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Sustainable reverse logistics network design: a case of waste electrical and electronic equipment management

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Abstract

In this study, we develop a reverse logistics network design model to recover value from waste electrical and electronic equipment (WEEE) under uncertainty. We propose a multi-objective, multi-period, and multi-product optimization model under uncertainty, focusing on economic, environmental, and social aspects for the WEEE management organization in India. The uncertainty associated with the price of reprocessed items, as well as the quantity and quality of product returns, is captured using the scenario generation technique. The augmented ε-constraint method is employed to address the multi-objective optimization problem to generate Pareto-optimal solutions. Our model incorporates the modular capacity expansion and inventory management aspects that accommodate the resilience of the reverse logistics network. Our results show that strategic inventory management can yield better outcomes from a sustainability perspective in the presence of fluctuating prices of reprocessed items. Furthermore, we observe that when the quality of the product returns decreases, the profit and social benefits decrease.

Keywords: sustainable operations; reverse logistics network design; multi-objective optimization; stochastic optimization

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1. Introduction

In recent years, the usage of electrical and electronic equipment has been growing rapidly, generating a stream of waste containing both hazardous and useful materials, known as waste electrical and electronic equipment (WEEE) or e-waste. In 2022, 62 million tonnes of e-waste, a per capita average of 7.8 kg was generated worldwide, and only 22% was properly collected and disposed of (Baldé et al., 2024). The e-waste generation is increasing at an alarming rate, with an 82% increase from 2010 to 2022, and is expected to increase by 32% by 2030 (United Nations Institute for

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Training and Research, 2024). The situation is no different in India, with a generation of e-waste of 1.75 million tonnes in 2023–2024, a 73% increase from 2018 to 2019 (Ministry of Housing and Urban Affairs, 2024).

In developing countries, the infrastructure for e-waste management is underdeveloped, wherein recycling is handled largely by the informal sector, which leads to severe undesirable consequences for the people and the environment. In India, e-waste recycling is largely controlled by the informal sector with a market share of than 90% (Sengupta et al., 2023). The informal sector lacks the proper standards for the reprocessing of e-waste, which can affect the health of living beings and the surroundings. For example, at the global level, 22% of mercury is used to make electrical and electronic equipment, and improperly disposed of mercury can affect the liver and spinal cord of humans (Annamalai, 2015). The formal sector mitigates such undesirable consequences of reprocessing due to proper collection and handling of e-waste by following worker protection, industrial hygiene, and pollution control policies (Fahimnia et al., 2015) as the formal sector is governed by legislative policies. For example, the WEEE directive in Europe (European Union Directive, 2012) and the e-waste (management) rules in India (Ministry of Environment, Forest and Climate Change, 2016, 2022) govern the reprocessing of e-waste. The presence of a legal framework can enhance formal recycling. In India, as per the e-waste (management) rules 2022 (Ministry of Environment, Forest and Climate Change, 2022), the producers are bound by the extended producer responsibility. E-waste (management) rules in India have helped to increase formal e-waste recyclers from 98 in 2013 with a total capacity of 0.29 million tonnes per year to 567 in 2023 with a total capacity of 1.72 million tonnes per year (Central Pollution Control Board, 2024). Apart from the legal bindings for the formal sector, organizations are motivated to incorporate environmental concerns in their operations due to the increased value generation, brand awareness, and the resulting increase in their business. WEEE contains valuable metals such as iron, copper, aluminum, and precious metals. Combining the informal e-waste sector with the formal e-waste sector can minimize the ill effects of e-waste (Li and Tee, 2012) and maximize the social aspect of the business.

Although the research on reverse logistics (RL) is fairly mature (please refer to Govindan et al., 2015, and Jahani et al., 2024, for a comprehensive review), exploring sustainability in an uncertain environment in RL network design is in the infant stage. Sustainability requires firms to focus on social and environmental dimensions in addition to traditional economic performance. Corporate social responsibility (CSR) activities and the number of people who benefit due to the business quantify the social aspect of sustainability, whereas the environmental impact due to the activities measures the environmental dimension. In the context of network design in the RL and closed-loop supply chain (CLSC), Govindan et al. (2016), Rahimi and Ghezavati (2018), and Gao and Cao (2020) consider the economic, environmental, and social aspects of sustainability in different industries. In the context of used syringe RL, Govindan et al. (2016) propose a sustainable network design model under uncertainty. Rahimi and Ghezavati (2018) consider the case of construction and demolition waste management and develop the RL network under uncertainty, whereas Gao and Cao (2020) redesign the existing forward supply chain under uncertainty to accommodate the RL activities in a CLSC.

Research on sustainable RL network design under uncertainty for e-waste from the perspective of real-world operations with capacity expansion and strategic inventory management is unexplored to the best of our knowledge. In this work, we design a sustainable RL network that considers economic (Eco), environmental (Env), and social (Soc) objectives for an e-waste management organization in the formal sector in India under uncertainty. The following features are considered in the modeling: First, the model incorporates the social aspect through the CSR activity of the firm by distributing the repaired items to the people free of cost, in addition to the number of jobs created. Second, the firm has inspection, recycling, and repair facilities located at the same location. Furthermore, we incorporate dynamic capacity through modular capacity expansion and strategic inventory management in a sustainable setting and evaluate their impact on the RL network's performance.

This research work considers a multi-objective optimization model under uncertainty in a multi-period and multi-product setting. The multi-objective optimization model is a widely adopted methodology to address multiple objectives, such as economic and environmental aspects in network design (Kchaou-Boujelben et al., 2023; Zhang et al., 2026; Ruiz-Barajas et al., 2025; Rodríguez-Escoto et al., 2025; Shukla et al., 2025). We consider the quantity and quality of returned products and the price of the recycled items as uncertain parameters based on the literature and the real-world case. In RL, the quantity and quality of the products returned are the most common sources of uncertainty (Ayvaz et al., 2015a; Yu and Solvang, 2018; Azizi et al., 2020; Li et al., 2023). From the market perspective of the RL activities, the price of the reprocessed items is a prominent source of uncertainty (Soleimani and Govindan, 2014; Yu and Solvang, 2018; Shukla et al., 2025). The three objectives are profit maximization (Eco), minimization of carbon dioxide (CO_2) emissions (Env), and maximization of the number of people who benefited due to the jobs created and free distribution of repaired products (Soc). We use the augmented ε-constraint method to solve the multi-objective optimization model. Our study aligns with United Nations sustainable development goals (SDGs) 11, 12, and 13—sustainable cities and communities, responsible consumption and production, and climate action, respectively. The RL activities considered in this study align with SDG 12, the environmental objective addresses SDG 13, and the social objective contributes to SDG 11.

The contributions of our study are elaborated as follows:

(i) We propose a sustainable RL network design model for WEEE in a multi-product, multi-period setting under uncertainty, incorporating an inventory management strategy with capacity adjustments.
(ii) We illustrate the application of the developed model with the case of a WEEE management organization in India.
(iii) We prove the inventory management strategy's role in sustainably improving RL performance.

The paper is organized in the following manner. In Section 2, relevant literature is reviewed. Mathematical modeling and solution methodology are explained in Section 3. Section 4 provides the case description for the analysis, and results and discussion are presented in Section 5. Section 6 concludes the paper with the scope for future work.

2. Literature review

We review the literature on sustainability in RL, uncertainty in RL, and RL for WEEE management.

2.1. Sustainability in the RL network design

Environmental concerns in supply chain management have been gaining significant attention in the recent two decades (Tseng et al., 2019). Kannan et al. (2012) incorporate the environmental aspect through the cost of CO_2 emissions in their economic objective in the RL network design for an organization in the plastic sector. In a global RL for e-waste management, Xu et al. (2017) include the environmental aspect through carbon cap constraint in their network design problem under uncertainty. Yu and Solvang (2018) consider CO_2 emissions from processing and transportation in their multi-objective RL network design problem and compare the quality of weighted sum and augmented ε-constraint techniques to show that the latter performs better in generating Pareto-optimal frontiers.

Under a carbon emissions cap, Tao et al. (2015) analyze the network equilibrium of a CLSC in a multi-period setting. In a CLSC setting for the case of geyser, Garg et al. (2015) incorporate the environmental objective for network design and solve their multi-objective optimization model using an interactive algorithm. Bing et al. (2014) consider the cost of transportation and CO_2 emissions in their optimization model for household plastic bottles RL in the Netherlands. Reddy et al. (2019) propose an optimization model to decide on the type of vehicle used to minimize the CO_2 emissions.

Incorporating three aspects of sustainability—economic, environmental, and social objectives, Govindan et al. (2016) design the RL network for syringes under fuzzy parameters using exact and heuristic methods for their multi-objective problem. Considering the aforementioned three aspects of sustainability, under a multi-objective setting, Rahimi and Ghezavati (2018) design the RL network for construction and demolition waste management organizations in Turkey using the augmented ε-constraint technique, whereas Safdar et al. (2020) design the RL network in a single-period single-product setting using the neutrosophic optimization technique. Dutta et al. (2020) designed the RL for an apparel product for an e-commerce organization in India, incorporating three pillars of sustainability, and solved the multi-objective model using a weighted goal programming approach. In a CLSC setting with the three sustainability objectives, Gao and Cao (2020) redesign the network under uncertainty. Zarbakhshnia et al. (2020) consider the processing time for RL activities as an objective in addition to the economic and social objectives in their CLSC network design problem. Reddy et al. (2022) incorporate the cost associated with carbon emissions in their objective function for an RL network design problem. Rodríguez-Escoto et al. (2025) consider a novel social dimension through minimization of obnoxious distance in their closed-loop supply chain network design problem having hybrid facilities.

