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ORIGINAL RESEARCH

An optimisation tool for strategic planning of multiple downgraded market levels in circular supply chain management

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Abstract
Recent legislation promotes the adoption of Circular Economy principles in supply chain design, to encourage reuse, remanufacture, and recycle end-of-life products. An efficient circular supply chain design can improve resource efficiency, extend product lifecycles, and reduce waste, providing competitive advantages while contributing to sustainability goals. This study develops a bi-objective mixed-integer linear programming model to optimise strategic decisions in circular supply chain design, including activation of downgraded market levels, facility locations, and product flows. The model also accounts for the impact of cannibalisation between new and recovered product demand. The improved version of the augmented epsilon-constraint method (AUGMECON2) is applied to solve the model. Numerical experiments and sensitivity analyses validate the performance of the model and provide managerial insights to practitioners. The results demonstrate the potential of the model to support strategic decision-making and enhance circular supply chain effectiveness.

Keywords Circular supply chain (CSC) · Circular economy (CE) · Mixed-integer linear programming (MILP) · Downgraded market level · Bi-objective optimisation

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1 Introduction

Supply chain network (SCN) design activities play a pivotal role in determining the most efficient and effective ways to manage the flow of products across facilities (Zandkarimkhani et al., 2020). In the current business environment, where sustainability and environmental responsibility are paramount, embracing innovative consumption and production approaches is not just a choice but a necessity (Rezaei & Kheirkhah, 2018). The urgent need to integrate Circular Economy (CE) principles into supply networks is driven by a combination of factors, including increased environmental awareness among consumers and more stringent government regulations. According to the European Commission (2015), CE envisions a system in which materials and products are kept within production cycles through feedback loops, thus reducing the reliance on virgin raw materials and minimising waste generation (EMF, 2015; Genovese et al., 2017). Consequently, both top-down legislation from governments and bottom-up innovations from industrial organisations are imperative to accelerate the transition towards a CE (Bressanelli et al., 2019). Supply chain (SC) design and planning, particularly in the context of Circular Supply Chains, are integral in laying the groundwork for the implementation of CE practices (Genovese et al., 2017). As such, the Sustainable Development Goals (SDGs) serve as a global benchmark for sustainability initiatives. SDG 12 (Responsible Consumption and Production) and SDG 9 (Industry, Innovation, and Infrastructure) directly relate to the integration of CE principles within supply chains. SDG 12 calls for sustainable management and efficient use of natural resources, while SDG 9 advocates for fostering innovation and building resilient infrastructure. This research aligns with these goals by promoting supply chain models that minimise waste, encourage product reuse, and extend product lifecycles, thereby addressing critical environmental and economic challenges.

Within the Supply Chain Management (SCM) context, there is a distinction between Closed-Loop Supply Chains (CLSCs) and Circular Supply Chains (CSCs). Although both share a common goal, the key difference lies in their approach to achieving their goals. CLSCs primarily focus on recovering end-of-life (EOL) products and materials. In contrast, CSCs adopt a broader approach, implementing CE principles that encompass various strategies, including slowing, closing, reducing, and intensifying, as illustrated in Fig. 1. This broader approach enables CSCs to reduce the consumption of virgin resources and the release of waste into the environment through multiple feedback loops.

In contemporary business practices, the distribution of manufactured products is limited to primary markets and, in some cases, to secondary market levels. However, the value of products, components, and materials is much higher than ending up in landfills. In particular, certain products, such as white goods, have the potential for multiple uses within a CSC. As such, this paper incorporates the new concept of “Downgraded Market Levels” in CSC network design. The downgraded market levels refer to the different markets where a product can be sold after its initial use, allowing multiple cycles of use and reuse before the product ultimately reaches the disposal centre (the whole process is referred to as “intensifying” use). The significance of introducing multiple downgraded market levels in a CSC becomes apparent for several reasons. Firstly, the multiple processing of products as they reach the end of their useful life allows for the recovery of resources and significantly reduces the need for virgin raw materials, a central tenet of CE principles. In addition, customers have varied preferences and requirements. By offering products at multiple downgraded market

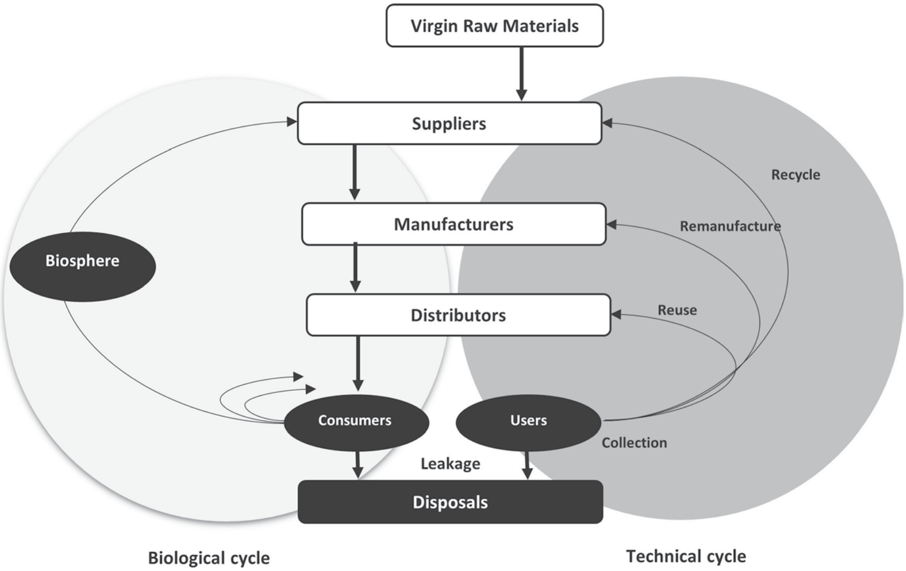


Fig. 1 The circular supply chains - adopted from the Ellen MacArthur foundation

levels, CSCs cater to different customer segments. Some customers prioritise high-quality products, while others seek affordability. By serving these diverse needs, companies can expand their market share and revenue while contributing to the social dimension of sustainability. Incorporating multiple downgraded market levels can also be useful for innovative circular business models such as product leasing as an alternative to outright buying of products, which offers a promising avenue for extending the life cycle of products. Furthermore, one noteworthy phenomenon within CSCs is the potential "cannibalisation effect". This occurs when lower-quality products cannibalise the sales of higher-quality ones, resulting in the loss of sales of the latter. Consequently, it is essential to evaluate the impact of recovered product sales on new product sales in CSCs.

As existing research fails to address these critical features while supporting CSC design, this research aims to bridge these gaps. The contributions of this study are threefold. (1) The compact bi-objective model of multi-product, multi-period, mixed-integer linear programming (MILP), supporting the design of the CSC with various recovery options, is introduced in the technical cycle of Fig. 1; (2) the new concept of multiple downgraded market levels is introduced with the aim of intensifying use is introduced; and finally, (3) the model suggests a novel approach to optimising facility locations, transportation flows and determining the optimal number of downgraded market levels, considering a wide range of demand scenarios as well as the cannibalisation effect.

The remainder of the paper is structured as follows. The next section provides an overview of the relevant literature, highlighting the research background in Circular Supply Chain Network design. Section 3 elaborates on the description and assumptions of the proposed model, along with the notations and problem formulation. In Sect. 4, the solution methodology for the proposed problem is explained and the model is validated through a numerical example in Sect. 5. Section 6 discusses the research findings and their implications in detail. Finally, concluding remarks and outline potential future research directions are suggested in Sect. 8.

2 Literature review

CSCs are a type of SCN which integrate CE principles whilst taking economic benefits into account. These types of networks play a crucial role in SCN design problems due to their sustainability and circularity advantages. Despite the increasing importance of CE practices and their appearance on the policy agenda, there is a disconnect between the SCN design and the CE grounding principles (MahmoumGonbadi et al., 2021). Hence, scholars have argued for the necessity of integrating CE and SCM related studies (Frei et al., 2020). Within this field, a review of the literature shows that CLSCs are the most investigated SCN design problems (MahmoumGonbadi et al., 2021). As a result, some scholars have gone beyond traditional CLSCs and instead focused on embedding CE principles in CLSCs. While some of the world's leading corporations are starting to adopt CE principles when designing their CSCs, research in this area still remains intact. For instance, unwanted clothes in H&M company, are now reused or recycled into new ones by designing CSCs for textiles. By embracing a circular approach in the flow of materials, components, and products, businesses can reduce waste and minimise the adverse ecological consequences stemming from their supply chain activities (Genovese et al., 2017). In this regard, the absence of a holistic approach is a significant challenge for businesses to implement CSCs (Mangla et al., 2018). To effectively manage and preserve the value of materials in a CE framework, it is necessary to rethink the conventional reverse SC procedures. This involves integrating CE practices such as reselling (reusing), remarketing, remanufacturing, and recycling, often in collaboration with one or more partners within the supply chain (Roy et al., 2022). To address this issue, several recently published articles have started incorporating CE principles into their mathematical models. As such, a circular food supply chain network design model is proposed by Kabadurmus et al. (2022); the Improved Augmented Epsilon Constraint method (AUGMECON2) has been utilised to solve the MILP model optimally. Similarly, Gholian-Jouybari et al. (2023) introduced an innovative MILP model to design a closed-loop agri-food SCN within the soybean industry, incorporating sustainability and CE principles. Foroozesh et al. (2023) proposed a novel three-stage optimisation approach with CE consideration to design a sustainable-resilient SCN for perishable goods. A circular CLSC network was proposed by Govindan et al. (2023) to address a location-inventory-routing (LIR) problem with carbon tax policy to achieve CE goals. A Lagrangian Relaxation (LR) algorithm developed by Tavana et al. (2023) to solve LIR problems within a multi-period and multi-product sustainable CSC network featuring heterogeneous vehicles. The designed Artificial Internet of Things (AIoT) enabled sustainable CSC aims to enhance network performance while establishing a secure and traceable environment. Dehshiri and Amiri (2024) also considered integrating CE when designing CLSC under hybrid uncertainties in different time horizons; their aim is to provide a robust scenario-based possibilistic-stochastic programming approach, allowing for the simultaneous consideration of cognitive and random uncertainties.

