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Uncertain remanufacturing reverse logistics network design in industry 5.0: Opportunities and challenges of digitalization

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ABSTRACT

Remanufacturing, a crucial step of reverse logistics, focuses on restoring or enhancing the functionality of waste products. The challenge in planning an effective remanufacturing reverse logistics system lies in the uncertainties from various sources. In addition, the evolving industrial landscape in Industry 5.0 necessitates adaptability to technological advancements. This paper proposes an integrated and digitalized architecture for uncertain reverse logistics network design. A fuzzy optimization model is first formulated to identify potential network configurations under varying demand-satisfying and capacity constraints. These solutions are automatically converted and assessed in a dynamic simulation environment with practical operational logic under a set of real-world scenarios. Numerical experiments are performed to validate the method and show the advantages of integrating optimization with dynamic simulation on a digital platform for strategic network planning. The results, built upon previous research, indicate that while initial investments in technology might be substantial, they may lead to long-term reductions in both costs and emissions. Moreover, collaborative decision-making is essential to mitigate potential disruptions and cascading effects. Our research contributes to the development of a novel integrated decision-support architecture and underscores the role of digitalization and Industry 5.0 in future smart and sustainable reverse logistics planning.

1. Introduction

To survive in the increasingly dynamic and globalized market, manufacturing companies and logistics systems need to adopt cutting-edge technologies to provide better-designed products and individualized services. However, the changing lifestyles and consumption patterns have led to drastically shortened product lifecycles and, consequently, increased quantity of both end-of-use (EOU) and end-of-life (EOL) returns (Mmereki et al., 2015). While the EOU return may promote new and e-commerce-based business models, the increased EOL products put a significant challenge on global waste management systems, which, if inappropriately treated, may cause adverse environmental impacts, waste of resources, excessive carbon emissions, and significant risks to the residents. For example, the worldwide generation of waste electrical and electronic equipment (WEEE) has increased to 53.6 million tonnes (Mairizal et al., 2021), among which only 17.4% were recorded for recycling (Forti et al., 2020). A recent study has shown that the exportation of WEEE plastics from the European Union may result in improper treatments and sustainability challenges (Cardamone et al., 2021). Furthermore, consumers are now becoming increasingly environmentally conscious and sustainability-focused (Caniato et al., 2012), which requires manufacturing companies to improve their social image by taking responsibility for the value recovery of their products in the EOL stage (Agarwal et al., 2016). Recently, proposed by the European Commission, the Industry 5.0 concept, namely the fifth Industrial Revolution, has put predominant focuses on sustainability, resilience, and human centricity (Jafari et al., 2022), which are considered the three pillars to support the transition of future manufacturing industries, supply chains, and even the whole society (Xu et al., 2021a).

Reverse logistics is a fundamental stage to achieving sustainable manufacturing and supply chains, which aims at recovering the remaining values from EOL products in compliance with stringent environmental policies and regulations (Shukla et al., 2022). Reverse logistics comprises different operations such as source collection/separation, disassembly and sorting, repair and reselling, remanufacturing, and material recycling (Kannan et al., 2023). The remaining residues and non-recyclables are sent for incineration or landfills. While

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recycling aims primarily at material recovery through, for instance, melting, refining, and reprocessing (Li et al., 2004), remanufacturing, on the other hand, focuses on restoring EOL products to at least their original functionality and performance (Abd Aziz et al., 2021), often, utilizing a combination of repair, refurbishment, and replacement of worn-out components with an aim of extending the product's lifecycle. Remanufacturing can provide equivalent functionality, quality standards, and warranty service as a newly manufactured product (Matsumoto and Ijomah, 2013). In some cases, remanufactured products need to reach a higher quality standard to comply with the new requirements (Beamon, 1999). As an essential link of reverse logistics, remanufacturing helps to enhance the triple-bottom-line of sustainable development (Raz et al., 2017). For instance, Liu et al. (2017) have shown that remanufacturing may help to achieve 50% and 40% savings in cost and energy consumption, respectively. In addition, remanufacturing can help create new job opportunities and enhance regional development. A large portion of jobs created only require entry-level skills, which helps to improve the social equity for less skilled workers (Matsumoto and Ijomah, 2013).

Designing a reverse logistics network is strategically important for the relevant stakeholders. However, it is complex due to high uncertainties from unstable return quantity and varied and unpredictable product quality (Ilgin and Gupta, 2013). Furthermore, the upcoming paradigm change of Industry 5.0 brings both opportunities and challenges. On the one hand, new technologies and solutions, i.e., additive manufacturing (AM), cleaner energy, internet of things (IoT), smart and collaborative robots, etc., are enablers for a digital transition, which allows sustainability goals can be better met in reverse logistics (Sun et al., 2022b; Teixeira et al., 2022). For example, employing AM and collaborative robots can drastically improve the effectiveness of remanufacturing operations (Kerin and Pham, 2019). Digital twins and reconfigurable systems may help change product traceability and system flexibility in order to achieve smart remanufacturing (Wang and Wang, 2019; Arnarson et al., 2023). However, on the other hand, performance improvement can be achieved only when new technologies are used in the best way. Thus, new models and methods are needed to better support strategic decisions and operational planning. Furthermore, digital technologies and solutions need to be increasingly used to provide better and more user-friendly interactions for modeling and analysis.

In this paper, our motivation is to provide a more comprehensive understanding of the impact of digitalization and Industry 5.0 in uncertain remanufacturing reverse logistics network design, where not only the quantity and quality variations but also the dynamic parameter changes and possible facility modifications are considered. We also consider two types of parametric uncertainties in the decision-making. One is related to imperfect data and incomplete knowledge, and the other is associated with randomness. The proposed architecture is essentially at two stages. First, a fuzzy optimization model is formulated to optimize the facility location decisions with imperfect data and under different demand-satisfying and capacity requirements. Then, these decisions are systematically evaluated with dynamic simulation models. A cutting-edge digital platform is utilized to seamlessly connect the optimization and dynamic simulation models in order to perform comprehensive analyses with real-road networks, dynamic network configurations, stochasticity, and customized operational policies. On the one hand, by using a digitalized platform, the method can take advantage of both optimization and simulation, while on the other hand, the network decisions can be more comprehensively evaluated considering the different types of uncertainty and the potential impacts of the technological revolution in Industry 5.0.

Thus, through the model development in a two-stage digitalized optimization-simulation platform and comprehensive experiments and analysis, this paper aims to answer the following two research questions.

RQ1: How different analytical methods can be seamlessly combined in a digitalized platform to support uncertain reverse logistics network design?

RQ2: What are the opportunities and challenges brought by digitalization and Industry 5.0 for reverse logistics planning and operations?

The rest of the paper is structured as follows. An extensive review of uncertain reverse logistics planning is given in Section 2, based on which the literature gaps and our contributions are thoroughly discussed. Section 3 describes the problem, develops the methodology, and formulates the models. Section 4 validates the proposed method with numerical experiments and discusses both managerial and research implications. The last section concludes the paper and recommends future research.

2. Literature review

First, an overall of the methodological development of reverse logistics planning is given, where the models with uncertainty are focused on. Then, we identify the gaps and discuss our contributions.

2.1. Reverse logistics network design

Reverse logistics is a concept that originated in the 1980s, and it describes an inverse material flow compared with that in forward logistics (Murphy, 1986). Starting from the early 1990s, the scope of this terminology was defined as the means to handle returned product flow with the reuse of components and materials, refurbishing, remanufacturing, recycling, and proper waste disposal (Stock, 1998), which helps companies to become more environmentally conscious and efficient (Carter and Ellram, 1998). With the increasing focus on sustainability, climate change, and recourse depletion from the whole society, reverse logistics has been extensively investigated in the last two decades. Several literature reviews were given for comprehensive overviews on theoretical development, methodology, and applications related to network optimization models and methods (Govindan et al., 2015), WEEE recycling (Islam and Huda, 2018), implementation barriers and drivers (Govindan and Bouzon, 2018), and circular economy (Mishra et al., 2023; Ding et al., 2023), to name a few.

Planning an effective reverse logistics system is important yet complex, where quantitative methods and operations research models have been extensively developed since the 1990s (Fleischmann et al., 1997; Dekker et al., 1998). Mixed integer program (MIP) is the most widely used technique to make both nodes (facilities) and arc (flow) decisions in this strategic planning (Fleischmann et al., 2004). For instance, some early research developed MIP models to either minimize the total cost (Cruz-Rivera and Ertel, 2009) or maximize the total profit (Sasikumar et al., 2010) for EOL vehicle recycling networks. Later, several studies considered more practical requirements in decision-making. Alumur et al. (2012) and John et al. (2018) developed multi-period MIPs to accommodate the dynamicity over the planning horizon. Alshamsi and Diabat (2015) took into account both in-house and outsourced transportation options in reverse logistics planning. Ramezani et al. (2013) considered the responsiveness and quality level for joint forward-reverse logistics planning problems. Recently, network flexibility has been increasingly investigated (Shukla et al., 2022; Yu and Solvang, 2018). Incorporating new technologies, e.g., big data, has become another research spotlight in this field (Khoei et al., 2023; Mishra and Singh, 2020).

Apart from the economic perspective, greenness and sustainability are increasingly emphasized in the initial network design stage (Kannan et al., 2012). In this regard, multi-objective program (MOP) has been widely modeled to balance the tradeoff between economic performance and other sustainability objectives. For instance, Amin and Zhang (2013) maximized the benefits of utilizing clean technologies and sustainable materials for joint forward-reverse logistics planning. Yu and Solvang (2016) and Rad and Nahavandi (2018) formulated bi-objective MOPs to balance the cost and greenhouse gas (GHG) emissions for designing sustainable reverse logistics systems. In addition, several studies considered the triple-bottom-line when planning a sustainable reverse logistics system (Budak, 2020). Govindan et al. (2016) incorporated economic, environmental, and social objectives in a MOP model. The environmental performance was measured using eco-indicator 99. The total job creation and the lost working days related to work are employed as indicators for improving social sustainability. Soleimani et al. (2017) investigated a MOP considering the tradeoff among profit, missed working days, and demand satisfaction rate. Safdar et al. (2020) maximized profit and job creation while minimizing the emissions from the WEEE recycling. Employing the Gini index as a measure, Battaïa et al. (2023) considered the social and environmental equity in locating recovery facilities of EOL products.

Since the optimization of reverse logistics planning is of high complexity, the implementation of improved computational algorithms has never lost its appeal. Among others, genetic algorithms (Min et al., 2006; Ko and Evans, 2007) and simulated annealing (Pishvaee et al., 2010) have been the most popular heuristic solutions since the early stage. To solve large problem instances of reverse logistics with multiple conflicting objectives, non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO) have been widely utilized, which can effectively yield Pareto optimal solutions (Zarbakhshnia et al., 2020). The computational effectiveness and efficiency of these methods can be further improved by combining other metaheuristics, e.g., simulated annealing (Farrokhi-Asl et al., 2019), in a hybrid algorithm structure. Besides, the implementation of new algorithms has also been focused on. For instance, Babaeinesami et al. (2022) and Tirkolaee et al. (2022) developed self-adaptive NSGA-II and grey wolf optimization to solve MOPs for sustainable integrated forward-reverse logistics planning problems considering the triple-bottom-line. Recently, the development of accelerated Benders decomposition (Goli and Tirkolaee, 2023; Borajee et al., 2023) and Benders-decomposition-based heuristic approach (Reddy et al., 2022) has gained increasing popularity in solving complex reverse logistics network problems.

2.2. Uncertain reverse logistics models

Uncertainty plays a pivotal role in strategic planning, which reflects the reality of real-world situations and operational environments (Listeş and Dekker, 2005). Ignoring the unpredictable and unstable reverse material flow in decision-making may result in the risk of overly optimistic or pessimistic decisions that do not represent the actual system's behavior. Furthermore, as a long-term decision, the initial network structure needs to be robust enough to adapt to dynamic changes caused, for example, by the upgrades of technologies in Industry 5.0. Therefore, significant efforts have been made for model development to tackle various uncertainties with stochastic optimization, fuzzy methods, robust models, and hybrid methods.