2.2. Uncertainty in the RL network design

As the network design decisions are long-term in nature, the uncertainty needs to be accounted for in the models (Govindan et al., 2015). Multiple approaches exist to address uncertainty in the supply chain. One of the predominant approaches to address the uncertainty in RL is through two-stage stochastic programming. Lee et al. (2010) consider CLSC with the quantity of products demanded and the quantity of products returned as uncertain parameters. A two-stage stochastic programming model is formulated, and the sample average approximation (SAA) technique is used to solve the model. Ayvaz et al. (2015b) consider the uncertainty of product returns and cost of transportation in their two-stage stochastic programming model to design the RL network under economic objective using the SAA technique. Azizi et al. (2020) and Fattahi and Govindan (2017) use a two-stage stochastic programming model, which is solved using scenario generation and reduction techniques under demand and product return uncertainties. Fattahi and Govindan (2017) use Latin hypercube sampling for the scenario generation, and backward scenario reduction is employed to reduce the number of scenarios. Trochu et al. (2020) assume uncertainty in recycling rate and the quantity of materials collected and use the SAA technique and augmented ε-constraint approach for a two-stage stochastic programming model with economic and environmental objectives for the construction, renovation, and demolition industry in Canada. Yu and Solvang (2018), Rahimi and Ghezavati (2018), Gao and Cao (2020), Shukla et al. (2025), and Kchaou-Boujelben et al. (2023) use the scenario generation technique to address the uncertainty in their respective stochastic multi-objective models.

De Rosa et al. (2013) use the robust optimization technique with the expected regret minimization criteria for their CLSC under product demand and return uncertainties. Xu et al. (2017) address the uncertainties in waste collection, transportation cost, and exchange rate through the robust optimization technique. Govindan et al. (2016) use fuzzy mathematical programming to capture the uncertainties in the parameters and employ a possibilistic programming approach to address the uncertainties in their multi-objective optimization model. Tosarkani et al. (2020) use a scenario-based robust possibilistic approach for the multi-objective RL design of WEEE in Canada. Probabilistic programming is employed by Zarbakhshnia et al. (2020) to address demand uncertainty in their multi-objective optimization model. Mishra and Singh (2022) employ the chance-constrained programming technique to address the uncertainties in the product demand and return in their CLSC network model. Li et al. (2023) use fuzzy mathematical programming to address the uncertainties in the quality and quantity of returns in their RL network. Han et al. (2024) use the expectation principle to quantify the uncertainty in demand in a CLSC network design together with a safety stock decision. Schleier and Walther (2024) analyze different scenarios to address uncertainty associated with business for the construction and demolition waste recycling network design in Germany.

2.3. RL for WEEE management

Previous studies have explored RL network design in different contexts of WEEE, predominantly from the economic objective perspective. Achillas et al. (2010) present a mixed-integer linear programming (MILP model for optimal RL network designW for WEEE products, with the case of an organization in Greece in a deterministic and single-period setting. Alumur et al. (2012) propose a multi-period, multi-product model for the case of washing machines and tumble dryers in Germany in a deterministic setting. In the context of WEEE products in Turkey, Ayvaz et al. (2015b) propose a two-stage stochastic programming model. In the Indian context, John et al. (2018) consider the case of used refrigerators in a multi-period setting with deterministic parameters and develop an optimal RL network design. From the economic and environmental perspectives, Garg et al. (2015) propose a bi-objective optimization model in a CLSC setting for the case of a geyser under certainty.

Several studies document the barriers in WEEE management and the ways to mitigate them. An et al. (2015) analyze the WEEE management in the Chinese context using the analytical hierarchy process to identify the barriers. They observe the support for the transition of the recyclers from the informal sector to the formal sector as an effective way to mitigate pollution. Park et al. (2020) analyze the behavioral aspect of consumers towards the disposal of WEEE. The study helps to narrow down the potential problems that can occur in the WEEE disposal process and also emphasizes the importance of formal sector intervention. Pekarkova et al. (2021) examine the reasons for improper disposal of WEEE. They illustrate the advantages of proper disposal of e-waste and analyze the economic and environmental impacts of the mishandling using a case in Europe. McMahon et al. (2021) estimate the potential employment opportunities by analyzing the labor requirement in the formal sector and highlighting the job opportunities lost due to the improper management of WEEE. Ríos-Mercado et al. (2023) consider the maximum dispersion territory problem in the collection of WEEE and propose an improvised tabu search metaheuristic that guarantees better solutions. Shi et al. (2023) consider the RL network design for WEEE in Canada, focusing on the environmental aspect through public campaign intensity and the economic aspect of the location of collection centers. The summary of the review of the most closely related literature is provided in Table 1.

Analyzing the existing literature, as summarized in Table 1, reveals the need to study the RL activities from three dimensions of sustainability—economic, environmental, and social aspects under uncertainty with the provision of capacity adjustments and inventory management as a strategic weapon with applications to the real-world problems such as WEEE. To the best of our knowledge, the literature has not addressed this problem. In our research work, we propose an RL network design for organizations in India, focusing on the products of air conditioners and central processing units (CPUs) under uncertainty, incorporating economic, environmental, and social objectives in a multi-period setting. We generate Pareto frontiers for the multi-objective optimization problem under different parameter settings and under an alternate model incorporating the inventory aspect.

3. The model

We follow the mathematical modeling and optimization approach to address our research problems. The model is developed under the following set of assumptions.

(i) The existence of high demand for recycled materials in the primary markets so that all recycled materials are sold in the market for revenue generation.
(ii) E-waste is collected free of cost.
(iii) Modular capacity expansion is allowed from the second period onwards for the facilities that are opened.
(iv) The flow of material can occur only between two sequential echelons.
(v) The quantity of returned products, the quality of returned products, and the price of recycled products are uncertain.
(vi) CO_2 emissions during transportation and processing are considered for environmental impact.
(vii) The products treated in the repair facility are not used for revenue generation and are given to the needy community for free as a social welfare measure.
(viii) The number of people who benefited due to job creation and receiving repaired products is considered for social impact.

Table 1
Summary of review of relevant literature

Work	Sustainability	Network	Uncertainty	Capacity adjustment	Inventory strategy	Case products (region)
Kannan et al. (2012)	Env	RL	—	—	—	Plastic waste (India)
Alumur et al. (2012)	Eco	RL	—	Yes	—	WEEE (Germany)
De Rosa et al. (2013)	Eco	CLSC	Yes	Yes	—	—
Ayvaz et al. (2015b)	Eco	RL	Yes	—	—	WEEE (Turkey)
Govindan et al. (2016)	Eco, Env, Soc	RL	Yes	—	—	Syringe (Iran)
Xu et al. (2017)	Eco, Env	RL	Yes	—	—	WEEE (Greece and China)
John et al. (2018)	Eco	RL	—	—	—	Refrigerators (India)
Rahimi and Ghezavati (2018)	Eco, Env, Soc	RL	Yes	Yes	—	—
Zarbakhshnia et al. (2020)	Eco, Env, Soc	CLSC	Yes	—	—	—
Trochu et al. (2020)	Eco, Env	RL	Yes	Yes	—	Wood (Canada)
Dutta et al. (2020)	Eco, Env, Soc	RL	Yes	—	—	e-Commerce (India)
Gao and Cao (2020)	Eco, Env, Soc	RL	Yes	—	—	—
Tosarkani et al. (2020)	Eco, Env	RL	Yes	—	—	WEEE (Canada)
Azizi et al. (2020)	Eco	RL	Yes	—	Yes	Consumer goods (Europe)
Shukla et al. (2025)	Eco, Env	RL	Yes	Yes	—	—
Mishra and Singh (2022)	Eco	CLSC	Yes	Yes	—	—
Reddy et al. (2022)	Eco, Env	RL	—	—	Yes	—
Li et al. (2023)	Eco	RL	Yes	—	Yes	—
Shi et al. (2023)	Eco, Env	RL	—	—	—	WEEE (Canada)
Kchaou-Boujelben et al. (2023)	Eco, Env	CLSC	Yes	—	—	—
Han et al. (2024)	Eco	CLSC	Yes	—	Yes	—
Schleier and Walther (2024)	Eco	RL	Yes	Yes	—	Construction and demolition waste (Germany)
This study	Eco, Env, Soc	RL	Yes	Yes	Yes	WEEE (India)

Note: Eco, Economic; Env, environmental; Soc, social; CLSC, closed-loop supply chain; RL, reverse logistics; WEEE, waste electrical and electronic equipment.

The aforementioned assumptions are based on the nature of the operation of the WEEE case organization in India, most of which resonate with general practice and the literature. Assumptions (i), (iv), (v), and (vi) align with the literature (Yu and Solvang, 2018; Li et al., 2023; Shukla et al., 2025). Assumption (ii) is supported by the e-waste (management) rules (Ministry of Environment, Forest and Climate Change, 2022) wherein the local bodies facilitate the setting up of collection centers. Assumption (vii) is specific to the practice followed by the case organization, and assumption (viii) conforms to the standard practice of accounting for the social benefit in the literature (Rahimi and Ghezavati, 2018). Assumption (iii) incorporates capacity expansion for a firm anticipating growth.