In practice, secondary and multiple levels of markets are key channels to sell End-of-Life (EOL) products, and CSCs are an effective means to perform the corresponding operations.

This is a common practice in the Electric and Electronics sector, where an EOL product is introduced into the market after several utilisation according to its life cycle instead of being disposed (Guo et al., 2018). Several studies have investigated the impact of incorporating secondary markets on SC performance (Lee & Whang, 2002; He & Zhang, 2010). In this regard, according to (Lee & Whang, 2002; He & Zhang, 2010) secondary market creates two interdependent effects on SC, namely a quantity effect that is related to the sales by a manufacturer and an allocation effect regarding the performance of SC. In this setting, Ramani and De Giovanni (2017) developed a two-period atypical CLSC model with taking cannibalisation effect of refurbished products into account for DellReconnect project. Baptista et al. (2019) developed a two-stage multi-period, multi-product stochastic mixed 0–1 bilinear optimisation model to address a CLSC problem and introduce a secondary market channel. Rani et al. (2020) introduced a fuzzy inventory mathematical model in the green supply chain with the cannibalisation effect of refurbished products sales on the new product sales. As such, Bal and Badurdeen (2022) proposed a simulation-based optimisation approach for CLSC design from the CE perspective and demonstrated that the sales price of EOL products in secondary markets has a greater impact on the profitability of the company.

Table 1 provides an organised comparison of recent contributions, highlighting the focus, employed approaches, findings, and limitations. The table illustrates that, while extensive research has been conducted on SCN design, notable gaps remain. For instance, studies often focus on limited treatment strategies, such as recycling, with less emphasis on innovative downgrading mechanisms across multiple market levels, wherein products can be recovered over and over again. Additionally, few models consider the cannibalisation effect. In a nutshell, the reviewed literature indicates that extensive research has been conducted in the areas of SCN design problems. However, according to (MahmoumGonbadi et al., 2021), there are still some research gaps identified in this field of study which this research tries

Table 1 Summary of recent contributions to CSC research

References	Key focus	Approach	Key findings	Limitations
Ramani and De Giovanni (2017)	Cannibalisation effect in CLSC (Dell Reconnect)	Two-period CLSC model	Captured internal competition between new and refurbished product sales	Limited to two-period settings
Kabadurmus et al. (2022)	Circular food SC network design	MILP with AUGMECON2 method	Demonstrated effective resource recirculation in the food industry	Limited focus on secondary markets
Bal and Badurdeen (2022)	CLSC design with CE principles	Simulation-based optimisation	Showed secondary market sales boost profitability	Relies on estimated input parameters
Gholian-Jouybari et al. (2023)	Closed-loop agri-food SCN for soybeans	MILP model	Incorporated sustainability goals in network design	Restricted to agricultural supply chains
Foroozesh et al. (2023)	Sustainable-resilient SCN for perishable goods	Three-stage optimisation approach	Showed resilience improvement in handling perishable goods under CE principles	High computational complexity
Govindan et al. (2023)	CLSC network with carbon tax policy	Location-inventory-routing (LIR)	Addressed environmental goals using taxation policies	Focused on policy impact without full CE integration
Tavana et al. (2023)	Multi-period, multi-product CSCN with AIoT integration	Lagrangian Relaxation (LR) method	Enhanced network performance through AI-based traceability	Neglects cannibalisation effect

to address some of the crucial ones; namely, lack of integration of CE principles in SCN design problems, the main focus on low treatment strategies (mainly recycling practices) in mathematical models, limited methodological developments and simplistic evaluation of environmental performance. To bridge these gaps, this study introduces a bi-objective model that optimises CSC networks by considering downgraded market levels and evaluating their economic and environmental impacts.

3 Problem description and model formulation

3.1 Problem statement

Strategic planning for CSCs involves long-term decisions on facility locations, product flows, and the number of downgraded market levels. The proposed deterministic bi-objective MILP model aims to maximise profit (encouraging companies to adopt CE practices) and minimise discarded products (improving sustainability and CE metrics).These objectives are achieved by optimising facility locations, market levels, and transportation flows while considering key treatment options: reusing, remanufacturing, and recycling. The CSC network illustrated in Fig. 2, includes forward nodes (suppliers, plants, distributors, primary markets) and reverse nodes (collection centres, reusing centres, remanufacturers, recyclers and disposal centres).

In the proposed mathematical CSC model, products that have reached the end of their life will be returned to the collection centres following a certain delay period. The delay refers to the amount of time it takes for the downgraded products to be returned to the collection centres after they have reached the superior-level customers. Such delay therefore includes usage time, logistics and transportation time, as well as any other practical considerations.

The model needs to optimise CSC based on four main treatment options: reusing, remanufacturing, recycling, and disposal. These options are ranked from the most optimal to the least optimal strategies. Hence, it shows that CSCs could practically have a number of successive product downgrading by sending more products to be treated in recovery facilities and resulting in activating more downgarded market levels to serve corresponding customer demands. Three recovery strategies considered for returned products are described below:

(i) *Reusing* the returned goods are of extremely good quality and their useful life is extended through reusing; products are reutilised as their original function and can be sent directly (after minor refurbishments in recycling centres) to distribution centres. They are sold at a discounted price as downgraded products after cleaning;
(ii) *Remanufacturing* the returned products are reprocessed and converted into "like new" condition for resale. Remanufacturing involves disassembling downgraded goods, substituting broken components, repairing any remaining flaws, and repacking the returned product for sale as a remanufactured item (Abbey et al., 2015).
(iii) *Recycling* Returned products that are not suitable for remanufacturing are recycled in recycling centres and the materials are reused to replace the extraction of virgin raw materials by the suppliers.
(iv) *Disposing* Products that due to low quality cannot be reused, remanufactured or recycled, are sent to disposal centres for final treatment.

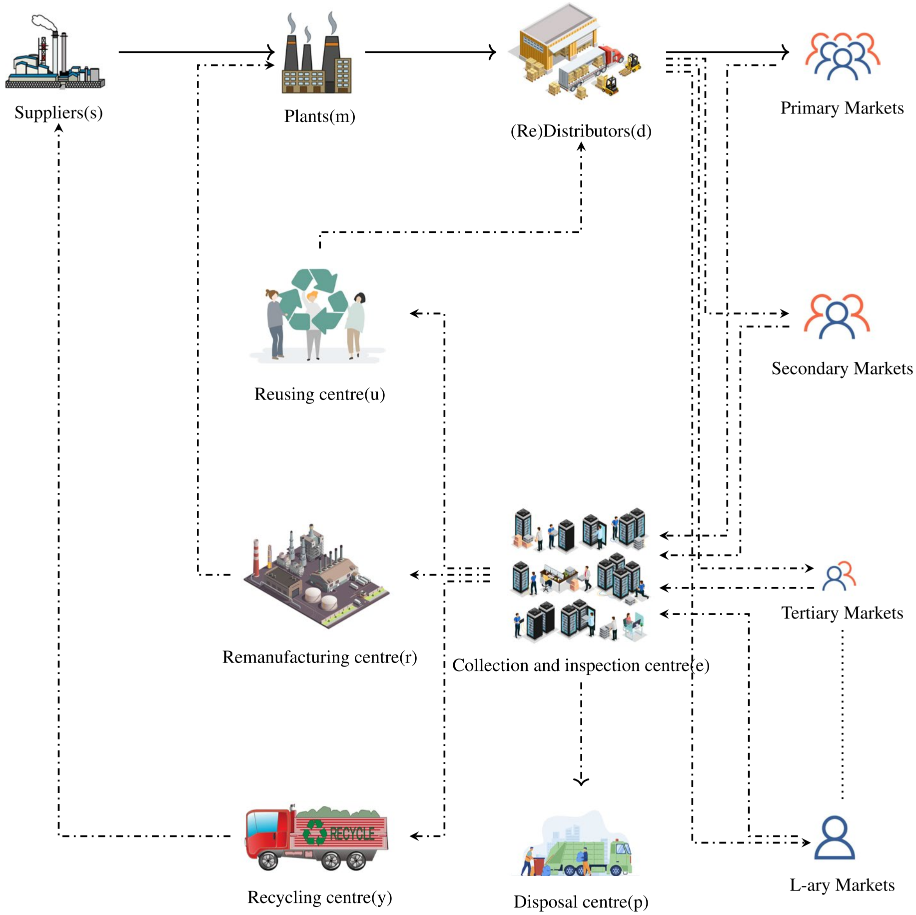


Fig. 2 CSC structure and schematic illustration of product flows in forward and reverse flows. Note: The solid and dashed arrows represent the forward and reverse flows respectively

By doing so, the recovering centres target the EOL products to be re-introduced into the economy considering their economic value and environmental benefits. This process will continue until the product reaches its end of life, and none of the components and materials are usable anymore. Finally, the fraction of returned products that have low quality is sent to the disposal centres for final treatment.

The proposed CSC model incorporates two types of materials as input for plants. The first type consists of virgin raw materials sourced from natural resources, only utilised in the primary market levels. Virgin raw materials refer to resources extracted from natural sources that are used in initial production processes (European Commission, 2015). In contrast, non-virgin materials consist of recycled components obtained from EoL products, which are utilised across downgraded market levels. The model aims to achieve full displacement by prioritising the use of non-virgin materials, thereby reducing dependency on new resource extraction and promoting sustainability. In this context, full displacement means completely replacing the use of virgin raw materials with recycled materials in the production process.

By achieving full displacement, the reliance on extracting new resources is minimised and the focus shifts toward reusing and recycling materials, thus promoting sustainability.

