The International Journal of Advanced Manufacturing Technology
https://doi.org/10.1007/s00170-024-14121-6

ORIGINAL ARTICLE

A two-level decision-support framework for reverse logistics network design considering technology transformation in Industry 4.0: a case study in Norway

Xu Sun[1] · Hao Yu[1] · Wei Deng Solvang[1] · Kannan Govindan[2,3]

Received: 26 March 2024 / Accepted: 8 July 2024

Abstract

Reverse logistics network design is a complex decision-making problem that involves the reuse, repair, remanufacturing, and recycling of end-of-life (EOL) under the tradeoff among conflicting objectives. The cutting-edge technologies in Industry 4.0 are now leading to an unprecedented and dynamic transformation of reverse logistics systems, which, however, further complicates the initial network design. In this paper, a two-level decision-support framework combined with both optimization and dynamic simulation is proposed to balance the cost, environmental impact, and service level in smart and sustainable reverse logistics network design under a dynamically evolving and stochastic environment. The results of a real-world case study in Norway show that the method can better support robust strategic decisions, eliminate dominated/near-dominated solutions, and yield holistic performance analyses considering smart reverse logistics transformation. The proposed two-level decision-support framework can better analyze the impact of the technology transformation of Industry 4.0 on reverse logistics systems, while it also provides a fundamental structure for digital reverse logistics twin.

Keywords Reverse logistics · Industry 4.0 · Network design · Decision-support system · Technology transformation · Digital twin

1 Introduction

Today, technological innovations have not only improved people's living standards and changed consumption patterns, but also significantly shortened product lifecycles and therefore accelerated the generation of end-of-life (EOL) products. The generation of waste electrical and electronic equipment (WEEE) has become one of the fastest-growing waste streams in Europe [25]. According to Eurostat [24], the annual generation of end-of-life vehicles (ELVs) in the EU-27 countries has increased by 22% from 5.54 million tons in 2011 to 6.732 million tons in 2018. To tackle this challenge, much attention has been given to the development of effective regional and international reverse logistics systems, with the special aim of increased value recovery from EOL products. Reverse logistics refers to activities of planning, operating, and managing the reverse material, information, and capital flows starting from the end-users toward initial manufacturers and suppliers [76]. Effective reverse logistics is considered a crucial countermeasure for sustainable development and circular economy [74]. Network design is the first step in managing reverse logistics and is considered the most important strategic decision [57]. Compared with forward logistics, a reverse logistics network embedded intricates due to its inhomogeneous items and complex flows with high uncertainties. Adding on the involvement of many stakeholders with often contradictive objectives, reverse

✉ Hao Yu
hao.yu@uit.no

Xu Sun
xu.sun@uit.no

Wei Deng Solvang
wei.d.solvang@uit.no

Kannan Govindan
kannan.govindan@adelaide.edu.au

1 Department of Industrial Engineering, UiT The Arctic University of Norway, 8514 Narvik, Norway

2 Centre for Sustainable Operations and Resilient Supply Chains, Adelaide Business School and Institute for Sustainability Energy and Resources, University of Adelaide, Adelaide, SA 5005, Australia

3 School of Business, Woxsen University, Sadasivpet, Telangana, India

logistics network design is a complex problem that needs advanced decision-support methods to properly manage the interactions among various influencing factors. During the last two decades, extensive research efforts have been given to the development of analytical methods [40] to improve economic effectiveness and reduce carbon emissions while complying with stricter environmental legislation.

Recently, with the rapid development and wide adoption of cutting-edge technologies in the Fourth Industrial Revolution, namely, Industry 4.0, global logistics systems and supply chains are experiencing an unprecedented and dynamic transformation [10, 20]. The paradigm of traditional reverse logistics has inevitably been shifting [17]. These new technologies, e.g., internet of things (IoT), artificial intelligence (AI), smart robots, etc., provide opportunities for smart operations and service innovation [11] to better meet the sustainability targets in the triple-bottom-line, say, a smart reverse logistics transformation [83]. One notable feature of a smart reverse logistics system is that the tactical and operational uncertainties can be drastically reduced with AI- and big data-enabled predictive analytics [33] and IoT-enabled real-time data. For example, a product-based digital twin can be used to monitor the product information through its whole lifecycle [90]. When a product comes to the EOL phase, its information can be captured via a cloud-based system and shared with the companies in reverse logistics. Besides, the end-users can also be involved via digital platforms, e.g., mobile apps, to provide information on the quality level and the time and location of return of their EOL products. In addition, the increasing use of cleaner energy helps reduce the fuel consumption and carbon emissions of reverse logistics activities.

However, the gradual but steady adoption of new technologies will change the operational conditions and introduce new planning challenges. Thus, new analytical models are needed [10, 63]. As shown in Fig. 1, various reverse logistics operations can become highly automated with AI-enabled smart robots, e.g., initial inspection and sorting of EOL products, which may reduce operating costs and safety concerns while replacing human workers from the harsh working environment. In this regard, recent research has focused on the optimal resource planning of a human–robot collaborative smart remanufacturing process [94]. In addition, the data collected from both cyber and physical environments can help companies effectively achieve proactive planning and real-time decision-making in various reverse logistics operations, which leads to increased use of data-driven optimization for real-time routing [54] and smart remanufacturing scheduling [104].

From the strategic network design perspective, the increasing technological innovation may result in significant changes in the operational parameters [60] related to both facilities and transportation within the lifespan of a reverse logistics system. Thus, the optimal solution obtained based on a static analysis may become biased and less attractive when new technologies are introduced. Furthermore, altering the initial facility location decisions is extremely expensive and may also lead to drastic disruptions of the reverse

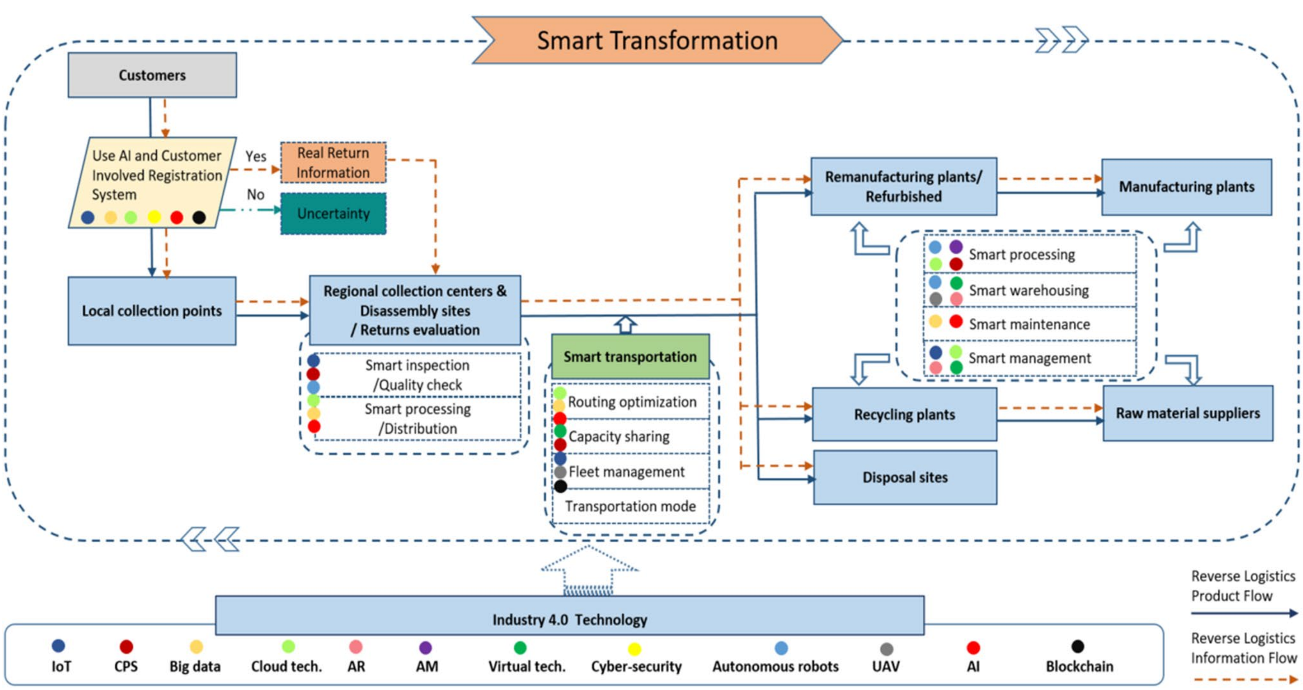


Fig. 1 Smart reverse logistics system

logistics flows. Therefore, not only the uncertainty from the external environment but also the dynamic configurational change and the disruption during the facility upgrades need to be holistically considered in the initial network design stage.

In this paper, a two-level decision-support framework is proposed for smart and sustainable reverse logistics network design, which can evaluate the impact of smart transformation and better analyze the system behaviors of different network alternatives. A bi-objective optimization model is first used to determine a set of candidate network configurations. Then, the selected candidate networks are evaluated by dynamic simulation. This decision-support framework uses the strengths of both methods [41], and the analytical results are obtained under realistic environments. We aim at answering the following research questions:

- RQ1: How to design a smart and sustainable reverse logistics system considering smart transformation?
- RQ2: What are the impacts of smart transformation on the reverse logistics network design?

By answering these research questions, we aim to make the following contributions:

1. From the methodological development perspective, a novel two-stage decision-support framework is proposed combined with both optimization and dynamic simulation for smart and sustainable reverse logistics network design.
2. From the practical implementation perspective, the impacts of dynamicity, uncertainty, and new technologies in Industry 4.0 on reverse logistics network design and operations are comprehensively analyzed, facilitating a smart and seamless transformation.

The rest of the paper is organized as follows. Section 2 presents a literature review and identifies the research gaps. Section 3 describes the problem under investigation. The two-level decision-support framework is given in Section 4. Sections 5 and 6 present the case study and discuss the experimental results. Finally, Section 7 concludes the paper.

2 Literature review

Reverse logistics network design can be considered an essential part of the supply chain with a focus on dealing with returned product flows [81]. A reverse logistics system can be either open-loop or closed-loop (incorporating forward logistics). Significant modeling efforts have been given since the beginning of the 2000s [29], and comprehensive literature reviews of model developments are provided by Govindan et al. [40], Kazemi et al. [51], Rachih et al. [68], and Abid and Mhada [1]. In connection with the focus of this paper, we reviewed the recent research related primarily to open-loop reverse logistics network design in three groups: (1) optimization, (2) simulation, and (3) smart reverse logistics network design.

2.1 Optimization

Optimization is the most extensively used method for reverse logistics network design [9]. Using mixed-integer program (MIP), both facility location and demand allocation can be determined in either cost minimization or profit maximization manner [66]. During the last decade, extensive efforts have been spent to model multiple objectives, tackle uncertainty, and improve computational performance.

2.1.1 Multi-objective optimization

Sustainable reverse logistics network design has been increasingly modeled by multi-objective programming [6, 49]. Carbon emissions and other environmental impacts were considered holistically alongside the economic objective [48]. Different carbon policies, e.g., carbon tax [73] and carbon cap [88], were formulated. Recently, the triple-bottom-line has been incorporated into reverse logistics network design [8], which aims at balancing the tradeoff among economic, environmental, and social sustainability. Considering social sustainability, various performance indicators, e.g., job creation [77], working conditions [39], GDP level [8], risks [38], and hybrid indicators [69], were employed. Several operational indicators have also been considered. Zarbakhshnia et al. [102] maximized the number of machines in reverse logistics operations. Xiao et al. [93] modeled the facility utilization rate as an objective function. Yu and Solvang [98] focused on the impact of network flexibility. Gao and Cao [31] integrated product recovery into the existing supply chains.

2.1.2 Uncertainty

Uncertainty is a crucial factor. If uncertainty is not considered in the initial stage, it will be difficult to impose major changes without excessive resources when the network is implemented. Many parameters cannot be predicted accurately over the entire planning horizon, and various modeling techniques have been applied to manage the uncertainty. To deal with randomness, stochastic programming has been extensively applied in reverse logistics network design [65]. Trochu et al. [87] developed a two-stage stochastic program to design an uncertain reverse logistics system. Khakbaz and Tirkolaee [52] developed a stochastic model for WEEE management. Rahimi and Ghezavati [69] proposed a multi-period stochastic model for sustainable management of construction waste, where the conditional value at risk (CVaR) was employed for risk aversion. To reduce the high data dependency of stochastic models, fuzzy programming and robust optimization have been increasingly used. Kuşakcı et al. [53] investigated a fuzzy MIP to minimize the total costs of end-of-life vehicle (ELV) recycling in Turkey. Govindan et al. [39] proposed a fuzzy multi-objective reverse logistics model to balance costs, environmental impacts, and social responsibility. Tosarkani et al. [86] developed a robust probabilistic optimization model for designing a sustainable WEEE reverse logistics system. Recently, the research focus has been given to the model development with hybrid techniques, i.e., robust-stochastic programming [78], fuzzy-stochastic programming [99], fuzzy-robust programming [58], and robust-fuzzy-stochastic programming [27], to tackle mixed uncertainty.

2.1.3 Computational efficiency

The inclusion of multiple objectives and uncertain parameters has led to increased computational complexity. The computational issues were tackled by algorithm development, e.g., heuristics and metaheuristics. The most extensively used metaheuristics include genetic algorithm (GA) and swarm intelligence (SI) [68]. For instance, Zarbakhshnia et al. [101] investigated a sustainable network design problem for an integrated forward/reverse logistics system under uncertainty, where a non-dominated sorting genetic algorithm (NSGA-II) was used to solve the problem. Wang et al. [91] modeled a collaborative multicenter reverse logistics network design problem, which was solved by the extended reference point-based non-dominated genetic algorithm-III. Reddy et al. [72] proposed Benders-decomposition-based heuristics for a dynamic and green reverse logistics network design problem.

2.2 Simulation

Computer-based simulation has recently gained increasing momentum due to its capability to model uncertainties, system complexity, and dynamic features. Simulation can help to compare real-world systems and evaluate several what-if scenarios [62], which is increasingly used for the performance evaluation of reverse logistics operations [7]. For example, Kara et al. [50] used a simulation model to estimate the collection cost in a reverse logistics system. Elia et al. [22] developed a simulation model to evaluate three different schemes for WEEE collection, i.e., the fixed schedule, the pure dynamic schedule, and the mixed schedule. Ghisolfi et al. [32] studied the impacts of the legal incentives and the bargaining power obtained by waste collection volume on a reverse logistics system of EOL PCs and laptops. The main simulation methods for logistics planning include discrete event simulation (DES), Monte Carlo simulation (MCS), and simulation-based optimization (SO). Besides, other simulation techniques, i.e., agent-based simulation (ABS), continuous simulation, and system dynamics (SD), as well as hybrid methods can also be used to solve some problems [1].