The flow of the returned products is as follows: The returned products are collected through the collection centers. The collected returned products reach inspection centers, where they are carefully inspected and sorted based on their useful remaining life. If the product has a high remaining useful life, then it is sent to the repairing center. The repaired products are handed over free of

Table 2
Notations: sets

T	Set of time periods in the planning horizon, indexed by t; $t \in \{1, \ldots, \tau\}$
P	Set of products, indexed by p
C	Set of local collection centers, indexed by c.
I	Set of inspection centers, indexed by i
M	Set of repairing centers, indexed by m
R	Set of recycling centers, indexed by r
D	Set of landfills, indexed by d
S	Set of scenarios, indexed by s
X	Set of locations for inspection, repairing, and recycling centers $X = \{I, M, R\}$ indexed by x
$G(y, z)$	Set of routes between different centers and markets $G(y, z) = \{(c, i), (i, m), (i, r), (i, d)\}$

cost to needy people for reuse. If the product has a low remaining useful life and if it has recyclable components, then it is sent to the recycling center. The materials recycled are sold to primary markets for revenue generation. The low remaining useful life products and items that cannot be reprocessed are sent to landfill centers. In our model, we consider the following three uncertain parameters: quantity of the returned product, quality of the returned product, and price of the recycled items. Table 2 shows the sets, and Table 3 shows the parameters used in the model. Table 4 gives the decision variables used in the model.

We propose a stochastic multi-objective mixed integer linear programming model for the RL network design. In our model, Objective 1 captures the expected profit generated, Objective 2 quantifies the expected CO_2 emissions due to processing and transportation, and Objective 3 measures the expected number of people benefited due to the RL activities, which are subjected to a set of constraints as described in detail below.

Maximize Objective 1

$$\begin{aligned}
&\sum_{t\in T}\Bigg[\sum_{p\in P}\sum_{r\in R}\sum_{s\in S} PS_s^t PR_{ps}^t QNT_{prs}^t - \Bigg[\sum_{p\in P}\sum_{i\in I}\sum_{s\in S} PS_s^t PRC_{pi}^t QNT_{pis}^t \\
&\quad + \sum_{p\in P}\sum_{r\in R}\sum_{s\in S} PS_s^t PRC_{pr}^t QNT_{prs}^t + \sum_{p\in P}\sum_{m\in M}\sum_{s\in S} PS_s^t PRC_{pm}^t QNT_{pms}^t \\
&\quad + \sum_{p\in P}\sum_{d\in D}\sum_{s\in S} PS_s^t PRC_{pd}^t QNT_{pds}^t\Bigg] - \Bigg[\sum_{p\in P}\sum_{c\in C}\sum_{i\in I}\sum_{s\in S} PS_s^t TC_{pci}^t QS_{pcis}^t \\
&\quad + \sum_{p\in P}\sum_{i\in I}\sum_{m\in M}\sum_{s\in S} PS_s^t TC_{pim}^t QS_{pims}^t + \sum_{p\in P}\sum_{i\in I}\sum_{d\in D}\sum_{s\in S} PS_s^t TC_{pid}^t QS_{pids}^t \\
&\quad \sum_{p\in P}\sum_{i\in I}\sum_{r\in R}\sum_{s\in S} PS_s^t TC_{pir}^t QS_{pirs}^t\Bigg] - \Bigg[\sum_{i\in I} ME_i^t N_i^t + \sum_{r\in R} ME_r^t N_r^t +
\end{aligned}$$

Table 3
Notations: parameters

PR^t_{ps}	Price of the recycled materials generated from 1 kg of product p in scenario s and in time period t
F^t_x	Fixed cost of opening a facility at location x in time period t
PRC^t_{px}	Cost of processing 1 kg of product p in time period t at facility x
PRC^t_{pd}	Cost of processing 1 kg of product p in time period t at landfill d
TC^t_{pyz}	Cost of transporting 1 kg of product p on route yz in time period t
HC^t_{px}	Cost of holding 1 kg of product p at facility x in time period t
FE^t_x	Fixed cost for adding a module to the facility x in time period t
ME^t_x	Variable cost for adding a module to the facility x in time period t
$MCAP_x$	Capacity of the module to be added to facility x
CAP_x	Initial capacity at facility x
CE^t_{px}	CO_2 emissions due to processing 1 kg of product p at facility x in time period t
CET^t_{pyz}	CO_2 emissions for transporting 1 kg of product p on route yz in time period t
PC^t_{pcs}	Quantity (in kg) of product p collected at center c in scenario s in period t
JF_x	Number of people employed due to establishing a facility of type x
JM_x	People employed due to modular capacity expansion in the facility of type x
BF_p	Number of people benefited from repaired product p
PS^t_s	Probability of occurrence of scenario s
γ_{px}	Fraction of product p suitable for facility x for the respective processing activity
π_{ps}	Quality level of the product p in scenario s
PR_p	Recoverable fraction if product p is of good quality
PRN_p	Nonrecoverable fraction if product p is of good quality
L^t_x	Maximum modules available in facility x in time period t
W_p	Average weight of product p

Table 4
Notations: decision variables

LOC_i	Equals 1 if inspection center i is open and 0 otherwise
LOC_r	Equals 1 if recycling center r is open in period t and 0 otherwise
LOC_m	Equals 1 if repairing center m is open and 0 otherwise
QNT^t_{pxs}	Quantity of the product p treated at facility x in time period t in scenario s
QNT^t_{pds}	Quantity of the product p treated at landfill d in time period t in scenario s
QS^t_{pyzs}	Quantity of product p shipped through route yz in time period t in scenario s
N^t_x	Number of modules added to facility x in time period t
Y^t_x	Equals 1 if the capacity of facility x is expanded in period t and 0 otherwise

$$\sum_{m\in M} ME^t_m N^t_m \Bigg] - \Bigg[\sum_{i\in I} FE^t_i Y^t_i + \sum_{r\in R} FE^t_r Y^t_r + \sum_{m\in M} FE^t_m Y^t_m \Bigg]\Bigg]$$

$$- \Bigg[\sum_{i\in I} F_i LOC_i + \sum_{r\in R} F_r LOC_r + \sum_{m\in M} F_m LOC_m \Bigg], \tag{1}$$

Minimize Objective 2

$$
\begin{aligned}
&\sum_{t\in T}\sum_{s\in S}\left[\left[\sum_{p\in P}\sum_{i\in I} PS_s^t CE_{pi} QNT_{pis}^t\right] + \left[\sum_{p\in P}\sum_{m\in M} PS_s^t CE_{pm} QNT_{pms}^t\right]\right]\\
&\quad + \left[\sum_{p\in P}\sum_{r\in R} PS_s^t CE_{pr} QNT_{prs}^t\right] + \left[\sum_{p\in P}\sum_{d\in D} PS_s^t CE_{pd} QNT_{pds}^t\right]\\
&+ \left[\sum_{p\in P}\sum_{c\in C}\sum_{i\in I} PS_s^t CET_{pci} QS_{pcis}^t\right] + \left[\sum_{p\in P}\sum_{i\in I}\sum_{m\in M} PS_s^t CET_{pim} QS_{pims}^t\right]\\
&\quad + \left[\sum_{p\in P}\sum_{i\in I}\sum_{r\in R} PS_s^t CET_{pir} QS_{pirs}^t\right] + \left[\sum_{p\in P}\sum_{i\in I}\sum_{d\in D} PS_s^t CET_{pid} QS_{pids}^t\right]
\end{aligned}
\tag{2}
$$

Maximize Objective 3

$$
\begin{aligned}
&\sum_{t\in T}\sum_{p\in P}\sum_{m\in M}\sum_{s\in S} PS_s^t BF_p \frac{QNT_{pms}^t}{W_p}\\
&+\sum_{i\in I} JF_i LOC_i + \sum_{m\in M} JF_m LOC_m + \sum_{r\in R} JF_r LOC_r\\
&+\sum_{i\in I}\sum_{t\in T} JM_i^t N_i^t + \sum_{m\in M}\sum_{t\in T} JM_m^t N_m^t + \sum_{r\in R}\sum_{t\in T} JM_r^t N_r^t,
\end{aligned}
\tag{3}
$$

Objective 1 maximizes the expected profit. The first term is the expected revenue generated by selling the recycling materials in the primary market, and the remaining terms represent the cost, which includes the expected cost of processing, the expected transportation cost, the cost incurred in modular capacity expansion, and the fixed cost of establishing the facilities. Objective 2 captures the expected CO_2 emissions due to reprocessing and transportation, which are to be minimized. Objective 3 incorporates the expected number of people benefited due to the RL activities. The first term contributes to the expected number of people who benefit from receiving the repaired products at no cost. The next set of terms captures the job opportunities created by establishing fixed capacity facilities and by installing modular capacities across the time periods.

