xi} \varpi_\xi \times F_l \times CDS_{m'm} \times Y_{lm'mt\xi} + ENF \times \sum_{l,d,m > 1, t, \xi} \varpi_\xi \times F_l \times DS_{dm} \times X_{ld} \times (Y_{l1mt\xi} + Y_{lm1t\xi}) \tag{2}$$

$$Max Z_3 = \sum_{p,d,t,\xi} \varpi_\xi \times JBDS_d \times \frac{YDS_{pdt\xi}}{CPDS_{pd}} + \sum_{p,l,d,m,t,\xi} \varpi_\xi \times JBDS_d \times \frac{PC_{pldmt\xi}}{CPSP_{pd}} + \sum_{p,d,r,t,\xi} \varpi_\xi \times JBR_r \times \frac{YDSR_{pdrt\xi}}{CPR_{pr}} + \sum_{p,r,n,t,\xi} \varpi_\xi \times JBD_n \times \frac{YRD_{prnt\xi}}{CPD_{pn}} \tag{3}$$

$$\sum_a YS_{csat\xi} \leq CPS_{cst} \forall c, s, t, \xi \tag{16}$$

s.t.
 $ET_{mt} \leq AVT_{lmt\xi} \leq FT'_{mt} \forall l, m, t, \xi$ (4)

$$\sum_d YDSR_{pdrt\xi} \leq CPR_{pr} \forall p, r, t, \xi \tag{17}$$

$$AVT_{lmt\xi} - FT_{mt} \leq Q_{lmt\xi} \forall l, m, t, \xi$$
 (5)

$$\sum_r YRD_{prnt\xi} \leq CPD_{pn} \forall p, n, t, \xi \tag{18}$$

$$AVT_{lmt\xi} + (1 - Y_{lm'mt\xi}) \times M \geq AVT_{lm't\xi} + CT_{lm'm} \forall l, m', m > 1, t, \xi$$
 (6)

$$\sum_p \gamma_{plmt\xi} + \sum_p \gamma'_{plmt\xi} + \sum_p DL_{pldmt\xi} \leq CPV_l \forall l, d, m, t, \xi \tag{19}$$

$$TW + (1 - Y_{lm1t\xi}) \times M \geq AVT_{lmt\xi} + CDT_{ldm} \times X_{ld} \forall l, m > 1, d, t, \xi$$
 (7)

$$X_{ld} \leq M \times XV_l \forall l, d \tag{20}$$

$$\sum_{m'} Y_{lm'mt\xi} - \sum_{m'} Y_{lmm't\xi} = 0 \forall l, m, t, \xi$$
 (8)

$$DL_{pldmt\xi} \leq M \times X_{ld} \forall p, l, d, m, t, \xi \tag{21}$$

$$PC_{pldmt\xi} \leq M \times X_{ld} \forall p, l, d, m, t, \xi \quad (22)$$

$$DL_{pldmt\xi} \leq M \times XDS_d \forall p, l, d, m, t, \xi \quad (23)$$

$$PC_{pldmt\xi} \leq M \times XDS_d \forall p, l, d, m, t, \xi \quad (24)$$

$$DL_{pldmt\xi} \leq M \times \sum_{m'} Y_{lm' m t \xi} \forall p, l, d, m, t, \xi \quad (25)$$

$$PC_{pldmt\xi} \leq M \times \sum_{m'} Y_{lm' m t \xi} \forall p, l, d, m, t, \xi \quad (26)$$

$$\sum_d X_{ld} \leq 1 \forall l \quad (27)$$

$$\sum_{l,d,t} PC_{pldmt\xi} = \sum_{l,d,t} A_{pmt} \times DL_{pldmt\xi} \forall p, m, \xi \quad (28)$$

$$\eta_{pmt\xi} = \eta_{pmt(t-1)\xi} + \sum_{l,d} DL_{pldmt\xi} - DMN_{pmt\xi} - \sum_{l,d} PC_{pldmt\xi} \forall p, m, t > 1, \xi \quad (29)$$

$$\eta_{pmt\xi} = \sum_{l,d} DL_{pldmt\xi} - DMN_{pmt\xi} - \sum_{l,d} PC_{pldmt\xi} \forall p, m, t = 1, \xi \quad (30)$$

$$\eta_{pmt\xi} = \alpha_{pmt\xi} - \beta_{pmt\xi} \forall p, m, t, \xi \quad (31)$$

$$\sum_{l,d,t} DL_{pldmt\xi} \geq \sum_t DMN_{pmt\xi} \forall p, m, \xi \quad (32)$$

$$\frac{\sum_{s,a} YS_{csat\xi}}{B_{cp}} \geq \sum_d YDS_{pdt\xi} \forall c, p, t = 1, \xi \quad (33)$$

$$\frac{\sum_{s,a} YS_{csat\xi}}{B_{cp}} + \sum_r YR_{prt\xi} \geq \sum_d YDS_{pdt\xi} \forall c, p, t > 1, \xi \quad (34)$$