2.2.1 Discrete event simulation (DES)

DES depicts a system and its behavior with a series of discrete events sequentially organized, and these events trigger the change of the system's states autonomously over a dynamic test horizon. It can be either deterministic or stochastic [1]. With minimum simplifications, DES is a powerful tool to model the real-world features of a system. Jayant et al. [45] developed a DES model to calculate different cost components of a battery reverse logistics system under several order assignments and scenarios. Gonçalves et al. [36] investigated a DES to evaluate 11 scenarios of a reverse logistics system for recycling EOL tires in Brazil [15], de Oliveira et al. 2019b. developed a DES in ProModel. With three waste disposal options, i.e., landfills, recycling, and incineration with energy recovery, 16 scenarios were evaluated to promote sustainability and eco-efficiency in municipal solid waste (MSW) management. Alamerew and Brissaud [4] developed a simulation model for a revere logistics system of battery recovery from e-vehicles, which explored the interplay among the main pillars of the circular economy. Elia et al. [23] investigated a DES for sustainable WEEE collection in Italy. Their results reveal that the hub-and-spoke network has better economic and environmental performances than traditional WEEE collection systems.

2.2.2 Simulation-based optimization (SO)

Even though simulation can model and comprehensively analyze the inputs and outputs of a complex system, it lacks the capability of determining the optimal decisions among a large set of alternatives [1]. Due to this reason, SO has been increasingly focused on in recent years [1], where simulation can be used as a part of the optimization algorithm to either accelerate the converging speed toward the near-optimal solutions or validate the parameters and solutions in stochastic environments [28]. For example, Shokohyar and Mansour [80] investigated a SO method for WEEE recovery network planning, where simulation was used to determine the optimal inputs of the optimization model. Fu et al. [30] defined SO is essentially an optimization problem with stochastic features in either parameters or solution procedures, e.g., a two-stage stochastic optimization with recourse decisions, which includes gradient-based methods, meta-model-based methods, statistical methods, and meta-heuristics [1].

Monte Carlo simulation (MCS), which is a wide category of numerical methods for calculating results through repeatedly solving a large number of random samples [71], has been extensively used in SO to ensure a high level of statistical stability of a stochastic optimization process [28]. In reverse logistics, Ameli et al. [5] proposed a SO model to evaluate the performance of manufacturers by considering both product design alternatives and EOL options. Yang and Chen [96] performed a MCS to approximate the robustness of a regional reverse logistics system for construction and demolition wastes. Yu et al. [100] investigated a two-stage stochastic optimization model for the reverse logistics network design of hazardous materials, where a MCS-based sampling method was used to analyze the impact of uncertainty.

2.3 Smart reverse logistics network design

Industry 4.0 provides new opportunities and enablers for smart and sustainable reverse logistics through internet-based connectivity, big data, analytical algorithms, and autonomous technologies [17]. For example, big-data-supported reverse logistics operations [33], 3D printing-assisted remanufacturing [55], IoT-based data-driven transportation planning [54], human–robot-collaborative remanufacturing [94], and digital twin for product recovery [90] have been investigated. The increasing use of new technologies enables smarter and more effective reverse logistics operations to better meet customer needs and sustainability goals [83].

These smart features on reverse logistics operations have been investigated in operational planning, e.g., vehicle routing and remanufacturing planning. However, from the strategic network design perspective, the impact has not been thoroughly analyzed and revealed. Technological innovation and adoption may drastically change the parameter settings of decision-support models. In this regard, to our knowledge, the only research considering the smart features in reverse logistics network design was provided by Govindan and Gholizadeh [37], where a scenario-based robust optimization model was proposed for designing a sustainable and resilient reverse logistics system. The big data's 3 V features (volume, velocity, and variety) were modeled by the uncertainty related to some key input parameters, e.g., return volume, quality, etc., and a cross-entropy algorithm was developed to solve the optimization problem.

2.4 Literature gaps

While optimization dominates the research in logistics network design, the combination of both optimization and simulation, especially DES, remains still under-explored in both forward and reverse logistics channels [15, 61]. As shown in Table 1, most research employs a single method either optimization or simulation. Despite several optimization models either employing MCS to validate uncertain parameters and scenarios [86] or incorporating heuristic methods, e.g., simulated annealing [1], they can only deal with parametric uncertainty and find the statistically optimum with a static and oversimplified representation of real-world problems [85]. In addition, some research only employs a simulation procedure to test different model inputs [80] and evaluate operational decisions, e.g., inventory control [105] and fleet sizing [13]. Besides, the combination of both optimization and advanced simulation, e.g., DES, has not been reported in reverse logistics network design due to several reasons, e.g., the complexity of building respective models, the requirement of different software, the conversion of data with different levels of aggregation, the setting up of realistic operational policies, and so forth. Furthermore, at the strategic level, there is a lack of efforts that consider both sustainability and smart transformation in Industry 4.0 on reverse logistics network design.

Therefore, this paper aims at filling the following two gaps:

1. From the decision-making perspective, no research has been conducted to provide models and managerial insights for reverse logistics network design considering the potential impact of smart transformation in Industry 4.0.
2. From the methodological perspective, no research has been done to combine both optimization and dynamic simulation, e.g., DES, in sustainable reverse logistics network design.

3 Problem description

A reverse logistics network consists of different facilities, i.e., local collection points, regional collection/disassembly centers, remanufacturing plants, recycling plants, and disposal sites. The EOL products are first collected at local collection points and then sent to regional collection centers, where these EOL products are inspected and disassembled into different components. At the regional collection center, the disassembled components can be categorized into three classes based on their product residual value (PRV), namely, high-PRV, low-PRV, and non-recyclable. The high-PRV components will be distributed to remanufacturing plants for refurbishing and function restoration based on the type of products. After that, they can be sold to manufacturers at lower prices [46]. The low-PRV components are sent to recycling plants, where they are degraded into new materials and then sold to the suppliers. The non-recyclable components and hazardous materials are sent for proper disposal.

Table 1 Relevant literature for reverse logistics network design

Authors	Sustainability	Smartness	Uncertainty		Method				Experiment
			Technique	Type	Optimization		Simulation		
					Single-Obj	Multi-Obj	DES	MCS	
Pishvaee et al. [66]	–	–	–	–	√	–	–	–	Numerical
Kannan et al. [48]	√	–	–	–	√	–	–	–	Numerical
Shokohyar and Mansour [80]	√	–	–	–	–	√	–	–	Case
Ramos et al. [70]	√	–	–	–	–	√	–	–	Case
Jayant et al. [45]	–	–	–	–	–	–	√	–	Case
Govindan et al. [39]	√	–	Fuzzy	Dynamic	–	√	–	–	Numerical
Rahimi and Ghezavati [69]	√	–	–	–	–	√	–	–	Numerical
Yu and Solvang [98]	√	–	Stochastic	Static	–	√	–	–	Numerical
Farrokh et al. [27]	–	–	Robust-fuzzy-stochastic	Dynamic	√	–	–	–	Numerical
Xiao et al. [93]	√	–	–	–	√	–	–	–	Case
Trochu et al. [87]	–	–	Stochastic	Dynamic	√	–	–	√	Case
Zarbakhshnia et al. [102]	√	–	–	–	–	√	–	–	Numerical
Kuşakcı et al. [53]	–	–	Fuzzy	Static	√	–	–	–	Case
Gonçalves et al. [36]	√	–	–	–	–	–	√	–	Case
[15], de Oliveira et al. 2019b	√	–	–	–	–	–	√	–	Case
Elia et al. [23]	√	–	–	–	–	–	√	–	Case
Ameli et al. [5]	√	–	Simulation	Static	–	√	–	√	Case
Safdar et al. [77]	√	–	–	–	–	√	–	–	Numerical
Budak [8]	√	–	–	–	–	√	–	–	Case
Gao and Cao [31]	√	–	Stochastic	Static	–	√	–	–	Numerical
Tosarkani et al. [86]	√	–	Robust	Dynamic	–	√	–	√	Case
Yu and Solvang [99]	√	–	Fuzzy-stochastic	Static	–	√	–	√	Numerical
Nayeri et al. [58]	√	–	Fuzzy-robust	Static	–	√	–	–	Case
Zarbakhshnia et al. [101]	√	–	Probabilistic	–	–	√	–	–	Numerical
Yang and Chen [96]	–	–	Robust	Static	√	–	–	√	Case
Yu et al. [100]	–	–	Stochastic	Static	–	√	–	√	Numerical and case
Shahparvari et al. [78]	√	–	Stochastic	Static	√	–	–	–	Numerical and case
Che et al. [9]	–	–	–	–	√	–	–	–	Case
Govindan and Gholizadeh [37]	√	√	Fuzzy-robust	Dynamic	√	–	–	–	Numerical
Govindan et al. [38]	√	–	–	Dynamic	–	√	–	–	Numerical
Khakbaz and Tirkolaee [52]	√	–	Scenario-based	Static	√	–	–	–	Numerical
Wang et al. [91]	–	–	–	Dynamic	–	√	–	–	Numerical
Reddy et al. [72]	√	–	–	Dynamic	√	–	–	–	Numerical
Kannan et al. [49]	√	–	–	Static	–	√	–	–	Case
This paper	√	√	Simulation	Dynamic	–	√	√	–	Case

Reverse logistics network design is a strategic decision that has long-term impacts on the system performance. The smart transformation may affect the reverse logistics operations and some key parameters over the planning horizon. For example, low-carbon equipment and vehicles will likely become much cheaper with technological advancement and be increasingly used in reverse logistics operations, but the adoption of new technologies is a dynamic process, and the change of system configurations occurs gradually over several periods. Thus, we aim at providing a decision-support framework to help with strategic decisions and evaluate the impacts of smart transformation on reverse logistics network design. On the other hand, the integration between optimization and dynamic simulation forms the initial step of a highly intelligent, visualized, and interactive digital reverse logistics twin [44].

4 Methodology

A two-level decision-support framework is developed in Fig. 2. First, the candidate network configurations are determined by a bi-objective MIP. The augmented ε-constraint method is used to solve the optimization problem and generate a set of efficient Pareto optimal solutions. Then, DES is used to further evaluate the selected network configurations in a more complex and realistic environment [42]. In this step, DES models are built upon the selected networks to depict the dynamic features, operations, and upgrades of facilities and transportation over the planning horizon. Due to the stochastic nature of the simulation process, several repetitions are performed to ensure a high level of statistical confidence in the analytical results. The purpose is to guarantee that the outputs of the simulation model are stable and are not affected by the scenario generation process. Finally, the performance indicators need to be measured to rank the selected networks and output the analytical results.

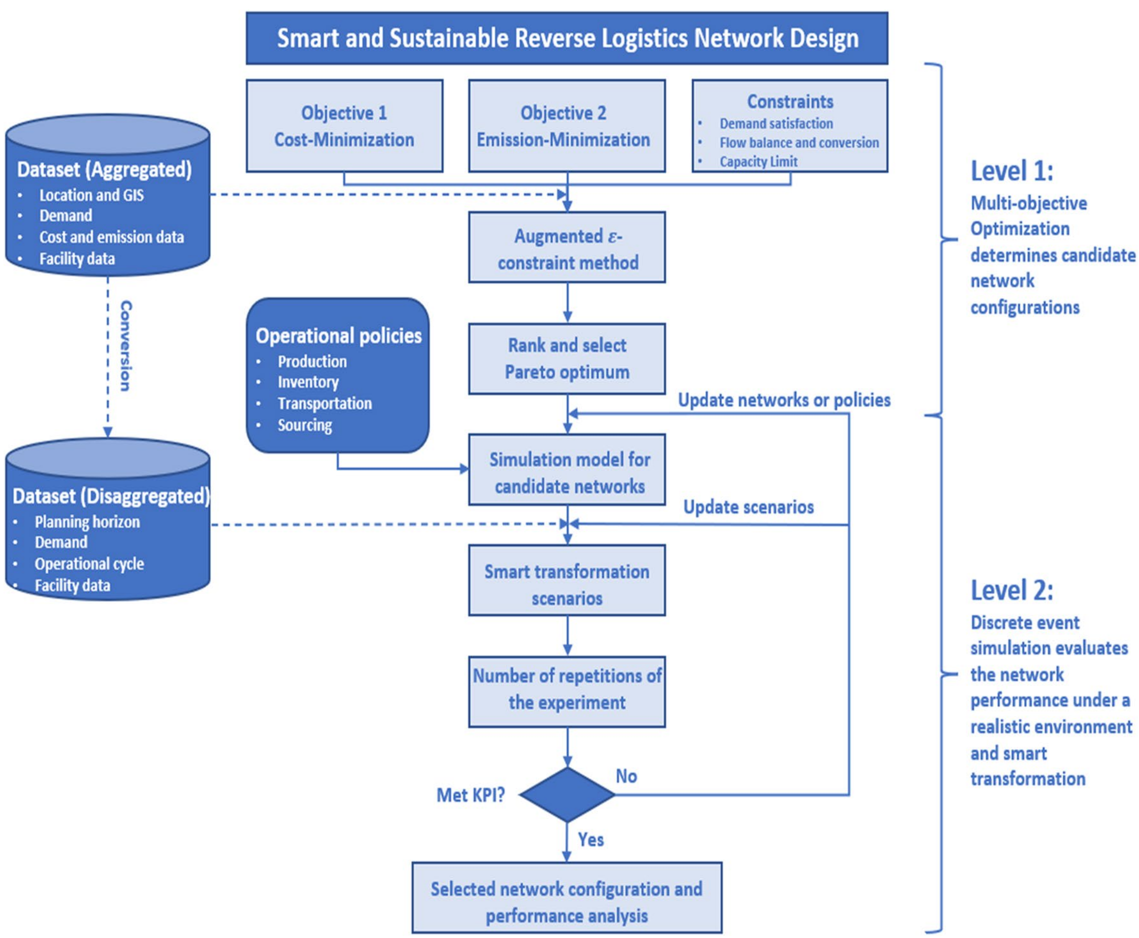


Fig. 2 The two-level decision-support framework

The combination of simulation and optimization in a two-level decision-support framework can explore the strengths of both methods. For example, in a simulation–optimization cycle, simulation can provide predictions of some critical inputs for optimization models [14]. On the other hand, in an optimization-simulation cycle, simulation can be used to better evaluate the solutions obtained from the mathematical model [85]. The proposed framework focuses on the optimization-simulation cycle, where the impact of Industry 4.0 is analyzed in the second-level simulation stage with a dynamic planning horizon, stochastic parameters, real-world geographic information systems (GIS), practical operational policies, and technology upgrades. Specifically, using the network structures optimized by the first-level bi-objective MIP model, decision-makers can assess various alternatives for integrating new Industry 4.0 technologies into the reverse logistics system. This analysis aids in determining the optimal timing and selection of these technologies to maximize economic benefits and environmental sustainability in reverse logistics operations. Furthermore, the simulation stage allows for the evaluation of more comprehensive performance indicators, such as the impact on service levels during facility upgrades. This methodological framework enables a holistic assessment of both the immediate and long-term effects of technological integrations into reverse logistics systems, reflecting real-world complexities and the evolving nature of industry demands.