The objectives discussed are subject to the following set of constraints:

$$
PC_{pcs}^t = \sum_{i\in I} QS_{pcis}^t, \qquad \forall p \in P, c \in C, t \in T, s \in S, \tag{4}
$$

$$
QNT_{pis}^t = \sum_{c\in C} QS_{pcis}^t, \qquad \forall p \in P, i \in I, t \in T, s \in S, \tag{5}
$$

$$QNT^t_{pms} = \sum_{i\in I} QS^t_{pims}, \qquad \forall p \in P, m \in M, t \in T, s \in S, \tag{6}$$

$$QNT^t_{prs} = \sum_{i\in I} QS^t_{pirs}, \qquad \forall p \in P, r \in R, t \in T, s \in S, \tag{7}$$

$$QNT^t_{pds} = \sum_{i\in I} QS^t_{pids}, \qquad \forall p \in P, d \in D, t \in T, s \in S, \tag{8}$$

$$QNT^t_{pis} = \sum_{m\in M} QS^t_{pims} + \sum_{r\in R} QS^t_{pirs} + \sum_{d\in D} QS^t_{pids}, \qquad \forall p \in P, i \in I, t \in T, s \in S, \tag{9}$$

$$FCAP^t_i = CAP_i LOC_i, \qquad \forall t = 1, i \in I, \tag{10}$$

$$FCAP^t_i = FCAP^{t-1}_i + N^t_i MCAP_i, \qquad \forall t > 1, i \in I, \tag{11}$$

$$FCAP^t_m = CAP_m LOC_i, \qquad \forall t = 1, m \in M, \tag{12}$$

$$FCAP^t_m = FCAP^{t-1}_m + N^t_m MCAP_m, \qquad \forall t > 1, m \in M, \tag{13}$$

$$FCAP^t_r = CAP_r LOC_r, \qquad \forall t = 1, r \in R, \tag{14}$$

$$FCAP^t_r = FCAP^{t-1}_r + N^t_r MCAP_r, \qquad \forall t > 1, r \in R, \tag{15}$$

$$Y^t_i = 0, \qquad \forall t = 1, i \in I, \tag{16}$$

$$Y^t_m = 0, \qquad \forall t = 1, m \in M, \tag{17}$$

$$Y^t_r = 0, \qquad \forall t = 1, r \in R, \tag{18}$$

$$Y^t_i \le LOC_i, \qquad \forall t > 1, i \in I, \tag{19}$$

$$Y^t_m \le LOC_m, \qquad \forall t > 1, m \in M, \tag{20}$$

$$Y^t_r \le LOC_r, \qquad \forall t > 1, r \in R, \tag{21}$$

$$N^t_i \le L^t_i Y^t_i, \qquad \forall t > 1, i \in I, \tag{22}$$

$$N^t_m \le L^t_m Y^t_m, \qquad \forall t > 1, m \in M, \tag{23}$$

$$N^t_r \le L^t_r Y^t_r, \qquad \forall t > 1, r \in R, \tag{24}$$

$$\sum_{p\in P} QNT^t_{pis} \le FCAP^t_i, \qquad \forall i \in I, t \in T, s \in S, \tag{25}$$

$$\sum_{p\in P} QNT^t_{pms} \le FCAP^t_m, \qquad \forall m \in M, t \in T, s \in S, \tag{26}$$

$$\sum_{p\in P} QNT^t_{prs} \le FCAP^t_r, \qquad \forall r\in R, t\in T, s\in S, \tag{27}$$

$$\pi_{ps}\gamma_{pm}QNT^t_{pis} \ge \sum_{m\in M} QS^t_{pims}, \qquad \forall p\in P, i\in I, t\in T, s\in S, \tag{28}$$

$$\pi_{ps}\gamma_{pr}QNT^t_{pis} \ge \sum_{r\in R} QS^t_{pirs}, \qquad \forall p\in P, i\in I, t\in T, s\in S, \tag{29}$$

$$QNT^t_{pis}(PRN_p + (1-\pi_{ps})PR_p) \le \sum_{d\in D} QS^t_{pids}, \qquad \forall p\in P, i\in I, t\in T, s\in S, \tag{30}$$

$$LOC_i, LOC_m, LOC_r, Y^t_i, Y^t_m, Y^t_r \in \{0,1\}, \qquad \forall t\in T, i\in I, m\in M, r\in R, \tag{31}$$

$$N^t_{pi}, N^t_{pr}, N^t_{pm} \in \{\mathbb{Z}\ge 0\}, \qquad \forall t\in T, i\in I, p\in P, r\in R, m\in M, \tag{32}$$

$$QNT^t_{pis}, QNT^t_{pms}, QNT^t_{prs}, QNT^t_{pds} \ge 0, \qquad \forall t\in T, p\in P, i\in I, m\in M, r\in R, d\in D, \tag{33}$$

$$QS^t_{pcis}, QS^t_{pims}, QS^t_{pirs}, QS^t_{pids} \ge 0, \forall p\in P, i\in I, m\in M, r\in R, d\in D, t\in T. \tag{34}$$

Constraint (4) ensures that the collected products are sent to the inspection center, which ensures the inflow of materials to the network structure. Flow balance in the network structure is ensured by Constraints (5)–(9). Constraint (10) ensures the capacity of the inspection center at $t = 1$ is equal to the initial capacity of the inspection center. Constraint (11) gives the capacity of the inspection center at period t as the sum of the capacity already available at the inspection center and the capacity modules added in period t. Constraints (12)–(15) are equivalent to (10) and (11) for repairing center and recycling center, respectively. Constraints (16)–(18) ensure that no capacity expansion is allowed in period $t = 1$ for inspection, repairing, and recycling centers, respectively. Constraints (19)–(21) guarantee that capacity expansion is allowed only for the facilities that are already established. Constraints (22)–(24) restrict the maximum number of modules that can be added to the inspection, repairing, and recycling center, respectively. Constraints (25)–(27) limit the quantity of products that can be processed in the facilities in each period. Different quantities of products are sent to different centers for reprocessing and disposal depending on the quality of products and proportion requirements, given by Constraints (28)–(30). Constraints (31)–(34) are domain constraints.

3.1. *Modified model: Incorporating the inventory aspect*

The analysis is extended to include the inventory aspect and the respective cost in the mathematical model. In the modified model incorporating the inventory aspect, the flow balance constraints (5)–(9) are replaced with the inventory balance constraints (36)–(41) and flow balance constraints (42) and (43) and the objective function 1 is modified to incorporate the holding cost, with necessary additional decision variables on inventory.

Objective 1 is replaced with the modified objective 1 (35) in the multi-objective optimization model incorporating the inventory aspect and is as follows: Maximize modified objective 1

$$
\begin{multline}
\sum_{t\in T}\Bigg[\sum_{p\in P}\sum_{r\in R}\sum_{s\in S} PS_s^t PR_{ps}^t QNT_{prs}^t - \Bigg[\sum_{p\in P}\sum_{c\in C}\sum_{i\in I}\sum_{s\in S} PS_s^t TC_{pci}^t QS_{pcis}^t \\
+\sum_{p\in P}\sum_{i\in I}\sum_{m\in M}\sum_{s\in S} PS_s^t TC_{pim}^t QS_{pims}^t + \sum_{p\in P}\sum_{i\in I}\sum_{d\in D}\sum_{s\in S} PS_s^t TC_{pid}^t QS_{pids}^t \\
\sum_{p\in P}\sum_{i\in I}\sum_{r\in R}\sum_{s\in S} PS_s^t TC_{pir}^t QS_{pirs}^t \Bigg] - \Bigg[\sum_{p\in P}\sum_{i\in I}\sum_{s\in S} PS_s^t PRC_{pi}^t QNT_{pis}^t \\
+\sum_{p\in P}\sum_{r\in R}\sum_{s\in S} PS_s^t PRC_{pr}^t QNT_{prs}^t + \sum_{p\in P}\sum_{m\in M}\sum_{s\in S} PS_s^t PRC_{pm}^t QNT_{pms}^t \\
+\sum_{p\in P}\sum_{d\in D}\sum_{s\in S} PS_s^t PRC_{pd}^t QNT_{pds}^t \Bigg] - \Bigg[\sum_{i\in I} ME_i^t N_i^t + \sum_{r\in R} ME_r^t N_r^t + \\
\sum_{m\in M} ME_m^t N_m^t \Bigg] - \Bigg[\sum_{i\in I} FE_i^t Y_i^t + \sum_{r\in R} FE_r^t Y_r^t + \sum_{m\in M} FE_m^t Y_m^t \Bigg] \\
-\Bigg[\sum_{p\in P}\sum_{i\in I}\sum_{s\in S} PS_s^t HC_{pi}^t INV_{pis}^t + \sum_{p\in P}\sum_{r\in R}\sum_{s\in S} PS_s^t HC_{pr}^t INV_{prs}^t \\
+\sum_{p\in P}\sum_{m\in M}\sum_{s\in S} PS_s^t HC_{pm}^t INV_{pms}^t \Bigg]\Bigg] - \Bigg[\sum_{i\in I} F_i LOC_i + \sum_{r\in R} F_r LOC_r + \sum_{m\in M} F_m LOC_m \Bigg]. \qquad (35)
\end{multline}
$$

The inventory balance constraints are as follows:

$$INV_{pis}^t = INV_{pis}^{t-1} + \sum_{i\in I} QS_{pcis}^t - QNT_{pis}^t \qquad \forall t > 0, p \in P, i \in I, s \in S, \qquad (36)$$

$$INV_{pis}^t = 0, \qquad \forall t = 0, \tau, p \in P, s \in S, i \in I, \qquad (37)$$

$$INV_{pms}^t = INV_{pms}^{t-1} + \sum_{m\in M} QS_{pims}^t - QNT_{pms}^t \qquad \forall t > 0, p \in P, m \in M, s \in S, \qquad (38)$$

$$INV_{pms}^t = 0, \qquad \forall t = 0, \tau, p \in Ps \in S, m \in M, \qquad (39)$$

$$INV_{prs}^t = INV_{prs}^{t-1} + \sum_{r\in R} QS_{pirs}^t - QNT_{pis}^t, \qquad \forall t > 0, p \in P, r \in R, s \in S, \qquad (40)$$

$$INV_{prs}^{t} = 0, \qquad \forall t = 0, \tau, p \in Ps \in S, r \in R, \tag{41}$$

$$QNT_{pds}^{t} = \sum_{i \in I} QS_{pids}^{t}, \qquad \forall p \in P, d \in D, t \in T, s \in S, \tag{42}$$

$$QNT_{pis}^{t} = \sum_{m \in M} QS_{pims}^{t} + \sum_{r \in R} QS_{pirs}^{t} + \sum_{d \in D} QS_{pids}^{t}, \qquad \forall p \in P, i \in I, t \in T, s \in S, \tag{43}$$

$$INV_{pms}^{t}, INV_{prs}^{t}, INV_{pis}^{t} \geq 0, \forall p \in P, i \in I, m \in M, r \in R, d \in D, t > 0 \in T \setminus \{\tau\}. \tag{44}$$

Constraints (36)–(41) capture the inventory aspects of the inspection, repairing, and recycling centers, respectively. The initial and ending inventories in the planning horizon at different facilities are considered to be zero. Furthermore, the additional decision variables associated with inventory are given by Constraint (44). Everything else in the base model holds for the inventory case as well.