The term “downgrading” in the CE context refers specifically to a process where products are sent from superior market levels to recovering centres for reutilisation in inferior market levels. Once products are transported from collection centres to recovery centres (reuse, remanufacturing, or recycling centres), they are counted as downgraded products. Downgrading, therefore, aims to extend the lifecycle of products by reintroducing them into lower market levels where their value or functionality may still be relevant. By doing so, it allows the optimisation of resources and reduces waste by giving these products a second life. The process of downgrading contributes to a more sustainable approach by maximising the utility of products and minimising their environmental impact. As illustrated in Fig. 2, various downgraded market levels are introduced in the proposed network based on the number of times that the EOL products are returned to the collection/inspection centres.

Downgraded products may lead to the cannibalisation of products in a way that some sales at superior market levels would be cannibalised by remarketing returned products of almost good quality with a reasonable price which causes internal competition. The cannibalisation effect in a CSC refers to the phenomenon where the introduction of a $(l - ary)$ product into the market reduces the demand for the new product, thereby cannibalising its own market share. Leveraging the strategy of maximising the retained value considering cannibalisation effect yields positive impacts on various CE principles, including waste minimisation, environmental benefits, and economic optimisation (Ripanti et al., 2016). This effect is often mathematically neglected in the context of CSC models. Hence, the cannibalisation effect is evaluated based on the number of customers who tend to switch from buying primary products to buying an equivalent secondary or other downgraded products with a certain percentage of discount in the original price of the new products. This is a critical aspect in a CSC design as the companies would be reluctant to introduce downgraded products and decline the increased market share and profit due to the risk of cannibalisation among primary and downgraded products sales. This cannibalisation fears procreated the remarkable delays in remarketing and downgrading returned products and even the inclination to discard products. However, according to (Atasu et al., 2008), cannibalisation is less likely to be harmful to B2C products than B2B commodities. As a consequence, the pricing of the new and downgraded products is a critical factor in designing a CSC mathematical model.

3.2 Model assumptions

- For strategic planning purposes, the model assumes that product demand and selling prices are deterministic, reflecting scenarios where demand and prices show relative stability.
- The recovery rate of downgraded products is modelled as a random variable, accounting for variability in the recovery process.
- The presence of a cannibalisation effect is acknowledged across all levels of markets within the model.
- There is no interdependency among various products, which means that each product follows a unique trajectory. Specifically, the utilisation of materials from one product

($p = 1$), for the remanufacturing of another product ($p = 2$), is not allowed.

3.3 Mathematical formulation of CSC

Figure 3 demonstrates the key components of the mathematical formulation (e.g. inputs, objective functions, constraints and outputs) in a conceptual framework. Accordingly, the main outputs of this model are as follows:

- Determining the number of downgraded market levels to be activated throughout the network. In practice, CSCs provide an effective means to collect returned goods and perform the relevant treatment strategy, while multiple downgraded market levels are the significant channels to sell all those (primary/recovered) products.
- Deciding on the amount of raw and recycled materials to be utilised at the supply level. The model tries to use recycled materials as a substitute for virgin raw materials as much as possible.
- Determining the product flow among network facilities to maximise the profit and minimise the amount of disposed products.
- Specifying the location(s) of the facilities.

Table 2 presents the notation used in the mathematical formulation of the proposed CSC model.

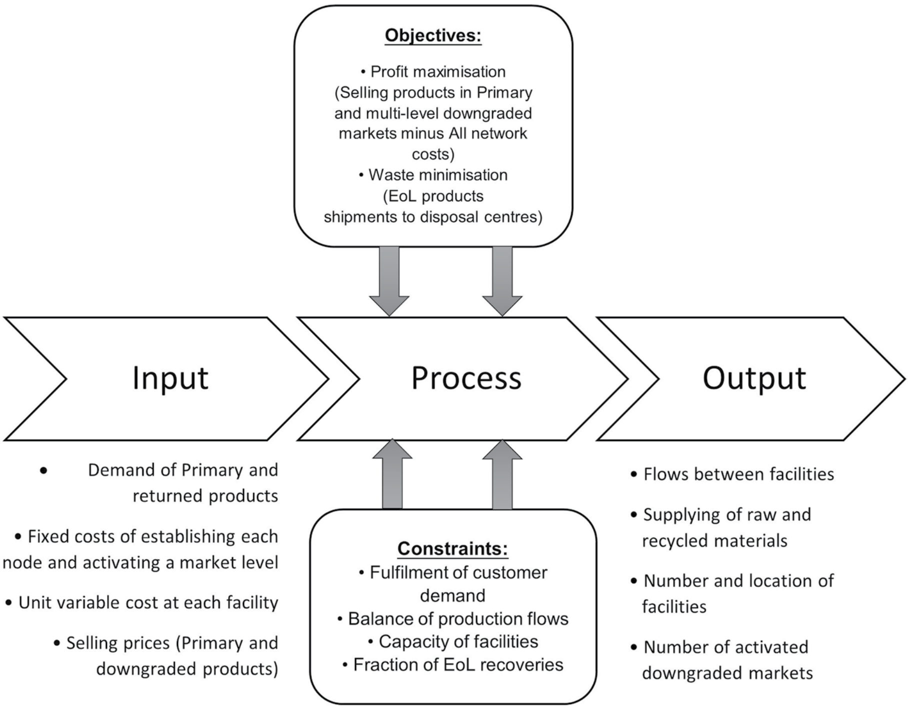


Fig. 3 Conceptual framework of CSC mathematical model

Table 2 Model notation

Indices:	
(i, j)	Set of indices denoting the nodes
a	Index of arcs between node *i* and *j* in $(i, j) \in A$
l	Market levels in $L = \{1, 2, ..., l\}$
k	Product (commodity) types in $P = \{1, 2, ..., k\}$
t	Time periods in $T = \{1, 2, ..., t\}$
Sets:	
N_s	Set of supplier nodes
N_m	Set of potential locations for the establishment of manufacturing centres
N_d	Set of potential locations for the establishment of distribution centres
N_c	Set of customer zones
N_e	Set of potential locations for the establishment of collection and inspection centres
N_u	Set of potential locations for the establishment of reusing centres
N_r	Set of potential locations for the establishment of remanufacturing centres
N_y	Set of potential locations for the establishment of recycling centres
N_p	Set of potential locations for the establishment of disposal centres
N	Set of all nodes $\{N_s \bigcup N_m \bigcup N_d \bigcup N_c \bigcup N_e \bigcup N_u \bigcup N_r \bigcup N_y \bigcup N_p\}$
BN	Set of backward nodes $\{N_c \bigcup N_e \bigcup N_u \bigcup N_r \bigcup N_y \bigcup N_p\}$
TN	Set of treatment nodes $\{N_u \bigcup N_r \bigcup N_y \bigcup N_p\}$
RN	Set of recovery nodes $\{N_u \bigcup N_r \bigcup N_y\}$
A	Set of all possible network flows, Where:
	$\{A^1 \bigcup A^2 \bigcup A^3 \bigcup A^4 \bigcup A^5 \bigcup A^6 \bigcup A^7 \bigcup A^8 \bigcup A^9 \bigcup A^{10} \bigcup A^{11}\}$
	$A^1 = \{(i, j):i \in N_s \wedge j \in N_m\}$
	$A^2 = \{(i, j):i \in N_m \wedge j \in N_d\}$
	$A^3 = \{(i, j):i \in N_d \wedge j \in N_c\}$
	$A^4 = \{(i, j):i \in N_c \wedge j \in N_e\}$
	$A^5 = \{(i, j):i \in N_e \wedge j \in N_u\}$
	$A^6 = \{(i, j):i \in N_e \wedge j \in N_r\}$
	$A^7 = \{(i, j):i \in N_e \wedge j \in N_y\}$
	$A^8 = \{(i, j):i \in N_e \wedge j \in N_p\}$
	$A^9 = \{(i, j):i \in N_u \wedge j \in N_d\}$
	$A^{10} = \{(i, j):i \in N_r \wedge j \in N_m\}$
	$A^{11} = \{(i, j):i \in N_y \wedge j \in N_s\}$
Parameters:	
m	Fixed cost of activating a market level (e.g. administrative and marketing expenses)
f_i	Fixed cost of activating node *i*
C_i	Capacity associated with node *i*
c_a	Unit variable cost of arc *a*; note this includes both processing cost at node *i* and transshipment cost between node *i* and *j*
ω_i	Supply cost of virgin raw materials at supplier *i*
d_{it}^{lk}	Demand level of customer centre *i* at time period *t* for *l*-th market level of product *k*
p_k	Selling price level per unit of product *k*
ψ_{lk}	Discount percentage in selling price of product *k* at market level *l*
η_{RN}	Recovery rate at each recovery centre (Reusing, Remanufacturing, Recycling)
α_i	Delay associated with node $i \in N_c$
β_i	Downgrade level at node $i \in N_e$

Table 2 (continued)

γ_t^{lk}	Cannibalisation ratio (demand leakage) of product *k* at time period *t* in *l*-th market level
Integer decision variables:	
x_{at}^{lk}	Amount of product type *k* transported through arc *a* at time period *t* for re/sell in *l*-th market level
s_{it}^{lk}	Supply level of product type *k* at node *i* in time period *t* for re/sale *l*-th market level
Binary decision variables:	
y_{it}^{lk}	1 if a facility is established at node *i* for producing product type *k* of *l*-th market level at time period *t*; 0 otherwise
v_{lk}	1 if *l*-th market level is activated for re/selling product *k*; 0 otherwise