More detailed introductions of the respective processes are given in the following subsections.

4.1 Optimization model

We consider the selection and operations of the regional collection centers, remanufacturing plants, recycling plants, and disposal sites, and the transportation of EOL products and disassembled components among these facilities. A bi-objective MIP model is formulated considering both cost-effectiveness and environmental footprint. In this paper, carbon emission is used to measure the environmental impact since it is one of the most widely used quantitative indicators and has been implemented by many industries.

The sets, parameters, and variables are first given as follows:

Sets	
P	Set of EOL product p
Q	Set of disassembled component q
E	Set of local collection center e
R	Set of potential locations for regional collection center r
I	Set of potential locations for remanufacturing/refurbishing plant i
J	Set of potential locations for recycling plant j
K	Set of potential locations for disposal site k
Parameters	
Fxr_r	Fixed opening and operating cost of regional collection center opened at r
Fxi_i	Fixed opening and operating cost of remanufacturing plant opened at i
Fxj_j	Fixed opening and operating cost of recycling plant opened at j
Fxk_k	Fixed opening and operating cost of disposal site opened at k
OCr_{rp}	Unit processing cost of EOL product p at regional collection center r
OCi_{iq}	Unit remanufacturing cost of component q at i
OCj_{jq}	Unit material recycling cost of component q at j
OCk_k	Unit disposal cost of unrecyclable at k
TCa_{erp}	Unit transportation cost of EOL product p on arc(e, r)
TCb_{riq}	Unit transportation cost of component q on arc(r, i)
TCc_{rjq}	Unit transportation cost of component q on arc(r, j)
TCd_{rkq}	Unit transportation cost of component q on arc(r, k)
$Flex_{ep}$	Unit flexible capacity cost including collection, transportation, and processing
Esr_{rp}	Unit carbon emissions of EOL product p processed at r
Esi_{iq}	Unit carbon emissions of component q remanufactured at i
Esj_{jq}	Unit carbon emissions of component q recycled at j
Esk_k	Unit carbon emissions at disposal site k
$TEsa_{erp}$	Unit carbon emissions of EOL product p transported on arc(e, r)
$TEsb_{riq}$	Unit carbon emissions of component q transported on arc(r, i)
$TEsc_{rjq}$	Unit carbon emissions of component q transported on arc(r, j)
$TEsd_{rkq}$	Unit carbon emissions of component q transported on arc(r, k)
$Fles_{ep}$	Unit carbon emissions of flexible capacity
EOL_{ep}	Amount of EOL product p collected at location e
CRM_{pq}	Conversion rate from EOL product p to component q for remanufacturing
CRC_{pq}	Conversion rate from EOL product p to component q for material recycling
CDP_{pq}	Conversion rate from EOL product p to component q for disposal
$Capr_{rp}$	Capacity of regional collection plant r for EOL product p
$Capi_{iq}$	Capacity of remanufacturing plant i for component q
$Capj_{jq}$	Capacity of recycling plant j for component q
$Capk_k$	Capacity of disposal site k
$UPFLX_p$	Upper limit of flexible capacity for EOL product p
Variables	
Dr_r	$\begin{cases} Dr_r = 1 \text{ Potential location for regional collection center } r \text{ is selected} \\ Dr_r = 0 \text{ Otherwise} \end{cases}$
Di_i	$\begin{cases} Di_i = 1 \text{ Potential location for remanufacturing plant } i \text{ is selected} \\ Di_i = 0 \text{ Otherwise} \end{cases}$
Dj_j	$\begin{cases} Dj_j = 1 \text{ Potential location from recycling plant } j \text{ is selected} \\ Dj_j = 0 \text{ Otherwise} \end{cases}$

Dk_k	$\begin{cases} Dk_k = 1 \text{ Potential location for disposal site} k \text{ is selected} \\ Dk_k = 0 \text{ Otherwise} \end{cases}$
Ur_{rp}	Amount of EOL product p processed at r
Ui_{iq}	Amount of component q remanufactured at i
Uj_{jq}	Amount of component q recycled at j
Uk_k	Amount of disposed component at k
UTa_{erp}	Amount of EOL product p transported via arc(e, r) for collection, inspection, and disassembly
UTb_{riq}	Amount of component q transported via arc(r, i) for remanufacturing
UTc_{rjq}	Amount of component q transported via arc(r, j) for material recycling
UTd_{rkq}	Amount of component q transported via arc(r, k) for disposal
UF_{ep}	Amount of EOL product p sent for flexible options from location e
URM_{rq}	Amount of disassembled component q for remanufacturing from regional collection center r
URC_{rq}	Amount of disassembled component q for material recycling from regional collection center r
UDP_{rp}	Amount of EOL product sent for disposal from regional collection center r

The model consists of two objectives. The first objective Eq. (1) minimizes the total costs for operating this reverse logistics system, which includes fixed facility cost FX, processing cost OX, transportation cost TX, and flexible capacity cost FLX. It is noteworthy that the inclusion of FLX is considered a soft constraint to allow a small violation of the capacity constraints, which helps to avoid the opening of a new facility to deal with a small demand increment and to yield robust strategic facility location decisions. In practice, it means the excessive customer demands can be fulfilled by various temporary solutions, i.e., outsourcing, overtime, seasonal workers, etc. Using these flexible solutions is more expensive, but they can effectively eliminate redundant facility configurations generated from the optimization model. For more details, see Yu and Solvang [99].

$$\mathrm{Min}Z1 = FX + OX + TX + FLX \tag{1}$$

The respective cost components in the objective function are calculated by Eqs. (2)–(5).

$$\begin{aligned} FX = & \sum_{r\in R} Fxr_r Dr_r + \sum_{i\in I} Fxi_i Di_i \\ & + \sum_{j\in J} Fxj_j Dj_j + \sum_{k\in K} Fxk_k Dk_k \end{aligned} \tag{2}$$

$$\begin{aligned} OX = & \sum_{r\in R}\sum_{p\in P} OCr_{rp} Ur_{rp} + \sum_{i\in I}\sum_{q\in Q} OCi_{iq} Ui_{iq} \\ & + \sum_{j\in J}\sum_{q\in Q} OCj_{jq} Uj_{jq} + \sum_{k\in K} DCk_k Uk_k \end{aligned} \tag{3}$$

$$\begin{aligned} TX = & \sum_{e\in E}\sum_{r\in R}\sum_{p\in P} TCa_{erp} UTa_{erp} + \sum_{r\in R}\sum_{i\in I}\sum_{q\in Q} TCb_{riq} UTb_{riq} \\ & + \sum_{r\in R}\sum_{j\in J}\sum_{q\in Q} TCc_{rjq} UTc_{rjq} + \sum_{r\in R}\sum_{k\in K}\sum_{q\in Q} TCd_{rkq} UTd_{rkq} \end{aligned} \tag{4}$$

$$FLX = \sum_{e\in E}\sum_{p\in P} Flex_{ep} UF_{ep} \tag{5}$$

The second objective Eq. (6) minimizes the carbon emissions of the reverse logistics system, which consists of the carbon emissions related to facility operation FES, transportation TES, and flexible capacity $FLES$.

$$\mathrm{Min}Z2 = FES + TES + FLES \tag{6}$$

Equations (7)–(9) calculate the respective carbon emissions.

$$\begin{aligned} FES = & \sum_{r\in R}\sum_{p\in P} Esr_{rp} Ur_{rp} + \sum_{i\in I}\sum_{q\in Q} Esi_{iq} Ui_{iq} \\ & + \sum_{j\in J}\sum_{q\in Q} Esj_{jq} Uj_{jq} + \sum_{k\in K} Esk_k Uk_k \end{aligned} \tag{7}$$

$$\begin{aligned} TES = & \sum_{e\in E}\sum_{r\in R}\sum_{p\in P} TEsa_{erp} UTa_{erp} + \sum_{r\in R}\sum_{i\in I}\sum_{q\in Q} TEsb_{riq} UTb_{riq} \\ & + \sum_{r\in R}\sum_{j\in J}\sum_{q\in Q} TEsc_{rjq} UTc_{rjq} + \sum_{r\in R}\sum_{k\in K}\sum_{q\in Q} TEsd_{rkq} UTd_{rkq} \end{aligned} \tag{8}$$

$$FLES = \sum_{e\in E}\sum_{p\in P} Fles_{ep} UF_{ep} \tag{9}$$

The model has six sets of constraints to satisfy the logistical flow requirements associated with facility operations and transportation. The first set of constraints depicts the relationship between local collection and regional collection. Constraint (10) ensures that all the local collection points will be served by the regional collection centers or by the flexible capacity. Constraint (11) calculates the types and the number of EOL products received by each regional collection center.

$$EOL_{ep} \le \sum_{r\in R} UTa_{erp} + UF_{ep}, \forall e \in E, p \in P \tag{10}$$

$$\sum_{e\in E} UTa_{erp} = Ur_{rp}, \forall r \in R, p \in P \tag{11}$$

Based on the composition and the quality level of different EOL products, constraints (12)–(14) convert the EOL products to respective components for remanufacturing/refurbishing, material recycling, and waste disposal, respectively. Herein, the sum of the conversion rates CRM_{pq}, CRC_{pq}, and CDP_{pq} for one EOL product equals to 1.

$$\sum_{p\in P} Ur_{rp}CRM_{pq} = URM_{rq}, \forall r \in R, q \in Q \tag{12}$$

$$\sum_{p\in P} Ur_{rp}CRC_{pq} = URC_{rq}, \forall r \in R, q \in Q \tag{13}$$

$$\sum_{p\in P} Ur_{rp}CDP_{pq} = UDP_{rq}, \forall r \in R, q \in Q \tag{14}$$

Constraints (15)–(17) calculate the output flows of different EOL products from regional collection centers to remanufacturing plants, recycling plants, and disposal sites.

$$URM_{rq} = \sum_{i\in I} UTb_{riq}, \forall r \in R, q \in Q \tag{15}$$

$$URC_{rq} = \sum_{j\in J} UTc_{rjq}, \forall r \in R, q \in Q \tag{16}$$

$$UDP_{rq} = \sum_{k\in K} UTd_{rkq}, \forall r \in R, q \in Q \tag{17}$$

Constraints (18) and (19) calculate the types and the number of components received at remanufacturing plants and at recycling plants. Constraint (20) calculates the total amount of different unrecyclable received at each disposal site.

$$\sum_{r\in R} UTb_{riq} = Ui_{iq}, \forall i \in I, q \in Q \tag{18}$$

$$\sum_{r\in R} UTc_{rjq} = Uj_{jq}, \forall j \in J, q \in Q \tag{19}$$

$$\sum_{r\in R}\sum_{q\in Q} UTd_{rkq} = Uk_k, \forall k \in K \tag{20}$$

Constraints (21)–(24) set up the maximal capacity of respective facilities. Meanwhile, the use of un-selected facilities is also restricted by this set of constraints.

$$Ur_{rp} \le Capr_{rp}Dr_r, \forall r \in R, p \in P \tag{21}$$

$$Ui_{iq} \le Capi_{iq}Di_i, \forall i \in I, q \in Q \tag{22}$$

$$Uj_{jq} \le Capj_{jq}Dj_j, \forall j \in J, q \in Q \tag{23}$$

$$Uk_k \le Capk_kDk_k, \forall k \in K \tag{24}$$

Constraint (25) is the upper limit of flexible capacity allowed in the reverse logistics system.

$$\sum_{e\in E} UF_{ep} \le UPFLX_{ep}, \forall \mathrm{e} \in \mathrm{E}, p \in P \tag{25}$$

In addition, constraints (26) and (27) define the domains of the variables.

$$Dr_r, Di_i, Dj_j, Dk_k \in \{0,1\}, \forall r \in R, i \in I, j \in J, k \in K \tag{26}$$

$$Ur_{rp}, Ui_{iq}, Uj_{jq}, Uk_k, UTa_{erp}, UTb_{riq}, UTc_{rjq}, UTd_{rkq}, URM_{rq}, URC_{rq}, UDP_{rp}, UF_{ep} \ge 0, \forall r \in R, p \in P, i \in I, q \in Q, j \in J, k \in K, e \in E \tag{27}$$

4.2 Solution approach

The augmented ε-constraint method is used to solve this bi-objective MIP, and it can solve the pitfalls of the traditional ε-constraint method by employing a lexicographic method in determining the payoff matrix. Besides, compared with other scalarization methods, e.g., weighted sum, it has a much better chance to yield evenly distributed Pareto optimal solutions. For more details, Mavrotas [56] can be referred to. Based on our model, the algorithmic procedures are described as follows.