Stochastic optimization is a widely utilized technique for modeling and solving uncertain reverse logistics planning problems, which incorporates the randomness from inputs in decision-making. It has been practiced since the early 2000s (Listeş and Dekker, 2005). Specifically, the two-stage stochastic program provides a well-established structure. The first-stage variables determine facility locations, while the second-stage variables can be recoursed and adjusted in different scenarios (Yu and Solvang, 2020). Demand fluctuations were considered a source of uncertainty in most stochastic models (Lee and Dong, 2009; Salema et al., 2007), while the stochasticity of other parameters, e.g., transportation cost, operating cost, pricing, delay, etc., were also considered in several studies (Pishvaee et al., 2009; Fattahi and Govindan, 2017). Several operational decisions in reverse logistics management, e.g., inventory management, capacity utilization, etc., were also evaluated under uncertainty environments (Khakbaz and Tirkolaee, 2022; Yu, 2022). To incorporate the risk measure of a stochastic reverse logistics model, conditional value at risk (CVaR) was widely implemented (Soleimani and Govindan, 2014; Rahimi and Ghezavati, 2018). Environmental performance is another focus of the recent stochastic reverse logistics network design models. Different carbon control policies (Shuang et al., 2019; Eslamipirharati et al., 2023), environmental regulations (Trochu et al., 2020), and carbon emission objectives (Yu and Solvang, 2018) were considered in stochastic environments. Due to the inherent uncertainty related to scenario generation and computational challenges, approximation methods and simulation-based optimization, e.g., sample average approximation (SAA) (Ayvaz et al., 2015), NSGA-II (Eslamipirharati et al., 2023) and improved Benders decomposition (Borajee et al., 2023), etc., were used to efficiently solve stochastic models.

One challenge to implementing a stochastic model is the data dependency for scenario generation, and the reliability of decision-making may be compromised without high-quality historical data. To solve this problem, fuzzy methods and robust optimization have become increasingly appealing. Fuzzy sets were incorporated into reverse logistics models to deal with imperfect data and incomplete knowledge, which are known as sources of epistemic uncertainty (Pishvaee and Torabi, 2010). In the last decade, fuzzy programming combined with MIP, MOP, and other techniques has been widely used to model sustainable reverse logistics network design (Govindan et al., 2016), integrated assembly-recycling systems (Lu et al., 2020), municipal waste collection (Hashemi, 2021), and EOL vehicle management (Kuşakcı et al., 2019). For example, Shaerpour et al. (2023) proposed a fuzzy MIP to optimize the reverse logistics network for medical waste management under the probability of accidental risk during the Covid-19 pandemic. Nosrati-Abarghooee et al. (2023) modeled a fuzzy-goal programming for medical waste reverse logistics under uncertainty, where a Monte-Carlo simulation (MCS) was employed in the initial stage for the estimation of the waste amount generated.

Robust optimization techniques were introduced in reverse logistics network models in the early 2010s (Pishvaee et al., 2011; Vahdani et al., 2012). Robust optimization uses bounded uncertainty sets to guarantee the solution feasibility under certain conditions, where, unlike stochastic programming, the specific probability distribution is not required. Recently, Kim et al. (2018) investigated a robust forward-reverse logistics network optimization problem. Xu et al. (2021b) developed a robust optimization model for planning a global plastic recycling system. Govindan and Gholizadeh (2021) investigated a robust MOP to design a resilient EOL vehicle recycling system considering big data. Huang et al. (2023) proposed a two-stage robust model and a column- and-constraint-generation-based method to solve the reverse logistics network design in a bike sharing system. Tirkolaee et al. (2024) investigated a bi-objective robust model for minimizing both cost and environmental impact for a waste management system. Karimi et al. (2024) modeled an uncertain healthcare reverse logistics problem during the Covid-19 pandemic using a robust possibilistic programming method.

The complexity of modeling and solution increases drastically when different types of uncertainty are simultaneously taken into account, say, mixed uncertainty. To tackle this challenge, several recent studies model reverse logistics network design problems with hybrid methods, i. e., fuzzy-robust methods (Ghahremani-Nahr et al., 2019) and fuzzy-stochastic methods (Yu and Solvang, 2020).

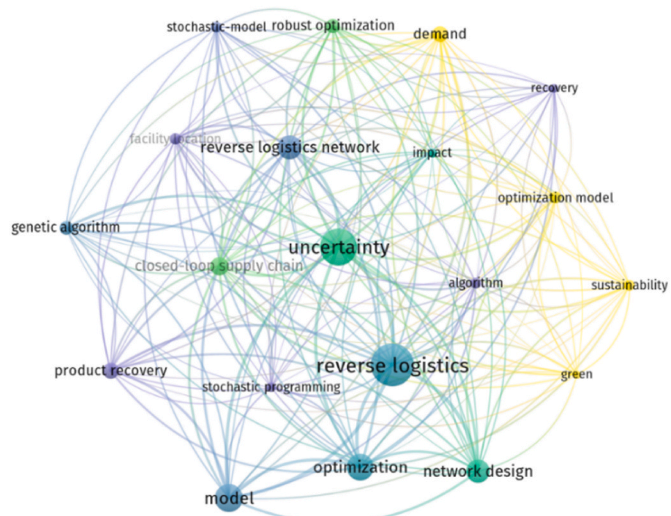


Fig. 1. Uncertain reverse logistics network design.

2.3. Summary

A keyword co-occurrence analysis was performed on the basis of the search results of 418 documents from the Web of Science combining the two keywords of "reverse logistics network design" and "uncertainty". A threshold of 30 co-occurrences was set, which resulted in 21 keywords given in Fig. 1. The analysis shows that the uncertain reverse logistics network design is closely linked to stochastic models and robust programming. In addition, Table 1 gives a vis-à-vis comparison of the uncertain reverse logistics models with respect to the objective functions, uncertain methods, validation, and impact of digitalization and technologies in Industry 5.0.

The literature review shows three major limitations. First, the impact of digitalization and technology adoption in Industry 5.0 has not been investigated for reverse logistics network design, and no modeling efforts have been given to provide quantitative analysis and deep insights into how future-oriented technologies will affect strategic network decision-making. Second, the use of combined optimization-simulation methods is less investigated for the planning of logistics networks (Oliveira et al., 2019). Despite some studies employing simulation either to test the optimal results of the optimization model (Tosarkani et al., 2020) or to generate scenarios for a stochastic model (Ayvaz et al., 2015; Abid and Mhada, 2021), this is just a statistical procedure, say, a MCS, that analyzes the system's behavior through random sampling. A MCS can only evaluate parametric uncertainty but cannot provide a comprehensive analysis of the dynamicity, interaction, and configurational change. In this regard, no research has been done to incorporate advanced or hybrid simulation methods with optimization models in the initial network design of a reverse logistics system. Last but not least, most previous models only consider a single type of uncertainty, and no research has been given to simultaneously consider different types of uncertainty in a dynamic environment.

Table 1
Comparison of uncertain reverse logistics network design.

Research	Objective function			Uncertainty method	Digitalization Industry 4.0/5.0	Validation	
	Econom.	Environm.	Social			Numerical	Case
Govindan et al. (2016)	✓	✓	✓	Fuzzy		✓	
Fattahi and Govindan (2017)	✓			Stochastic		✓	
Kim et al. (2018)	✓			Robust		✓	
Rahimi and Ghezavati (2018)	✓	✓	✓	Stochastic		✓	
Yu and Solvang (2018)	✓	✓		Stochastic		✓	
Ghahremani-Nahr et al. (2019)	✓			Fuzzy-Robust		✓	
Kuşakcı et al. (2019)	✓			Fuzzy			✓
Shuang et al. (2019)	✓	✓		Stochastic			✓
Lu et al. (2020)	✓			Fuzzy		✓	
Tosarkani et al. (2020)	✓			Fuzzy-Robust-MCS			✓
Trochu et al. (2020)	✓	✓		Stochastic			✓
Yu and Solvang (2020)	✓	✓		Fuzzy-Stochastic		✓	
Govindan and Gholizadeh (2021)	✓			Robust			✓
Hashemi (2021)	✓		✓	Fuzzy		✓	
Xu et al. (2021b)	✓	✓		Robust		✓	
Al-Refaie and Kokash (2023)	✓	✓	✓	Stochastic			✓
Borajee et al. (2023)	✓			Stochastic		✓	
Eslamipirharati et al. (2023)	✓		✓	Stochastic		✓	
Huang et al. (2023)	✓			Robust			✓
Nosrati-Abarghooee et al. (2023)	✓		✓	Fuzzy		✓	
Shaerpour et al. (2023)	✓		✓	Fuzzy			✓
Karimi et al. (2024)	✓		✓	Robust-possibilistic			✓
Khalili-Fard et al. (2024)	✓	✓	✓	Stochastic		✓	
Tirkolaee et al. (2024)	✓	✓		Robust		✓	
Yan et al. (2024)	✓	✓		Stochastic			✓
This paper	✓	✓		Fuzzy-possibilistic-sim (MCS + DES)	✓		✓

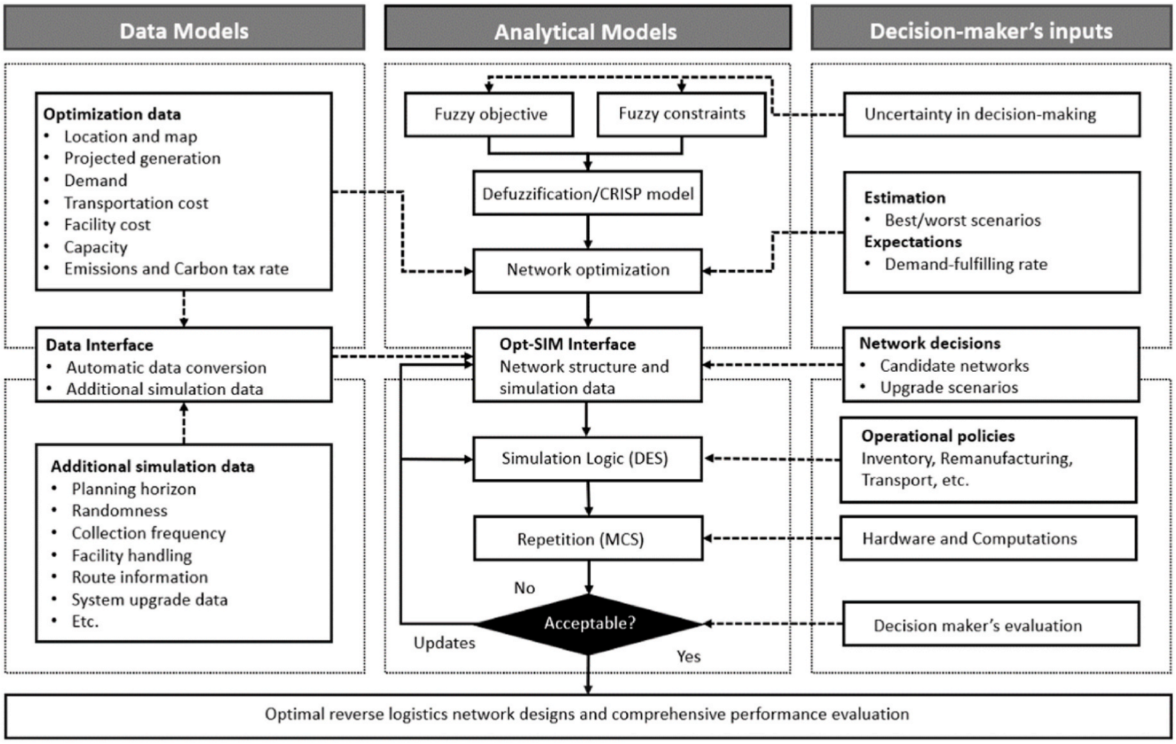


Fig. 2. Digitalized and integrated optimization-simulation architecture.

Thus, to fill the literature gaps, we proposed a digitalized and integrated optimization-simulation architecture. Our scientific contributions are given as follows.

1 We propose a novel digitalized and integrated optimization-simulation architecture for remanufacturing reverse network design under mixed uncertainty.
2 We incorporate dynamic simulation with a fuzzy MIP. Herein, dynamic simulation is a hybrid method that combines both discrete-event simulation (DES) and MCS.
3 We consider epistemic uncertainty, stochasticity, and dynamic system modifications in decision-making.
4 Through the numerical experiment, we illustrate the applicability of the method and discuss both managerial and research implications to reveal the impact of digitalization and Industry 5.0.