The proposed CSC is formulated as a bi-objective MILP model. The first objective function, denoted as Eq. (1), is designed to maximise overall profit. This is achieved by subtracting the total costs incurred throughout the entire CSC (first component) from the general revenues. The revenue stream encompasses profits derived from the activation of primary, secondary, or *l*-th level markets, involving the sale of different products indexed by *k* at different price levels during time period *t*. *T* serves as an indexing variable, allowing the sum to be calculated over each distinct time period *t* within the specified set *T* when calculating the objective functions. This enables the model to account for variations in profit, costs, and other parameters across different time periods, contributing to the temporal dynamics considered in the proposed generic CSC model. Technically, the pricing mechanism involves setting the price of the downgraded products as a percentage of the price of the original primary products (p_k). In practical terms, units recovered from returns are sold at a discounted rate (ψ) to consumers. Primary products are assumed to be marketed at a fixed unit price (p_k), while downgraded products are sold at a reduced fraction of the price of the primary product per unit (ψ_{lk}), reflecting their origin from returned items. Consequently, the revenue generated from the sale of both primary and downgraded products is expressed as $\psi_{lk} p_k x_{at}^{lk}$. Furthermore, overall supply chain costs include operational costs linked to the supply cost of virgin raw materials, which is only applicable when catering to primary markets. In contrast, for the remaining downgraded markets, the use of downgraded materials results in zero supply costs. In addition to this, activation of specific market levels, fixed establishment costs for each facility, and additional unit variable costs are the associated costs throughout the CSC.

$$
\begin{aligned}
max \quad obj1 = & \sum_{\substack{a:(i,j) \in A \\ j \in N_c}} \sum_{l \in L} \sum_{k \in P} \sum_{t \in T} \psi_{lk} p_k x_{at}^{lk} - \sum_{i \in N} \sum_{l \in L} \sum_{k \in P} \sum_{t \in T} \omega_i s_{it}^{lk} - \sum_{l \in L} \sum_{k \in P} m v_{lk} \\
& - \sum_{\substack{i \in N \\ i \notin N_c}} \sum_{l \in L} \sum_{k \in P} \sum_{t \in T} f_i y_{it}^{lk} - \sum_{a:(i,j) \in A} \sum_{l \in L} \sum_{k \in P} \sum_{t \in T} c_a x_{at}^{lk}
\end{aligned}
\tag{1}
$$

To adjust the second objective function (2), it is considered that the overall time from production to disposal is aligned with the principles of CE and sustainable SCM. In this objective, the generated waste flow is discounted on the market levels they are collected from. This strategic approach serves to incentivise the activation of further downgraded market levels, thereby promoting the circularity degree of the CSC. The optimisation model, seeking minimisation of the defined objective function, strategically incorporates a normalisation process for waste disposal by aligning it with the respective market level. This measure fosters the activation of inferior market levels for multiple utilisations of products, thereby elevating the circularity degree within the CSC. Specifically, the function operates to curtail the overall amount of disposed products by iteratively diverting EOL products to inferior market levels subsequent to multiple product utilisations. This will provide an incentive for companies to engage with downgraded market levels, thereby supporting the system with a heightened circular disposition. By minimising the volume of products directed to disposal centres, the model inherently advocates waste reduction, aligning with the overarching objective of cultivating a highly CSC as formulated below:

$$min \quad obj2 = \sum_{\substack{a:(i,j) \in A \\ j \in N_p}} \sum_{l \in L} \sum_{k \in P} \sum_{t \in (1,T-1)} x_{at}^{lk}/l \tag{2}$$

In terms of constraints, the capacity constraint (3) indicates that, in each period, the total amount of products shipped from node *i* to node *j* should be lower than the capacity of node *i*.

$$s.t{:}$$

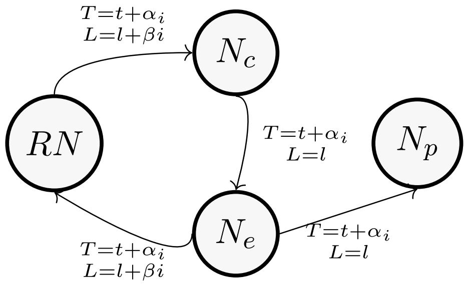
$$\sum_{\substack{a:(i,j) \in A \\ i \notin N_c}} x_{at}^{lk} \le C_i y_{it}^{lk} \qquad \forall i \in N, \quad \forall l \in L, \quad \forall k \in P, \quad \forall t \in T \tag{3}$$

Balance constraint (4), is one of the well-known constraints in the CSC problem that ensures in each period, the output of a node should be equal to its input.

$$\begin{aligned} &\sum_{\substack{a:(i,j) \in A, \\ j \notin N_p}} x_{a(t+\alpha i)}^{(l+\beta_i)k} + \sum_{\substack{a:(i,j) \in A, \\ j \in N_p}} x_{a(t+\alpha i)}^{lk} \\ &- \sum_{\substack{a:(i,j) \in A, \\ j \notin N_e}} x_{at}^{lk} - \sum_{\substack{a:(i,j) \in A, \\ j \in N_e}} x_{a(t+\alpha i)}^{lk} = s_{it}^{lk} \\ &\forall i \in N, \quad \forall t \in T{:}t + \alpha_i \le T, \quad \forall l \in L{:}l + \beta_i \le L, \quad \forall k \in P \end{aligned} \tag{4}$$

Figure 4 demonstrates the relationship between nodes and the movement of EOL products immediately after customers have given up. This visualisation helps to understand the dynamic flow and interactions within the downgraded market levels for managing EOL products. As illustrated in this figure, for customers (N_c) to return unwanted products to collection centres (N_e), there would be a temporal lag denoted by α_i, resulting in a delay in the return of those products to collection centres throughout the entire time horizon. Upon exiting abandoned products from collection centres(N_e), there are two pathways available. They could be disposed of in disposal centres (N_p), due to their low quality, or they have to be shipped to recovery centres (*RN*) to implement their relevant treatment strategies based on their quality level. In the lateral case, products undergo downgrading by a factor of β_i,

Fig. 4 Flow conservation at collection and inspection centre (N_e)



leading to their downgrading and being sold at downgraded market levels; these two parameters are included in the flow conservation constraint (Eq. 4).

The demand constraint (5) is formulated for customer nodes (N_c) and incorporates the cannibalisation effect, wherein the influence of an inferior market level diverting sales from a superior market level is considered. This effect is systematically integrated through a summative term that includes the remaining market levels, parameterised by a cannibalisation rate denoted as γ_t^{lk}. This rate signifies the proportion of demand for downgraded products that, in the absence of the recovered product, would have been directed towards the primary product. Consequently, the demand for the new product is reduced by a factor of γ_t^{lk}. The effective demand for the primary product is thereby articulated as $d_{it}^{lk}(1 - \sum_{q\in(l+1,L)} \gamma_t^{qk} v_{qk})$.

The demand constraint is structured to ensure that the total amount of flow of each product to each customer node at each market level during each time period must be less than or equal to the corresponding demand, adjusted for cannibalisation effect. In this context, the study considers a spectrum of product types denoted as L. The total demand for all products is represented by d_{it}^{lk}, the aggregate demand for products being the sum of primary products ($l = 1$) and downgraded products ($l = 2, 3, ..., L$), expressed as $D = \sum_{l\in(1,L)} d_{it}^{lk}$. The paper introduces two distinct functions to quantify cannibalisation effects. One is derived from a discount percentage parameterized as ψ_{lk}, which is applied to the original price of new products (p_k). The degree of downgrading a returned product correlates positively with the assigned discount on the product's price. The second function postulates a partial substitution of demand at lower market levels. In particular, this study represents a pioneering effort in addressing the dynamic interaction across multiple market levels within a Circular Economy-based supply chain, offering a nuanced and realistic portrayal of the associated complexities.

$$\sum_{a:(j,i)\in A} x_{at}^{lk} \leq d_{it}^{lk}(1 - \sum_{q\in(l+1,L)} \gamma_t^{qk} v_{qk}) \quad \forall i \in N_c, \quad \forall t \in T, \quad \forall l \in L, \quad \forall k \in P \tag{5}$$

The production of recovered products, including those that are reused, remanufactured, or recycled, is based on a recovery rate denoted η_{RN}. This rate signifies the proportion of returned products directed to recovery facilities for treatment. Consequently, the supply of recovered products is formulated as $\eta_{RN} x_{at}^{(l-1)k}$, where $x_{at}^{(l-1)k}$ denotes the quantity of returned products allocated to the collection centres at the market level $(l-1)$. The constraint expressed in Eq. (6) articulates that a certain percentage of returned products originating from market level l is eligible for transportation to recovery centres, where they undergo treatment processes such as reuse, remanufacturing or recycling.

$$\sum_{\substack{a:(i,j)\in A \\ i\in N_e \\ j\in RN}} x_{at}^{lk} \leq \eta_{RN} \sum_{\substack{a:(j,i)\in A \\ j\in N_c \\ i\in N_e}} x_{at}^{(l-1)k} \quad \forall t\in\{2,3,...,T\},\ \ \forall l\in\{2,3,...,L\},\ \ \forall k\in P \tag{6}$$

Constraints (7) ensure that in the first time period, there should be no transportation flow between backward facilities; similarly, constraints (8) restrict the reverse flow at the first market level.

$$\sum_{a:(i,j)\in A} x_{at}^{lk} = 0 \qquad \forall i\in BN\neq N_p,\ \ \forall t\in T{:}t=1,\ \ \forall l\in L,\ \ \forall k\in P \tag{7}$$

$$\sum_{a:(i,j)\in A} x_{at}^{lk} = 0 \qquad \forall i\in RN,\ \ \forall t\in T,\ \ \forall l\in L{:}l=1,\ \ \forall k\in P \tag{8}$$

Constraint (9) forces the activation of markets levels that is consistent with nodes.

$$y_{it}^{lk} \leq v_{lk} \qquad \forall i\in N,\ \ \forall t\in T,\ \ \forall l\in L,\ \ \forall k\in P \tag{9}$$

Constraint (10), denotes that if a node is established in a certain period of time, it should always remain open. In other words, it ensures that the decision to open a facility is a permanent one, and once a facility is opened, it cannot be closed in future time periods.

$$y_{i(t-1)}^{lk} \leq y_{it}^{lk} \qquad \forall i\in N,\ \ \forall t\in\{2,3,...,T\},\ \ \forall l\in L,\ \ \forall k\in P \tag{10}$$

Constraint (11) represents the non-negativity and integrality of variables and the ranges each variable can adopt according to their specific features.

$$x_{at}^{lk}\geq 0,\ \ s_{it}^{lk}\in\mathbb{R}\begin{cases}\geq 0, & i\in N_s,\ l=1\\ \leq 0, & i\in N_p\\ =0, & otherwise\end{cases},\ \ y_{it}^{lk}\in\{0,1\},\ \ z_t^{lk}\in\{0,1\} \tag{11}$$

As represented in Table 3, the paper introduces a highly compact and comprehensive formulation for the CSC design model, leveraging the model's ability to encapsulate all facilities and flows through an aggregate description. Table 3 presents a comparative analysis, highlighting the efficiency of the proposed model in terms of the number of parameters, decision variables, and sets of equations required to operationalise objective functions and constraints. The formulation presented in this study stands out for its compactness, as it enables the amalgamation of expanded (e.g., balance and capacity) constraints into a single overarching equation, mitigating redundancy.