3.2. Solution methodology

The augmented ε-constraint method proposed by Mavrotas (2009) provides a Pareto-optimal frontier to the multi-objective optimization. The augmented ε-constraint method transforms a multi-objective problem into a single-objective problem and to obtain the guaranteed efficient solutions, the remaining objective functions are converted to equality constraints by incorporating slack (for minimization) or surplus (for maximization) variables depending on the nature of the respective objective function and the normalized weighted values of these variables are added in the objective function. Augmented ε-constraint method involving maximization of $f_1(x)$ and minimization of $f_2(x)$) is as follows:

$$\text{Max}(f_1(x) + eps \times (s_2/r_2))$$
$$f_2(x) + s_2 = \varepsilon_2$$
$$x \in X; s_2 \in R^+,$$

where ε_2 is the constraint limit for the objective function 2, depending on the lexicographically generated pay-off matrix and grid points, r_2 is the range of pay-offs, and s_2 is the slack variable. The weight, known as *eps*, is considered to be 0.001 in our study, which is consistent with the literature (Mavrotas, 2009; Shukla et al., 2025). The number of solutions in the Pareto-frontier is driven by the grid points chosen; we consider 20 grid points in our study.

We use the scenario generation technique (Yu and Solvang, 2018; Rahimi and Ghezavati, 2018) to address the uncertainty prevalent in the RL activities. For the uncertain parameters, we assume a uniform distribution and we classify them into three categories: low, mean, and high. Values are generated using the corresponding uniform distribution range for the three uncertain parameters: quantity, quality, and price. The data generated is then used to form the nine scenarios given in Table 5. The scenarios corresponding to high and low will have four scenarios each. These eight scenarios have a 10% probability of occurrence. We also assume one scenario, which is deterministic, that captures the central tendency of the data with an associated probability of occurrence of 20%.

Table 5
Scenario generation for stochastic parameters

Scenario	Probability	Stochastic parameters		
		Quantity of returns	Quality of returns	Price of reprocessed
1	0.1	Low	Low	Low
2	0.1	Low	Low	High
3	0.1	Low	High	Low
4	0.1	Low	High	High
5	0.2	Mean	Mean	Mean
6	0.1	High	Low	Low
7	0.1	High	Low	High
8	0.1	High	High	Low
9	0.1	High	High	High

3.3. Case description

The mathematical model in the previous section is analyzed with an RL network that handles air conditioners ($p1$) and CPUs ($p2$). The data for the computational experiment are collected from a prominent e-waste handling organization in Hyderabad, India. The organization collects, dismantles, and reprocesses the e-waste from residential, commercial, and industrial areas. Their reprocessing facilities in the location (inspection center, repairing center, and recycling center) format is as follows: Hyderabad ($i1$, $m1$, $r1$), Visakhapatnam ($i2$, $m2$, $r2$), and Goa ($i3$, $m3$, $r3$), and the collection centers considered are as follows: Ibrahimpatnam ($c1$), Kukatpally ($c2$), Ameerpet ($c3$), Kirlampudi ($c4$), Gajuwaka ($c5$), Madhurawada ($c6$), Panjim ($c7$), and Majorda ($c8$). These collection centers ensure the inflow of end-of-life or end-of-use air conditioners and CPUs into the RL network. The collected products are then moved to the inspection centers. From the inspection centers, according to the remaining useful life of the product, the products are sent to repairing centers, recycling centers, or disposal centers. Kakinada ($d1$) and Candolim ($d2$) are the locations for disposal centers. The repaired products are handed over to the needy community for reuse, whereas the recycled materials are sent to the primary market in Mumbai, India, for revenue generation. At each of the three reprocessing facilities, inspection, recycling, and repairing centers are located together. This implies that the transportation between these reprocessing centers at a particular location is negligible. The general algebraic modeling system is used to perform the computational analysis.

In Table 6, cost parameters related to the facilities and the price of recycled items are given. Table 7 provides the range of values for the uncertain parameters. Table 8 gives the annualized fixed cost for facilities for the planning horizon of two years. Initial capacity, capacity of modules, and the maximum number of modules that can be added for a given period are given in Table 9. The product-specific parameters are given in Table 10. As the case organization plans to expand its capacity and does not have a modular capacity expansion, the related figures are based on assumptions.

We quantify the environmental impact through CO_2 emissions due to transportation and processing. CO_2 emissions due to transportation are calculated based on the product of fuel consumption due to transportation, density of fuel, calorific value of the fuel, and the emission factor of

Table 6
Parameters: cost and price

Parameters	:	Value
Processing cost for inspection center PRC^t_{pi} (INR/kg)	:	$U(10{,}15)$
Processing cost for repairing center PRC^t_{pm} (INR/kg)	:	$U(25{,}40)$
Processing cost for recycling center PRC^t_{pr} (INR/kg)	:	$U(5{,}10)$
Processing cost for disposal center PRC^t_{pd} (INR/kg)	:	$U(3{,}5)$
Price generated due to recycling of air conditioner PR^t_{p1rs} (INR/kg)	:	$U(250{,}400)$
Price generated due to recycling of CPU PR^t_{p2rs} (INR/kg)	:	$U(200{,}400)$
Holding cost HC^t_{px} (INR/kg/period)	:	$U(25{,}40)$
Fixed cost of capacity expansion for inspection center FE^t_i (INR)	:	50,000
Variable cost of capacity expansion for inspection center ME^t_i (INR/module)	:	60,000
Fixed cost of capacity expansion for repairing center FE^t_m (INR)	:	50,000
Variable cost of capacity expansion for repairing center ME^t_r (INR/module)	:	30,000
Fixed cost of capacity expansion for recycling center FE^t_r (INR)	:	50,000
Variable cost of capacity expansion for recycling center ME^t_r (INR/module)	:	60,000
Jobs created due to inspection facility JF_i	:	50
Jobs created due to repairing facility JF_m	:	25
Jobs created due to recycling facility JF_r	:	35
Jobs created due to an inspection module JM_i	:	6
Jobs created due to a repairing module JM_m	:	4
Jobs created due to a recycling facility JM_r	:	4

Table 7
Uncertain parameters

Parameter	Low	High	Mean
Quantity of products collected PC^t_{pcs} for $c1$ to $c6$	$U(4000, 8000)$	$U(8000, 12,000)$	8000
Quantity of products collected PC^t_{pcs} for $c7$, $c8$	$U(6000, 12,000)$	$U(12,000, 18,000)$	12,000
Quality of products collected π_{ps}	$U(0.50 - 0.75)$	$U(0.75 - 1)$	0.75
Price of products recycled PR^t_{p1s}	$U(250, 325)$	$U(325, 400)$	325
Price of products recycled PR^t_{p2s}	$U(200, 300)$	$U(300, 400)$	300

Table 8
Annualized fixed cost for the planning horizon

Facility	Center 1	Center 2	Center 3
Inspection F_i	300,000	290,000	295,000
Repairing F_m	205,000	200,000	210,000
Recycling F_r	204,000	206,000	202,000

Table 9
Available annual capacities

Facility x	Initial capacity CAP_x (kg)	Modular capacity $MCAP_x$ (kg)	Maximum modules L^t_x
Inspection	120,000	5000	6
Repairing	120,000	5000	6
Recycling	120,000	5000	6

Table 10
Product-specific parameters

Parameter	Air conditioner ($p1$)	CPU ($p2$)
Product suitability fraction for repairing γ_m	0.2	0.2
Product suitability fraction for recycling γ_r	0.8	0.8
Recoverable fraction PR_p	0.75	0.75
Non-recoverable fraction PRN_p	0.25	0.25
Number of people benefited by BF_p	1	1
Average weight of the product W_p (kg)	18	3

Table 11
Location of facilities and capacity modules added: base case

Facility	Period	Solution A Center (modules)	Solution B Center (modules)
Inspection	1	$i1(0), i2(0), i3(0)$	$i1(0), i2(0), i3(0)$
	2	$i1(0), i2(0), i3(0)$	$i1(6), i2(6), i3(6)$
Repairing	1	$m1(0), m2(0), m3(0)$	$m1(0), m2(0), m3(0)$
	2	$m1(0), m2(0), m3(0)$	$m1(6), m2(6), m3(6)$
Recycling	1	$r1(0), r2(0)$	$r1(0), r2(0), r3(0)$
	2	$r1(0), r2(0)$	$r1(6), r2(6), r3(6)$

the fuel[1] (Kakouei et al., 2012). CO_2 emissions due to recycling are obtained from the Bureau of International Recycling (Grimes et al., 2008). CO_2 emissions for repairing, inspection, and disposal activities are assumed at 10%, 20%, and 10% of that of the recycling activity. The emissions due to the processing of the products at respective facilities are evaluated based on the composition of the materials.[2] We assume the holding cost as 10% of the price of the items. We assume the values for the parameters–quality of returned product and recoverable fraction of returned products based on the qualitative input from the discussion with the case organization and with the support of the literature (Yu and Solvang, 2018; Shukla et al., 2025).