$$YDS_{pdt\xi} \geq \sum_{l,m} DL_{pldmt\xi} \forall p, d, t, \xi \quad (35)$$

$$\sum_r YDSR_{pdrt\xi} = \sum_{l,m} PC_{pldmt\xi} \forall p, d, t, \xi \quad (36)$$

$$\sum_d YDSR_{pdrt\xi} = \sum_n YRD_{prnt\xi} + YR_{prt\xi} \forall p, r, t, \xi \quad (37)$$

$$YR_{prt\xi} = \sum_d E_{prt} \times YDSR_{pdrt\xi} \forall p, r, t, \xi \quad (38)$$

$$YS_{csat\xi} \leq M \times XS_{cs t \xi} \forall c, s, a, t, \xi \quad (39)$$

$$YDS_{pdt\xi} \leq M \times XDS_d \forall p, d, t, \xi \quad (40)$$

$$YDSR_{pdrt\xi} \leq M \times XDS_d \forall p, d, r, t, \xi \quad (41)$$

$$YDSR_{pdrt\xi} \leq M \times XR_r \forall p, d, r, t, \xi \quad (42)$$

$$YRD_{prnt\xi} \leq M \times XR_r \forall p, r, n, t, \xi \quad (43)$$

$$YR_{prt\xi} \leq M \times XR_r \forall p, r, t, \xi \quad (44)$$

$$YRD_{prnt\xi} \leq M \times XD_n \forall p, r, n, t, \xi \quad (45)$$

The first objective function is intended to minimize the total costs of the supply chain, including the ordering costs, the costs associated with the distribution, remanufacturing, and disposal centers, vehicle costs, raw materials, delivery and return costs in the cross-docks, costs associated with remanufacturing and disposing of products, costs of shipping raw materials and products between the supply chain echelons, holding costs, shortage costs, and the costs associated with exceeding the delivery time window. The second objective function is used to minimize the CO₂ produced from the transportation and shipping of the raw materials. The third objective function considers the social responsibility aspect of sustainability by maximizing the job opportunities created by opening new distribution, remanufacturing, and disposal centers. Constraint (4) guarantees that the arrival time of vehicles to the customers' location is within a specific time window. Constraint (5) represents the penalty for going over the specific delivery time window. Constraints (6) and (7) determine the arrival time of the vehicle to the customer's location and pertain to the sub-tour elimination constraint. The maximum time allowed for the vehicle to return to the cross-dock is controlled by Constraint (7). Constraint (8) ensures the exit of vehicles entering a node (customer's location). Constraint (9) limit the number of times a vehicle can visit a customer to one. Constraints (10) and (11) compute the amounts of product available in the vehicles when leaving the customer's location. Similarly, Constraints (12) and (13) calculate the amounts of returned products existing in the vehicle when entering the customer's location. Not exceeding the capacity of cross-docks, suppliers, remanufacturing, and disposal centers, and vehicles have been addressed in Constraints (14) to (19), respectively. The vehicle can only be assigned to a cross-dock if the cross-dock is open. Constraint (20) represents this requirement. Constraints (21) and (22) guarantee that there will be no possibility of product delivery and pickup by a vehicle that has not been assigned to a cross-dock. In addition, if the cross-dock is not open, the delivery and pickup will not be possible. These

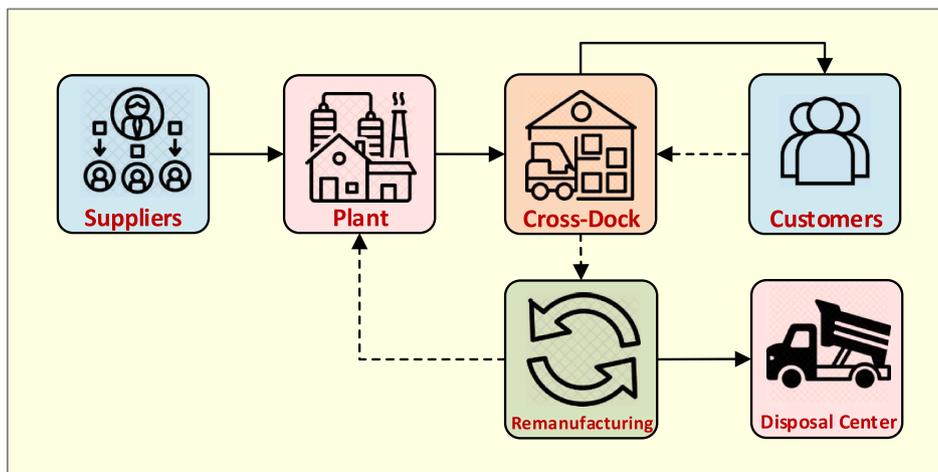


Fig. 1. Comprehensive sustainable closed-loop supply chain network.

conditions are considered in Constraints (23) and (24), respectively.