While the specific quantities of variables, constraints, and parameters are contingent on the network scale, the formulation's inherent capacity to consolidate various constraints underscores its superiority. The enumeration of the diverse variations in parameters, vari-

Table 3 Number of Parameters, decision variables (DVs) and Equations in comparable CSC formulations

References	No. of parameters	No. of DVs	No. of equations (Objective functions & Constraints)
Ren et al. (2020)	44	12	31
Darestani and Hemmati (2019)	47	25	39
Atabaki et al. (2019)	62	28	50
Pourjavad and Mayorga (2019)	42	26	47
Sahebjamnia et al. (2018)	69	11	22
This study	12	4	11

ables, and constraints underscores the dominance of the proposed formulation compared to comparable studies in the literature. This efficiency not only contributes to the model's elegance but also enhances its practical applicability to any type of business and computational efficiency.

4 Adopted solution method

One of the most challenging phenomena in multi-objective problems is the need for identifying the set of Pareto-optimal solutions, thus enabling decision makers to select efficiently the most preferable alternative from a restricted set of non-dominated options. To this end, the Augmented Epsilon Constraint Method (AUGMECON) has proven to be among the most efficient solution methods (Mavrotas, 2009), as it produces a set of Pareto optimal solutions for a given set of objective functions by iteratively optimising a single-objective mathematical model. Whilst tackling the CSC model presented in Sect. 3, the improved version of the Augmented ϵ-Constraint Method (Mavrotas & Florios, 2013) was adopted, known as AUGMECON2, as it represents one of the advanced techniques to deal with multi-objective problems for both convex and non-convex functions (Ahmadi & Amin, 2019). The selection of AUGMECON2 is a strategic choice aligned with the objective of efficiently navigating the multi-objective landscape inherent in the design of the proposed CSC model. This method, therefore, enhances the robustness of the optimisation process and facilitates the identification of Pareto-optimal solutions. AUGMECON2 is particularly well suited for the proposed model as it accommodates both convex and non-convex objective functions. The method's reliance on bypass jumps, leveraging slack/surplus variables, contributes to computational efficiency, reducing the number of iterations required for convergence. This is a significant advantage, especially when dealing with a compact model that encapsulates the complexity of a circular supply chain.

The bypass coefficient in AUGMECON2 indicates the number of consecutive iterations that can be skipped, a strategic measure designed to prevent redundancy and expedite the overall conclusion of the algorithm (Mavrotas & Florios, 2013).

The whole procedure associated with this method is described in pseudo-code format in Table 4:

First, the payoff table needs to be computed (line 1) to obtain the lower bounds of each objective function (Line 2). As such, according to AUGMECON2, the right-hand side of

Table 4 Pseudo-code

The pseudo-code of AUGMECON2	
1:	**procedure**
2:	Create payoff table (lexmax $f_k(x), k = 1, .., p$)
3:	Set lower bounds lb_k for $k = 2, .., p$
4:	Compute ranges for objective functions r_k for $k = 2, .., p$
5:	Define number g_k of gridpoints for each objetive function k
6:	Calculate step value for the objective function k: $step_k = \frac{r_k}{g_k}$
7:	Initialize counters: $i_k = 0$
8:	**for**$k = 2, ..., p, \quad n_p = 0$**do**
9:	**while**$i_p < g_p$**do**
10:	Solve problem P: $max\ f_1(x) + eps \times (\frac{S_2}{r_2} + 10^{-1} * \frac{S_3}{r_3} + ... + 10^{-(p-2)} * \frac{S_p}{r_p})$
11:	Subject to: $f_k(x) - S_k = e_k \quad k = 2, ..., p, \quad x \in F$
12:	**if** the Solution is feasible **then**
13:	$n_p = n_p + 1$
14:	Calculate Bypass coefficient $b = int(\frac{S_k}{step_k})$
15:	$i_k = i_k + b$
16:	**else**
17:	$i_p = i_p + 1$
18:	**end if**
19:	**end while**
20:	**end for**
21:	**return** Pareto Optimal Set
22:	**end procedure**

the k -th objective function (Line 6) can be obtained by dividing the range of each objective function into equal intervals using intermediate grid points (Mavrotas & Florios, 2013). The larger the number of grid points, the better the representation of the Pareto-optimal set. In each iteration, the slack/surplus variable which corresponds to the innermost objective function is checked, and hence the bypass coefficient is calculated (Line 14). In this way, the exact Pareto optimal front in the bi-objective MILP model is obtained in a reasonable computation time.

The application of AUGMECON2 to the CSC model is obtained by defining the optimisation problem P as shown below:

$$
\begin{aligned}
& max\ f_1(x) + eps \times \frac{s_2}{f_{max_2} - f_{min_2}} \\
& f_2(x) + s_2 = f_{min_2} + t \times \frac{f_{max_2} - f_{min_2}}{q_2} \\
& x \in S \quad and \quad s_i \in R^+
\end{aligned}
\tag{12}
$$

In Eq. (12), f_1 and f_2 correspond to the economic and environmental objectives, respectively; s_2 is used as the surplus variable for the second objective (f_2). The f_{max_2} and f_{min_2}

represent the maximum and minimum values of the objective function, and *eps* is a fairly small number between 10^{-6} and 10^{-3} (Mavrotas & Florios, 2013).

The AUGMECON2 method is then coded using the Python programming language and, by adopting the *docplex* libraries, mixed-integer programming models are iteratively solved by calling the IBM ILOG CPLEX solver version 12.6.

5 Experimental evaluation

In this section, numerical experiments are conducted and described to validate the performance of the proposed mathematical model and verify the solution methodology. All experiments were run on a server equipped with 64bit Intel Xeon CPU at 2.80 gigahertz with 64 gigabytes memory, running Ubuntu 18.04.6 LTS. The details of generated data are described in the following subsections.

5.1 Data generation

An appropriate setting of the parameters can lead to more reliable and robust experiments (Devika et al., 2014). In this regard, the testbed for this specific problem is based on benchmark instances employed by similar SCN mathematical models in the literature (Devika et al., 2014; Soleimani & Kannan, 2015), as represented in the following tables.

In order to determine the cardinality of the sets and the values of other parameters, a careful scrutiny and review of the literature is conducted in Table 5. Firstly, the number of facilities has a substantial impact on the size of the supply network (Yavari & Geraeli, 2019). Hence, the cardinality of typical facility sets in comparable problems is reviewed; then, the ratios among these numbers (see Appendices, Table A1) and appropriate ranges for parameter values are calculated as shown in Tables 5 and 7. As a result, more realistic values for each sets of facilities (**s**: suppliers, **m**: manufacturers, **d**: distributors, **c**: customers, **e**: collection/inspection centres, **u**: reusing centres, **r**: remanufacturers, **y**: recyclers,**p**: disposal centres) and parameters is employed in the computational experiments.

In order to evaluate the performance of the proposed model as well as the solution methodology, three classes of problems with different sizes are defined, as represented in Table 6. In this regard, numerical analyses were also carried out to provide managerial insight into circular-based supply networks.

The values of some parameters are presented in Table 7. For each parameter, appropriate ranges are established, based on similar studies available in the literature (Soleimani et al., 2014; Wang et al., 2016). For structuring the computational testbed, instances are generated in a random way, considering uniform distributions for all parameters, within specified ranges. It is worth noting that, given the presence of markets for reused, remanufactured, and recycled products, a fraction of the demand for primary products might be cannibalised by the existence of the downgraded products.

When the cannibalisation rate is zero ($\gamma_t^{lk} = 0$), the CSC operates at the superior market level (L = 5) where both primary and downgraded products are sold in all sets of Pareto solutions, regardless of the size of the supply network or the level of customer demand. This is because the introduction of downgraded products does not replace the demand for

Table 5 Number of facilities

Number	References	s	m	d	c	e	u	r	y	p	DataType
1	Saedinia et al. (2019)	3	4	7	28	3	–	–	3	2	Test instance (small scale)
2	Ren et al. (2020)	–	3	5	–	7	–	–	5	2	Real-world problem
3	Devika et al. (2014)	–	4	7	–	3	2	–	2	–	Real-world problem
4	Devika et al. (2014)	8	4	8	12	8	2	3	2	2	Test instance (small scale)
5	Fakhrzad and Goodarzian (2019)	8	4	2	8	12	–	–	–	–	Test instance (small scale)
6	Shen (2019)	–	6	–	15	10	–	–	4	–	Test instance
7	Tosarkani and Amin (2019)	5	6	–	15	–	–	2	–	–	Real-world problem
8	Ahmadi and Amin (2019)	5	4	15	44	7	–	5	–	3	Real-world problem
9	Masoudipour et al. (2019)	–	2	2	7	2	–	1	–	–	Test instance
10	Shamsi et al. (2019)	2	1	3	–	–	–	–	–	–	Real-world problem
11	Guo et al. (2019)	–	5	–	30	–	–	–	–	–	Test instance (small scale)
12	Yang et al. (2019)	2	4	6	20	2	–	–	–	–	Test instance
13	Baptista et al. (2019)	–	3	3	18	3	–	–	–	–	Test instance
14	Papen and Amin (2019)	5	3	6	–	6	–	–	–	–	Real-world problem
15	Darestani and Hemmati (2019)	3	3	3	4	2	–	2	2	–	Test instance (small scale)
16	Polo et al. (2019)	–	5	4	7	–	–	–	–	4	Real-world problem
17	Sherif et al. (2019)	2	1	14	35	14	-	–	3	1	Real-world problem
18	Almaraj and Trafalis (2019)	3	2	3	5	3	–	–	–	2	Test instance (small scale)
19	Almaraj and Trafalis (2019)	5	3	5	10	5	–	–	–	3	Test instance (medium scale)
20	Almaraj and Trafalis (2019)	7	5	7	20	7	–	–	–	5	Test instance (large scale)
21	Zhen et al. (2019)	–	5	7	7	–	–	–	–	–	Test instance (small scale)
22	Yadegari et al. (2019)	–	5	3	4	2	–	1	–	–	Test instance (small scale)
23	Fazli-Khalaf et al. (2019)	–	6	5	9	–	–	–	4	–	Real-world problem
24	Taheri-Moghadam et al. (2019)	–	2	2	2	–	–	–	–	–	Test instance (small scale)