3. Methodology

We first introduce the problem and methodological framework. The models and methods are then introduced in detail.

3.1. Problem description and methodological framework

A remanufacturing reverse logistics network design problem is considered concerning: 1) how to configure the network and 2) how to utilize the network, where the use of different operational policies, potential technological adoption, and uncertainty may dynamically influence the network performance and alter the initial network design decisions. The material flow of the system under investigation starts from local waste management companies, which are responsible for EOL product collection from consumers. Based on the demand allocation and proximity, the collected EOL products will then be transported to several large nationwide collection facilities for sorting, disassembly, and cleaning. The remanufacturing company only purchases the high-valued components, which are remanufactured and resold in the market. The non-remanufactured components will then be treated at either the recycling center or the waste disposal plants.

To solve the problem, we propose a digitalized and integrated optimization-simulation architecture that consists of three essential parts, namely, data models, analytical models, and decision-maker's inputs, where the analytical models are the core of the decision support. The methodological framework of a two-stage optimization-simulation cycle is given in Fig. 2. In the first optimization stage, a fuzzy MIP is

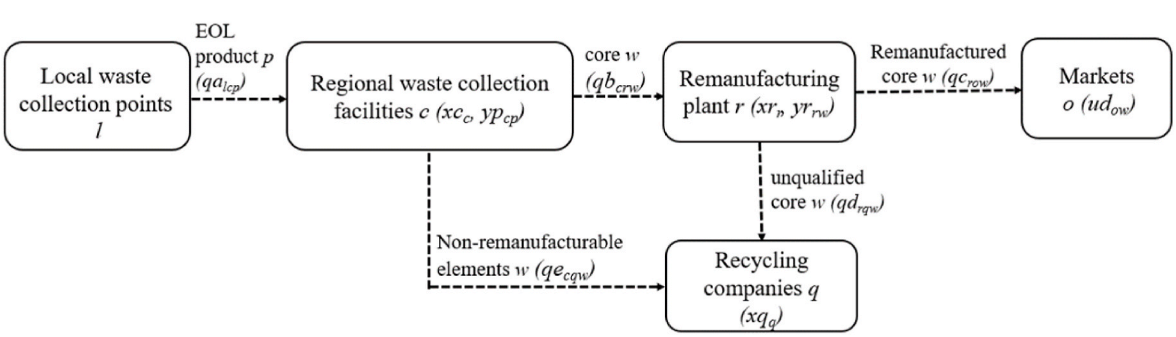


Fig. 3. Network structure of the remanufacturing reverse logistics system.

modeled and solved to obtain a set of candidate network configurations under epistemic uncertainty, and the decision-maker's inputs determine the fuzzy parameters, estimations, and expectations of demand-fulfillment and capacity requirements. The second stage employs the selected outputs of the optimization in building the simulation model. To perform the dynamic simulation, the data in the previous step need to be converted accordingly. For example, the generation of EOL products needs to be disaggregated at a much smaller level, e.g., weekly or monthly collection cycles. Besides, since simulation is a much more comprehensive system representation compared with a mathematical optimization model (Ivanov, 2021), additional data needs to be included, and real-world operational policies need to be implemented to set up the logic of the DES. Randomness and different dynamic scenarios can be tested to analyze the impact of, for example, parametric stochasticity and variation, technological adoption, and disruptions, on the initial network decisions. Because stochastic parameters are used in the model, dynamic simulation experiments should be conducted over a number of repetitions so that statistically confident analytical results can be found (Yu and Solvang, 2020). Finally, the results need to be evaluated by either the decision-makers or the predefined performance indicators. In this stage, new candidate network configurations, updated operational policies, and different technology upgrade scenarios may be further evaluated.

The proposed methodological architecture utilizes the advantages of both optimization and simulation (Ivanov, 2021; Andoh and Yu, 2022). Optimization is used to obtain good decisions among a large number of potential network configurations with imperfect information. Simulation is utilized for a comprehensive performance measurement under dynamicity and stochasticity. It is noteworthy that the two stages of analytical processes can be seamlessly linked via a cutting-edge digitalized platform—anyLogistix (Ivanov, 2021). It helps to visualize the optimization result and to build the simulation model over the optimized network obtained, and the first-stage data can be automatically converted to the appropriate aggregation level in the second stage. System integration is important in realizing this integrated architecture, which features cloud-based systems, shared databases, flexible network structure, built-in analytical modules for modeling, and user-friendly interfaces (Sun et al., 2022a). This methodological architecture forms the foundation for a system-based digital twin in Industry 5.0 (Ivanov and Dolgui, 2021).

3.2. First-stage mathematical model

In this section, a fuzzy MIP is first formulated to determine the candidate networks. Fig. 3 illustrates the network structure of the remanufacturing reverse logistics system. Rooted in fuzzy set theory, fuzzy logic provides a comprehensive framework for modeling and handling uncertainty by allowing objects to belong to multiple sets with varying degrees of membership, rather than conforming to binary true or false categorizations. Over the years, the fuzzy set theory, fuzzy logic, and various methods have been widely used in prediction and forecasting (Kropat, E., 2016), decision support, and image processing (Kuter., 2018) across various complex and intelligence systems such as financial systems (Kalaycı et al., 2024), social and organizational studies (Özcan et al., 2024), enterprise systems (Więcek-Janka et al., 2021), transportation networks (Ghosh et al., 2021), energy production (Yörük et al., 2023), and healthcare sectors (Çevik et al., 2017). Fuzzy logic is particularly useful in complex decision-making processes, where it captures the ambiguity and vagueness inherent in human reasoning (Celikyilmaz and Turksen, 2009). In reverse logistics network design, the employment of fuzzy logic in the modeling helps with decision-making with imperfect and incomplete data.

Notations

We define the notations below.

Sets and Index	
L, l	Local waste collection points
C, c	Centralized/Regional waste collection facilities
R, r	Remanufacturing plant
O, o	Markets
Q, q	Recycling companies
P, p	Type of EOL products
W, w	Type of cores
Parameters	
$\widetilde{fc}_c$	Fixed cost of centralized/regional waste collection center c
$\widetilde{fr}_r$	Fixed cost of remanufacturing plant r
$\widetilde{fq}_q$	Fixed cost for contracting a recycling company q
$\widetilde{cp}_{cp}$	Variable cost for the treatment of one unit p at centralized/regional collection center c
$\widetilde{rp}_{rw}$	Variable cost for the treatment of one unit w at remanufacturing plant r
$\widetilde{tra}_{lcp}$	Transportation cost of one unit p from local waste collection center l to centralized/regional waste collection center c
$\widetilde{trb}_{crw}$	Transportation cost of one unit w from centralized/regional waste collection center c to remanufacturing plant r
$\widetilde{trc}_{row}$	Transportation cost of one unit remanufactured w from remanufacturing plant r to market o
$\widetilde{trd}_{rqw}$	Transportation cost of one unit unqualified core w from remanufacturing plant r to recycling company q
$\widetilde{tre}_{cqw}$	Transportation cost of non-remanufacturable elements of w from centralized/regional waste collection center c to recycling company q
$\widetilde{pn}_w$	Unit cost for demand fulfillment with flexible capacity
$\widetilde{CE}$	Total carbon emission of the system
$Ctax$	Carbon tax per unit emission
$\widetilde{Eec}_c$	Unit carbon emission for processing an EOL product c
$\widetilde{Eer}_w$	Unit carbon emission for processing a core p
$\widetilde{Eta}_{lcp}$	Unit carbon emission for transporting p from local waste collection center l to centralized/regional waste collection center c
$\widetilde{Etb}_{crw}$	Unit carbon emission for transporting a core w from centralized/regional waste collection center c to remanufacturing plant r
$\widetilde{Etc}_{row}$	Unit carbon emission for transporting a remanufactured core w from remanufacturing plant r to market o
$\widetilde{Etd}_{rqw}$	Unit carbon emission for transporting an unqualified core w from remanufacturing plant r to recycling company q
$\widetilde{Epn}_w$	Unit carbon emission for demand fulfillment with flexible capacity
$\widetilde{dm}_{ow}$	Demand for remanufactured core w at market o
$\widetilde{capc}_c$	Capacity installed at regional collection center c
$\widetilde{capr}_r$	Capacity installed at remanufacturing plant r
$\widetilde{capr}_q$	Capacity of contracted recycling company q
ϑ_{pw}	Conversion rate between EOL product p and core w
$\widetilde{\theta}_w$	Fraction of qualified core for remanufacturing
Gen_{lp}	Amount of EOL product p at local waste collection point l
Decision variables	
xc_c	Binary variable decides whether a centralized/reginal waste collection center is open
xr_r	Binary variable decides whether a remanufacturing plant is open
xq_q	Binary variable decides whether a recycling company is selected
yp_{cp}	Quantity of p processed at centralized/regional waste collection center c
yr_{rw}	Quantity of core w processed at remanufacturing plant r
yq_{qw}	Quantity of core w processed by recycling company q
qa_{lcp}	Quantity of p transported from local waste collection point l to centralized/regional waste collection center c
qb_{crw}	Quantity of EOL core w transported from centralized/regional waste collection center c to remanufacturing plant r
qc_{row}	Quantity of remanufactured core w transported from remanufacturing plant r to market o
qd_{rqw}	Quantity of unqualified core w transported from remanufacturing plant r to recycling company q
qe_{cqw}	Quantity of non-remanufacturable part w transported from centralized/regional waste collection center c to recycling company q
ud_{ow}	Unfulfilled demand of remanufactured core w at market o

3.2.1. Mathematical model

The objective function is given in Eq. (1), which minimizes the total costs of the remanufacturing reverse logistics system. In the equation, the first three components calculate the fixed facility costs for centralized/regional waste collection centers, remanufacturing plants, and recycling plants, respectively. The fourth to sixth elements address the variable costs associated with these facilities. The seventh component represents the transportation costs for EOL products from local collection points to centralized/regional collection centers. The eighth element accounts for the transportation costs of EOL cores to remanufacturing plants. The ninth component covers the transportation costs of remanufactured cores to their respective markets. The tenth element represents the costs of transporting unqualified cores from remanufacturing plants to recycling companies. The eleventh component calculates the transportation costs for non-remanufacturable parts sent to recycling from centralized/regional collection centers. The twelfth element pertains to flexible capacity costs, and the final component accounts for carbon emission costs.