The condition for product delivery to a customer and product pickup from a customer requires the vehicle to arrive at the customer's location. These conditions are represented by Constraints (25) and (26), respectively. Each vehicle belongs to a specific cross-dock. This requirement is considered by Constraint (27). Constraint (28) calculates the amounts of returned products from each customer. The inventory level in the customer's warehouse is represented by Constraints (29) and (30). Constraint (31) demonstrates the relationship between inventory level, amount of storage, and the amount of shortage. Constraint (32) is related to meeting customers' demands. Backorder demand has also been considered in this constraint. Inventory level in the plant has been represented by Constraints (33) and (34). In addition, inventory levels for delivering and returning products in the cross-dock is represented by Constraints (35) and (36), respectively. The inventory level in the remanufacturing center has been represented by Constraint (37). Constraint (38) calculates the amounts of products shipped from the cross-dock to the remanufacturing centers. Purchasing from a supplier is possible only after the supplier is contacted. Constraint (39) represents this requirement. Location conditions for the cross-docks have been represented by Constraints (40) and (41), for the remanufacturing centers have been represented by Constraints (42) to (44), and for the disposal, centers have been represented by Constraint (45).

3.2. Linearization process

A nonlinear term is created by multiplying the two binary variables $Y_{lm't}$ and X_{ld} in the second objective function. $XY_{ldm't}$ is defined as a new binary variable and replaced with a nonlinear term (i.e., $Y_{lm't} \times X_{ld}$) for linearization of this term. Finally, we should determine the relationship between the new binary variable and two other variables. The second linearized objective function and the required constraints are presented as follows.

$$Min Z_2 = \sum_{c,s,d,t} ENS_{csat} \times YS_{csat} + ENF \times \sum_{l,d,m>1,t} F_l \times DS_{dm} \times (XY_{ldm't} + XY_{ldm't})ENF \times \sum_{l,m>1,m>1,t} F_l \times CDS_{m'm} \times Y_{lm't} \tag{46}$$

$$XY_{ldm't} \leq Y_{lm't} + M \times (1 - X_{ld}) \forall l, d, m', m, t \tag{47}$$

$$XY_{ldm't} \leq X_{ld} + M \times (1 - Y_{lm't}) \forall l, d, m', m, t \tag{48}$$

$$XY_{ldm't} \geq 1 + M \times (X_{ld} + Y_{lm't} - 2) \forall l, d, m', m, t \tag{49}$$

$$XY_{ldm't} \leq M \times (X_{ld} + Y_{lm't}) \forall l, d, m', m, t \tag{50}$$

3.3. Solution approach

There are a number of methods for solving the multi-objective programming problems; however, it is best to use goal programming to solve problems with a large number of objective functions (Zandkarimkhani et al., 2020). Moreover, fuzzy planning methods could be used in multi-objective problems for handling uncertainties (Tavana et al., 2020). Therefore, a fuzzy goal programming approach has been presented in this paper to solve the proposed multi-objective model as follows:

Step 1: Identifying goals

This step is used to formulate the problem goals by the decision-makers. For this purpose, the proposed model is independently solved with respect to each objective function to determine the optimal value of the objective functions. In other words, decision-makers determine the problem goals. For example, the current proposed model assumes that Z_1^{ind} , Z_2^{ind} , and Z_3^{ind} represent the objective function values for the first, second, and third objective functions, respectively. The following propositions are then held true when the goals of the first, second, and third objective functions are represented by GL_1 , GL_2 , and GL_3 , respectively.

$$Z_1^{ind} \leq GL_1, Z_2^{ind} \leq GL_2, Z_3^{ind} \geq GL_3$$

Step 2: Goal programming model

This step deals with setting the problem goals and constructing the corresponding goal programming model as follows:

$$\begin{aligned} &Min dev_1^+ \\ &Min dev_2^+ \\ &Min dev_3^- \\ &s.t. \\ &Z_1 - dev_1^+ + dev_1^- = GL_1 \\ &Z_2 - dev_2^+ + dev_2^- = GL_2 \\ &Z_3 - dev_3^+ + dev_3^- = GL_3 \\ &System Constraints \end{aligned} \tag{51}$$

where the positive deviations are represented by dev_1^+ , dev_2^+ and, dev_3^+ , and the negative deviations of the first, second, and third goals are represented by dev_1^- , dev_2^- , and dev_3^- , respectively. In fact, the constraints of the system constitute those of the proposed model.