Table 6 Problem sizes

Problem levels	Problem size	s	m	d	c	e	u	r	y	p	Total number of facilities
Small scale	P1	2	1	3	6	3	1	1	2	1	20
Medium scale	P2	4	2	6	12	6	2	2	4	2	40
Large scale	P3	6	3	9	18	9	3	3	6	3	60

primary products, and all types of products can co-exist in the market without affecting the profit or environmental objectives.

On the other hand, when the cannibalisation rate is equal to one ($\gamma_t^{lk} = 1$), the CSC operates at inferior market levels (L = 1) where only primary products are sold and no downgraded products are available. This is because the introduction of downgraded products does not contribute to the profit objective and the demand for the primary product is fully retained. However, when the environmental objective is also considered, the CSC can activate up to two market levels, and EOL goods are discarded only after two utilizations.

In summary, the impact of cannibalisation on market levels in a CSC depends on the cannibalisation rate. A zero cannibalisation rate allows the coexistence of both primary and downgraded products at the highest market level, whereas a full cannibalisation effect results in the operation of the CSC at lower market levels with only primary products sold. However, when environmental considerations are taken into account, the CSC may operate at intermediate market levels and extend the product life cycle through multiple utilisations.

Table 7 Parameters and their values

Parameters	Definition	Values
L	Number of market levels	5
P	Number of products	2
T	Number of Periods	15
f_i	Fixed cost of starting a contract with supplier *s*	$\sim U$ (7,10 million)
	Fixed cost of opening a plant *m*	$\sim U$ (70,150 million)
	Fixed cost of establishing a distribution centre *d*	$\sim U$ (1,2 million)
	Fixed cost of establishing a collection centre *e*	$\sim U$ (0.1,1 million)
	Fixed cost of establishing all recovering centrs	$\sim U$ (0.1,1 million)
	Fixed cost of establishing a disposal centre *p*	$\sim U$ (0.1,1 million)
m	Fixed cost of activating a market level	$\sim U$ (0.1,1 million)
C	Capacity level of supplier *s*	$\sim U$ (18000,42000)
	Capacity level of plant *m*	$\sim U$ (6000,14000)
	Capacity level of distribution centre *d*	$\sim U$ (6000,14000)
	Capacity level of collection centre *e*	$\sim U$ (6000,14000)
	Capacity level of reusing centre *u*	50 % of Distributer capacity
	Capacity level of remanufacturing centre *r*	50 % of Manufacturer capacity
	Capacity level of recycling centre *y*	50 % of Supplier capacity
	Capacity level of disposal centre *p*	$\sim U$ (6000,14000)
c_a	Unit variable cost at forward nodes	$\sim U$ (100,1000)
	Unit variable cost at reverse nodes	$\sim U$ (10,100)
p_k	Selling price level per unit	$\sim U$ (15000,20000)
ψ_{lk}	Discount percentage (% of original price(p_k))	$\sim U$ (0,1)
γ_t^{lk}	Cannibalisation ratio (% of $(l-1)$ market demand)	$\sim U$ (0,0.5)
η_l	Recovery rate	$\sim U$ (0,0.5)
α_i	Delay (at customer node)	$\{0, 1\}$
β_i	Downgrade (at collection centre)	$\{0, 1\}$

Table 8 Upper bound of Recovery options

References	Reusing rate	Remanufacturing rate	Recycling rate
Ramezani et al. (2013)	0.45	0.25	0.15
Devika et al. (2014)	0.5	0.5	0.5
Kalaitzidou et al. (2015)	0.4	0.3	0.2
Atabaki et al. (2019)	0.2	0.3	0.3
Average	0.39	0.34	0.29

Therefore, the range of the cannibalisation ratio is specified as a uniform fraction $\gamma_t^{lk} \sim U(0, 0.5)$, which represents this cannibalisation effect. In addition, c_a is considered as the average total cost of all variable costs related to each facility including purchasing, manufacturing, distribution, collection, recovery, disposal, and transportation costs for products manufactured or taken back to the relevant stage in both forward and reverse SCs.

Due to the strategic nature of the model, predetermined upper bounds for each of the R options are derived by calculating the average values in the literature as shown in Table 8. Accordingly, the selling prices and demand levels for brand new items are determined based on findings from the academic literature, using the minimum, maximum, and average values of these parameters as presented in Tables A2 and A3 (see Appendices).

6 Findings and implications

The developed MILP model and the experimental results have produced interesting findings that can contribute to the SCM and CE literature and provide some managerial implications. The findings verifies the validation of the proposed model and its applicability to the real world.

In general, the results show that the introduction of downgraded market levels as well as various recovery options present a significant impact on the whole SC. More specifically, by activating more market levels, the percentage of recollected items from customers increases, and therefore, the circularity degree of the whole CSC improves by keeping the unwanted products in the circle for as long as possible. To address the instability in demand, this paper proposes three scenarios to consider all potential demand levels that a CSC could possess during a certain time period. From an application perspective, it makes more sense to make the demand profile more stable, by restricting the random element to a small variation ($\pm\rho\%$) from the initial demand level (D_0). Hence, the computational results of the model for various problem's scale (small, medium, and large) under three various demand profiles (Decreasing, Constant, and Increasing) are presented in the following subsections. The effect on each Key Performance Indicator (KPI) is described and the corresponding managerial implications are reported. The demand level for each defined scenario is formulated as follows:

- *Scenario (1) Decreasing Demand Profile:* In scenario (1), which is characterised by a decreasing trend and random fluctuations within $\pm\rho\%$, the demand profile is described by equation (13), where D_0 represents the initial demand and $U(-\rho,\rho)$ shows a uniformly distributed random variable between $-\rho$ and ρ.

$$d_t^{lk} = D_0.\big[(1 - 0.05 * t) + U(-\rho,\rho)\big] \quad \forall t \in T, \;\; l \in L, \;\; k \in P \tag{13}$$

- *Scenario (2) Constant Demand Profile*
  In this scenario, the demand profile (Eq. 14) is described as having a constant trend, but with random fluctuations within $\rho\%$ around the initial demand (D_0).

$$d_t^{lk} = D_0.\big[1 + U(-\rho,\rho)\big] \quad \forall t \in T, \;\; l \in L, \;\; k \in P \tag{14}$$

- *Scenario (3) Increasing Demand Profile*
  Scenario (3) also describes the demand profile as having an increasing trend per time period, along with random fluctuations within $\rho\%$ around the initial demand D_0.

$$d_t^{lk} = D_0.\big[(1 + 0.05 * t) + U(-\rho,\rho)\big] \quad \forall t \in T, \;\; l \in L, \;\; k \in P \tag{15}$$

6.1 Key performance indicators (KPIs)

This research is expected to provide a generic formulation that enables companies to incorporate CE principles in the strategic design and optimisation of their SCs, in accordance with regulatory requirements. In pursuit of this goal, critical Key Performance Indicators (KPIs) are formulated to assess the performance of CSC, integrating economic and environmental sustainability perspectives. These indicators offer a multifaceted evaluation of the effectiveness and efficiency of multiple downgraded market levels within the CSC, as detailed in Table 9. These KPIs facilitate the determination of the optimal number of activated downgraded market levels for decision makers, based on the associated market activation costs expressed in the first objective function. Consequently, the analysis of all remaining KPIs is based on market activation costs, serving as a pivotal metric that inherently captures the extent of the activated downgraded market levels.

6.1.1 Number of activated market levels

The results suggest that the number of activated market levels in the SC model is affected by several factors, including market activation costs, demand trend, and problem size. Figure 5 illustrates the number of activated market levels for each problem (1 to 3) under three different scenarios. (e.g., P(1.2) represents a problem investigated under the first scenario and second size of facilities).

Increasing market activation costs results in fewer market levels being activated, as firms prioritise maximising profit over environmental objectives.

In the case of an increasing demand trend, there is a higher demand for downgraded products over the investigated time period, which leads to a need to activate more market levels to meet customer demand. As can be observed in Fig. 5, the minimum level of markets that are activated over the whole time horizon is higher when the demand trend is increasing, constant, and decreasing, respectively. The results also indicate that problem size plays a role in the number of activated market levels. In the large size of instances, where there are more facilities across CSC, the minimum level of market levels which are activated in a set of Pareto solutions is higher as compared to the medium and small sizes. In general, the results suggest that the number of activated market levels in a SC model is influenced by multiple factors, and firms must carefully consider these factors to strike a balance between profitability and environmental sustainability.