Notably, flexible capacity is considered a penalty cost that increases the flexibility of the model to ensure reliable and non-redundant facility location decisions (Yu and Solvang, 2020). Using flexible capacity is expensive, but it helps relax the demand fulfillment constraint and avoid opening more facilities for a small demand increment. From a practical perspective, flexible capacity may, under different circumstances, be interpreted as outsourcing, use of overtime, etc., which typically represent more expensive alternatives (Yu and Solvang, 2020). Furthermore, this approach aids in achieving feasible solutions in the scenario when demand exceeds the generation of EOL products:

$$\begin{aligned}\text{minimize } \tilde{z} \cong & \sum_{c\in C}\widetilde{fc}_c xc_c + \sum_{r\in R}\widetilde{fr}_r xr_r + \sum_{q\in Q}\widetilde{fq}_q xq_q + \sum_{c\in C}\sum_{p\in P}\widetilde{cp}_{cp} yp_{cp} \\ & + \sum_{r\in R}\sum_{w\in W}\widetilde{rp}_{rw} yr_{rw} + \sum_{c\in C}\sum_{w\in W}\widetilde{qp}_{qw} yq_{qw} + \sum_{l\in L}\sum_{c\in C}\sum_{p\in P}\widetilde{tra}_{lcp} qa_{lcp} \\ & + \sum_{c\in C}\sum_{r\in R}\sum_{w\in W}\widetilde{trb}_{crw} qb_{crw} + \sum_{r\in R}\sum_{o\in O}\sum_{w\in W}\widetilde{trc}_{row} qc_{row} + \sum_{r\in R}\sum_{q\in Q}\sum_{w\in W}\widetilde{trd}_{rqw} qd_{rqw} \\ & + \sum_{c\in C}\sum_{r\in R}\sum_{w\in W}\widetilde{tre}_{cqw} qe_{cqw} + \sum_{o\in O}\sum_{w\in W}\widetilde{pn}_w ud_{ow} + \widetilde{CE},\end{aligned} \tag{1}$$

The carbon emission costs are determined by Eq. (2), which accounts for the carbon taxes resulting from the facility operations and transportation activities. Within the parentheses, the initial three components correspond to carbon emissions from the operations of regional collection centers, remanufacturing plants, and recycling plants, respectively. The fourth to eighth elements calculate the carbon emissions associated with transportation across respective links. Lastly, the final component represents the carbon emissions attributable to the utilization of flexible capacity:

$$\begin{aligned}\widetilde{CE} \cong Ctax\Bigg(& \sum_{c\in C}\sum_{p\in P}\widetilde{Eec}_c yp_{cp} + \sum_{r\in R}\sum_{w\in W}\widetilde{Eer}_r yr_{rw} + \sum_{q\in Q}\sum_{w\in W}\widetilde{Eeq}_q yq_{qw} \\ & + \sum_{l\in L}\sum_{c\in C}\sum_{p\in P}\widetilde{Eta}_{lcp} qa_{lcp} + \sum_{c\in C}\sum_{r\in R}\sum_{w\in W}\widetilde{Etb}_{crw} qb_{crw} \\ & + \sum_{r\in R}\sum_{o\in O}\sum_{w\in W}\widetilde{Etc}_{row} qc_{row} + \sum_{r\in R}\sum_{q\in Q}\sum_{w\in W}\widetilde{Etd}_{rqw} qd_{rqw} \\ & + \sum_{c\in R}\sum_{q\in Q}\sum_{w\in W}\widetilde{Ete}_{cqw} qe_{cqw} + \sum_{o\in O}\sum_{w\in W}\widetilde{Epn}_w ud_{ow}\Bigg),\end{aligned} \tag{2}$$

The model is restricted by constraints (3–15). Notably, the signs "$\tilde{\cong}$", "$\tilde{\geq}$" and "$\tilde{\leq}$" in the model are used to represent the imprecise objective value and inequalities due to the use of fuzzy parameters (Darbari et al., 2019). Constraint (3) is the demand fulfillment requirement specifying that all the demands for remanufactured products need to be fulfilled, where a small portion of demand may be fulfilled by flexible capacity:

$$\sum_{r\in R} qc_{row} + ud_{ow} \tilde{\geq} \widetilde{dm}_{ow}, \forall o \in O, w \in W, \tag{3}$$

Constraints (4–6) are capacity constraints of the centralized/regional waste collection center, remanufacturing plant, and contracted recycling company, respectively. The fuzzy capacity is due to the quality variation of remanufactured products which may lead to different processing times and thus uncertain and fluctuating processing rates at a facility:

$$\sum_{p\in P} yp_{cp} \tilde{\leq} xc_c \widetilde{capc}_c, \forall c \in C, \tag{4}$$

$$\sum_{w\in W} yr_{rw} \tilde{\leq} xr_r \widetilde{capr}_r, \forall r \in R, \tag{5}$$

$$\sum_{w\in W} yq_{qw} \tilde{\leq} xr_q \widetilde{capr}_q, \forall q \in Q, \tag{6}$$

Eqs. (7)–(9) are flow balance requirements at the centralized/regional waste collection center, where EOL products are disassembled into different types of components, materials, and waste for further treatment in the reverse logistics system. The model takes into account the overall reverse logistics operations, but, in reality, collection centers and remanufacturers may make individual decisions on selecting recycling companies. Thus, these constraints may be adjusted accordingly based on the scope of the analysis:

$$yp_{cp} = \sum_{l\in L} qa_{lcp}, \forall c \in C;\ p \in P, \tag{7}$$

$$\sum_{p\in P} \vartheta_{pw} yp_{cp} = \sum_{r\in R} qb_{crw}, \forall c \in C;\ w \in W, \tag{8}$$

$$\sum_{p\in P} (1 - \vartheta_{pw}) yp_{cp} = \sum_{r\in R} qe_{cqw}, \forall c \in C;\ w \in W, \tag{9}$$

Eqs. 10–12 give flow balance requirements in remanufacturing plants. Eq. (10) determines the total quantity of the cores acquired. Eq. (11) guarantees that only a specific proportion of cores meeting the quality criteria are selected for remanufacturing, given that the quality level of acquired components is, however, uncertain. Cores that do not meet the quality standards are directed to recycling, as shown in Eq. (12):

$$yr_{rw} = \sum_{c\in C} qb_{crw}, \forall r \in R;\ w \in W, \tag{10}$$

$$\tilde{\theta}_w yr_{rw} \tilde{\cong} \sum_{o\in O} qc_{row}, \forall r \in R;\ w \in W, \tag{11}$$

$$(1 - \tilde{\theta}_w) yr_{rw} \tilde{\cong} \sum_{q\in Q} qd_{rqw}, \forall r \in R;\ w \in W, \tag{12}$$

Constraint (13) ensures that the volume of outbound transportation at local waste collection points does not exceed the total quantity of EOL products collected:

$$\sum_{c\in C} qa_{lcp} \leq Gen_{lp}, \forall l \in L;\ p \in P, \tag{13}$$

Constraints (14) and (15) are requirements for both binary and continuous variables:

$$xc_c, xr_r, xq_q \in \{0, 1\}, \forall c \in C;\ r \in R, \tag{14}$$

$$\begin{aligned} & yp_{cp}, yr_{rw}, yq_{qw}, qa_{lcp}, qb_{crw}, qc_{row}, qd_{rqw}, qe_{cqw}, ud_{ow} \geq 0, \forall c \in C;\ p \in P;\ r \\ & \in R;\ l \in L;\ o \in O;\ q \in Q;\ w \in W.\end{aligned} \tag{15}$$

3.2.2. Defuzzification and crisp model

Due to the inclusion of fuzzy parameters and constraints, the proposed model needs to be defuzzilized into its crisp counterpart before solving. In this paper, we utilize the defuzzification method developed by Jiménez et al. (2007) and Pishvaee and Torabi (2010). To obtain the equivalent crisp model from a fuzzy optimization problem, one needs to consider both the optimality of the objective function and the feasibility of the constraints (Jiménez et al., 2007). The uncertain parameters in a fuzzy model can be given with the membership function, e.g., triangular fuzzy number or trapezoidal fuzzy number. Eq. (16) defines the membership function for a fuzzy triangular number $\widetilde{h}$, where h^l, h^m and h^u depict the lower bound estimation, the most likely estimation, and the upper bound estimation. As shown in Eqs. (17) and (18), we use both expected value and expected interval to convert a fuzzy number (Jiménez et al., 2007). Based on this, the fuzzy parameters can be transformed and replaced with their expected values ($EV(\widetilde{h})$) in Eq. (1). Then, this fuzzy objective function is re-written to its crisp form by replacing the "≅" with "$=$":

$$g_{\widetilde{h}}(x) = \begin{cases} f^1_{\widetilde{h}}(x) = \dfrac{x - h^l}{h^m - h^l}, \text{if } h^l \le x \le h^m \\ 1, \text{if } x = h^m \\ f^2_{\widetilde{h}}(x) = \dfrac{h^u - x}{h^u - h^m}, \text{if } h^m \le x \le h^u \\ 0, \text{if } x < h^l \text{ or } x > h^u, \end{cases} \tag{16}$$

$$EI(\widetilde{h}) = \left[E^h_1, E^h_2\right] = \left[\frac{h^l + h^m}{2}, \frac{h^m + h^u}{2}\right], \tag{17}$$

$$EV(\widetilde{h}) = \frac{E^h_1 + E^h_2}{2} = \frac{h^l + 2h^m + h^u}{4}, \tag{18}$$

To solve the feasibility issue of the model, the α-degree approach is used. First, for any two fuzzy numbers $\widetilde{i}$ and $\widetilde{j}$, Eq. (19) defines the situation where $\widetilde{i}$ is greater than $\widetilde{j}$ (Jiménez, 1996):

$$\mu(\widetilde{i},\widetilde{j}) = \begin{cases} 1, \text{if } E^i_1 - E^j_2 > 0 \\ \dfrac{E^i_2 - E^j_1}{E^i_2 - E^j_1 - \left(E^i_1 - E^j_2\right)}, \text{if } 0 \in \left[E^i_1 - E^j_2, E^i_2 - E^j_1\right] \\ 0, \text{if } E^j_1 - E^i_2 > 0, \end{cases} \tag{19}$$

Furthermore, $\mu(\widetilde{i},\widetilde{j})$ indicates that $\widetilde{i}$ is greater than $\widetilde{j}$ to, at least, α degree (Pishvaee and Torabi, 2010), which can be rewritten as $\widetilde{i} \ge \alpha\widetilde{j}$. Based on this, the "$\widetilde{\ge}$" can be converted to "$\ge$" by Eqs. (20) and (21), which help eliminate fuzzy inequality and transform them into crisp constraints:

$$\frac{E^i_2 - E^j_1}{E^i_2 - E^i_1 + E^j_2 - E^j_1} \ge \alpha, \tag{20}$$

$$\left[(1-\alpha)E^i_2 + \alpha E^i_1\right]x \ge \alpha E^j_2 + (1-\alpha)E^j_1, \tag{21}$$

$$\frac{\alpha}{2} \le \mu(\widetilde{i},\widetilde{j}) \le 1 - \frac{\alpha}{2}, \tag{22}$$

$$\frac{\alpha}{2} \le \frac{E^i_2 - E^j_1}{E^i_2 - E^i_1 + E^j_2 - E^j_1} \le 1 - \frac{\alpha}{2}, \tag{23}$$

$$\left[\left(1-\frac{\alpha}{2}\right)E^i_2 + \frac{\alpha}{2}E^i_1\right]x \ge \frac{\alpha}{2}E^j_2 + \left(1-\frac{\alpha}{2}\right)E^j_1, \tag{24}$$

$$\left[\frac{\alpha}{2}E^{\,i}_{\,2} + \left(1-\frac{\alpha}{2}\right)E^{\,i}_{\,1}\right]x \le \left(1-\frac{\alpha}{2}\right)E^j_2 + \frac{\alpha}{2}E^j_1, \tag{25}$$

To convert the equality constraints, the definition of equivalent fuzzy numbers is first given. For two fuzzy numbers $\widetilde{i}$ and $\widetilde{j}$, when $\widetilde{i} \ge \alpha/2\widetilde{j}$ and $\widetilde{i} \le \alpha/2\widetilde{j}$, they are considered indifferent (Parra et al., 2005), which can be written as Eqs. (22) and (23). These can be further divided into Eqs. (24) and (25) to transform fuzzy equality constraints (Pishvaee and Torabi, 2010):