Step 3: Equivalent single objective model

In this step, the multi-objective goal programming model obtained from Step 2 is converted to a single objective model for any deviation from the objective functions and, then, a membership function is developed using the method proposed by Zandkarimkhani et al. (2020). The goal programming model minimizes the unwanted deviations from the goals predefined by the decision-makers using the following membership function:

$$\mu_{dev_i}^{Min}(x) = \begin{cases} 1 & dev_i(x) > Udev_i \\ 0 & dev_i(x) < Ldev_i \\ \frac{Udev_i - dev_i(x)}{Udev_i - Ldev_i}, & Ldev_i \leq dev_i(x) \leq Udev_i \end{cases} \tag{52}$$

where the lower and upper levels of the unwanted deviations from goal i are represented by $Ldev_i$ and $Udev_i$, respectively. Moreover, the membership function of such deviations from this goal is represented by $\mu_{dev_i}^{Min}$. Hence, the following indicates the fuzzy single objective model:

$$Max \varphi = \sum_i w_i \times \varphi_i s.t. \varphi_i \leq \mu_{dev_i}^{Min}(x) Z_i - dev_i^+ + dev_i^- = GL_i System Constraints \tag{53}$$

The intended mathematical model is obtained based on Eq. (53) as follows:

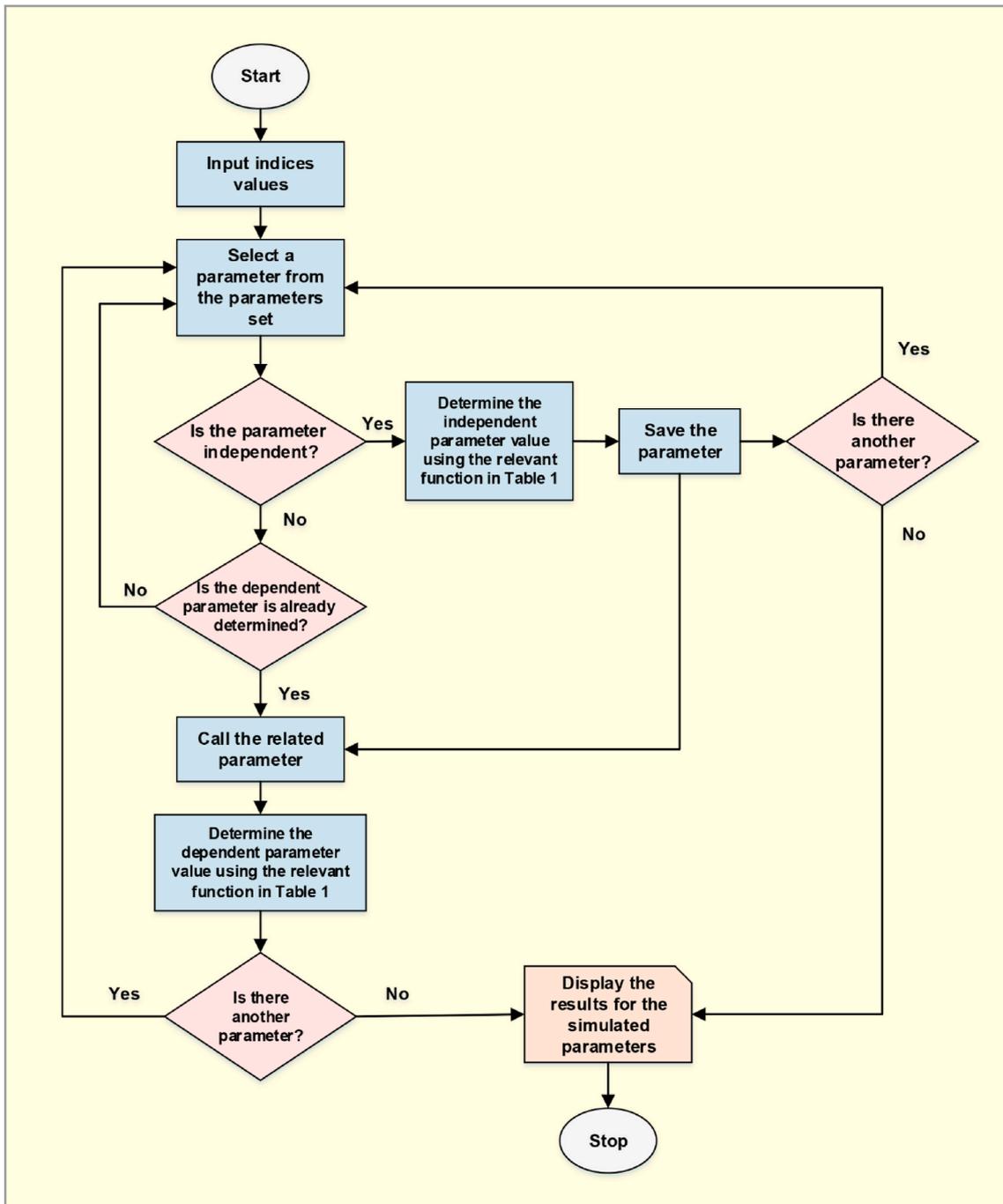


Fig. 2. The simulation flowchart.

4. Experimental results

In this section, the performance and efficiency of the proposed model and the solution approach are assessed using simulated data. To this end, an intelligent algorithm is proposed for the simulation by generating eight small and medium-size problems. Finally, the proposed single objective model is implemented using the eight simulated problems with the GAMS software.