Table 9 Key performance indicators (KPIs)

sKPIs	Measurements
Number of activated market levels	Active markets
Objective functions	Profitability
	Environmental impact
Treatment options	Reused products (%)
	Remanufactured components (%)
	Recycled materials (%)
	Disposed EOLs (%)
Satisfied demand level	Customer demand satisfaction

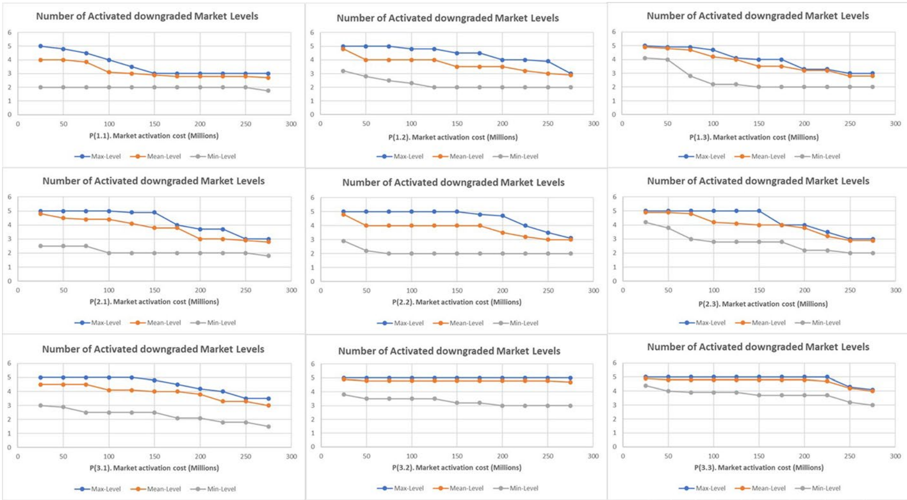


Fig. 5 Number of activated market levels

6.1.2 Objective functions

The objective functions of the proposed CSC model aim to balance both economic and environmental considerations. Remarketing of returned products will not only generate a new source of revenue but also prevent the waste of valuable materials. The first objective is to maximise the profit of the organisations, which is achieved by considering different market levels and price differentiation. The model seeks to find the optimal combination of market levels that will yield the highest profit. The second objective is to minimise the total number of discarded products, which is an important environmental consideration. The model achieves this objective by keeping the products in use through remarketing of returned EOL products. The results demonstrated in Figure 6 show that activating more market levels is more effective in reducing the number of discarded products. This is because with more market levels, the products have a higher chance of being sold and reused rather than discarded. In general, manufacturers generate waste if they produce more primary goods; however, in the proposed CSC, fewer products end up in landfills by keeping them in use.

In general, the proposed CSC model demonstrates that both economic and environmental objectives can be achieved by considering different market levels and price differentiation. Activating downgraded market levels is shown to be more effective in achieving both objectives regardless of the size of the companies or the level of customer demands. This is a valuable insight for organisations seeking to optimise their SC operations while also reducing their environmental impact.

6.1.3 Treatment options

In this subsection, different treatment options are considered for EOL products, which are products that have reached the end of their useful life and are no longer needed by customers. Instead of transporting these EOL products to disposals, the model proposes to recover them and reuse their valuable materials. We explore various recovery options, such as reus-

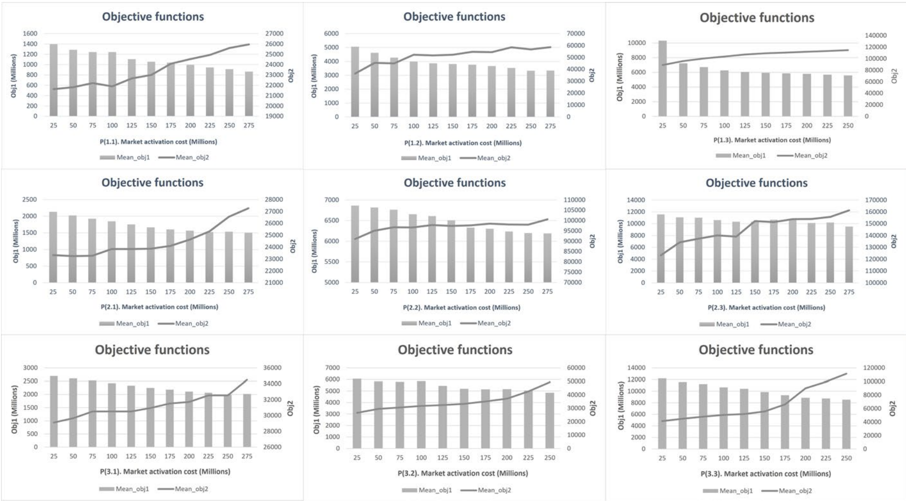


Fig. 6 Objective functions

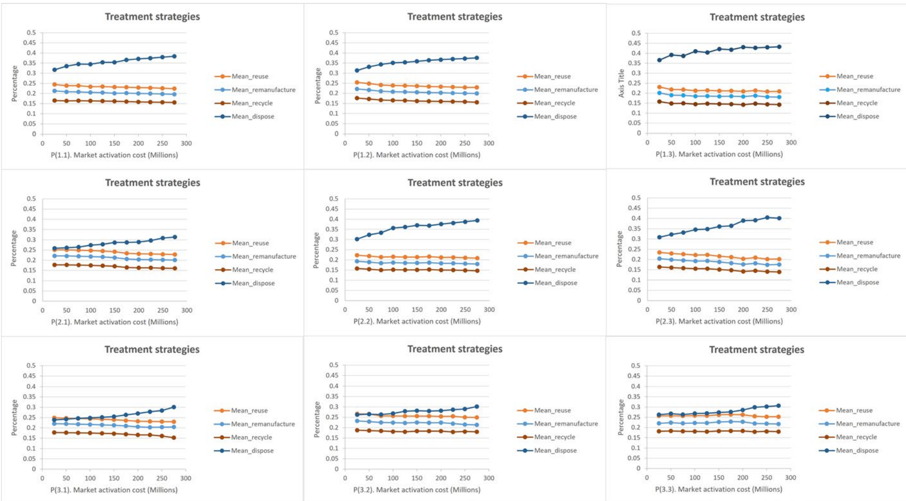


Fig. 7 Treatment options

ing, remanufacturing, and recycling centres, and investigate the effect of activating different market levels on the number of discarded products.

The findings show that activating more market levels leads to a gradual decrease in the number of discarded products and an increase in the number of products treated in recovery centres. As illustrated in Fig. 7, by activating more market levels, from $L = 2$ (higher market activation cost) to $L = 5$ (lower market activation cost), it can be seen that the number of discarded products is gradually decreasing and treated in recovery centres (reusing, remanufacturing, and recycling centres) instead to create a more circular supply chain. The most convenient and rational recovery option is to reuse a large percentage of the products, followed by remanufacturing and recycling in a cascaded way. This approach creates a higher CSC and reduces the amount of products that are shipped to disposals.

It is also observed that in the first scenario where there is a decreasing trend on the demand level, more products are considered as waste and transported directly to disposals; this might be due to the customers' willingness to buy the downgraded products at lower market levels. In general, the results suggest that activating more market levels and promoting recovery options can lead to a more profitable and environmentally friendly CSC.

6.1.4 Satisfied demand levels

According to the results, as shown in Fig. 8, under the current setting, more demand is satisfied by activating more markets $L = 5$ (where the market activation cost is lower) compared to traditional SC with only primary or secondary market levels. As mentioned above, the model does not have to meet the demand in total, which is one of the significant features of the model; so, in essence, the model also advises the firm about the optimal market share it needs to target. In this sense, given the overall stability in demand for consumer goods (such as white goods), a less volatile demand profile would be more realistic. The vertical axis in Fig. 8 represents the average percentage of the maximum number of satisfied demand in each combination of Pareto optimal solutions. In this paper, the satisfied demand level is based on the market share of each level; in this regard, by activating more market levels at lower market activation costs, the model tries to satisfy more demand from downgraded products and, therefore, more primary resources are saved.

The downgraded products can lead to cannibalisation of primary market sales. In contrast, some scholars (Ramani & De Giovanni, 2017) claimed that cannibalisation does not decrease manufacturers sales, but negatively impacts the company's obtained profit. In order to overcome the negative impact of the cannibalisation of the new products, the recovery costs should be fairly low, or an appropriate price should be assigned to the downgraded products. From a managerial point of view, in order to avoid the severe effect of cannibalisa-

Fig. 8 Satisfied demand levels

tion on a company, a shifting mindset of consumers are required by the governments. Therefore, businesses could obtain an optimal market share by selling pricey primary products to consumers who prefer to buy new products and selling downgraded products to people with an environmental consciousness mindset.

According to the authors' best knowledge, CLSC and CE scholars had considered either absolute substitution (cannibalisation = 1) or secondary markets (cannibalisation =0); while in reality, the cannibalisation is somewhere between these two extreme scenarios in the range (0,1). Therefore, a certain degree of cannibalisation might be admissible if downgraded products contribute adequately to profit margin.

6.2 Managerial insights and real-world applications

This study aims to offer practical guidance as well as proper managerial insights to managers and decision makers in supply chain management. While the model primarily focusses on designing a CSC with multiple downgraded market levels, its principles and findings can be applied across various industries and sectors, which some examples are described below.

International white goods manufacturing company This research highlights the complexity of the problem when applied to an international white goods manufacturing company with a diverse supply chain. The size and scale of their operations matter. In regions with extensive production facilities like Europe and North America, activating a higher number of downgraded market levels can effectively manage their returned products. Instead of sending returned appliances to landfills, they can partner with remanufacturing and recycling facilities to treat the EOL products. This multilevel market helps increase the number of appliances treated in recovery centres and keep products in use. This proactive approach extends the lifecycle of devices while promoting sustainability.

Fashion retail industry Imagine a fashion retailer operating physical stores and online platforms. Inspired by this research, they can implement the model to significantly reduce clothing waste. The surge in online shopping, driven by the COVID-19 pandemic, has increased the demand for sustainable clothing. The retailer can create a programme to collect and sell gently used or returned garments, keeping these items in circulation. By activating multiple downgraded market levels, including outlets, online platforms, and partnerships for reselling, they can drastically reduce the clothing items that would otherwise end up in landfills. This approach encourages multiple owners for clothing items, ensuring they do not go to waste. Clothes can be resold to a second owner at a lower price if their quality is comparable to brand-new ones. This cycle continues until the clothes are no longer wearable, at which point they can be remanufactured or recycled as a last resort. Individual or business owners can decide how many market levels are practical for their specific situation.