4. Results and discussion

The Pareto-optimal frontier for the base multi-objective optimization problem with the parameters as mentioned before is shown in Fig. 1. To illustrate the decisions and their resulting performance measures better, solutions A and B in the Pareto-frontier, as marked in Fig. 1 are chosen. Table 11

---

[1] The fuel in our case is diesel, and the calculation of CO_2 emissions due to transportation evaluation is as follows: CO_2 emissions per kg of product transported = Distance traveled (km)/mileage (10 km/L) $\times 10^{-3} \times$ 852 kg/m^3 $\times$ 10,750 kcal/kg $\times 4190 \times 74$ tCO$_2$/TJ $\times 10^{-9}$/ weight of products in the vehicle (800 kg).

[2] The amount of CO_2 emissions due to recycling of a kg of Al, Cu, and Fe are 0.29, 0.44, 0.70, respectively (Grimes et al., 2008). In our case setting, based on the discussion with the organization, for product 1, the average composition fraction of Al, Cu, and Fe is 0.1, 0.2, and 0.5, respectively, and for product 2, the respective figures are 0.05, 0.05, and 0.6. Combining this information, the emissions from recycling, repairing, and inspection centers are evaluated.

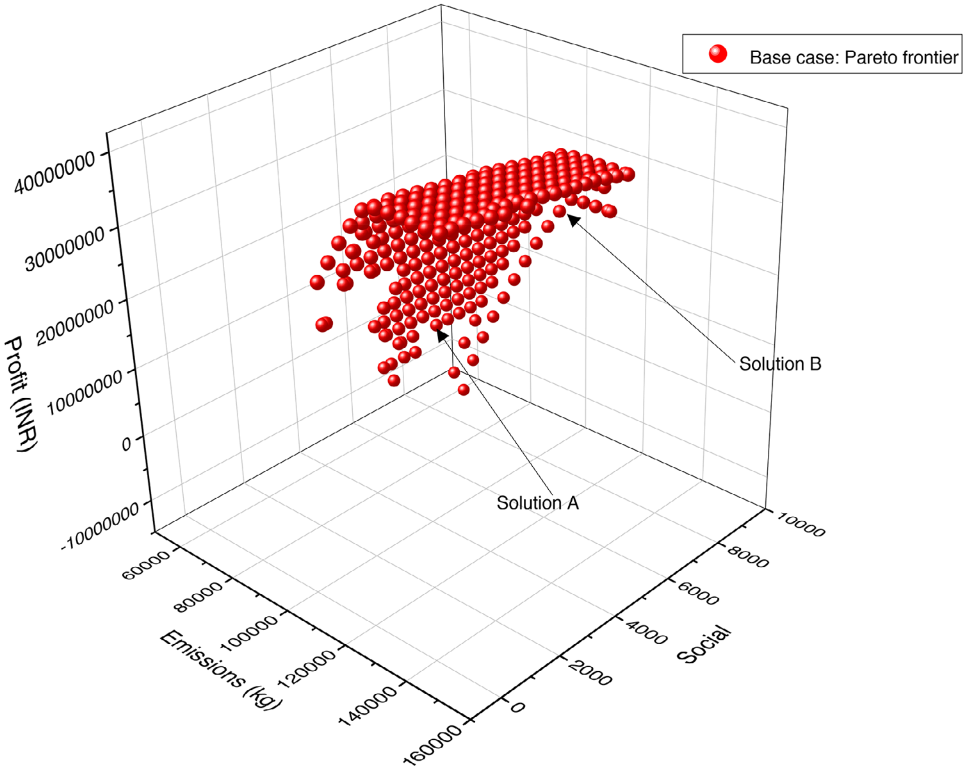

Fig. 1. Pareto-optimal solutions: base case.

shows the location decisions and the capacity expansion decisions for solutions A and B. In the former solution, inspection and repairing centers are opened at all three locations, and the recycling facility is opened at two facilities, and there is no capacity expansion at any of the facilities. In the latter solution, we can observe that three types of facilities are open at all three locations, and the capacities of these facilities are expanded to the maximum modules possible in the second period.

The comparison of performance measures between solutions A and B, as documented in Table 12, yields the following insights. Solution A has lower values for expected profit, expected emissions, and expected number of people benefited. This is due to the lower level of activities carried out in solution A. An interesting observation is the increased profit in solution B, even though the capacity investments are high. This is due to the higher recycling rate, the only revenue-generating activity, in solution B compared to solution A. In addition, the repairing rate is higher in solution B. As a result, the expected CO_2 emissions due to processing and the number of people benefited in solution B are higher. More quantities are moved to the landfill in solution A, which requires a longer distance to be traveled, leading to a higher transportation cost and CO_2 emissions in solution A. A decision-maker can choose from the set of solutions in the Pareto-frontier according to their preference, yielding a unique set of decisions with the respective performance measures.

Table 12
Key performance measures: base case

Measure	Solution A	Solution B
Expected profit	INR 4,591,344.88	INR 2,1473,250.00
Expected CO_2 emissions	76,904.27 kg	100,679.13 kg
Expected CO_2 emissions due to processing	56,487.00 kg	83,173.37 kg
Expected CO_2 emissions due to transportation	20,417.27 kg	17,505.76 kg
Expected number of people benefited	6700.79	8869.13
Expected number of people receiving the products	6405.79	8287.13
Expected number of people employed	295.00	582.00
Expected revenue	INR 13,902,820.00	INR 34,393,330.00
Expected transportation cost	INR 1,630,387.86	INR 1,405,247.40
Expected processing cost	INR 5,771,091.54	INR 6,252,833.30
Fixed facility cost	INR 1,910,000.00	INR 2,112,000.00
Capacity expansion cost	0	INR 3,150,000.00

Table 13
Location of facilities and capacity modules added: high product return case

Facility	Period	Solution C Center (modules)
Inspection	1	$i1(0)$, $i2(0)$, $i3(0)$
	2	$i1(6)$, $i2(6)$, $i3(6)$
Repairing	1	$m1(0)$, $m2(0)$, $m3(0)$
	2	$m1(6)$, $m2(6)$, $m3(6)$
Recycling	1	$r1(0)$, $r2(0)$, $r3(0)$
	2	$r1(6)$, $r2(6)$, $r3(6)$

4.1. Effect of an increase in the amount of products returned

Awareness about the adverse effects of mishandling e-waste and implementing stringent e-waste management rules can lead to an increase in the amount of products returned. Hence, we carry out a sensitivity analysis with an increase in the amount of products returned. The modular capacity expansion proposed in our model allows us to increase the capacity to meet the increased product returns. For our analysis, we keep the first-period product returns the same as the base case and increase the product returns for the second period by 100%.

The Pareto-optimal frontier for the high product return case is shown in Fig. 2. The expected emission level, in this case, at any point in the Pareto frontier, is higher than that of the base case. This intuitive result is due to the higher amount of product return associated with mandatory transportation of all the returned products to inspection centers and then to respective processing centers, yielding higher emissions when compared to those of the base case. The expected profit and expected number of people who benefited can be higher than those of the base case, depending on the quantities processed at recycling and repairing facilities. Table 13 provides solution D on the Pareto-frontier, wherein all the facilities that are operating in the first period are expanded in the second period with the maximum modules available.

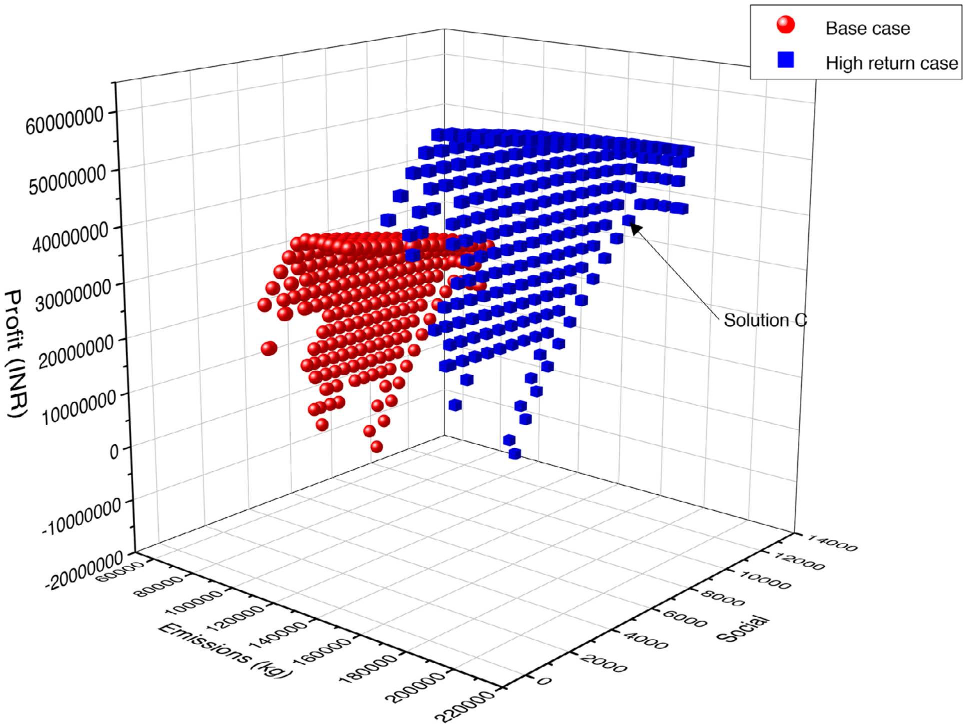

Fig. 2. Pareto-optimal solutions: high product return case.