4.1. Data simulation

An intelligent simulation algorithm with probabilistic distribution functions is used to generate data following a logical pattern. The proposed algorithm allows the user to adopt any value desired for the

indices and always stay in the feasible solution space. In other words, parameters leading to infeasible solution space are defined as a function of other parameters to ensure the availability of the feasible solution spaces. Table 2 presents the proposed intelligent simulation algorithm for data generation. The data simulation procedure is illustrated in Fig. 2 using probabilistic distribution functions. The simulation parameters are divided into independent and dependent categories. The values for the independent parameters are generated with the probabilistic distributions proposed in Table 2, and the values for the dependent variables are determined as a function of their corresponding independent variable. Obviously, dependent parameters can be generated after their corresponding independent parameters have been simulated. As shown in Fig. 2, the user starts by entering the values of indices and select one parameter depending on the proposed simulation procedure. If the

Table 3
The customer demands for each product in each time period and scenario.

DMN _{pmξ}		ξ = 1				ξ = 2				ξ = 3			
		t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4	t = 1	t = 2	t = 3	t = 4
p = 1	m = 1	0	0	0	0	0	0	0	0	0	0	0	0
p = 1	m = 2	418	410	426	406	439	431	447	426	461	453	469	447
p = 1	m = 3	424	420	434	430	445	441	456	452	467	463	479	475
p = 1	m = 4	438	418	420	418	460	439	441	439	483	461	463	461
p = 1	m = 5	412	424	412	430	433	445	433	452	455	467	455	475
p = 2	m = 1	0	0	0	0	0	0	0	0	0	0	0	0
p = 2	m = 2	440	416	418	406	462	437	439	426	485	459	461	447
p = 2	m = 3	404	424	432	428	424	445	454	449	445	467	477	471
p = 2	m = 4	424	424	426	404	445	445	447	424	467	467	469	445
p = 2	m = 5	406	412	424	404	426	433	445	424	447	455	467	445
p = 3	m = 1	0	0	0	0	0	0	0	0	0	0	0	0
p = 3	m = 2	402	402	406	412	422	422	426	433	443	443	447	455
p = 3	m = 3	412	412	412	428	433	433	433	449	455	455	455	471
p = 3	m = 4	422	424	402	438	443	445	422	460	465	467	443	483
p = 3	m = 5	420	428	416	430	441	449	437	452	463	471	459	475

Table 4
Dimensions (indices values) for the simulated problems.

Problem	$ c \times p \times d \times r \times n \times m \times s \times l \times a \times t \times \xi $
PR1	$ 1 \times 2 \times 2 \times 2 \times 2 \times 3 \times 2 \times 2 \times 2 \times 2 \times 2 $
PR2	$ 2 \times 2 \times 3 \times 2 \times 2 \times 4 \times 3 \times 3 \times 2 \times 3 \times 3 $
PR3	$ 3 \times 3 \times 3 \times 2 \times 2 \times 5 \times 4 \times 3 \times 3 \times 4 \times 3 $
PR4	$ 4 \times 3 \times 3 \times 3 \times 3 \times 6 \times 4 \times 3 \times 3 \times 4 \times 4 $
PR5	$ 4 \times 4 \times 4 \times 3 \times 3 \times 6 \times 4 \times 4 \times 3 \times 5 \times 4 $
PR6	$ 4 \times 4 \times 4 \times 3 \times 3 \times 7 \times 4 \times 4 \times 3 \times 5 \times 5 $
PR7	$ 4 \times 5 \times 4 \times 4 \times 3 \times 8 \times 4 \times 4 \times 4 \times 5 \times 5 $
PR8	$ 5 \times 5 \times 4 \times 4 \times 4 \times 9 \times 4 \times 4 \times 4 \times 6 \times 5 $

Table 5
The runtime and the optimal values of the objective function for different scenarios.

Problem	The first objective function	The second objective function	The third objective function	Runtime (Second)
PR1	834,527,390	3115.4	752.12	26.64
PR2	893,637,292	3167.8	783.53	89.76
PR3	971,999,845	3153.3	877.47	302.96
PR4	1,246,867,247	3538.7	1211.11	654.38
PR5	1,727,608,756	5618.8	1476.34	883.36
PR6	1,787,398,291	5591.4	1653.64	1547.36
PR7	1,988,681,517	6011.2	1860.47	235.87
PR8	2,273,704,194	6789.1	2089.38	3011.34

selected parameter is independent, the data for that parameter is generated using the functions proposed in Table 2, and the values of the generated data are saved. On the other hand, if the selected parameter is dependent, the algorithm ensures its corresponding independent parameter is generated. If the independent parameter is generated, the dependent parameter is simulated using the function proposed in Table 2, and the simulated parameter is saved; otherwise, the next parameter is selected. This procedure continues until all the parameters are simulated.

For example, assume that the user assigns the following values to the simulation indices $c = 3, p = 3, d = 3, r = 2, n = 2, m = 5, s = 4, l = 3, a = 3, t = 4$, and $\xi = 3$, and runs the proposed simulation algorithm. The execution of the algorithm will produce customer demand for each product in each time period for each scenario, as the output of the algorithm, presented in Table 3. For example, the value 418 in the second row of Table 3 indicates the demand for customer 2 for product 1 in time period 1 in scenario 1 is equal to 418 units. Note that customer demand for all products in all time periods and for all scenarios is always zero

Table 6
The routes traveled by each vehicle in each time period for each scenario.