Algorithmic procedures

Step 1	***The priority level*** of the objective functions is determined based on the inputs of decision-makers. For example, in this model, $Z1$ has a higher priority level.
Step 2	***The payoff matrix*** is calculated with the Lexicographic method. **2.1** Calculate the individual optimal solutions $Z1_{opt}$ and $Z2_{opt}$ by solving the single objective functions $Z1$ and $Z2$. **2.2** Calculate the nadir values of the two objective functions $Z1_{nad}$ and $Z2_{nad}$ with the lexicographic method. For example, optimize $Z2$ by adding an additional constraint $Z1 \leq Z1_{opt}$.
Step 3	***The ranges*** of the objective functions can be calculated by $Z1_{nad} - Z1_{opt}$ and $Z2_{nad} - Z2_{opt}$.
Step 4	***The value of ε*** is determined based on the priority level and the number of divided grids (NG). For example, $Z1$ has a higher priority, and Z2 can be converted to a set of additional constraints with $\Delta\varepsilon_{Z2} = {Z2_{nad} - Z2_{opt}}/{NG}$
Step 5	***Conversion*** of the multi-objective optimization problem into a single-objective optimization problem based on the priority level and the value of ε. For example, the proposed model can be converted to: $\min\ (Z1(\boldsymbol{x}) + eps \times s_{Z2})$ S.t. $Z2(\boldsymbol{x}) + s_{Z2} = \varepsilon_{Z2}$ $\boldsymbol{x} \in X$ and $\varepsilon_{Z2} \in \mathbb{R}^{+}$ Herein, s_{Z2} is a slack variable and *eps* is a sufficiently small adjustment parameter ranging normally from 10^{-6} to 10^{-3} (Mavrotas, 2009)
Step 6	***Optimization*** of the single-objective problem and generating a set of efficient Pareto solutions

4.3 Simulation model

Due to the limitation of optimization, e.g., over-simplified real-world problems, many assumptions, etc., the analytical results from the bi-objective MIP may be significantly compromised. Thus, these optimal solutions cannot be automatically converted into managerial decisions [41]. Instead, they need to be further evaluated with management expertise and better interpreted through the analysis of different alternatives. Thus, in the second level, a simulation model is used to provide a comprehensive performance analysis of the candidate networks considering realistic operations, parametric uncertainties, and scenario analyses of the impact of smart transformation.

To perform the simulation, a state-of-the-art simulation package called anyLogistix is used, which can effectively set up and perform experiments related to multi-stage logistics networks, production control, inventory control, transportation and shipping control, and sourcing analysis [41]. To build the simulation model, the planning horizon is first decided, and the selected networks are used to configure the reverse logistics systems. Logic needs to be specified to create the operations of both facilities and transportation, and the operational parameters are converted into a lower level of data aggregation. Stochastic parameters can be used to provide insights into the key parameters concerning randomness. Simulation explores the system performance in a more detailed manner, so operational policies and conditions over different periods need to be determined by the decision-makers to better model the real-world behaviors of a reverse logistics system. The following operational policies can be configurated:

- Demand generation: Stochastic demands can be set up in both local collection points and the markets for recovered products. Periodic demands can be placed on customer-defined intervals, e.g., weekly or monthly. Besides, seasonal factors may be added if needed [43].
- Inventory policy: Different inventory control policies, e.g., periodic review, continuous review, etc., can be implemented to control the inventory level. A back-order policy is allowed so that the order is pending until the required amount is available for delivery.
- Production policy: Individual BOMs and different production policies, e.g., simple production, partial production, etc., can be used in different facilities. Stochastic and dynamic parameters can be set up to evaluate the influences of smart transformation.

- Sourcing policy: Different sourcing policies, e.g., closest source, multiple sources, fixed source, etc., can be defined at different stages of the reverse logistics system.
- Transportation policy: Various operational parameters, e.g., vehicle type, vehicle capacity, speed, loading policy, etc., can be defined to model the real-life situation.

In addition, simulation can also be used to test the impacts of operational uncertainty, configuration upgrades over different periods and network disruption. For example, the temporary closure or capacity reduction during the facility upgrades, the improvement of productivity and environmental performance after the upgrades, and so forth. These test scenarios can be set up in this stage, and the possible impacts and strategies can be evaluated. Finally, the number of repetitions of the simulation experiment needs to be defined.

5 Case study

Considering the smart transformation during the planning horizon, we investigated a reverse logistics network design problem for sustainable WEEE management in Norway. With a population density of 15 people/km^2, Norway is one of the most sparsely populated countries in Europe. The low population density and the geographically dispersed municipalities result in complex logistics planning problems to simultaneously balance the economic performance, environmental impact, and service level, due to the loss of economy of scale. Thus, the use of new technological solutions becomes attractive and needs to be considered in long-term strategic planning. With a focus on sustainable development and a low-carbon economy, Norway has a long history in the reuse and recycling of WEEE [97]. The first regulatory system for WEEE management in Norway was implemented in 1999. The relevant WEEE regulations require that all the manufacturers of EEE joining in the collective compliance

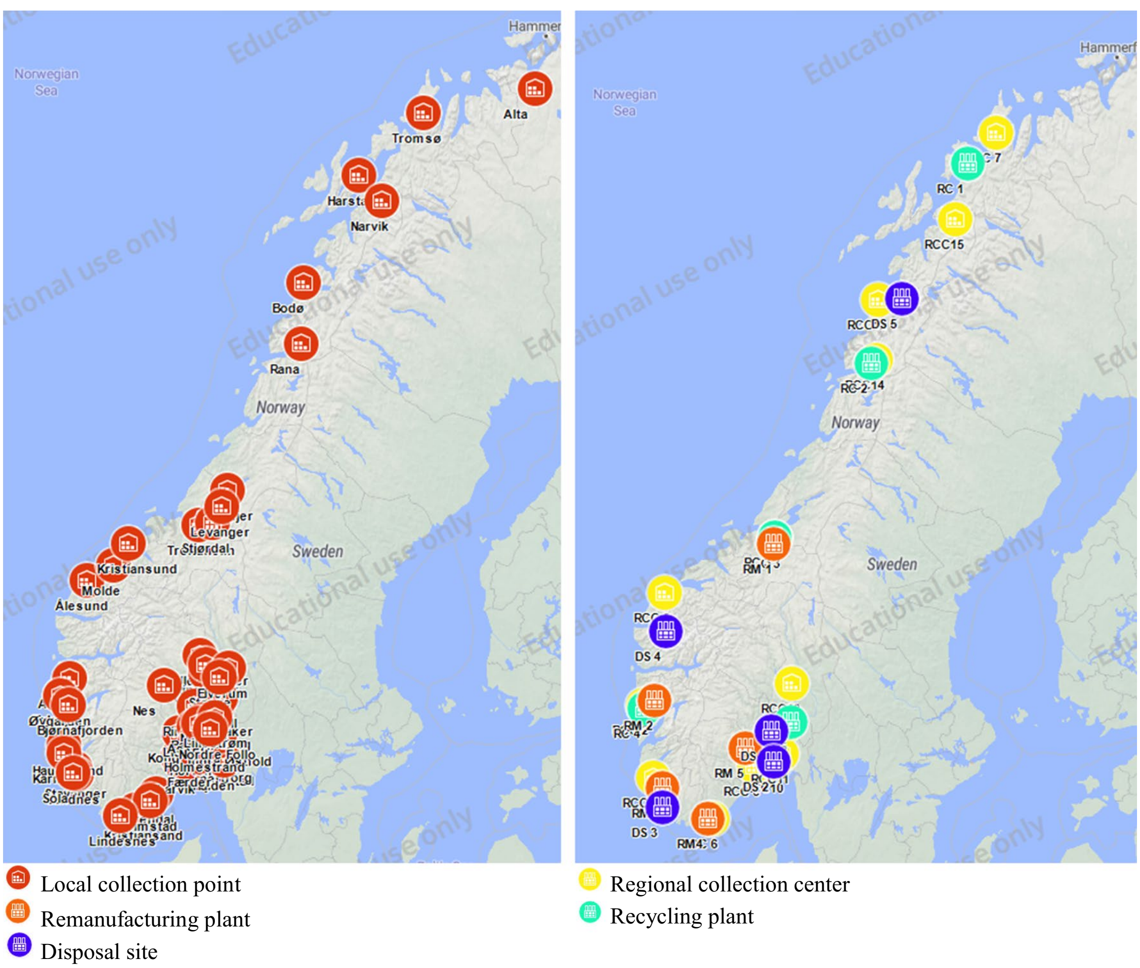


Fig. 3 The locations of the local collection centers and the candidate locations of respective facilities

systems for the EOL recovery of their products, which are operated by third parties. The European Recycling Platform (ERP) Norway is a nationwide compliance scheme, which ensures the environmentally friendly treatment of WEEE. As a part of the regulatory system, the two major ERP service providers (El-Retur and RENAS) take 94% of the total share of the WEEE collection and recycling in Norway. In addition, there is another smaller compliance scheme called Eurovironment, which is operated by 14 manufacturers of IT equipment [12]. Even though the relevant regulations for WEEE recovery have been well formulated and implemented in Norway, the reverse logistics system has, however, not been effective since the transportation network is sub-optimized and most of the facilities are small-scale and located near Oslo. This requires frequent and long-distance transportation of WEEE from the northern parts to the southern parts of the country [97], which results in increased transportation costs and carbon emissions. Besides, an effective remanufacturing system has not been established and a portion of WEEE is exported. Thus, from a holistic perspective, we optimized the WEEE reverse logistics network in Norway.

In Norway, the total collection rate of WEEE, the households collection rate of WEEE, and the collection rate of large household appliances in 2018 are 18.16 kg/capita/year, 11.32 kg/capita/year, and 8.45 kg/capita/year, respectively [26]. The EU Directive [19] categorizes ten types of EEE, i.e., large household appliances, small household appliances, IT and telecommunications equipment, consumer equipment and photovoltaic panels, lighting equipment, etc., where the large household appliances account for 47% of the total WEEE in Norway [26]. In this experiment, we selected 7 types of large household appliances based on the EU Directive [19], which were then divided into three groups, namely, refrigerators/freezers (P1), washing machines/dishwashers/clothes dryers (P2), and stoves/cookers (P3). These three groups constitute approximately 80% of the total large household appliances [89]. The proportions of the WEEE generation of P1, P2, and P3 were assumed to be 40%, 40%, and 20%. The collection and recovery of the three groups of WEEE from the 60 largest municipalities in Norway were considered, and the name, the number, and the population of these municipalities are given in Appendix A. The WEEE generation was assumed to be proportional to the population of the municipalities, obtained from Statistics Norway [82]. The average generation per capita was obtained from the database of the European Commission [26].

To improve the effectiveness and efficiency of the reverse logistics system, 15 candidate locations were selected for opening the regional collection centers, which are Oslo (R1), Bergen (R2), Trondheim (R3), Stavanger (R4), Drammen (R5), Kristiansand (R6), Tromsø (R7), Skien (R8), Ålesund (R9), Tønsberg (R10), Moss (R11), Bodø (R12), Hamar (R13), Rana (R14), and Narvik (R15). Several candidate locations for the EOL recovery were chosen considering the

Table 4 Unit transportation costs and carbon emissions between different facilities

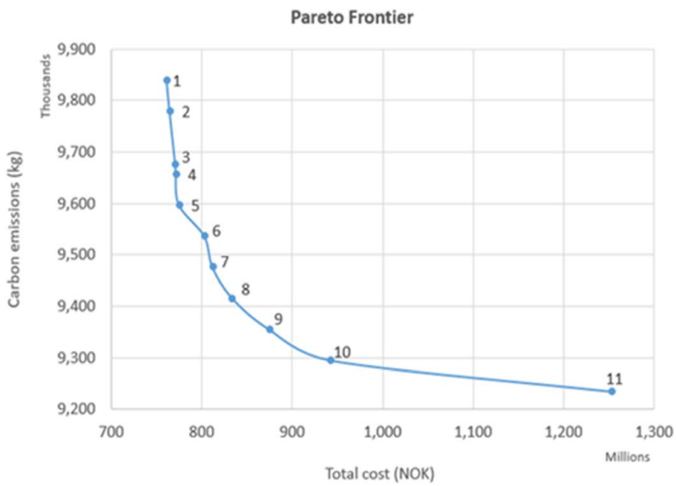
Links	Product/ components	Transportation cost (NOK/km/kg)	Carbon emissions (kg/km/kg)
LCP → RCC	P1	0.014286	0.000159
	P2	0.012444	0.000148
	P3	0.012037	0.000154
RCC → RM	q1	0.008750	0.000081
	q4	0.008000	0.000081
RCC → RC	q2	0.008235	0.000076
	q3	0.008000	0.000081
RCC → DS	qw	0.011765	0.000076

Table 2 The disassembly BOMs of the selected WEEE groups

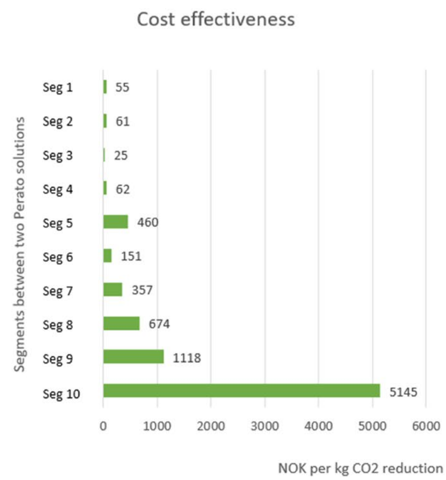
BOM	CRM_{pq}		CRC_{pq}		CRD_{pq}
	q1	q4	q2	q3	qw
P1	0.0947	0	0.7895	0.0737	0.0421
P2	0	0.0500	0.5750	0.1000	0.2750
P3	0	0	0.9500	0.0357	0.0143

Table 3 Parameter generation intervals of respective facilities

Facility	Fixed cost (10^3 NOK/year)	Product/components	Variable cost (NOK/kg)	Carbon emissions (kg/kg)	Capacity (10^3 kg)
Regional collection center	[21,400, 21,800]	P1	[13, 16]	[0.16, 0.17]	[2000, 2220]
		P2	[13, 16]	[0.161, 0.17]	[2000, 2200]
		P3	[13, 16]	[0.163, 0.17]	[820, 950]
Remanufacturing plant	[38,200, 40,160]	q1	[9, 11]	[1.161, 1.165]	[875, 900]
		q4	[13, 14]	[1.16, 1.169]	[580, 610]
Recycling plant	[26,108, 27,686]	q2	[4, 5]	[0.161, 0.169]	[810, 950]
		q3	[9, 10]	[0.16, 0.17]	[850, 900]
Disposal plant	[18,595, 20,475]	qw	[10, 12]	[0.243, 0.25]	[1395, 1550]



(A) Pareto Frontier



(B) Cost/Carbon ratio

Fig. 4 Computational results

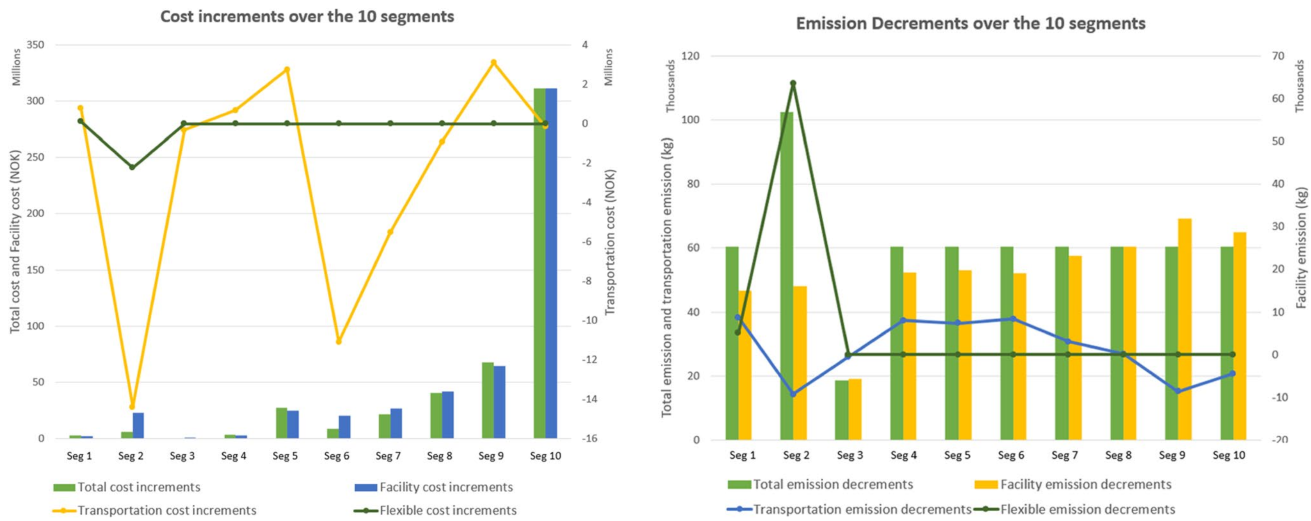
fair geographical access. In total, the candidate locations for remanufacturing plants, recycling plants, and disposal sites are 5, 5, and 5, respectively. Figure 3 illustrates the locations of the municipalities and the candidate locations for respective facilities. Table 2 shows the disassembly BOMs of P1, P2, and P3. The main components are compressors (q1), metal components (q2), plastics (q3), pump/motor components (q4), and non-recyclables (qw), where q1 and q4 can be remanufactured and q2 and q3 are for material recycling.