$$\begin{aligned} \text{minimize } z = & \sum_{c\in C}\left(\frac{fc^l_c + 2fc^m_c + fc^u_c}{4}\right)xc_c + \sum_{r\in R}\left(\frac{fr^l_r + 2fr^m_r + fr^u_r}{4}\right)xr_r \\ & + \sum_{q\in Q}\left(\frac{fr^l_q + 2fr^m_q + fr^u_q}{4}\right)xq_q + \sum_{c\in C}\sum_{p\in P}\left(\frac{cp^l_{cp} + 2cp^m_{cp} + cp^u_{cp}}{4}\right)yp_{cp} \\ & + \sum_{r\in R}\sum_{w\in W}\left(\frac{rp^l_{rw} + 2rp^m_{rw} + rp^u_{rw}}{4}\right)yr_{rw} \\ & + \sum_{q\in Q}\sum_{w\in W}\left(\frac{qp^l_{qw} + 2qp^m_{qw} + qp^u_{qw}}{4}\right)yq_{qw} \\ & + \sum_{l\in L}\sum_{c\in C}\sum_{p\in P}\left(\frac{tra^l_{lcp} + 2tra^m_{lcp} + tra^u_{lcp}}{4}\right)qa_{lcp} \\ & + \sum_{c\in C}\sum_{r\in R}\sum_{w\in W}\left(\frac{trb^l_{crw} + 2trb^m_{crw} + trb^u_{crw}}{4}\right)qb_{crw} \\ & + \sum_{r\in R}\sum_{o\in O}\sum_{w\in W}\left(\frac{trc^l_{row} + 2trc^m_{row} + trc^u_{row}}{4}\right)qc_{row} \\ & + \sum_{r\in R}\sum_{q\in Q}\sum_{w\in W}\left(\frac{trd^l_{rqw} + 2trd^m_{rqw} + trd^u_{rqw}}{4}\right)qd_{rqw} \\ & + \sum_{c\in C}\sum_{q\in Q}\sum_{w\in W}\left(\frac{tre^l_{cqw} + 2tre^m_{cqw} + tre^u_{cqw}}{4}\right)qe_{cqw} \\ & + \sum_{o\in O}\sum_{w\in W}\widetilde{pn}_w\left(\frac{pn^l_w + 2pn^m_w + pn^u_w}{4}\right)ud_{ow} \\ & + Ctax\left[\sum_{c\in C}\sum_{p\in P}\left(\frac{Eec^l_c + 2Eec^m_c + Eec^u_c}{4}\right)yp_{cp}\right. \\ & + \sum_{r\in R}\sum_{w\in W}\left(\frac{Eer^l_w + 2Eer^m_w + Eer^u_w}{4}\right)yr_{rw} \\ & + \sum_{q\in Q}\sum_{w\in W}\left(\frac{Eeq^l_w + 2Eeq^m_w + Eeq^u_w}{4}\right)yq_{qw} \\ & + \sum_{l\in L}\sum_{c\in C}\sum_{p\in P}\left(\frac{Eta^l_{lcp} + 2Eta^m_{lcp} + Eta^u_{lcp}}{4}\right)qa_{lcp} \\ & + \sum_{c\in C}\sum_{r\in R}\sum_{w\in W}\left(\frac{Etb^l_{crw} + 2Etb^m_{crw} + Etb^u_{crw}}{4}\right)qb_{crw} \\ & + \sum_{r\in R}\sum_{o\in O}\sum_{w\in W}\left(\frac{Etc^l_{row} + 2Etc^m_{row} + Etc^u_{row}}{4}\right)qc_{row} \\ & + \sum_{r\in R}\sum_{q\in Q}\sum_{w\in W}\left(\frac{Etd^l_{rqw} + 2Etd^m_{rqw} + Etd^u_{rpw}}{4}\right)qd_{rqw} \\ & + + \sum_{c\in C}\sum_{q\in Q}\sum_{w\in W}\left(\frac{Ete^l_{cqw} + 2Ete^m_{cqw} + Ete^u_{cpw}}{4}\right)qe_{cqw} \\ & \left. + \sum_{o\in O}\sum_{w\in W}\widetilde{Epn}_w\left(\frac{Epn^l_w + 2Epn^m_w + Epn^u_w}{4}\right)ud_{ow}\right], \end{aligned} \tag{26}$$

S.t.

$$\sum_{r\in R} qc_{row} + ud_{ow} \ge \alpha\left(\frac{dm^m_{ow} + dm^u_{ow}}{2}\right) + (1-\alpha)\left(\frac{dm^l_{ow} + dm^m_{ow}}{2}\right), \forall o \in O;\ w \in W, \tag{27}$$

$$\sum_{p\in P} yp_{cp} \le xc_c\left[\alpha\left(\frac{capc^l_c + capc^m_c}{2}\right) + (1-\alpha)\left(\frac{capc^m_c + capc^u_c}{2}\right)\right], \forall c \in C, \tag{28}$$

$$\sum_{w\in W} yr_{rw} \le xr_r\left[\alpha\left(\frac{capr^l_r + capr^m_r}{2}\right) + (1-\alpha)\left(\frac{ca\ pr^m_r + capr^u_r}{2}\right)\right], \forall r \in R, \tag{29}$$

$$\sum_{w\in W} yq_{qw} \le xq_q \left[\alpha\left(\frac{capq_q^l + capq_q^m}{2}\right) + (1-\alpha)\left(\frac{capq_q^m + capq_q^u}{2}\right)\right], \forall q \in Q, \tag{30}$$

$$\left[\left(\frac{\alpha}{2}\right)\left(\frac{\theta_w^u + \theta_w^m}{2}\right) + \left(1-\frac{\alpha}{2}\right)\left(\frac{\theta_w^l + \theta_w^m}{2}\right)\right] yr_{rw} \le \sum_{o\in O} qc_{row}, \forall r \in R, \tag{31}$$

$$\left[\left(1-\frac{\alpha}{2}\right)\left(\frac{\theta_w^u + \theta_w^m}{2}\right) + \left(\frac{\alpha}{2}\right)\left(\frac{\theta_w^l + \theta_w^m}{2}\right)\right] yr_{rw} \ge \sum_{o\in O} qc_{row}, \forall r \in R, \tag{32}$$

$$\left[1-\left(\frac{\alpha}{2}\right)\left(\frac{\theta_w^l + \theta_w^m}{2}\right) - \left(1-\frac{\alpha}{2}\right)\left(\frac{\theta_w^u + \theta_w^m}{2}\right)\right] yr_{rw} \le \sum_{q\in Q} qd_{rqw}, \forall r \in R, \tag{33}$$

$$\left[1-\left(1-\frac{\alpha}{2}\right)\left(\frac{\theta_w^l + \theta_w^m}{2}\right) - \left(\frac{\alpha}{2}\right)\left(\frac{\theta_w^u + \theta_w^m}{2}\right)\right] yr_{rw} \ge \sum_{q\in Q} qd_{rqw}, \forall r \in R. \tag{34}$$

Thus, the original model can be converted to its crisp counterpart given in Eqs. 26–34. In addition, constraints (7-10) and (13-15) will still be held.

3.3. Second-stage dynamic simulation

In the second stage, dynamic simulation is run over candidate network structures obtained under different demand-fulfillment and capacity requirements, say the α-degree. Simulation can model the system behaviors and operations in a much more comprehensive and detailed manner, which can effectively solve the challenges of optimization, e.g., oversimplified systems and many assumptions (Ivanov, 2021). In this paper, dynamic simulation is a combination of both DES and MCS. DES creates an event-driven step-by-step sequence of the simulation logic to analyze complex system behaviors that evolve over time. While the simulation proceeds the events from one to the next in chronological order, dynamic reverse logistics operations, configurational upgrades, and different operational policies can be modeled and evaluated. Specifically, setting up the simulation logic requires inventory management (e.g., continuous review and periodic review, etc.), processing rules at the facilities (e.g., product-specified disassembly BOMs, simple production, partial production, etc.), and transportation (e.g., vehicle type, capacity, emissions, speed, etc.) and loading rules (e.g., full load or partial load) to operate the reverse logistics system under a close-to-reality environment. Additionally, the backorder policy needs to be defined to ensure, for example, an order is pending to be sent until the required number of remanufactured

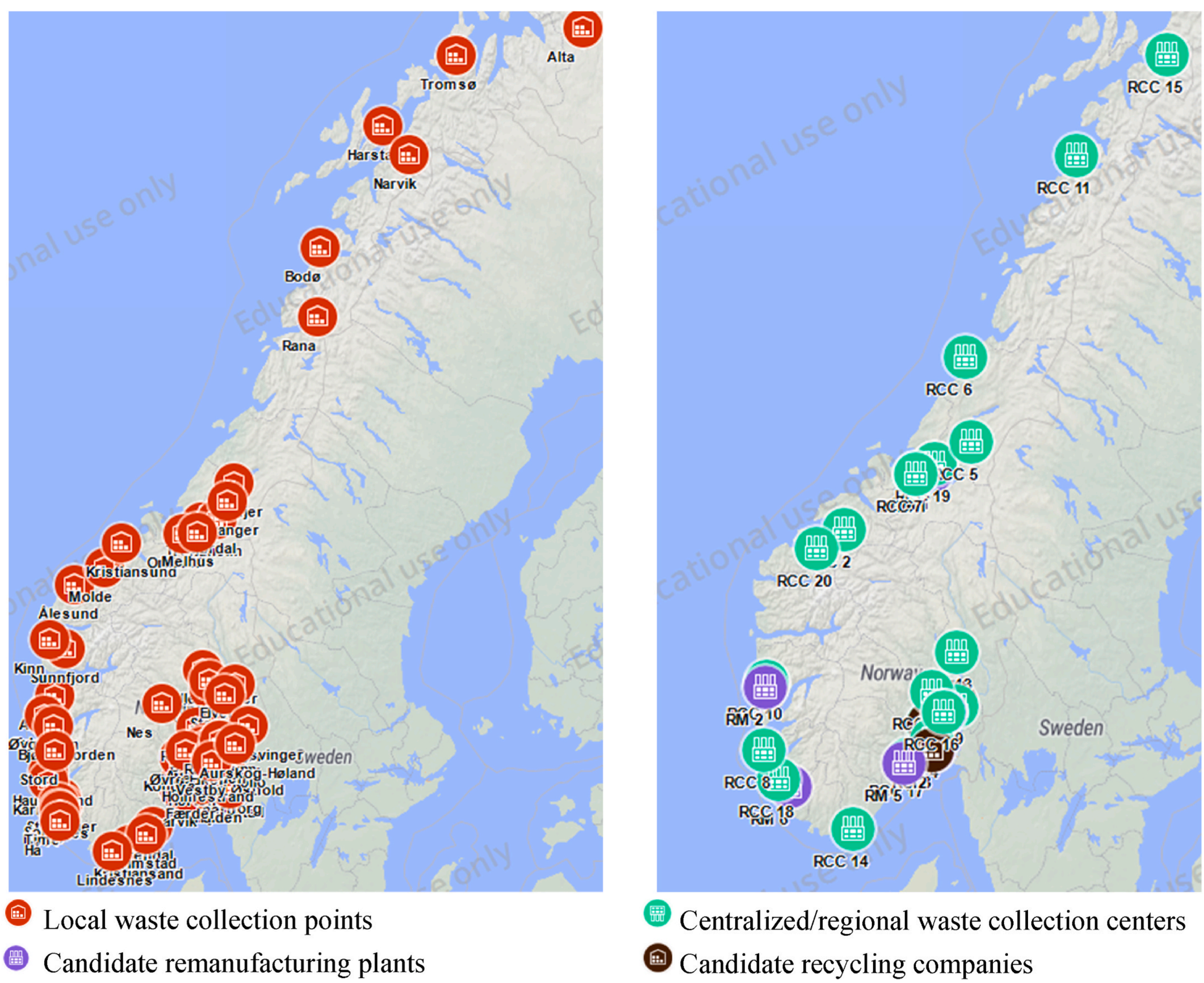


Fig. 4. The locations respective facilities and candidate points.

products are available.

While some parameters lack historical data, e.g., cost and demand, etc., and are treated with fuzzy sets in the first stage, others may suffer from randomness, e.g., EOL product generation. Randomness is an important source of uncertainty and needs to be treated with stochastic parameters. In this paper, we take into account the stochasticity of EOL return in the simulation experiments to better understand its impact on demand fulfillment and variation of remanufacturing processes. Since these stochastic parameters are randomly generated from given distributions, the parameter generation itself is a stochastic process. As argued by King (2012), for a reliable stochastic model, it is of significant importance to ensure that the output is statistically confident and is not affected by the parameter generation. Therefore, the simulation experiments need to be repeated many times considering the tradeoff between the level of statistical confidence and the computational efficiency. This procedure is essentially a MCS.

While the first-stage optimization makes strategic decisions, the second-stage dynamic simulation helps to test a set of what-if scenarios and to yield a much more comprehensive performance analysis into several key performance indicators (KPIs). Below are some examples.

- *Economic performance*: total cost, fixed cost, production cost, transportation cost, penalties, and other costs.
- *Environmental performance*: total emissions, emissions from production and transportation, and other environmental impacts.
- *Operational performance*: demand fulfillment, inventory level, and resource utilization.
- *Service level performance*: lead time (max/mean), on-time delivery, and backlog.