		ξ = 1	ξ = 2	ξ = 3
l =	t =	d = 2 → m = 5 → m =	d = 2 → m = 3 → m =	d = 2 → m = 5 → m =
1	1	3 → d = 2	= 4 → d = 2	= 4 → d = 2
l =	t =	d = 2 → m = 5 → m = 4 →	d = 2 → m = 5 → m =	d = 2 → m = 2 → m =
1	2	m = 2 → d = 2	= 2 → d = 2	= 3 → d = 2
l =	t =	d = 2 → m = 4 → m =	d = 2 → m = 4 → m =	d = 2 → m = 3 → m =
1	3	2 → d = 2	= 3 → d = 2	= 4 → d = 2
l =	t =	d = 2 → m = 3 → m =	d = 2 → m = 3 → m =	d = 2 → m = 5 → m =
1	4	4 → d = 2	= 4 → d = 2	= 4 → d = 2
l =	t =	d = 1 → m = 5 → m =	d = 1 → m = 4 → m =	d = 1 → m = 4 → m =
2	1	2 → d = 1	= 5 → d = 1	= 3 → d = 1
l =	t =	d = 1 → m = 3 → m =	d = 1 → m = 2 → m =	d = 1 → m = 3 → m =
2	2	4 → d = 1	= 3 → d = 1	= 4 → d = 1
l =	t =	d = 1 → m = 3 → m =	d = 1 → m = 3 → m =	d = 1 → m = 2 → m =
2	3	4 → d = 1	= 5 → d = 1	= 5 → d = 1
l =	t =	d = 1 → m = 5 → m =	d = 1 → m = 5 → m =	d = 1 → m = 5 → m =
2	4	3 → d = 1	= 3 → d = 1	= 3 → d = 1
l =	t =	d = 3 → m = 5 → m =	d = 3 → m = 5 → m =	d = 3 → m = 5 → m =
3	1	4 → d = 3	= 2 → d = 3	= 2 → d = 3
l =	t =	d = 3 → m = 4 → m =	d = 3 → m = 4 → m =	d = 3 → m = 5 → m =
3	2	2 → d = 3	= 3 → d = 3	= 4 → d = 3
l =	t =	d = 3 → m = 2 → m =	d = 3 → m = 2 → m =	d = 3 → m = 5 → m =
3	3	5 → d = 3	= 5 → d = 3	= 3 → d = 3
l =	t =	d = 3 → m = 4 → m =	d = 3 → m = 4 → m =	d = 3 → m = 3 → m =
3	4	2 → d = 3	= 2 → d = 3	= 2 → d = 3

Table 7
Results for the sensitivity analysis of the objective function coefficients.

Scenario	w ₁	w ₂	w ₃	Z ₁	Z ₂	Z ₃
SCN1	0.20	0.40	0.40	1,158,390,012	3021.6	1016.65
SCN2	0.30	0.35	0.35	1,023,882,203	3088.5	982.01
SCN3	0.40	0.30	0.30	982,738,621	3094.2	901.63
SCN4 (PR3)	0.50	0.25	0.25	971,999,845	3153.3	877.47
SCN5	0.60	0.20	0.20	968,656,519	3180.4	743.73
SCN6	0.70	0.15	0.15	956,674,940	3268.5	686.14
SCN7	0.80	0.10	0.10	952,690,173	3564.1	595.50

because customer 1 is considered a cross-dock.

5. Results and discussion

In this section, the performance and efficiency of the proposed mathematical model are assessed using data from the eight simulated small and medium-size problems. Small and medium problems refer to problems that take fewer than 3600 s to solve with the GAMS software. Table 4 presents the index values for the eight simulated problems. The