Based on relevant research, the fixed facility operating costs [35, 59], the capacities of different facilities, the unit processing costs of EOL products or components [95], and the unit carbon emissions [18, 64, 75, 79] were estimated. Considering the generality, we randomly generated these parameters from the respective parameter intervals, as shown in Table 3. The transportation costs and carbon emissions are directly proportional to the travel distances. Thus, the distance matrixes were first established. In this experiment, we considered two types of vehicles with truckloads of 6.3 tons and 13.4 tons [3]. The first type is used for transportation from the local collection centers to the regional collection centers, and the second type is used for transportation from the regional collection centers to the other facilities. Besides, the unit transportation cost and unit carbon emissions are also affected by the loading rate of the vehicles. The loading rates of the transportation at the first and the second stages of the reverse logistics were generated from the intervals [0.7, 0.75] and [0.8, 0.85], respectively. The unit transportation costs were estimated based on Delgado et al. [16], and the unit carbon emissions were given based on the report of freight transportation and logistics from the European Automobile Manufacturer Association [3]. Table 4 presents the unit transportation costs and carbon emissions.

Finally, to avoid opening more facilities due to a small demand increment, the costs and unit carbon emissions for using flexible capacities were set to approximately 1.5 times higher than using an opened facility [99], and the upper limit of flexible capacity was set to 10% of the total generation of EOL products at each municipality. The full set of the parameters in the experiment is given in Appendix B.

Table 5 The facility selections in the five chosen Pareto optimal solutions

Pareto optimum	Regional collection center	Remanufacturing plant	Recycling plant	Disposal plant
1	(1), (2), (3), (5), (8)	(5)	(4), (5)	(1), (4)
2	(1), (2), (3), (5), (8)	(5)	(4), (5)	(1), (2)
4	(1), (2), (3), (5), (8)	(5)	(3), (4), (5)	(1), (4)
5	(1), (2), (3), (5), (8)	(5)	(3), (4), (5)	(1), (2)
7	(1), (2), (3), (5), (6), (13), (15)	(5)	(3), (4), (5)	(1), (2)



(A) Cost components **(B)** Emission components

Fig. 5 Comparison of the cost increments and the emission decrements over the 10 segments

6 Experiments, results, and discussions

6.1 Optimization experiment

The optimization problems with changing values of ε were first solved to generate a set of Pareto optimal solutions. The optimization problems were solved by Lingo 19.0, and the maximum computational time was approximately 3 min. Figure 4A illustrates the Pareto optimal frontier formed by 11 points. Points 1 and 11 are the cost-minimization solution and the emission-minimization solution, and the ranges of the two objectives are [761,527,290 NOK, 1,253,751,898 NOK] and [9,234,054 kg, 9,839,252 kg], respectively.

For comparison purposes, the Pareto frontier is divided into 10 segments. For example, segment 1 is between Pareto optimal solutions 1 and 2. The cost increments and the emission decrements of each segment between two adjacent Pareto optimal solutions can be calculated by $Costincrements_n^x = Cost_{n+1}^x - Cost_n^x$ and $Emissiondecrements_n^x = Emission_n^x - Emission_{n+1}^x$, where $x \in \{Total, Facility, Transportation\}$ and $n \in \{1, \ldots, 10\}$. It is noteworthy that the cost increments for reducing one unit of carbon emissions at each segment are by no means identical, and the cost for reducing one unit of carbon emissions between two Pareto optimal solutions n and $n+1$ can be calculated by $Costincrements_n^{Total} / Emissiondecrements_n^{Total}$. Thus, a lower ratio leads to better cost-effectiveness in carbon reduction. Based on Fig. 4B, five candidate Pareto optimal solutions were chosen for the simulation experiment. Exempt from the cost-minimization solution, the selected solutions are points 2, 4, 5, and 7, which show better cost-effectiveness in carbon emission reduction. The respective reverse logistics network configurations are given in Table 5. In the first four networks, five regional collection centers are opened in Oslo, Bergen, Trondheim, Drammen, and Skien. In network 7, instead of opening the regional collection center in Skien, another three candidate locations in Kristiansand, Hamar, and Narvik are selected. Besides, remanufacturing plant 5, recycling plants 4 and 5, and disposal site 1 are selected in all solutions.

Figure 5 compares the cost increments and the emission increments related to facility operations and transportation. The facility operations predominantly determine the overall system costs. Even though the transportation costs vary drastically with the change of the network configurations, the impacts on the overall system costs are relatively insignificant compared with those incurred from facility operations. However, facility operations yield relatively small impacts on total carbon emissions, and the reduction is primarily led by the reduced carbon emissions from transportation. Therefore, the minimum number of facilities was opened in points 1 and 2 to minimize the total system costs, and the exceeded EOL generations were treated using flexible capacities. On the other hand, more facilities were opened when the emphasis was given to the minimization of carbon emissions to shorten the overall transportation distance in the reverse logistics network.

6.2 Simulation experiment

6.2.1 Parameter conversion

The five selected network configurations were used to build simulation models. Based on the same dataset, the relevant simulation parameters were generated. The simulation time was set to 10 years, and the number of repetitions was set to 50. It is noteworthy that several parameters need to be converted due to the practical requirements of simulation models. For example, the annual generations of WEEE were disaggregated into shorter periods. Besides, the facility capacity constraint was converted into production time and was restricted by the annual working hours. The purpose of the reverse logistics system is to manage the WEEE generated in each period. The periodic demands for remanufactured products q1 and q4 and for recycled materials q2 and q3 were thus calculated based on the generation of WEEE. The collection cycle of WEEE at the regional collection centers was set to 15 days, and the customer ordering cycle for recovered items was set to 7–10 days.

We considered two sources of uncertainty with stochastic parameters, namely, quantity and quality. First, the quality of WEEE generated at different locations is defined as stochastic parameters. Besides, the quality levels of different EOL products vary significantly, which leads to varied processing times at the facility level. The two stochastic parameters were assumed to follow a uniform distribution. The lower and upper bounds of the uniform distribution can be calculated by $[p_d(1-\sigma), p_d(1+\sigma)]$, where p_d is the respective deterministic value and σ is the deviational adjustment in [0, 1] [67]. In this experiment, σ was set to 10% for the generation of WEEE and 20% for the processing time [60].

6.2.2 Operational policies

Inventory policy is important. We considered different production and inventory policies at different facilities to fulfill the demands and operate the reverse logistics system. For example, the continuous review (R, Q) policy was used by the remanufacturer to replenish the components q1 and q4 from regional collection centers. With this policy, an order quantity at (Q) is sent when the inventory level reaches the reordering point (R). The reordering point and reordering quantity can be calculated by the following equations [21]:

$$R = \mu_D \mu_L + z_\alpha \sqrt{\mu_L \sigma_D^2 + \mu_D^2 \sigma_L^2}$$

$$Q = \sqrt{\frac{2\mu_D c_0}{c_h}}$$

whereas:

μ_D	average weekly demand
σ_D	weekly standard deviation
μ_L	average lead time
σ_L	standard deviation of average lead time
c_0	fixed ordering cost
c_h	weekly inventory holding cost per unit
z_α	value from the standard normal distribution table

We used the same method given by Gianesello et al. [34] to set up the inventory levels. First, the (R, Q) values were assumed, and the values of inventory were then projected backward along with the reverse logistics network to ensure the production capability and the available material inventory. To determine the inventory levels of the new products and new materials at the remanufacturing plant and the recycling plant, we used a min–max policy with safety stock (s, S). The (s, S) policy requires periodic checks and replenishment of the inventory at discrete intervals. Based on Gianesello et al. [34], the safety stock (ss) was assumed to be equal to the mean weekly demand σd, and the min (s) and the max (S) inventory levels were then calculated by the following equations, where LT is the lead time.

$$s = ss + (\sigma d * LT)$$

$$S = 2 * s$$

For the other facilities, the (R, Q) policy was implemented, and the full set of inventory policies and parameters is given in Appendix C. Production policy is another important factor that is closely linked to the inventory policy and sourcing policy. In this paper, a simple manufacturing strategy is implemented, where the production pattern is driven by the requirements of replenished products defined by the inventory policy. In addition, stochastic production times were defined in the remanufacturing, recycling, and disposal processes to analyze the uncertainty related to the quality of WEEE. A fixed sourcing strategy was used in the first-level transportation, which means a fixed cluster of municipalities is served by a given regional collection center. On the other hand, multiple sourcing strategies were implemented by the remanufacturers and the recycling plants to optimize the recourse decisions over the planning horizon. Finally, to improve the service level, a partial shipment policy was used in the experiments, and two types of vehicles were defined accordingly with stochastic speeds.

6.2.3 Smart transformation in industry 4.0

We next explored the potential for smart transformations driven by new Industry 4.0 technologies over the planning horizon. At the system level, new technologies will impact operating parameters. For example, the use of AI-based robots may increase productivity in many industries by 30% by 2025, while cutting labor costs by 18–33% [92]. Adopting AR may achieve up to 25% improvement in operator productivity while providing a safe working environment [84, 92]. Recent research shows that using IoT-enabled smart

Table 6 Test scenarios for technological upgrades and smart transformation

Scenario	Period	Facility upgrade plan	Expected impacts on facility				Expected impacts on transportation	
			Average production time/unit	Uniform distribution of processing time	Production cost/unit	CO_2 emissions from the facility	Expected CO_2 reduction/unit	Potential cost impact/unit
S1	Year 4	RM for q1, q4 RC for q3	−10%	[95%, 105%]	−10%	−15%	−10%	
	Year 6	RC for q2	−15%	[95%, 105%]	−15%	−15%	−20%	
S2	Year 4	RM for q1, q4	−10%	[95%, 105%]	−10%	−15%	−10%	
	Year 6	RC for q2, q3	−15%	[95%, 105%]	−15%	−15%	−20%	
S3	Year 6	RM for q1, q4 RC for q3	−10%	[95%, 105%]	−10%	−15%	−10%	
	Year 8	RC for q2	−15%	[95%, 105%]	−15%	−15%	−20%	
S4	Year 6	RM for q1, q4 RC for q3	−15%	[95%, 105%]	−15%	−18%	−15%	
	Year 8	RC for q2	−25%	[95%, 105%]	−20%	−18%	−25%	
S5	Year 8	RM for q1, q4 RC for q2, q3	−25%	[95%, 105%]	−20%	−18%	−25%	
S6	Year 8	RM for q1, q4 RC for q2, q3	−25%	[95%, 105%]	−25%	−20%	−25%	
S7	Year 4	RM for q1, q4 RC for q3	−10%	[95%, 105%]	−10%	−15%	−10%	−8%
	Year 6	RC for q2	−15%	[95%, 105%]	−15%	−15%	−20%	−15%
S8	Year 6	RM for q1, q4 RC for q3	−10%	[95%, 105%]	−10%	−15%	−10%	−8%
	Year 8	RC for q2	−15%	[95%, 105%]	−15%	−15%	−20%	−15%
S9	Year 8	RM for q1, q4 RC for q2, q3	−25%	[95%, 105%]	−25%	−20%	−25%	−22%

regulated temperature technology may reduce 20% of carbon emissions and energy consumption on a manufacturing floor [47]. In reverse logistics, the digital twin tracks the quality level of EOL products through a cloud-based system, so remanufacturing can be better planned to minimize the stochasticity related to the processing time. Besides, technological advancement will also yield significant impacts on transportation through the increased use of cleaner energy and improved fuel efficiency [2]. The use of intelligent transport systems and truck platooning has the potential to reduce CO_2 emissions by 10–25% [2, 103]. In addition, the increased use of electric vehicles, hydrogen vehicles, and hybrid trucks may lead to a 10–15% reduction in CO_2 emissions per vehicle basis [2].

In this experiment, we tested 10 scenarios. S0 is the basic scenario without technological upgrades, and S1–S6 are scenarios with different plans for technological upgrades of the remanufacturing process, recycling process, and transportation. Besides, S7–S9 are counterpart scenarios of S1, S3, and S6 considering potential cost impacts on transportation. Table 6 shows the schedule and the expected influence on the operating parameters of the planned upgrades. The investment for facility upgrades was set to 2 million NOK each. The required time was set to 2 months for each facility upgrade, during which period the respective facility was temporarily closed.

6.2.4 Simulation results

Computer-based simulation can provide powerful visualization of the analytical results [42]. Figure 6 shows an established reverse logistics network, and the key performance indicators (KPIs), e.g., costs, emissions, service levels, etc., at both the facility level and system level can be graphically presented and easily outputted for further analysis.