Furthermore, the analytical results can be better presented and interpreted in real-life situations. For example, the flexible capacity imposes a penalty cost in Eq. (1) to avoid opening a redundant facility for a small increment of the generation of EOL products. This term is mathematically justifiable, but its practical meaning may be unclear for decision-makers. When operating the remanufacturing reverse logistics system in simulation, the same situation is handled in a different but more practical way. The unfulfilled demand due to capacity limitation will be postponed to the next sending period, e.g., after several weeks. However, this will impose negative impacts on the system's service level. Thus, the proposed method can help decision-makers with robust strategic network configurations and better performance analysis.

4. Numerical experiments

To show the application of the proposed digitalized optimization-simulation architecture, numerical experiments were given using real-life case data in Norway. Waste treatment in Norway includes material recycling, composting and biogas production, filling compound and cover materials, incineration, landfill, and other disposals. Based on the data of Statistics Norway in 2022, the percentages of WEEE sent for material recycling, incineration, and landfill as well as other disposal are 78.6%, 11.7%, and 3.5%, respectively, and the others are unknown. Currently, WEEE is primarily treated for material recycling, but remanufacturing has not been widely practiced in Norway. Thus, we consider setting up a potential remanufacturing network for compressors from EOL refrigerators. In 2018, global household appliance sales for refrigerators amounted to 108.12 billion USD, and the market size was expected to expand to $166.35 billion by 2028 (Statista, 2023). Compressor is the most valuable component when it comes to the value recovery of refrigerators.

Table 2
Unit transportation cost and carbon emissions.

Transport link	Item	Unit transportation cost (NOK/km/kg)	Unit carbon emissions (kg/km/kg)
(l,c)	EOL refrigerator	0.014286	0.000159
(c,r)	Compressor	0.008750	0.000081
(r,q)	Rejected compressor	0.008750	0.000081

Table 3
Facility-related data.

Facility	Fixed cost (10^3NOK/Year)	Item	Variable cost (NOK/kg)	Carbon emissions (kg/kg)	Capacity (kg)
c	[21,400, 21,800]	Refrigerator	16	0.17	148,500
r	[38,200, 40,160]	Compressor	14	1.161	675,000

4.1. Parameter and operational policies

In the experiment, with a population threshold of 15,000, 75 cities and towns in Norway were selected for local collection points. The EOL refrigerators from small towns and villages are sent to the closest location collection points. We selected 20 candidates for the regional collection center and 6 candidates for the remanufacturing plant. Most locations of the candidates for regional collection centers are based on the existing facilities from local waste management companies. Besides, 5 existing recycling companies were selected as potential candidates in this network for the non-remanufactured parts. Fig. 4 shows the locations of the respective facilities and candidates. The names, numbers, and locations of these points are given in Appendix A. According to Eurostat (2021), the annual collection rate per capita of large household appliances is 8.45 kg in Norway. In our experiment, the proportion of refrigerators in large household appliances was assumed to be 40%, of which 80% could reach the quality standard for further processing. The compressor is approximately 10% of the total weight of a residential refrigerator. At the remanufacturing plant, the rejection rate of the received compressors was assumed to be 10%, which would be sent to recycling plants. The customer demands were generated based on the total number of EOL compressors that reached the quality level to be remanufactured.

Two types of transport vehicles were considered for transporting the EOL refrigerators and compressors among different facilities. Their truckloads are 6.3 and 13.4 tons, and their annual mileages are 73,000 and 108,000 km, respectively (Acea, 2020). In the experiment, we used distance-based calculation to estimate the costs and carbon emissions related to transportation. Table 2 presents the transportation-related parameters. Delgado et al. (2017) provided the basis for estimating the transportation costs per unit of EOL products and cores. The European Automobile Manufacturer Association (Acea, 2020) provided data on unit carbon emissions from their report on freight transportation and logistics. Table 3 gives facility-related data for the numerical experiments. Gk (2021) and Bazan et al. (2015) were used to estimate the parameter generation interval of the annual fixed operating cost at different facilities. The facility capacities and the variable processing cost per unit of EOL product or compressor were set based on the relevant research (Qu and Williams, 2008; Yan and Yan, 2019). Furthermore, Zheng et al. (2023), Cachon (2011), Habib et al. (2021), Park et al. (2019), Nakano et al. (2007) were used to estimate the unit carbon emissions related to different facilities. Finally, the fuzzy triangular numbers for the uncertain parameters were generated by $w^l = (1 - r_1)w^m$ and $w^u = (1 + r_2)w^m$, where r_1 and r_2 were set to 0.2 and 0.1, respectively. To perform the network optimization, we tested five different requirements with α decreasing from 1 to 0.6.

In the simulation experiment, we considered a 10-year evaluation period. Several parameters need to be converted accordingly in a more

Table 4
Comparison of the network optimization results.

Instance	Problem size				anyLogistix		Gurobi/Cplex		Gap
	L	C	R	Q	Decisions	Objective	Decisions	Objective	
1	5	5	5	5	*c2,c3,r1,q4*	90,163,841	*c2,c3,r1,q4*	90,054,564	−0.12%
2	10	8	5	5	*c2,c3,r1,q4*	98,287,565	*c2,c3,r1,q4*	98,307,707	0.02%
3	15	10	8	5	*c2,c3,r1,q4*	106,450,409	*c2,c3,r1,q4*	106,461,993	0.01%

Table 5
Experimental results.

α	Total cost (1000NOK/ year)	CO_2 emission (Ton/ year)	Network structure		
			Regional collection center	Remanufacturing plant	Recycling center
1	242,154	1217	4, 7, 10, 14,15, 16, 18	5	2
0.9	241,657	1202	4, 7, 10, 14,15, 16, 18	5	2
0.8	241,244	1189	4, 7, 10, 14,15, 16, 18	5	2
0.7	195,255	1166	7, 10, 15, 16, 17, 18	5	2
0.6	194,877	1154	7, 10, 15, 16, 17, 18	5	2

practical manner. For instance, instead of the highly aggregated data, the EOL refrigerator collection cycle was set to a more practical period, say 2 weeks. A uniform distribution [7, 10] days was used for random periodical demand generation. Besides, facility capacity needs to be converted to the unit processing time, which is then restricted by the total available working time. As a more detailed replica of the real-world remanufacturing reverse logistics systems, operational policies need to be properly defined in the simulation model. First, we considered inventory management as it helps balance both efficiency and responsiveness to market demands. In our experiment, the continuous review *RQ* policy was employed by the remanufacturers and the regional collection centers for the replenishment of EOL refrigerators and compressors. The inventory level is continuously tracked, and a replenishment order (*Q*) is triggered when the reorder point (*ROP*) is reached. The safety stock (*ss*) is calculated by Eq. (35) (Longeagne, 2022), and the *ROP* is calculated by Eq. (36) (Abcsupplychain, 2022). Herein, $S_{\max}$ and S_{avg} represent the maximum and average inventory levels, and LT_{max} and LT_{avg} are the maximum and average lead times:

$$ss = (S_{max} \times LT_{max}) - (S_{avg} \times LT_{avg}), \tag{35}$$

$$ROC = ss + S_{avg} \times LT_{avg}, \tag{36}$$

The min-max policy with safety stock (*s, S*) was used to restock the remanufactured compressors. The inventory status is checked at regular periodic intervals, and the order size can vary based on fluctuating demands. Gianesello et al. (2017) posited that the safety stock (ss) corresponds to the average weekly demand σd. Subsequently, the inventory levels for min (s) and max (S) were derived using Eqs. (37) and (38):

$$s = ss + (\sigma d \times LT), \tag{37}$$

$$S = 2 \times s. \tag{38}$$

The production management is determined in connection with both inventory management policy and sourcing. We employed a simple production policy in our experiment, which determines the production pattern based on the inventory policy's replenishment needs. In reality, cities and towns in the same region are served by the same waste management company. Thus, we used a fixed sourcing policy for the collection and transportation of EOL refrigerators from local collection points to regional collection centers. In contrast, the remanufacturing plants utilized multiple sourcing strategies to optimize their resource management and cost throughout different planning periods. In addition, we defined varying speeds for the vehicles, and a partial shipment policy was implemented. To ensure a high service level, a trip can start when a minimum loading rate of 0.7 is reached for both types of vehicles.

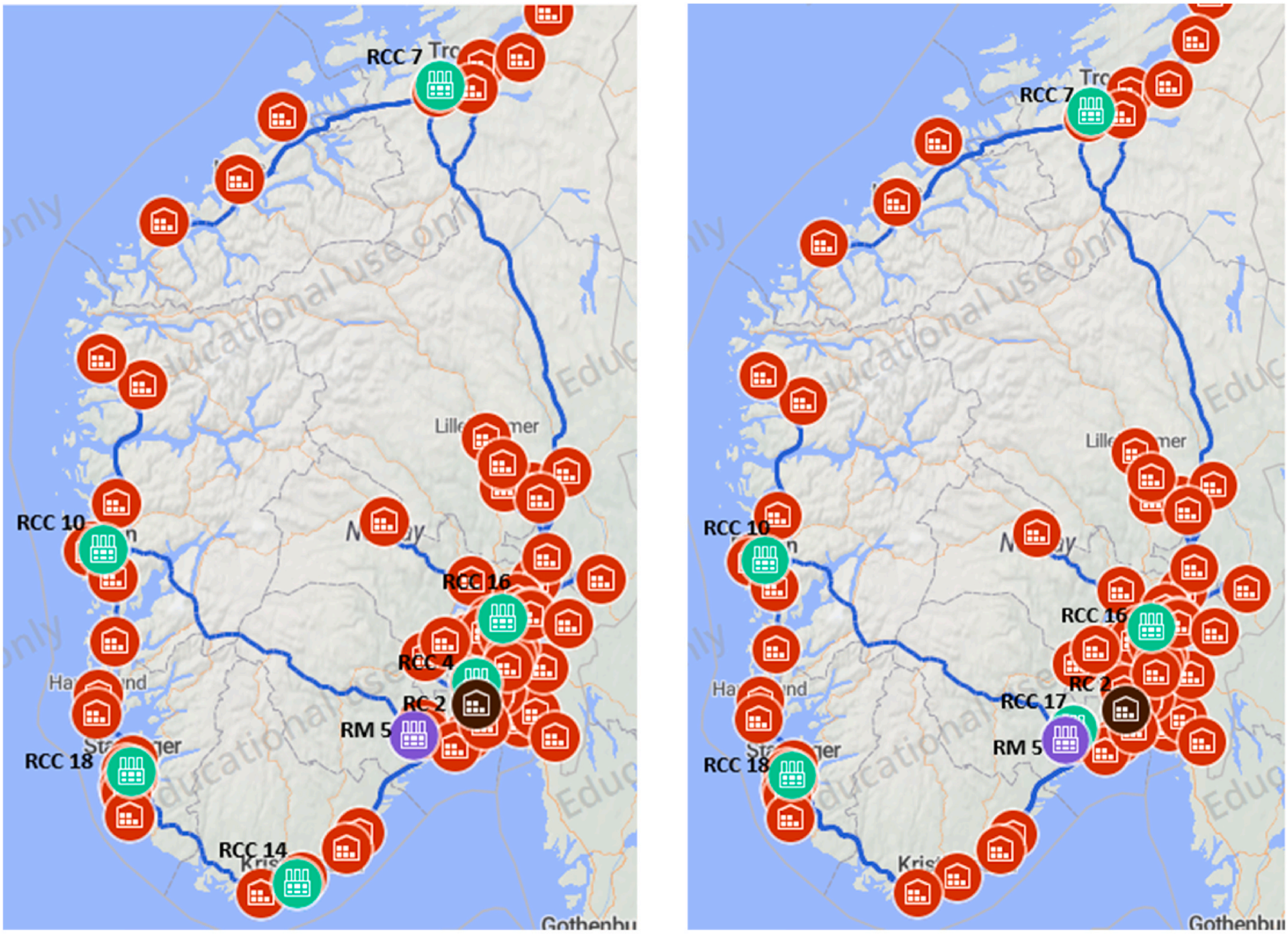
4.2. Experimental results and further evaluation

The experiment was performed by anyLogistix version 2.15.3. The network problem was optimized by the in-built Cplex solver, and the simulation (AnyLogic) was run over the optimal network structures obtained. The same optimization problem was also coded with AMPL and solved with both Gurobi 10.0.2 and Cplex 22.1.1.0. For the verification purpose of the anyLogistix platform, we first compared the optimization results found in three small instances with real locations and random parameters, where the google map was used to generate the distance information for the inputs of the AMPL model. As shown in Table 4, anyLogistix can yield reliable decisions, and the gaps in the objective value are caused by the different maps used for distance calculation.