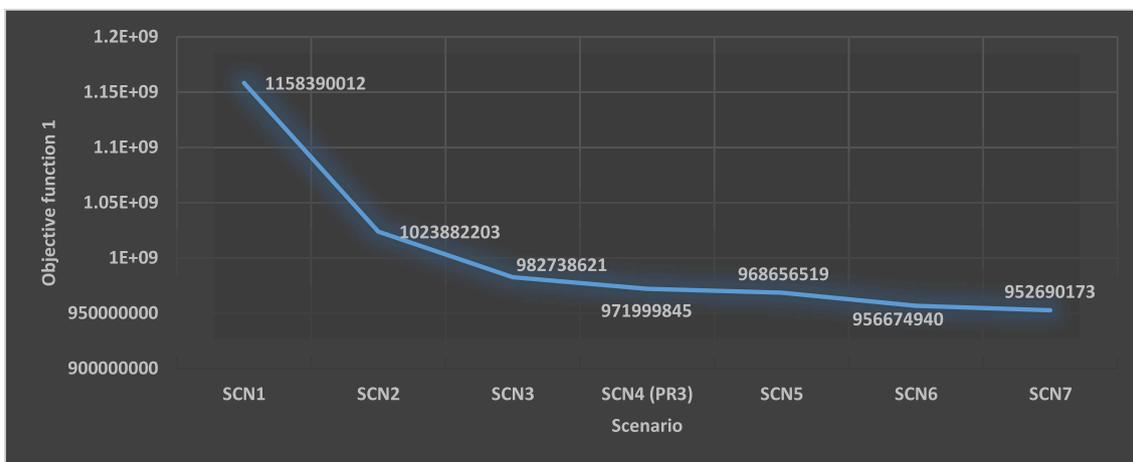


Fig. 3. The behavior of the first objective function in the face of different scenarios.

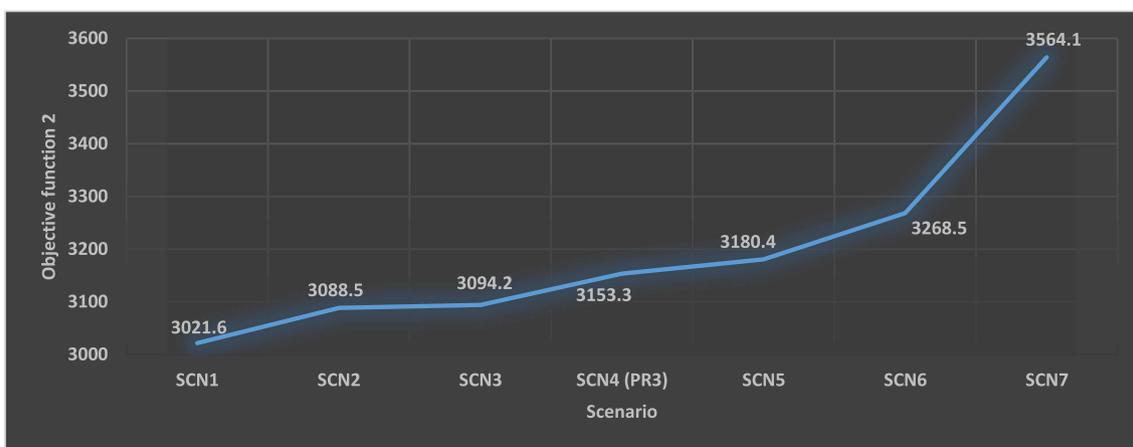


Fig. 4. The behavior of the second objective function in the face of different scenarios.



Fig. 5. The behavior of the third objective function in the face of different scenarios.

proposed model was run with the CPLEX solver and by considering $w_1 = 0.5$, $w_2 = 0.25$ and $w_3 = 0.25$ in the GAMS software. The optimal values of the objective functions and the runtime for each problem are calculated and presented in Table 5.

Problem 3 (i.e., PR3) is examined in more detail below as an example. By running the simulated data for this problem in GAMS, the

following results are obtained:

- The values of the first, second, and third objective functions are equal to 971,999,845; 3153.3; and 877.47, respectively.
- All four suppliers are selected.

Table 8
Results for the sensitivity analysis of the demand.

Scenario	Amount of demand	Z ₁	Z ₂	Z ₃
SC1	0.8 × DMN _{pmtξ}	937,762,716	3031.7	812.87
SC2	0.85 × DMN _{pmtξ}	943,029,671	3064.1	833.12
SC3	0.9 × DMN _{pmtξ}	959,239,175	3082.9	843.25
SC4	0.95 × DMN _{pmtξ}	965,653,016	3114.7	852.62
SC5 (PR3)	DMN _{pmtξ}	971,999,845	3153.3	877.47
SC6	1.05 × DMN _{pmtξ}	982,043,911	3194.5	891.04
SC7	1.1 × DMN _{pmtξ}	991,235,807	3223.8	915.66
SC8	1.15 × DMN _{pmtξ}	998,165,786	3271.4	949.76
SC9	1.2 × DMN _{pmtξ}	1,008,654,781	3301.2	968.85

- The cross-docks 1, 2, and 3, the remanufacturing center 2, and the disposal center 2 is established.
- Vehicle 1 is assigned to cross-dock 2, vehicle 2 is assigned to cross-dock 1, and vehicle 3 is assigned to cross-dock 3.
- The route traveled by each vehicle in each time period, and each scenario is shown in Table 6.
- The amount of storage and shortage in all time periods is zero.

The results presented in Table 6 show that all three vehicles have been used in all time periods. For example, the first line of this table states that vehicle 1 starts from cross-dock 2 in time period 1 and scenario 1 and returns to cross-dock 2 after service delivery to customers 5 and 3. This vehicle has chosen other routes in scenarios 2 and 3. In addition, we can see that customer demand is fully satisfied in all periods, and all returned products have been picked up from customers in all periods since storage and shortage amounts are equal to zero in all periods. Therefore, the cost of facing shortage and storage (holding costs) in problem 3 (i.e., PR3) are zero. Sensitivity analyses are used to evaluate the sensitivity of the proposed model to changes in the coefficients of the objective functions.