We first considered two scenarios: (1) the basic scenario without facility upgrade (S0) and (2) the facility upgrade scenario (S1). As shown in Fig. 7A, there are two dominated or near-dominated solutions in the simulation results. In S0, network 2 is a dominated solution by network 1. In S1, network 1 is a dominated solution. This result reveals that, by incorporating uncertainty, dynamic operational policies, and smart transformation, the performance of the optimal solutions obtained by the mathematical model may be drastically affected, which shows the impacts of including more

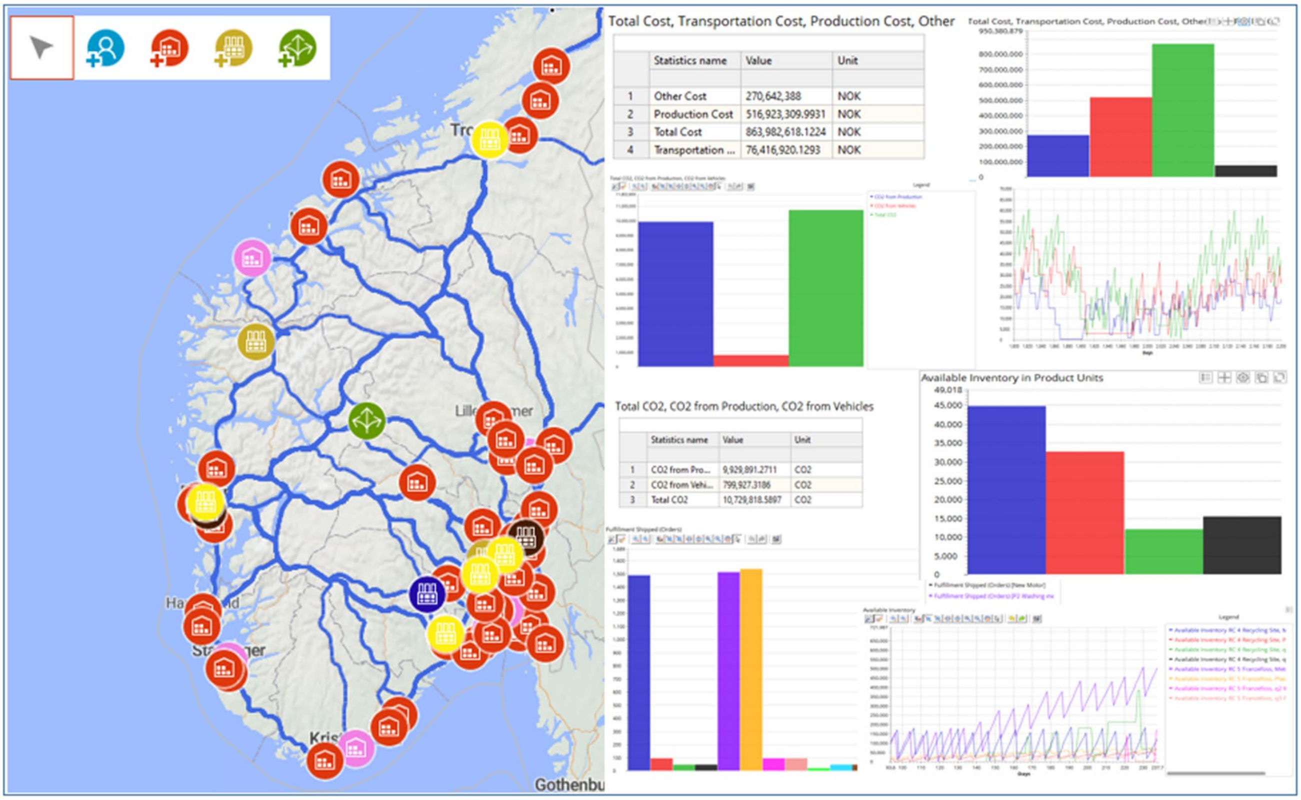
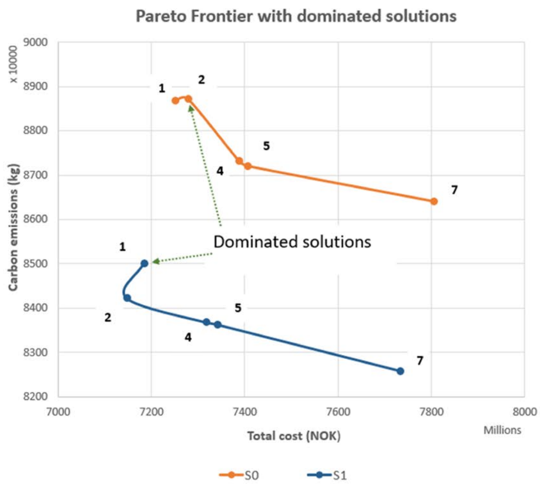


Fig. 6 Result visualization

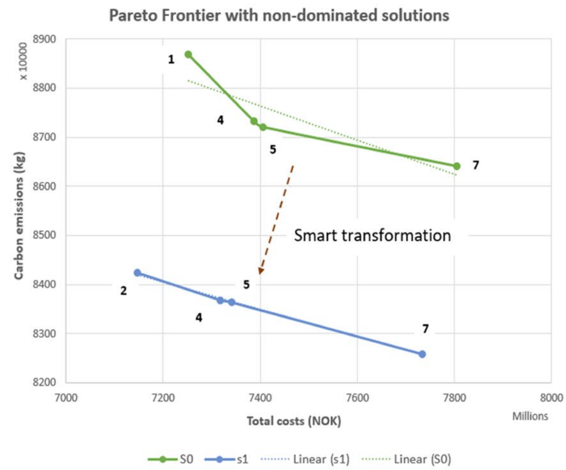
real-world conditions on reverse logistics network design. In the simulation experiment, dominated and near-dominated solutions may be observed, and the Pareto frontier may thus be changed.

Figure 7B illustrates the non-dominated Pareto frontiers of the two scenarios. First, it is observed that, by adopting new technologies in S1, both economic effectiveness and environmental performance can be dramatically improved. For example, in network 4, the mid-term facility upgrades will help to reduce the total system operating costs by 70,042,629 NOK and the total carbon emissions by 3,646,539 kg within the planning horizon. This shows the value of the smart transformation for the selected network under the given upgrade plan. Second, it is also observed that the Pareto frontier in S1 becomes flatter compared with that in the basic scenario. This result implies that the difference in the carbon reductions per unit cost in the Pareto frontier becomes smaller, and the network structure yields less impact on emission reductions. Therefore, opening more facilities for carbon reductions in S1, e.g., network 7, becomes less attractive. In this scenario, the carbon emissions of networks 2 and 4 can be reduced to better balance the tradeoff between economic and environmental sustainability through technological upgrades and smart transformation.

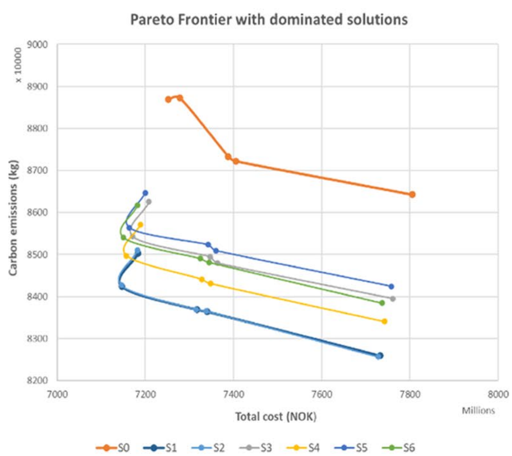
Next, we compared scenarios 1–6 with different plans for technological upgrades of facilities and transportation in Fig. 7C and D. As shown, both the schedule and the expected impacts yield significant impacts on the performance of the reverse logistics networks. For instance, if the planned technological upgrades for respective facilities and transportation are postponed by 2 years from S1 to S3, the total costs of networks 2 and 5 will increase by 24,248,178 NOK and 22,722,489 NOK, while the carbon emissions of these two networks will increase by 1,191,348 kg and 1,162,535 kg, respectively. However, the impacts from the schedule of technological upgrades may be compensated by the expected impacts on operational parameters. For example, compared with S3, even though the upgrades of facilities and transportation in S6 are delayed, the difference between the Pareto frontier in these two scenarios is extremely insignificant due to a higher performance improvement expected in S6. Figure 7E and F compare the scenarios with expected cost impacts on transportation. For the test scenarios, the improvement in cost efficiency of transportation leads to better performance of the selected networks, but the impact is insignificant due to its small proportion of the total costs. The results show that the schedule and expected impacts of smart transformation may dramatically affect the performance of a



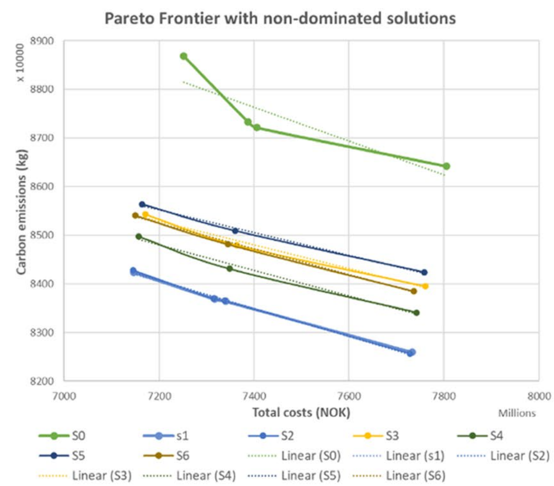
(A) Pareto Frontiers with dominated solutions of S0 and S1.



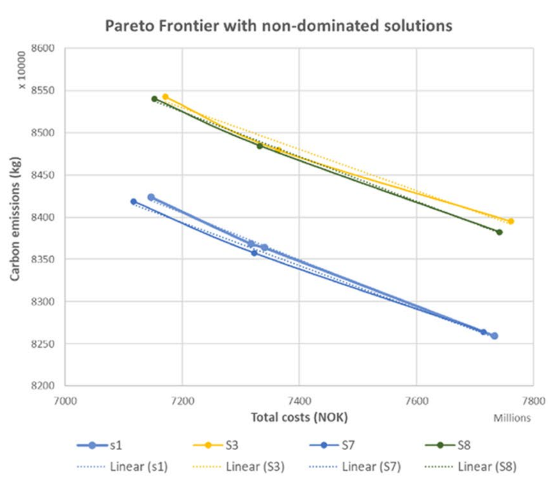
(B) Pareto Frontiers with non-dominated solutions of S0 and S1.



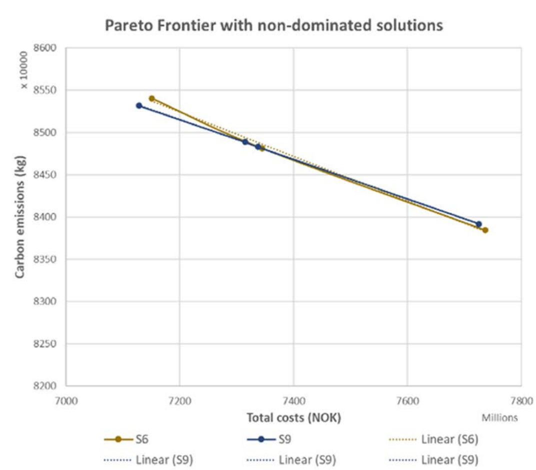
(C) Pareto Frontiers with dominated solutions of S0, S1, S2, S3, S4, S5, and S6.



(D) Pareto Frontiers with non-dominated solutions of S0, S1, S2, S3, S4, S5, and S6.



(E) Pareto Frontiers with non-dominated solutions of S1 vs. S7 and S3 vs. S8.



(F) Pareto Frontiers with non-dominated solutions of S6 vs. S9.

Fig. 7 Simulation results

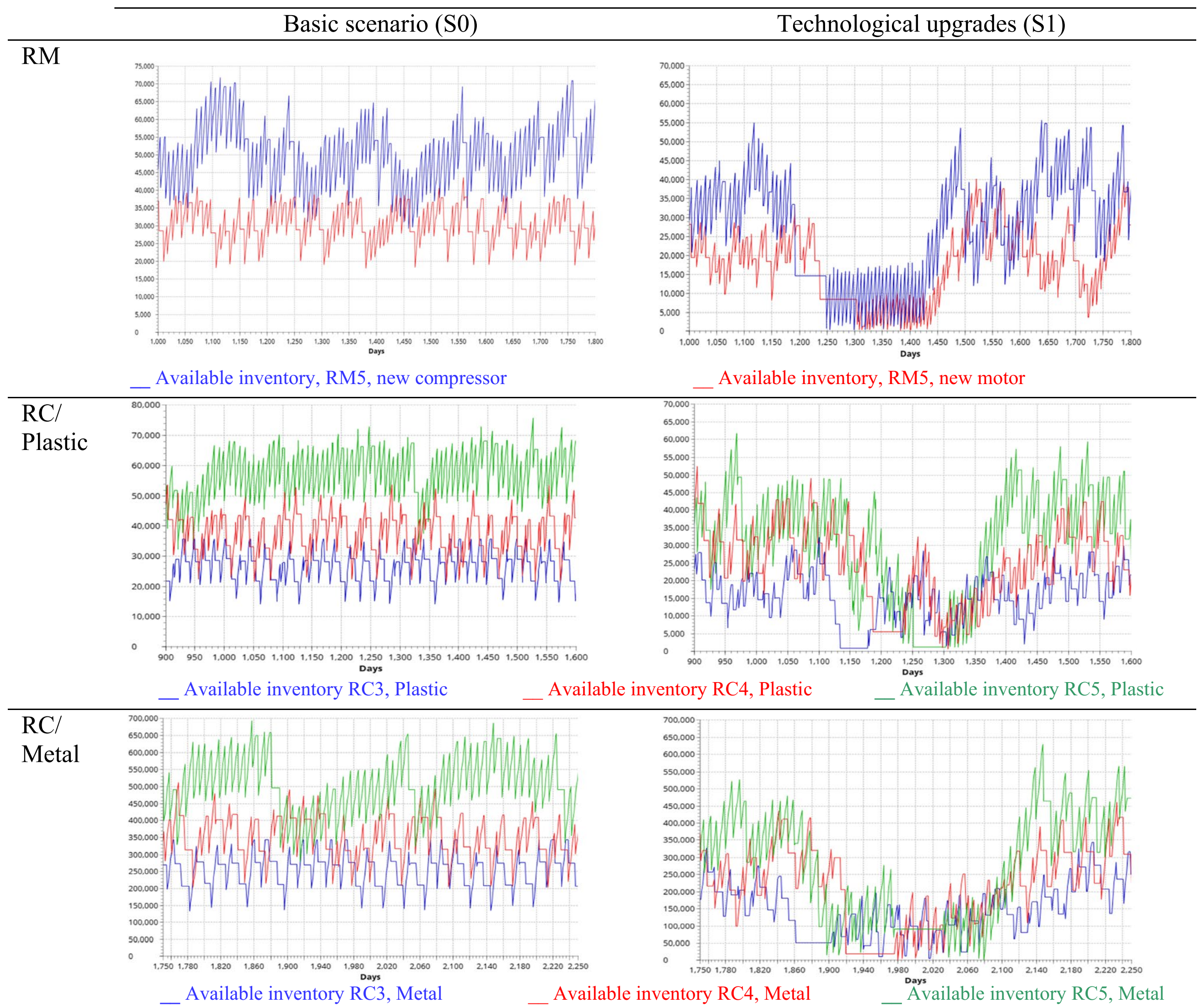


Fig. 8 The change of inventory level during facility upgrades of network 4

Table 7 Comparison of the service levels of network 4

Product	Order fulfillment rate		Late order	
	S0	S1	S0	S1
q1 (compressor)	94.4%	90%	3	15
q2 (metal)	98.8%	97.7%	6	13
q3 (plastic)	98.2%	97.8%	10	9
q4 (motor)	96.7%	90.4%	2	13

reverse logistics system and need thus to be holistically considered in the network design.