Then, we performed the full-size experiment to validate the proposed method. Table 5 shows the annualized optimal costs and carbon emissions with α decreasing from 1 to 0.6. As shown in the table, two network configurations were obtained. When α is from 1 to 0.8, seven regional collection centers are opened at Holmestrand (RCC4), Orkanger (RCC7), Bergen (RCC10), Kristiansand (RCC14), Narvik (RCC15), Olso (RCC16), and Stavanger (RCC18). The remanufacturing plant will be established at Skien (RM5), and the recycling company at Revetal will be contacted. When α decreases to 0.7 and 0.6, the regional collection centers at Holmestrand and Kristiansand are excluded, but another regional collection center is opened at Skien (RCC17). These changes result in nearly a 20% cost reduction and a 2% emission reduction. Fig. 5 shows the two obtained optimal network structures in the southern part of Norway.

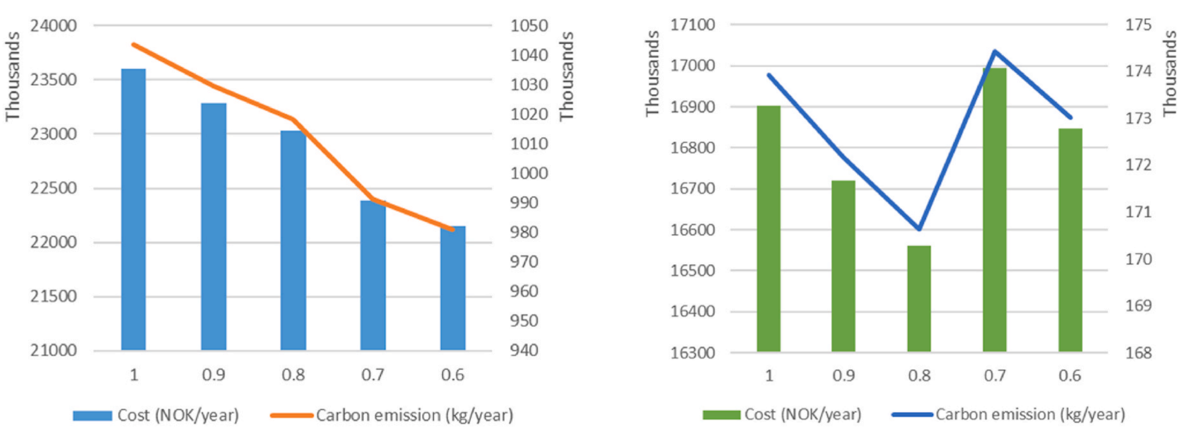
The cost reduction is mainly due to the decrease in fixed facility cost, which takes the most significant share of the total cost. Fig. 6 depicts the variations of both facility- and transportation-related costs and carbon emissions. As shown, both variable facility operating cost and carbon emissions decrease when α changes from 1 to 0.6. Conversely, when the total count of regional collection centers drops to 6, the transportation cost and carbon emissions associated with EOL refrigerators and compressors rise. For instance, when α changes from 0.8 to 0.7, the transportation cost will increase by 2.6%, and the carbon emissions will increase by 2.2%. This can be explained that, when fewer regional collation centers are opened, more and longer transportation is needed in the remanufacturing reverse logistics system.

To further evaluate the two network configurations obtained, we first considered the stochasticity of the EOL flow. First, the EOL generation was also considered, where a uniform distribution with ± 10% was used for random parameter generation. Additionally, due to the high quality variation and different failures of EOL compressors, e.g., failure



Network 1 (α=1, 0.9 and 0.8) Network 2 (α=0.7 and 0.6)

Fig. 5. Optimal network structures obtained in southern Norway.



(A) **(B)**

Fig. 6. Annualized (A) facility-related cost and carbon emissions; (B) transportation-related cost and carbon emissions.

to start, getting stuck, excessive oil injection, uneven air-exhaust, abnormal noise, etc. (Liu et al., 2014), the remanufacturing time may differ drastically. Thus, to evaluate the network resilience and the impact brought by quality variation, the remanufacturing time of each EOL component in the simulation model was randomly generated from a uniform distribution with ± 20% from the nominal remanufacturing time (Okorie et al., 2020).

Next, we considered technological upgrades that may occur within the planning horizon. These new technologies may drastically alter the operational parameters used in the initial network optimization and lead

Table 6
Test scenarios.

Scenario	Year	Remanufacturing upgrades				Transport fleet upgrades		
		Remanuf. time	Variation	Remanuf. cost	Remanuf. Emissions	Purchasing cost	Transport cost	Transport emissions
S1	2025					+90%	−20%	−30%
	2030	−10%	[90%,110%]	−10%	−15%			
S2	2025					+90%	−20%	−30%
	2030	−20%	[95%,105%]	−15%	−20%			
S3	2030	−10%	[90%,110%]	−10%	−15%	+50%	−30%	−45%
S4	2030	−20%	[95%,105%]	−15%	−20%	+50%	−30%	−45%

Table 7
Total cost and CO_2 emissions of the two networks.

Scenario	Network 1				Network 2			
	Total cost (1000NOK/year)		CO_2 emission (Ton/year)		Total cost (1000NOK/year)		CO_2 emission (Ton/year)	
	10 years	15 years	10 years	15 years	10 years	15 years	10 years	15 years
S1	241,793	239,237	1129	1072	196,136	192,857	1118	1041
S2	241,972	239,153	1108	1044	196,270	192,758	1096	1013
S3	241,010	238,250	1119	1059	195,345	191,863	1107	1027
S4	241,148	238,111	1096	1029	195,475	191,766	1085	1000

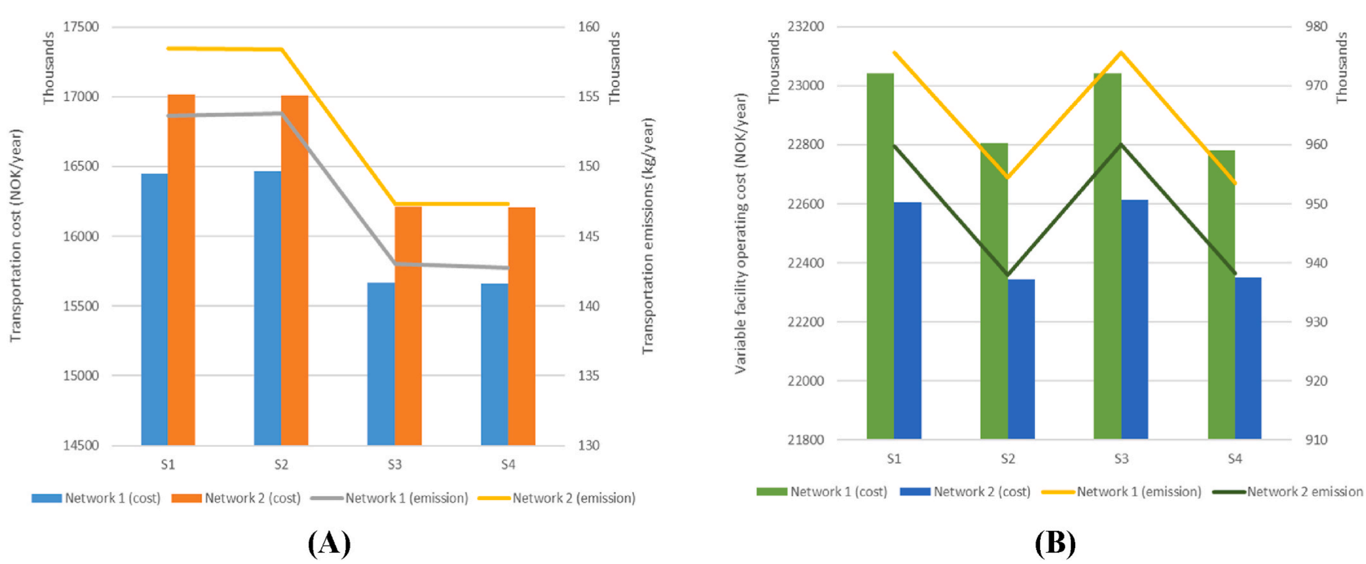


Fig. 7. The change of cost and emissions over the four test scenarios related to (A) transportation and (B) facility operation.

Table 8
Service level KPIs for network 1.

Scenario	Lead time (days)		Service level by orders	Utilization	On-time delivery
	mean	max			
Original	1.8	27.1	98.1%	77.5%	99.3%
S1	1.8	27.1	97.9%	73.4%	99.3%
S2	2.1	44.5	96.3%	69.9%	98.4%
S3	1.8	27.1	97.9%	73.4%	99.3%
S4	2.1	44.5	96.3%	69.9%	98.4%

Table 9
Service level KPIs for network 2.

Scenario	Lead time (days)		Service level by orders	Utilization	On-time delivery
	mean	max			
Original	4.1	249.2	81.1%	75.1%	93.9%
S1	3.1	64.1	83.7%	71.7%	93.0%
S2	4.3	195.9	80.9%	67.8%	92.5%
S3	3.1	64.1	83.7%	71.7%	93.0%
S4	4.3	195.9	80.9%	67.8%	92.5%

to varied performance indicators. For example, implementing IoT-enabled live scheduling in automobile engine remanufacturing can decrease both energy use and costs by approximately 34% (Zhang et al., 2018). Human-robot collaborative disassembly provides a more flexible solution to reduce the variation of remanufacturing time brought by the uncertain quality (Huang et al., 2021). Digital twins can provide product information for the EOL stage, which helps reduce uncertainty and operating expenses by up to 15% (Mckinsey&Company, 2022). The adoption of these new technologies may help reduce the remanufacturing time and variation, cost, and carbon emissions. Norway is at the forefront of developing green and innovative transportation solutions to reduce climate impact (Johnson, 2023). Based on Sustainable-truck&Van (2022), the potential cost of battery-electric trucks is projected to decrease by about 31% in 2035 due to the savings on both