6. Sensitivity analysis

In this section, two sets of scenarios based on the coefficients of objective functions and the demand values are used to measure performance and examine the behavior of the proposed model and solution approach.

6.1. Sensitivity analysis of objective functions coefficient

In this section, a sensitivity analysis is used to evaluate the performance and behavior of the proposed simulation algorithm to changes in the coefficients of the objective functions. In general, it is expected that the value of the objective function does not deteriorate by increasing its coefficient and that the value does not improve by decreasing its coefficient. Table 7 presents the scenarios and the optimal values of the objective functions for each scenario in Problem 3 (i.e., PR3). Other variations for the objective function in different scenarios are shown in Figs. 3–5. The consistency of the results with the expectations confirms the validity and logical performance of the proposed model.

Table 7 shows as one moves from scenario 1 to scenario 7, the coefficient of objective function 1 increases, and the coefficients of the other two objective functions decrease simultaneously. The value of objective function 1 is expected to reduce by increasing the coefficient of objective function 1. Fig. 3 shows the implementation of this scenario causes a reduction in the objective function value. Similarly, decreasing the coefficients in the objective functions 2 and 3 results in an increase in the objective functions 2 and 3. The results obtained from implementing the scenarios confirm the expected behavior of the proposed model and solution approach.

6.2. Sensitivity analysis of demand values

In this section, several scenarios are constructed by changing the demand values. We expect the values of the first and second objective functions not to improve and the value of the third objective function to deteriorate when demand increases. We also expect that when the amount of demand decrease, values of the first and second objective functions will not deteriorate, and the value of the third objective function will not improve. The results from the implementation of these scenarios are presented in Table 8.

This table shows increasing the demand results in increasing the values of all three objective functions, and decreasing the demand results in decreasing the values of all three objective functions. The results obtained for each objective function in different scenarios meet the expectations; therefore, the logical performance of the proposed model and solution approach is confirmed.

7. Managerial implications

The purpose of this study is to present a comprehensive MOMILP model for designing sustainable CLSC networks under uncertainty. The model is considered “comprehensive” because it contains a complete set of assumptions commonly used in the literature. In this regard, many papers that considered at least one of the assumptions of the LIR problem, CLSC network, pickup and delivery, split-delivery, cross-docking, supplier selection, order allocation, storage capability, backorder shortage, and uncertainty in demand, were reviewed. Finally, an integrated MOMILP model was proposed by considering all the above assumptions to design sustainable CLSC networks. The proposed model can be implemented in supply chains/industries where pickup, delivery, and recycling are paramount. For example, the proposed model can be easily customized for logistics services in the catering industry to disinfect tableware (Hu et al., 2015), home appliance remanufacturing (Shuang et al., 2019), and bread delivery (Navazi et al., 2021), among others.

8. Conclusion and future research directions

Concerns about sustainable CLSC networks have increased in recent years as more and more manufacturers realize the economic, social, and environmental benefits of product returns and recovery management. We proposed an integrated MOMILP model for the optimal design of sustainable CLSC networks with cross-docking, storage capability, backorder shortage, split-delivery, supplier selection, order allocation, time window, location-inventory-routing, and simultaneous pickup and delivery, under uncertainty. The proposed framework can handle multi-product, multi-period, and multi-echelon problems with economic, environmental, and social sustainability considerations. In general, the contributions of this study are threefold. We develop: (1) a novel and comprehensive MOMILP model for designing and optimizing a sustainable CLSC network; (2) an intelligent simulation approach for generating the supply chain network data using probabilistic distribution functions with feasible solution space; and (3) a fuzzy goal programming approach for solving the proposed multi-objective mathematical model under uncertainty. We validated the performance of the proposed model and solution approach using eight small instances. We examined the accuracy of the proposed model using two sensitivity analysis categories, including the coefficients of the objective functions and the demand. The results confirmed the validity and logical performance of the proposed model.

Undoubtedly, every research suffers from limitations in addition to the benefits it brings. This paper is no exception. One of the biggest limitations of this research is the inability of the proposed model to solve large-size problems. For this purpose, we suggest developing an efficient heuristic or metaheuristic algorithm for solving large-size problems. Vehicles failure, supplier evaluations using evaluation techniques,

discounts on supplier purchases are among the assumptions not considered in this study. Adding these assumptions to the proposed model leads to the development of a more comprehensive model.

CRedit authorship contribution statement

Madjid Tavana: Conceptualization, Writing – original draft, review & editing, Visualization. **Hadi Kian:** Investigation, Resources, Validation. **Arash Khalili Nasr:** Conceptualization, Methodology, Investigation, Software, Data curation. **Kannan Govindan:** Methodology, Formal analysis, Review & editing, Supervision. **Hassan Mina:** Conceptualization, Methodology, Writing - original draft, Formal analysis.

Declaration of competing interest

The above authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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