Finally, we observed the inventory change during the facility upgrades. Figure 8 depicts the change in inventory level at the respective facilities of network 4 in S1. Due to the production line being temporarily closed during the period of facility upgrades, this disruption led to a reduction of the available inventory of new products. At the remanufacturing plant, it took nearly 6 months after the facility upgrades to restore the normal inventory level of the new motor, and for the new compressor, the recovery time of the inventory level was approximately 10 months. At the recycling plants, the inventory levels of the recycled plastic began to drop when the disruption had occurred, and recycling plants 3 and 4 took a short time to restore their normal inventory level, while nearly 4 months were needed for recycling plant 5. For metal recycling, the recovery time of inventory level at all plants was approximately 8 months. These disruptions at the remanufacturing plant and the recycling plants may cause a ripple effect throughout the reverse logistics system, which may further cause backlogs of customer orders and excessive inventory at regional collection centers. Thus, the service level of the reverse logistics system will be drastically influenced. For example, as shown in Table 7, the smart transformation in S1 may yield more significant impacts on the remanufacturing process, which leads to 4.4% and 6.3% reductions in the overall order fulfillment rates of q1 and q4. Meanwhile, the late orders of these two remanufactured products increase by 400% and 550%, respectively.

6.3 Discussions and implications

Although our analysis focuses on a specific case study, it opens discussions that address the key research questions proposed:

RQ1: By using the two-level decision-support framework, the impact of technology transformation in Industry 4.0 on reverse logistics network design can be better analyzed under uncertainties and practical operational policies. The results show the weakness of the optimization models used in most previous literature, say, a mathematically optimized solution may become a dominated or near-dominated solution when considering new technology adoption and the complexity of real-life situations. In this regard, the second-level simulation model is an enhanced approach for effectively eliminating these dominated solutions, yielding robust strategic facility location decisions and comprehensive performance analyses. Consequently, the proposed framework outperforms traditional optimization-only decision models, providing enhanced support for reverse logistics network design and facilitating the adoption of new technologies in Industry 4.0.

RQ2: Smart transformation by adopting new technologies in Industry 4.0 may affect both the economic and environmental performances of reverse logistics systems, particularly in the long run. As shown, the trend of the Pareto frontier may be changed by the future adoption of new Industry 4.0 technologies, and opening more facilities for emission reduction in the initial optimal solutions may become less attractive from a long-term perspective. Moreover, the schedule and the expected influence of technological upgrades may have significant impacts on the system's performance. In addition, the temporary facility closure may yield a ripple effect and lead to a reduced service level for both the EOL product collection and the supply of recovered products and materials. Thus, technological upgrades need to be planned in a smart and coordinated way to maximize performance improvement while minimizing the disruption of the reverse flows.

Even though the discussions are based on a case study in Norway, it shows the behavior and performance of a reverse logistics network can be better analyzed with the proposed decision-support framework. Furthermore, four generic implications can be given based on the discussions:

1. The adoption of new technologies and smart transformations within Industry 4.0 could significantly impact decision-making and performance in reverse logistics networks, e.g., overall operating costs, carbon emissions, and service levels, throughout the planning horizon. Thus, these factors must be comprehensively considered and analyzed at the initial network design stage.
2. Timing and collaboration are of crucial importance in adopting Industry 4.0 technologies for the smart transformation of reverse logistics systems. Proper timing and collaborative planning can reduce costs, enhance environmental performance, and minimize disruptions to operations and service levels.
3. In addition, new technologies, cutting-edge tools, and digital platforms in Industry 4.0 provide opportunities to better visualize the reverse logistics system and effectively integrate different sources of data and decision models, e.g., optimization models and advanced simulation models, to better support more challenging decisions with real-life complexities.
4. Finally, from a methodological standpoint, employing advanced simulation analysis can effectively address the limitations of optimization-only modeling in the design of smart and sustainable reverse logistics networks, such as dominated solutions under realistic conditions.

7 Conclusions

In this paper, a two-level decision-support framework is proposed for smart and sustainable reverse logistics network design. A bi-objective MIP is first used to calculate a set of Pareto optimal solutions balancing both total operating costs and carbon emissions, which are considered candidate reverse logistics networks. In the second level, DES models are built with stochastic parameters, dynamic features, operational policies, technological upgrades, and a realistic planning horizon. The application of the proposed decision-support framework is shown through a real-world case study of WEEE reverse logistics in Norway.

The experimental results illustrate that smart transformation driven by Industry 4.0 may affect both the economic and environmental performances of a reverse logistics system, and the carbon emissions from a more economically efficient network may be largely reduced by new technology adoption in the later stage at a much lower cost. Besides, the incorporation of the DES model can well complement the shortcomings of the traditional optimization-only models and can thus help to yield better performance analyses of various scenarios and robust strategic facility location decisions. Furthermore, by systematically incorporating Industry 4.0 innovations, the proposed framework not only enhances decision-making capabilities but also fosters resilience and adaptability in reverse logistics networks, ensuring they are equipped to handle future challenges.

7.1 Industrial and managerial implications

This paper provides a hands-on decision-support framework to combine optimization models and advanced simulation methods, which allows policymakers, supply chain managers, companies in reverse logistics, etc., to optimize the strategic network decisions and to evaluate new technologies and new operational policies holistically. With the help of DES, the system behavior and performance, e.g., inventory, service level, etc., can be analyzed more thoroughly. Furthermore, the analysis of the real-world case study of sustainable WEEE management in Norway may provide some practical insights and generic managerial implications for Industry 4.0 technology adoption and smart reverse logistics transformation.

7.2 Research implications

This paper provides new perspectives for inspiring researchers in reverse logistics network design, which is dominated by using a single method today. From the methodological perspective, different analytical methods, i.e., predictive analytics, prescriptive analytics, and descriptive analytics [44], need to be further integrated to better model the characteristics of a reverse logistics system, particularly the impact of Industry 4.0. From the system integration perspective, the effective and seamless integration of different platforms to implement these analytical methods is still at the beginning stage due to several technological challenges, e.g., database conversion, software flexibility, etc. Thus, this paper provides a generic structure for the next-generation smart digital reverse logistics twin [44].

7.3 Limitations and future research

This paper has four main limitations. First, the parametric uncertainty is not considered in the bi-objective MIP model but is assessed by the simulation. However, uncertainty may affect the strategic location decisions in reverse logistics network design. Second, validating the method with a single case study may be incapable of fully demonstrating the impacts of Industry 4.0 and new technologies on smart reverse logistics transformation, particularly considering the sparsely populated nature of Norway, and different insights may be obtained from other regions. Third, several assumptions have been made due to data unavailability, e.g., quantitative data related to smart transformation. Fourth, the analysis currently only considers carbon emissions as a metric of environmental performance. However, incorporating other sustainability indicators could provide a more comprehensive view. In addition, the analysis should account for variations across different industries, such as those in the low-carbon sector, to enhance its applicability and accuracy.

Therefore, future research is suggested to tackle these limitations. For example, the optimization model can be enhanced with uncertain parameters and constraints, e.g., robust optimization, to ensure more reliable strategic decisions. Besides, the application and validation of the proposed method in other regions and with more comprehensive datasets and sustainability indicators are expected.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00170-024-14121-6.

Acknowledgements Thanks are due to the editor and the anonymous reviewers for their invaluable comments and suggestions.

Author contribution Xu Sun: conceptualization, methodology, data curation, software, investigation, formal analysis, validation, writing—original draft, writing—review and editing. Hao Yu: conceptualization, methodology, data curation, software, investigation, formal analysis, validation, funding acquisition, writing—original draft, writing—review and editing. Wei Deng Solvang: conceptualization, funding acquisition, writing—review and editing. Kannan Govindan: conceptualization, writing—review and editing.

Funding Open access funding provided by UiT The Arctic University of Norway (incl University Hospital of North Norway). This research is supported by the Industry 5.0 enabled Smart Logistics: A Global Perspective project financed by the Norwegian Directorate for Higher Education and Skills (HK-dir) under the Utforsk Programme (Grant: UTF-2021/10166) and by the UiT Aurora project MASCOT.

Declarations

Competing interests The authors declare no competing interests.

References

1. Abid S, Mhada FZ (2021) Simulation optimisation methods applied in reverse logistics: a systematic review. Int J Sustain Eng 14:1463–1483

2. Acea (2017) Reducing CO2 emissions from heavy-duty vehicles. Accessed on: https://reducingco2together.eu/assets/pdf/trucks.pdf [09.02.2022]
3. Acea (2020) CO2 emissions from heavy-duty vehicles preliminary CO2 baseline (Q3-Q4 2019) estimate. Accessed on: https://www.acea.auto/uploads/publications/ACEA_preliminary_CO2_baseline_heavy-duty_vehicles.pdf [01.06.2021]
4. Alamerew YA, Brissaud D (2020) Modelling reverse supply chain through system dynamics for realizing the transition towards the circular economy: a case study on electric vehicle batteries. J Clean Prod 254:120025
5. Ameli M, Mansour S, Ahmadi-Javid A (2019) A simulation-optimization model for sustainable product design and efficient end-of-life management based on individual producer responsibility. Resour Conserv Recycl 140:246–258
6. Barbosa-Póvoa AP, Da Silva C, Carvalho A (2018) Opportunities and challenges in sustainable supply chain: an operations research perspective. Eur J Oper Res 268:399–431
7. Bottani E, Montanari R, Rinaldi M (2019) Simulation and performance improvement of a reverse logistics system for waste electrical and electronic equipment: a case study in Italy. Int J Simul Process Model 14:308–323
8. Budak A (2020) Sustainable reverse logistics optimization with triple bottom line approach: an integration of disassembly line balancing. J Clean Prod 270:122475
9. Che A, Lei J, Jiang Z (2021) Optimised redesign of reverse logistics network with multi-level capacity choices for household appliances. Int J Prod Res 60:1–18
10. Choi TM, Kumar S, Yue X, Chan HL (2022) Disruptive technologies and operations management in the Industry 4.0 era and beyond. Prod Oper Manag 31:9–31
11. Chung S-H (2021) Applications of smart technologies in logistics and transport: a review. Transp Res Part E: Logist Transp Rev 153:102455
12. Corning 2021. Sustainability, WEEE information-Norway, WEEE compliance information for Corning customers in Norway. Available on: https://www.corning.com/in/en/sustainability/articles/preservation/environmental-protection/weee-information-for-corning-customers-and-recyclers/norway.html [20.06.2021]
13. Costa-Salas Y, Sarache W, Überwimmer M (2017) Fleet size optimization in the discarded tire collection process. Res Transp Bus Manag 24:81–89
14. Costa Y, Duarte A, Sarache W (2017) A decisional simulation-optimization framework for sustainable facility location of a biodiesel plant in Colombia. J Clean Prod 167:174–191
15. De Oliveira RL, Fagundes LD, Da Silva Lima R, Montaño M (2019) Discrete event simulation to aid decision-making and mitigation in solid waste management. Mitig Adapt Strat Global Change 25:67–85
16. Delgado O, Rodríguez F, Muncrief R (2017) Fuel efficiency technology in European heavy-duty vehicles: baseline and potential for the 2020–2030 timeframe. Available on: https://theicct.org/sites/default/files/publications/EU-HDV-Tech-Potential_ICCT-white-paper_14072017_vF.pdf [20.07.2021]
17. Dev NK, Shankar R, Swami S (2020) Diffusion of green products in industry 4.0: reverse logistics issues during design of inventory and production planning system. Int J Prod Econ 223:107519
18. Dias AS, Kim H, Sivakumar PK, Liu Z-C, Zhang H-C (2013) Life cycle assessment: a comparison of manufacturing and remanufacturing processes of a diesel engine. Springer, Reengineering Manufacturing for Sustainability
19. Directive E (2012) Directive 2012/19/EU of the European Parliament and of the Council of 4 July 2012 on waste electrical and electronic equipment, WEEE. Official Journal of the European Union L 197:38–71
20 Dolgui A, Ivanov D, Sokolov B (2022) Supply network dynamics and control. Springer Nature
21. Du D (2021) Supply chain management: inventory management. Faculty of Business Administration, University of New Brunswick. Available on: http://www2.unb.ca/~ddu/4690/Lecture_notes/Lec2.pdf [15.07.2021]
22. Elia V, Gnoni MG, Tornese F (2018) Improving logistic efficiency of WEEE collection through dynamic scheduling using simulation modeling. Waste Manage 72:78–86
23. Elia V, Gnoni MG, Tornese F (2019) Designing a sustainable dynamic collection service for WEEE: an economic and environmental analysis through simulation. Waste Manage Res 37:402–411
24. Eurostat (2021a) End-of-life vehicles - reuse, recycling and recovery, totals (online data code: ENV_WASELVT). Available on: https://ec.europa.eu/eurostat/databrowser/view/ENV_WASELVT/default/table?lang=en&category=env.env_was.env_wasst [20.07.2021]
25. Eurostat 2021b. Eurostat's EU partners in environment data management-waste electrical & electronic equipment (WEEE). Available on: https://ec.europa.eu/eurostat/web/waste/links [20.07.2021]
26. Eurostat, E. W. 2021c. Waste electrical and electronic equipment (WEEE) by waste management operations. Accessed on: https://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do [12.05.2021].
27. Farrokh M, Azar A, Jandaghi G, Ahmadi E (2018) A novel robust fuzzy stochastic programming for closed loop supply chain network design under hybrid uncertainty. Fuzzy Sets Syst 341:69–91
28. Figueira G, Almada-Lobo B (2014) Hybrid simulation–optimization methods: a taxonomy and discussion. Simul Model Pract Theory 46:118–134
29. Fleischmann M, Bloemhof-Ruwaard JM, Beullens P, Dekker R (2004) Reverse logistics network design. Springer, Reverse logistics
30 Fu C, Fu C, Michael M (2015) Handbook of simulation optimization. Springer
31. Gao X, Cao C (2020) A novel multi-objective scenario-based optimization model for sustainable reverse logistics supply chain network redesign considering facility reconstruction. J Clean Prod 270:122405
32. Ghisolfi V, Chaves G, Siman RR, Xavier LH (2017) System dynamics applied to closed loop supply chains of desktops and laptops in Brazil: a perspective for social inclusion of waste pickers. Waste Manage 60:14–31
33. Gholizadeh H, Fazlollahtabar H, Khalilzadeh M (2020) A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using big data. J Clean Prod 258:120640
34. Gianesello P, Ivanov D, Battini D (2017) Closed-loop supply chain simulation with disruption considerations: a case-study on Tesla. Int J Invent Res 4:257–280
35. Gk (2021) How to start a recycling business: cost and all. Available on: https://www.generalkinematics.com/blog/cost-starting-full-force-recycling-program/ [16.05.2021]
36. Gonçalves ATT, Fagundes LD, De Carvalho Miranda R, Da Silva Lima R (2019) Discrete event simulation as a decision-making tool for end-of-life tire reverse logistics in a Brazilian city consortium. Environ Sci Pollut Res 26:23994–24009
37. Govindan K, Gholizadeh H (2021) Robust network design for sustainable-resilient reverse logistics network using big data:

a case study of end-of-life vehicles. Transp Res Part E: Logist Transp Rev 149:102279
38. Govindan K, Nosrati-Abarghooee S, Nasiri MM, Jolai F (2022) Green reverse logistics network design for medical waste management: a circular economy transition through case approach. J Environ Manage 322:115888
39. Govindan K, Paam P, Abtahi A-R (2016) A fuzzy multi-objective optimization model for sustainable reverse logistics network design. Ecol Ind 67:753–768
40. Govindan K, Soleimani H, Kannan D (2015) Reverse logistics and closed-loop supply chain: a comprehensive review to explore the future. Eur J Oper Res 240:603–626
41. Ivanov D (2017) Simulation-based ripple effect modelling in the supply chain. Int J Prod Res 55:2083–2101
42. Ivanov D (2018) Revealing interfaces of supply chain resilience and sustainability: a simulation study. Int J Prod Res 56:3507–3523
43. Ivanov D (2019) Disruption tails and revival policies: a simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods. Comput Ind Eng 127:558–570
44. Ivanov D, Dolgui A (2020) A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod Plan Control 32:775
45. Jayant A, Gupta P, Garg S (2014) Reverse logistics network design for spent batteries: a simulation study. Int J Logist Syst Manag 18:343–365
46. John ST, Sridharan R, Kumar PNR (2018) Reverse logistics network design: a case of mobile phones and digital cameras. Int J Adv Manuf Technol 94:615–631
47. Josefsson E (2019) Industry 4.0 can be a game changer for climate action. Accessed on: https://www.ericsson.com/en/blog/2019/9/industry-4.0-can-be-a-game-changer-for-climate-action [09.02.2022]
48. Kannan D, Diabat A, Alrefaei M, Govindan K, Yong G (2012) A carbon footprint based reverse logistics network design model. Resour Conserv Recycl 67:75–79
49. Kannan D, Solanki R, Darbari JD, Govindan K, Jha P (2023) A novel bi-objective optimization model for an eco-efficient reverse logistics network design configuration. J Clean Prod 394:136357
50. Kara S, Rugrungruang F, Kaebernick H (2007) Simulation modelling of reverse logistics networks. Int J Prod Econ 106:61–69
51. Kazemi N, Modak NM, Govindan K (2019) A review of reverse logistics and closed loop supply chain management studies published in IJPR: a bibliometric and content analysis. Int J Prod Res 57:4937–4960
52. Khakbaz A, Tirkolaee EB (2022) A sustainable hybrid manufacturing/remanufacturing system with two-way substitution and WEEE directive under different market conditions. Optimization 71:3083–3106
53. Kuşakcı AO, Ayvaz B, Cin E, Aydın N (2019) Optimization of reverse logistics network of end of life vehicles under fuzzy supply: a case study for Istanbul metropolitan area. J Clean Prod 215:1036–1051
54. Liu S, Zhang Y, Liu Y, Wang L, Wang XV (2019) An 'internet of things' enabled dynamic optimization method for smart vehicles and logistics tasks. J Clean Prod 215:806–820
55. Mantelli A, Levi M, Turri S, Suriano R (2019) Remanufacturing of end-of-life glass-fiber reinforced composites via UV-assisted 3D printing. Rapid Prototyp J 26:981
56. Mavrotas G (2009) Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. Appl Math Comput 213:455–465
57. Melo MT, Nickel S, Saldanha-Da-Gama F (2009) Facility location and supply chain management–a review. Eur J Oper Res 196:401–412
58. Nayeri S, Paydar MM, Asadi-Gangraj E, Emami S (2020) Multi-objective fuzzy robust optimization approach to sustainable closed-loop supply chain network design. Comput Ind Eng 148:106716
59. Neto RO, Gastineau P, Cazacliu BG, Le Guen L, Paranhos RS, Petter CO (2017) An economic analysis of the processing technologies in CDW recycling platforms. Waste Manage 60:277–289
60. Okorie O, Charnley F, Ehiagwina A, Tiwari D, Salonitis K (2024) Towards a simulation-based understanding of smart remanufacturing operations: a comparative analysis. J Remanuf 14:45–68
61. Oliveira JB, Jin M, Lima RS, Kobza JE, Montevechi JAB (2019) The role of simulation and optimization methods in supply chain risk management: performance and review standpoints. Simul Model Pract Theory 92:17–44
62. Oliveira JB, Lima RS, Montevechi JAB (2016) Perspectives and relationships in supply chain simulation: a systematic literature review. Simul Model Pract Theory 62:166–191
63. Olsen TL, Tomlin B (2020) Industry 4.0: opportunities and challenges for operations management. Manuf Serv Oper Manag 22:113–122
64. Park J, Jung I, Choi W, Choi SO, Han SW (2019) Greenhouse gas emission offsetting by refrigerant recovery from WEEE: a case study on a WEEE recycling plant in Korea. Resour Conserv Recycl 142:167–176
65. Pishvaee MS, Jolai F, Razmi J (2009) A stochastic optimization model for integrated forward/reverse logistics network design. J Manuf Syst 28:107–114
66. Pishvaee MS, Kianfar K, Karimi B (2010) Reverse logistics network design using simulated annealing. Int J Adv Manuf Technol 47:269–281
67. Pishvaee MS, Torabi SA (2010) A possibilistic programming approach for closed-loop supply chain network design under uncertainty. Fuzzy Sets Syst 161:2668–2683
68. Rachih H, Mhada FZ, Chiheb R (2019) Meta-heuristics for reverse logistics: a literature review and perspectives. Comput Ind Eng 127:45–62
69. Rahimi M, Ghezavati V (2018) Sustainable multi-period reverse logistics network design and planning under uncertainty utilizing conditional value at risk (CVaR) for recycling construction and demolition waste. J Clean Prod 172:1567–1581
70. Ramos TRP, Gomes MI, Barbosa-Póvoa AP (2014) Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. Omega 48:60–74
71. Raychaudhuri S (2008) Introduction to Monte Carlo simulation. Proceeding of the (2008) Winter Simulation Conference, Miami, FL, USA. IEEE 91–100. https://doi.org/10.1109/WSC.2008.4736059
72. Reddy KN, Kumar A, Choudhary A, Cheng TE (2022) Multi-period green reverse logistics network design: an improved Benders-decomposition-based heuristic approach. Eur J Oper Res 303:735–752
73. Reddy KN, Kumar A, Sarkis J, Tiwari MK (2020) Effect of carbon tax on reverse logistics network design. Comput Ind Eng 139:106184
74. Rentizelas A, Trivyza N, Oswald S, Siegl S (2021) Reverse supply network design for circular economy pathways of wind turbine blades in Europe. Int J Prod Res 60:1795
75. Ritchie N, Smith C (2009) Comparison of greenhouse gas emissions from waste-to-energy facilities and the Vancouver landfill. City of Vancouver
76. Rogers DS, Tibben-Lembke R (2001) An examination of reverse logistics practices. J Bus Logist 22:129–148

77. Safdar N, Khalid R, Ahmed W, Imran M (2020) Reverse logistics network design of e-waste management under the triple bottom line approach. J Clean Prod 272:122662
78. Shahparvari S, Soleimani H, Govindan K, Bodaghi B, Fard MT, Jafari H (2021) Closing the loop: redesigning sustainable reverse logistics network in uncertain supply chains. Comput Ind Eng 157:107093
79. Shi J, Li T, Peng S, Liu Z, Zhang H, Jiang Q (2015) Comparative life cycle assessment of remanufactured liquefied natural gas and diesel engines in China. J Clean Prod 101:129–136
80. Shokohyar S, Mansour S (2013) Simulation-based optimisation of a sustainable recovery network for waste from electrical and electronic equipment (WEEE). Int J Comput Integr Manuf 26:487–503
81. Srivastava SK (2008) Network design for reverse logistics. Omega 36:535–548
82. Ssb 2021. Population of municipalities in Norway (2021). Accessed on: https://www.ssb.no/en/statbank/table/11366/tableViewLayout1/ [04.05.2021]
83. Sun X, Yu H, Solvang WD (2022) Towards the smart and sustainable transformation of Reverse Logistics 4.0: a conceptualization and research agenda. Environ Sci Pollut Res 29:69275
84. Symons K (2021) Green-tech and Industry 4.0: supporting a sustainable future. Accessed on: https://www.orange-business.com/en/blogs/green-tech-and-industry-40-supporting-sustainable-future [09.02.2022]
85. Timperio G, Tiwari S, Gaspar Sánchez JM, García Martín RA, De Souza R (2020) Integrated decision support framework for distribution network design. Int J Prod Res 58:2490–2509
86. Tosarkani BM, Amin SH, Zolfagharinia H (2020) A scenario-based robust possibilistic model for a multi-objective electronic reverse logistics network. Int J Prod Econ 224:107557
87. Trochu J, Chaabane A, Ouhimmou M (2019) A two-stage stochastic optimization model for reverse logistics network design under dynamic suppliers' locations. Waste Manage 95:569–583
88. Trochu J, Chaabane A, Ouhimmou M (2020) A carbon-constrained stochastic model for eco-efficient reverse logistics network design under environmental regulations in the CRD industry. J Clean Prod 245:118818
89. Vailshery LS (2017) Major electrical household appliances sales value in Norway 2016, by type of product. Accessed on: https://www.statista.com/statistics/746662/major-electrical-household-appliances-sales-value-in-norway-by-type-of-product/ [10.05.2021]
90. Wang XV, Wang L (2019) Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0. Int J Prod Res 57:3892–3902
91. Wang Y, Zhe J, Wang X, Fan J, Wang Z, Wang H (2022) Collaborative multicenter reverse logistics network design with dynamic customer demands. Expert Syst Appl 206:117926
92. Wef 2017. Technology and innovation for the future of production: accelerating value creation. Accessed on: https://www3.weforum.org/docs/WEF_White_Paper_Technology_Innovation_Future_of_Production_2017.pdf [10.02.2022]
93. Xiao Z, Sun J, Shu W, Wang T (2019) Location-allocation problem of reverse logistics for end-of-life vehicles based on the measurement of carbon emissions. Comput Ind Eng 127:169–181
94. Xu W, Cui J, Liu B, Liu J, Yao B, Zhou Z (2021) Human-robot collaborative disassembly line balancing considering the safe strategy in remanufacturing. J Clean Prod 324:129158
95. Yan R, Yan B (2019) Location model for a remanufacturing reverse logistics network based on adaptive genetic algorithm. Simul-Trans Soc Model Simul Int 95:1069–1084
96. Yang CX, Chen JG (2020) Robust design for a multi-echelon regional construction and demolition waste reverse logistics network based on decision maker's conservative attitude. J Clean Prod 273:122909
97. Ylä-Mella J, Poikela K, Lehtinen U, Tanskanen P, Román E, Keiski RL, Pongrácz E (2014) Overview of the WEEE directive and its implementation in the Nordic countries: national realisations and best practices. J Waste Manag 2014:457372
98. Yu H, Solvang WD (2018) Incorporating flexible capacity in the planning of a multi-product multi-echelon sustainable reverse logistics network under uncertainty. J Clean Prod 198:285–303
99. Yu H, Solvang WD (2020) A fuzzy-stochastic multi-objective model for sustainable planning of a closed-loop supply chain considering mixed uncertainty and network flexibility. J Clean Prod 266:121702
100. Yu H, Sun X, Solvang WD, Laporte G, Lee CKM (2020) A stochastic network design problem for hazardous waste management. J Clean Prod 277:123566
101. Zarbakhshnia N, Kannan D, Mavi RK, Soleimani H (2020) A novel sustainable multi-objective optimization model for forward and reverse logistics system under demand uncertainty. Ann Oper Res 295:843–880
102. Zarbakhshnia N, Soleimani H, Goh M, Razavi SS (2019) A novel multi-objective model for green forward and reverse logistics network design. J Clean Prod 208:1304–1316
103. Zhang L, Chen F, Ma X, Pan X (2020) Fuel economy in truck platooning: a literature overview and directions for future research. J Adv Transp 2020:2604012
104. Zhang Y, Liu S, Liu Y, Yang H, Li M, Huisingh D, Wang L (2018) The 'internet of things' enabled real-time scheduling for remanufacturing of automobile engines. J Clean Prod 185:562–575
105. Zolfagharinia H, Hafezi M, Farahani RZ, Fahimnia B (2014) A hybrid two-stock inventory control model for a reverse supply chain. Transp Res Part E: Logist Transp Rev 67:141–161

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.