4.2. *Impact of the provision of inventory at the processing centers*

The system is investigated with the aspects of inventory management incorporated in the base model, with the modified profit objective and the associated set of inventory constraints replacing the flow balance constraints. We evaluate the inventory management enabled system under two cases: (i) inventory case and (ii) inventory-high price case.

4.2.1. *Inventory case*

In the analysis of the system with inventory management provision, all the parameters in the system, except the holding cost of inventory, are maintained at the same level as that of the base case. Figure 3 shows the Pareto-frontier for this case, which is the same as the base case with no inventory maintained at any of the facilities. In this case, the provision of the inventory aspect yields the same decisions on the facility location, capacity expansion, quantity processed, quantity transported, and the resulting performance measures as those of the base case. The reason is that there is no benefit in holding the inventory by incurring the holding cost as the price in the future period is not significantly different from the first period's price, and there is enough capacity to handle the product returns in the second period.

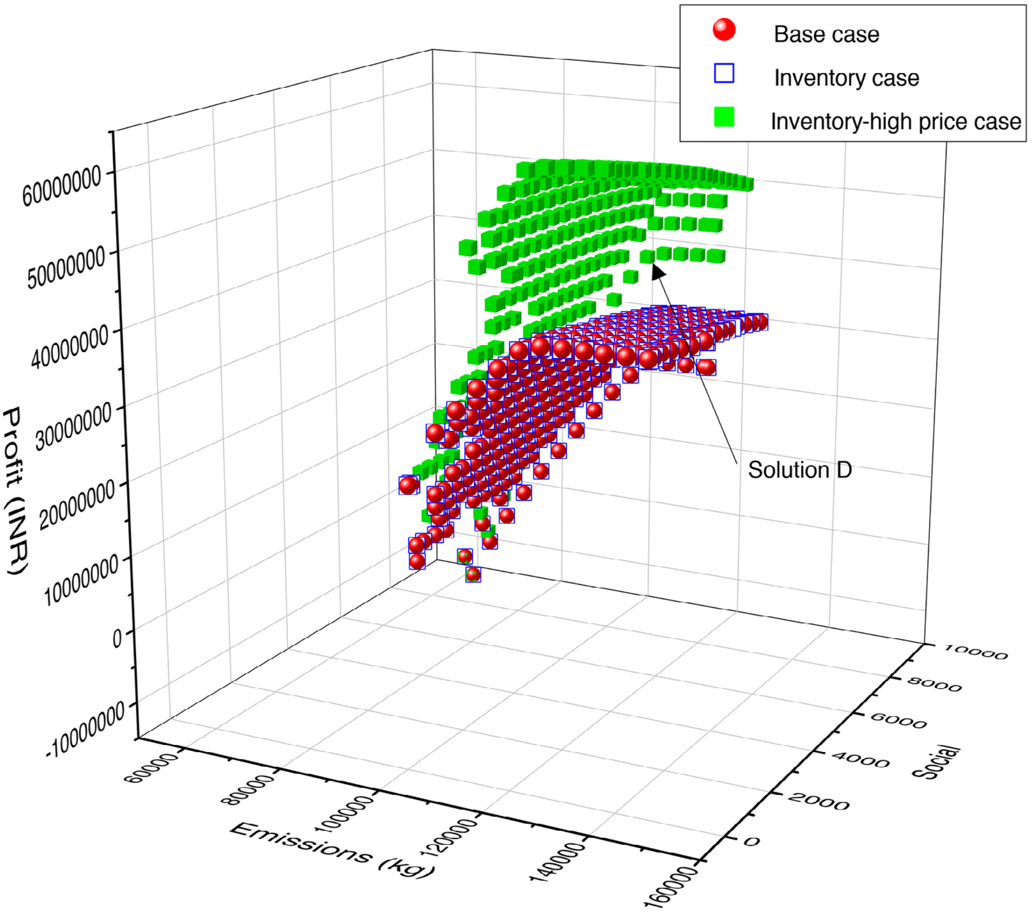

Fig. 3. Pareto-optimal solutions: inventory case.

4.2.2. *Inventory-high price case*

Next, we investigate the impact of incorporating the inventory aspect in the setting where the price of recycled items in the second period is 150% of the first period's price. Figure 3 gives the Pareto-frontier in this case. One can observe that the Pareto-frontier dominates that of the base case. In this case, merely holding the items in the first period, processing those in the second, and selling in the second period increases the expected profit without compromising on the emissions and social aspects. As recycling is the only revenue-generating activity in this problem, the inventory is held only at the recycling centers. Solution D is documented in Table 14 to better illustrate the opening and expansion of facilities and in Table 15 for the inventory at the recycling centers. It can be inferred that all the facilities are open in both periods, and the capacity is expanded with the maximum modules in the second period. Furthermore, all recycling centers in period 1 hold inventory for both types of products to be reprocessed and sold in period 2. Hence, holding inventory can be proven significantly advantageous in certain business environments.

Table 14
Location of facilities and capacity modules added: inventory case

Facility	Period	Solution D Center (modules)
Inspection	1	$i1(0)$, $i2(0)$, $i3(0)$
	2	$i1(6)$, $i2(6)$, $i3(6)$
Repairing	1	$m1(0)$, $m2(0)$, $m3(0)$
	2	$m1(6)$, $m2(6)$, $m3(6)$
Recycling	1	$r1(0)$, $r2(0)$, $r3(0)$
	2	$r1(6)$, $r2(6)$, $r3(6)$

Table 15
Inventory at the recycling centers: inventory-high price case

Recycling	Scenario								
(product)	s1	s2	s3	s4	s5	s6	s7	s8	s9
$r1(p1)$	5272.25	5272.25	7300.04	7300.04	6600	6647.03	6647.03	9203.58	9203.58
$r2(p1)$	7785.44	7785.44	10779.84	10779.84	13200	15511.26	15511.26	21477.13	21477.13
$r3(p1)$	5546.26	5546.26	7679.43	7679.43	9900	11399.64	11399.64	15784.11	15784.11
$r1(p2)$	3326.55	3326.55	4805.01	4805.01	6600	5922.31	5922.31	8554.45	8554.45
$r2(p2)$	7944.26	7944.26	11475.05	11475.05	13200	12566.65	12566.65	18151.82	18151.82
$r3(p2)$	4938.76	4938.76	7133.77	7133.77	9900	8650.40	8650.40	6385.63	12495.01

4.3. Sensitivity analysis

We conduct a sensitivity analysis of (i) the quality of the products collected, (ii) the recoverable fraction of the products, and (iii) the product suitability fraction for repairing and recycling on the network performance. In the case of return quality, we consider the case of poor quality of returned products, and the range of values of poor quality is considered as follows: high $\in$ U(0.25–0.50), mean 0.25, low $\in$ U (0, 0.25). We find that the poor quality of product returns results in low social and economic outcomes, as evident in Fig. 4.

Next, we consider the case of a low recoverable fraction of the returned products with a value of 0.25. The results show that the products are moved to the disposal units, resulting in a lower reprocessing rate, leading to low economic and social outcomes and low emissions, as shown in Fig. 5.

Finally, we conduct an analysis of product suitability for repairing and recycling. In this case, we consider a high product suitability fraction for repairing (0.8) and a low product suitability for recycling (0.2). We observe that a high product suitability fraction for repairing increases the social outcome and decreases the economic outcome, as illustrated in Fig. 6. This is due to the organization donating the repaired products to society, which increases the social outcomes, naturally resulting in decreased economic outcomes as the product suitability fraction of recycling—the revenue-generating stream of reprocessing is proportionately lowered. Furthermore, in this case, we can observe reduced emissions as a result of the reduced recycling activity.

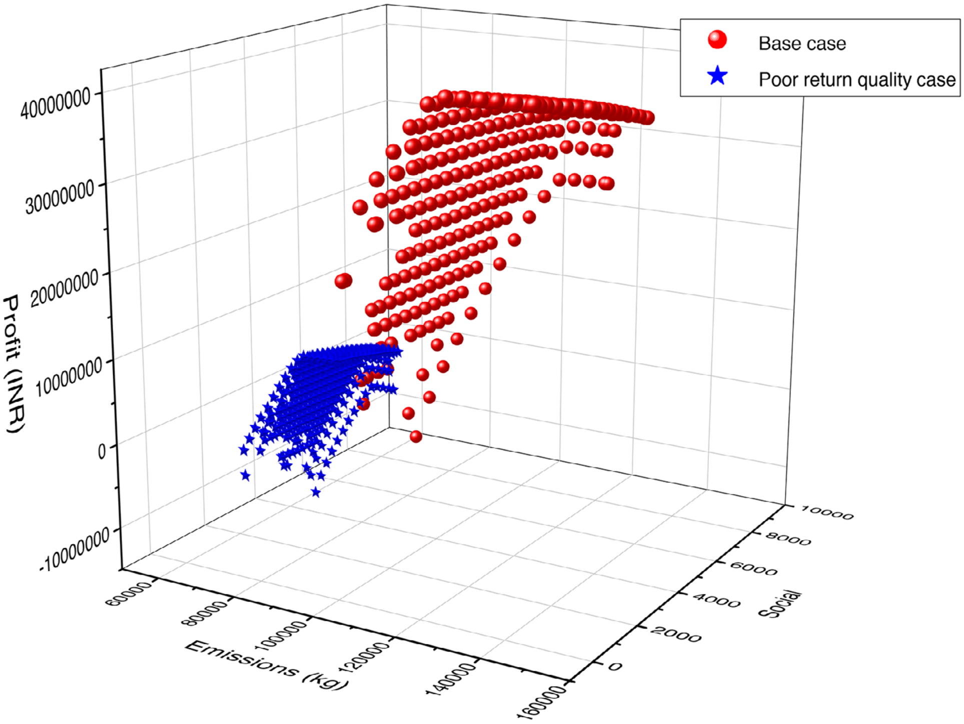

Fig. 4. Impact of poor quality of return products on the performance of the base model.