Multinational consumer goods This conglomerate can put the research into practice by activating downgraded market levels and adjusting pricing based on market segments. This approach enables them to boost sales for both primary and returned products, ensuring a balance between sustainability and profitability.

These real-world examples demonstrate how businesses can practically apply the managerial insights gleaned from this research. They show how factors such as market activation costs, demand trends, and scale of operations can be leveraged to make informed decisions about activating downgraded market levels that align with sustainability and profitability objectives within CSC.

7 Discussion

The results show that activating a higher number of downgraded market levels and implementing various recovery options simultaneously can significantly reduce the number of discarded products and create a more circular supply chain. In this context, multiple downgraded market levels have emerged as an effective strategy to achieve both environmental and economic benefits. Specifically, activating a higher number of downgraded market levels (beyond just secondary markets) in a CSC not only contributes to reducing waste but also provides businesses with additional revenue streams. From an environmental perspective, activating downgraded market levels enables the utilisation of products at their fullest capacity. When a product reaches its end of life, it can be reused, disassembled, and remanufactured or recycled to extend its useful life, creating a circular system. The products can then be sold to different downgraded markets, from high-end to low-end, depending on their conditions. By doing so, the CSC can reduce waste generation and decrease environmental pollution, which ultimately helps businesses comply with government regulations. Activating more downgraded market levels also offers significant economic advantages. By optimising product utilisation, businesses can create additional revenue streams and lower their production costs. This approach also creates opportunities for innovation and differentiation, as companies can design products that can be easily disassembled and reused. Furthermore, activating a bigger number of downgraded market levels aligns with government regulations and promotes a CE. The EU Waste Framework Directive requires the adoption of waste prevention strategies and aims to reduce waste generation by 50% by 2030. Incorporating downgraded market levels in a CSC aligns with the principles of CE and encourages businesses to adopt sustainable practices. Thus, companies that adopt this approach can not only comply with government regulations but also create a competitive advantage for themselves by reducing costs and generating revenue streams. Therefore, the adoption of a CSC with multiple downgraded market levels is a win-win strategy for businesses, the environment, and society as a whole. Speaking of government regulations and policies, it is noteworthy that policies aimed at increasing the cost of landfill and promoting recycling can have a significant impact on the decision to establish facilities in a SCN based on CE principles. For instance, landfill taxes can increase the cost of EOL product disposal, making it more expensive to dispose of waste in landfills, and thus incentivising firms to invest in other recovering facilities. Similarly, recycling taxes can increase the cost of recycling and incentivise firms to invest in more efficient and cost-effective recycling technologies, which can lead to a reduction in overall costs and increased revenue streams. Overall, policy options such as landfill taxes and recycling taxes can help to promote the adoption of CSCs and can encourage firms to pursue more sustainable and environmentally friendly business practices. The results also show that market activation costs are an important consideration while designing CSCs. Market activation costs refer to the costs of introducing a new or downgraded product or service to the market. Moreover, the model experiments suggest that a certain degree of cannibalisation can be accepted at any market level, as long as downgraded products contribute adequately to profit margins, thus counterbalancing the effect of upper-level cannibalisation. The optimal market share for a manufacturer can be obtained by selling primary products to consumers who prefer new products and downgraded products to consumers with an environmental consciousness mindset. In a nutshell, this research offers valuable insights into the decision-making process when designing all tiers of CSC models. It underscores the significance of considering various recovery options to decide on activating multiple downgraded market levels for various products over a certain time, optimal facility locations and transportation flow among all nodes to enhance both the sustainability and profitability of business operations.

8 Conclusion

The adoption of CE principles into SCs has gained momentum in the past decade. The main findings of the review of the academic literature highlighted that there is a disconnection between SC design models and the founding principles of CE; particularly relying on reductionist sustainability measurement methods and failing to address CE implementation. While the academic literature has developed an abundant stream of work related to the mathematical models for SC design problems, such modelling proposals tend to be over-specific and lack generality. In order to fill this gap, this research proposes a comprehensive approach considering various recovery options - such as reusing, remanufacturing, and recycling - as a decision-making support tool to define the optimal number of downgraded market levels in a CSC. The proposed tool is based on a bi-objective optimisation MILP model that integrates CE principles into SC mathematical models, by maximising profit and minimising environmental impact. The AUGMECON2 algorithm is utilised to compute Pareto-optimal solutions for the proposed bi-objective model on a synthetic dataset, an EOL built upon realistic assumptions derived from an analysis of the related literature.

8.1 Limitations and future research

Future directions of research in this area could focus on several key aspects to further advance the understanding and applicability of the proposed model. One direction for future research is to extend the data set and validate the proposed model using real-world data from specific industries, such as the white goods sector or other relevant sectors. This would involve collecting and analysing data from actual supply chains, considering factors such as product characteristics, market dynamics, and recovery options specific to those industries. By applying the model to real-world scenarios, researchers can evaluate its effectiveness, identify potential challenges, and fine-tune the model parameters and constraints for practical implementation. While the proposed model focuses on maximising profit and minimising CE-based environmental impact as objective functions, future studies could incorporate additional dimensions of sustainability, specifically addressing social sustainability and impact. This would involve integrating social metrics and indicators into the decision-making process, considering aspects such as worker well-being, community engagement, and ethical considerations. By expanding the objective functions to include social sustainability, the model would provide a more holistic approach to evaluating the overall sustainability performance of closed-loop supply chains. Another avenue for future research is to explore the role of uncertainty and incorporate scenario-based optimisation techniques into the model. In real-world SC operations, uncertainties related to demand fluctuations, market conditions, and resource availability are common. By explicitly considering uncertainty in the model, researchers can develop robust decision-making approaches that account for different potential scenarios and their associated risks. This would enhance the model's suitability for real-world management purposes, enabling SC managers to make informed decisions under varying conditions and uncertainties. Finally, future research could also explore the integration of emerging technologies and innovations into the proposed model. For example, advances in data analytics, Internet of Things (IoT) and blockchain can enable more accurate tracking and traceability of products throughout the CSC. Incorporating these technologies into the model would provide opportunities for increased transparency, efficiency, and collaboration among supply chain partners. Future research could investigate how these technological advancements can be integrated into the model to further optimise CSC operations and support the implementation of CE principles. By addressing these future research directions, scholars can advance the understanding and practical applicability of SC design models for CE implementation.

Appendix 1:

See Tables A1, A2 and A3.

Table A1 Normalization

Number	s	m	d	c	e	u	r	y	p
1	0.75	1	1.75	7	0.75	0	0	0.75	0.5
2	0	1	1.67	0	2.33	0	0	1.67	0.67
3	0	1	1.75	0	0.75	0.5	0	0.5	0
4	2	1	2	3	2	0.5	0.75	0.5	0.5
5	2	1	0.5	2	3	0	0	0	0
6	0	1	0	2.5	1.67	0	0	0.67	0
7	0.83	1	0	2.5	0	0	0.33	0	0
8	1.25	1	3.75	11	1.75	0	1.25	0	0.75
9	0	1	1	3.5	1	0	0.5	0	0
10	2	1	3	0	0	0	0	0	0
11	0	1	0	6	0	0	0	0	0
12	0.5	1	1.5	5	0.5	0	0	0	0
13	0	1	1	6	1	0	0	0	0
14	1.67	1	2	0	2	0	0	0	0
15	1	1	1	1.33	0.67	0	0.67	0.67	0
16	0	1	0.8	1.4	0	0	0	0	0
17	2	1	14	35	14	0	0	3	1
18	1.5	1	1.5	2.5	1.5	0	0	0	1
19	1.67	1	1.67	3.33	1.67	0	0	0	1
20	1.4	1	1.4	4	1.4	0	0	0	1
21	0	1	1.4	1.4	0	0	0	0	0
22	0	1	0.6	0.8	0.4	0	0.2	0	0
23	0	1	0.83	1.5	0	0	0	0.67	0
24	0	1	1	1	0	0	0	0	0
Average (Base size)	2	1	3	6	3	1	1	2	1

Table A2 Selling price of brand new products

References	Min price	Max price
Faccio et al. (2011)	200	500
Ramezani et al. (2013)	120	140
Keyvanshokooh et al. (2016)	160	230
Jeihoonian et al. (2016)	600	1300
Ahmadi and Amin (2019)	100	100
Atabaki et al. (2019)	50	95
Average price value	≈200	≈400

Table A3 Demand for brand new products

References	Customer nodes $i(=N_c)$	Demand (d_t^{lk})		Total Demand $(d_{it}^{lk}=N_c.d_t^{lk})$	
		min	max	min	max
Pishvaee et al. (2010)	5	80	250	400	1250
Faccio et al. (2011)	7	100	1000	700	7000
Ramezani et al. (2013)	20	150	280	3000	5600
Devika et al. (2014)	20	100	200	2000	4000
Kalaitzidou et al. (2015)	18	100	700	1800	12600
Keyvanshokooh et al. (2016)	10	2100	2950	21000	29500
Keyvanshokooh et al. (2016)	20	1500	3100	30000	62000
Jeihoonian et al. (2016)	60	600	1000	36000	60000
Dehghan et al. (2019)	15	30	250	450	3750
Goli et al. (2019)	5	10	50	50	250
Goli et al. (2019)	5	20	45	100	225
Shen (2019)	15	50	300	750	4500
Guo et al. (2019)	30	20	30	600	900
Average level of demand				≈ 7500	≈ 15000

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Declarations

Conflict of interest Dr A. MahmoumGonbadi declares that she has no Conflict of interest. Prof. A. Genovese declares that he has no Conflict of interest. Prof. A. Sgalambro declares that he has no Conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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