This work advances the literature on sustainable RL network design with the strategic inventory management and modular capacity aspects, incorporating economic, environmental, and social objectives for the case of WEEEs. This work reinforces the findings from Rahimi and Ghezavati (2018), Zarbakhshnia et al. (2020), and Dutta et al. (2020) on the relevance of the multi-objective optimization approach in designing the RL network with the aforementioned objectives. Our work resonates with the findings of Shukla et al. (2025) on the need for capacity flexibility in a multi-objective (i.e., economic and environmental) RL setting and expands the knowledge to illustrate the role of strategic inventory management together with capacity flexibility on the RL network performance in the presence of social objective in addition to the aforementioned ones with the case of WEEEs.

5. Conclusions

E-waste management in India, largely controlled by the informal sector, collects only 10% of the generated e-waste (Central Pollution Control Board, 2020). An optimal design of a reverse logistics network can facilitate the formal sector to improve the recycling percentage, reduce the consequences of improper handling, and improve the e-waste recovery efficiency. This study develops an RL network to carry out value recovery from WEEE with a case study in the Indian context. We

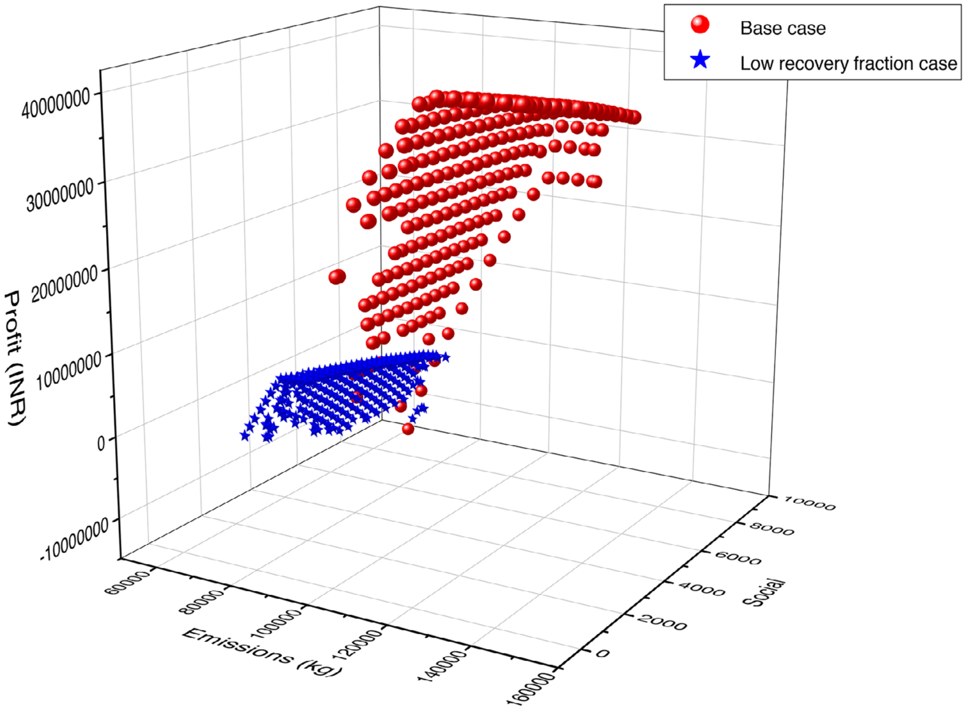

Fig. 5. Impact of low recovery fraction on the performance of the base model.

consider economic, environmental, and social aspects of sustainability in e-waste management and propose a multi-objective optimization model for the RL network design under uncertainty.

The augmented ε-constraint method is employed to generate Pareto-optimal solutions under different settings. We assess the impact of increased product returns as the e-waste generation is growing in India at a higher rate. We observe that the increased product returns increase the emissions. The profit and social dimensions can be improved when the returned items are reprocessed at recycling and repairing facilities, respectively. We incorporate the inventory aspect in the model to evaluate the significance of inventory management in RL activities. The comparison of the results of the inventory case with those of the no-inventory case reveals that inventory can be a key driver in improving the performance of the RL network. Finally, we evaluate the sensitivity of the model with respect to the quality of returns, the product recoverability, and the suitability of the products for reprocessing, which shows that the business and operating conditions significantly affect the performance of the sustainable RL network.

Our research work has both sustainable and managerial implications. By considering the maximization of the number of jobs and the number of people who benefited from receiving the repaired products free of cost, our research contributes to SDG 11. The optimal design of the reverse logistics network addresses SDG 12. The optimal choice of location and reprocessing activities, and their transportation that minimizes the CO_2 emissions, our research contributes to SDG 13. From the managerial viewpoint, this study offers insights into strategically managing the RL activities that address social and environmental goals together with economic benefits. Managers can choose

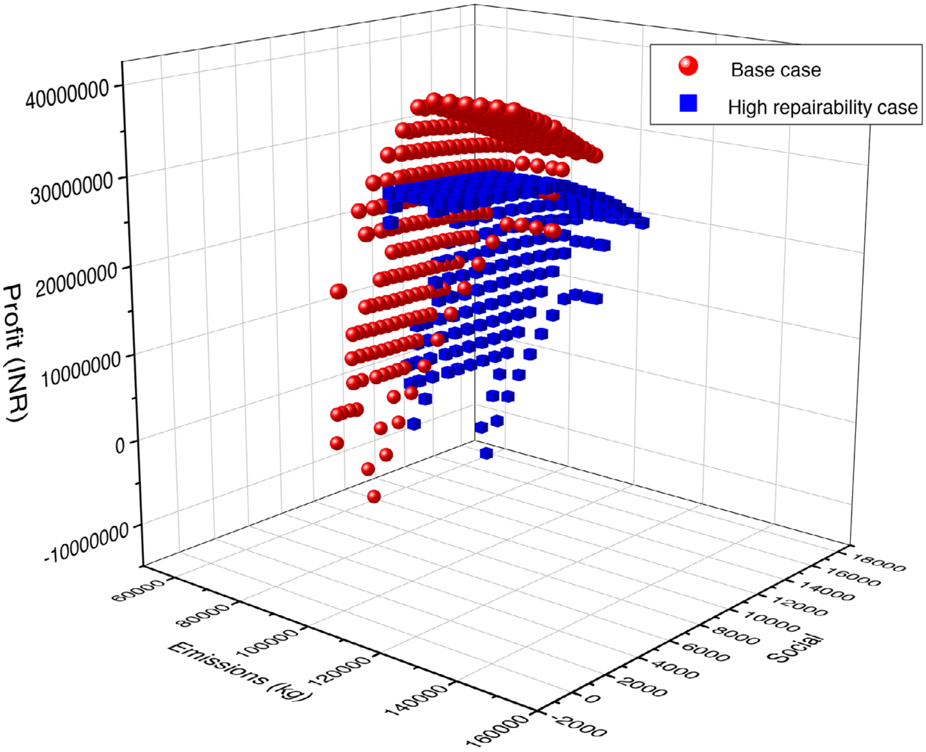

Fig. 6. Impact of high repairability fraction on the performance of the base model.

the solution points from the Pareto-optimal frontier and the corresponding set of decisions, such as facility locations, capacity expansion, and quantities to be transported and processed at different facilities, depending on their preference towards economic, environmental, and social aspects. We observe that managers need to put effort into ensuring the quality of returned products for improved social and economic outcomes. Managers can strategically use inventory as a driver to improve the economic benefits without compromising the social and environmental aspects.

Our study utilizes the scenario-generation technique to address the uncertainty in parameters. Other stochastic optimization techniques, such as robust optimization, can be employed to capture the uncertainty of the parameters and additional parameters such as stochastic demand for reprocessed items in the setting. This work has several limitations. The safety stock driven inventory management is not captured in this study, which results in a mixed-integer nonlinear optimization model that requires alternate solution methodology. Furthermore, this work does not incorporate any form of competition between agents in formal and informal sectors, which demands integrating the game-theoretic framework with our proposed methodology. Modeling competition between the informal and formal sectors in the WEEE recycling setting and analyzing their impact on RL performance is a promising research avenue. Our model can be extended to other recycling settings in different case-specific contexts with suitable modifications to the model. Since the research work aims to reduce the environmental consequences of reverse logistics, an avenue is to explore the impact of using electric vehicles and the resulting CO_2 emissions reduction. Furthermore, in the servitization context, an interesting research topic is to explore the design of reverse logistics with the products that are leased or available for pay-per-use and pay-per-period.

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