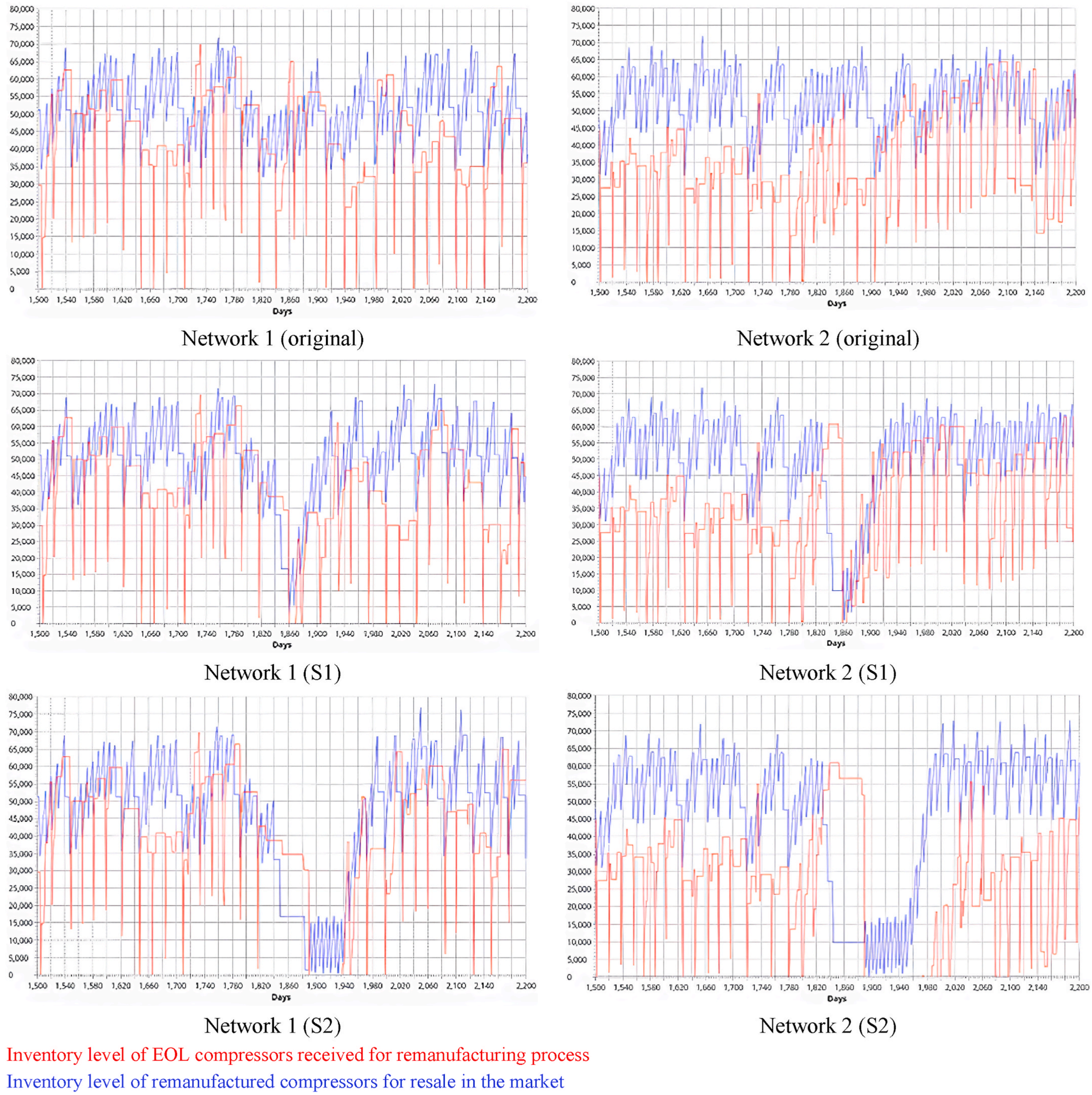


Fig. 8. Inventory patterns at the remanufacturing plant.

fuel consumption and maintenance costs. According to the revised Regulation (EU) 2019/1242 of the legislative proposal by the European Commission on February 14, 2023 (Regulation (Eu), 2023), CO_2 emissions are expected to be reduced by 45% with battery-electric vehicles. With increased technological and commercial maturity, the adoption of new technologies will become less expensive. As estimated by Buysse (2022), the purchasing cost of a battery electric truck will be approximately 1.9 times higher than its diesel counterpart in 2025, while this difference will become 1.5 times in 2030.

In the experiment, we set up four scenarios through different combinations of the upgrade plans of the remanufacturing plant and the transport fleet, as shown in Table 6. Each scenario was run over both 10 and 15 years. We considered two conditions for the updates of the transport fleet in 2025 and 2030, respectively. The purchasing costs of both diesel trucks and battery-electric trucks were estimated based on Sharpe and Basma (2022), Osamyynti (2023), Moch (2019). The vehicle's lifespan was set to 15 years, and the increment of the unit transportation cost brought by the higher purchasing cost could then be estimated by $\frac{\text{Increased purchasing cost}}{\text{Vehicle lifespan}\times\text{annual mileage}\times\text{vehicle load}}$. For the updates of the remanufacturing plant at Skien in 2030, two conditions were taken into account with different initial investments, update duration, and operational parameters. For scenarios S1 and S3, the initial investment and the update duration were set to 6 million NOK and 1 month, respectively. For the other two scenarios, 10 million and 2 months were used.

Table 7 shows the performances of the two network configurations across four test scenarios. Compared with the original scenario without technological upgrades in a 10-year run, the total cost can be reduced in a range of [0.53%, 1.11%], and there is a potential reduction in carbon emissions between 7.16% and 10.1%. As the planning period extends to 15 years, there's a potential for further cost reductions by up to 2.93% and for emission reductions by up to 17.02%. When the planning horizon increases to 15 years, the total cost and the carbon emissions can be further reduced to up to 2.93% and 17.02%, respectively. Fig. 7 illustrates the variations in facility- and transportation-related costs and carbon emissions. As shown, for both network structures, it would be more beneficial when the upgrades of the transport fleets are to be done in 2030, which may help achieve approximately a 5% reduction in the transportation cost and a 7% reduction in carbon emissions. This can be explained by two reasons. One is the lowered purchasing cost of battery-electric vehicles by 2030, and the other is the more matured technology that will likely reduce both operating and maintenance costs and carbon emissions. For the upgrades of the remanufacturing plant at Skien, both networks favor the high-tech solution, say scenarios S2 and S4. Even though the initial investment is 66.6% higher than its counterpart, this solution can lead to much lower total cost and emission reductions throughout a long planning period.

Tables 8 and 9 present the service level KPIs of both networks, which include the average and maximum lead time, service level by orders, utilization, and on-time delivery. The service level by orders is calculated by $\frac{\textit{Total received order} - \textit{unavailabe order}}{\textit{Total received order}}$, where the unavailable order includes drop-off orders and unavailable inventory when an order comes. As shown, network 1 has a higher level of service than that of network 2. For instance, network 1 has a 127.8% shorter average lead time in the original scenario. Furthermore, the maximum lead time is 819.6% shorter than that in network 2. Besides, compared to network 2, the service level by orders, utilization, and on-time delivery of network 1 can be improved by 21%, 3.2%, and 5.8%, respectively. The simulation results reveal that, by opening one more regional collection center and restructuring the network, the service level of the remanufacturing network can be improved.

It is noteworthy that the service level is affected by the upgrades of the remanufacturing plant at varying degrees. For network 1, the facility upgrades in S1 and S3 lead to a slightly reduced performance in service level by orders and utilization, but all KPIs decrease in S2 and S4. For network 2, the result is more interesting. The facility upgrades in S1 and S3 resulted in a 24.4% reduction in average lead time and a 72.3% reduction in maximum lead time. Besides, the service level by orders is also improved by 3.2%. However, except for the maximum lead time, all the other KPIs decreased in S2 and S4. This impact can be explained by the disruption caused by the facility upgrades, as shown in Fig. 8. Since the situations in S3 and S4 are similar to those in S1 and S2, we only show these two scenarios in the figure.

In general, facility upgrades will lead to negative impacts on utilization and on-time delivery caused by the temporary facility close-out. However, for the other service level KPIs, the impacts are by no means identical. Compared to its counterpart, network 1 has a higher inventory level of EOL compressors to support responsive remanufacturing processes and to ensure a high service level. In S1 and S3 when a one-month facility upgrade takes place, both networks can quickly recover the inventory level within approximately one and a half months. Thus, in this case, the disruption's effect on service-level KPIs is relatively minor. However, when having a two-month facility upgrade in S2 and S4, network 1 needs approximately 4–5 months to recover its inventory level for remanufactured compressors, while network 2 requires nearly 6 months. Considering the ripple effect throughout the entire remanufacturing reverse logistics system, technology adoption at the facility level should be planned collaboratively to mitigate its negative effects.

4.3. Discussions

4.3.1. Comparison with relevant research

As illustrated by earlier research (Kannan et al., 2023; Govindan et al., 2016), our experimental results also confirm that reverse logistics planning is affected by the cost and emissions, especially in the transportation planning of the reverse channels (De and Giri, 2020). The decision that favors one dimension may compromise the others (Kannan et al., 2023). For the given example, network 2 has a better performance in the total cost and emissions, even though more transportation is required due to the fewer regional collection centers being opened. Network 1 has shown a better service level and is more resilient to disruption. Besides, different uncertainties, i.e., epistemic uncertainty and randomness, may exist in various stages of reverse logistics planning (Yu and Solvang, 2020), which can hardly be tackled with a deterministic approach (Tosarkani et al., 2020). Incorporating imperfect and incomplete information in the decision-making, the performance measures and network configurations were by no means identical under different demand satisfying and capacity requirements, as also shown by Pishvaee and Torabi (2010). Furthermore, our results also complied with the suggestions from (Tosarkani et al., 2020) that simulation could effectively evaluate the result from the reverse logistics optimization, even though only a MCS was used in that research.

Our research not only confirms the pervious findings but also offers new perspectives. First, new technologies are becoming increasingly appealing in reverse logistics. On the one hand, our research confirms the findings by Govindan and Gholizadeh (2021) that the high cost may become a hindrance to technology adoption. On the other hand, to further complement this finding, we reveal the long-term benefits by taking a dynamic analysis to uncover both the proper technology and the time of adoption to maximize the potential benefits. Thus, different from this research, our results show that the initial investment may be fully recovered within a 10–15 planning horizon, and both costs and emissions could be significantly reduced over the planning period. Second, in contrast to previous research, we present more close-to-reality scenarios by incorporating dynamic simulations, which enable the evaluation of different uncertainties and the comparison and analysis of new performance measures, e.g., service level. Our results suggest that, apart from cost and emissions, the impact of service level needs to be evaluated when network designs are made. In a multi-stakeholder system, we recommend that the facility upgrade needs to be planned collaboratively to minimize the adverse ripple effect. Last but not least, we first reveal the potential impact of digitalization and future technology evolvement in reverse logistics planning, where the traditionally ad-hoc analytical process can be better linked.

4.3.2. Managerial implications

Our research offers practical insights for the managers and practitioners in reverse logistics. When planning a reverse logistics system, managers need to understand the different types of uncertainty that may be encountered and the ways of modeling and treating them in the decision-making. A dynamic view needs to be devised in the initial network design and facility configuration stage, where not only a static cost-emission analysis is given but also realistic factors, e.g., operational policies, inventory management, and transportation need to be holistically evaluated. Furthermore, new technologies in Industry 5.0 are likely to make a significant impact on reverse logistics strategies and operations. Even though the initial investment in new technologies may be high, their potential benefits may offset the initial cost and, in the long run, lead to improved economic and environmental performance. Our findings also reveal that the timing of technology adoption is important. On the one hand, technology maturity will eventually lower the initial investment. On the other hand, technology adoption may not be a painless process for the company. For instance, our experimental results show that facility upgrades may cause reduced service level, network disruption, and ripple effects throughout the entire reverse logistics system, but, if well planned, its adverse effects could be minimized and the service level of the entire planning horizon may be improved. In our example, network structure 2 with upgrade plan S3 could be a favorable choice for decision-makers due to the balance among cost, emissions, and service level. Thus, managers need to consider this in technology adoption and make collaborative planning decisions to reduce the ripple effect throughout the whole system. Finally, our research provides managers and practitioners with a highly integrated architecture and easy-going method to perform a comprehensive analysis under different uncertainties and realistic operating scenarios in a close-to-reality environment.

4.3.3. Research implications

We then discuss two research implications. On the one hand, digitalization and new technologies in Industry 5.0 are enablers to seamlessly connect different analytical methods and tools. Traditionally, connecting optimization with dynamic simulation is difficult due to the building of respective models, data conversion, result interpretation, and so forth. In reverse logistics, digitalization and the use of new technologies in Industry 5.0 will drastically simplify the model building, execution, and result presentation to support different decisions. Thus, researchers need to focus on how digitalized tools can better help in problem-solving with analytical models. On the other hand, analytical models, e.g., optimization and simulation, provide powerful tools to determine which and when new technologies should be implemented in a reverse logistics system or, to a larger extent, other systems. In this regard, future works should focus on developing new models and methods to better accommodate technology adoption in the decision-making of system design and operations to facilitate a smooth industrial and social transition.

5. Conclusions

Over the past two decades, reverse logistics network design has become an extensively investigated area for both academia and industrial practitioners. In this study, by incorporating a fuzzy MILP with dynamic simulation, we propose a novel digitalized and integrated method for planning uncertain remanufacturing reverse logistics networks. The first-stage fuzzy MILP determines the optimal network structures with imperfect and incomplete input information under diverse demand-satisfying and capacity requirements. Subsequently, these optimal network structures are evaluated in a comprehensive and close-to-reality simulation environment that takes into account technology-driven dynamic system development parametric stochasticity, practical operational policies and planning horizon, and stochasticity. The dynamic simulation models combine both DES and MCS, where DES is used to set up the simulation logic and MCS is used to account for the parametric stochasticity. The application is shown through a set of numerical experiments based mostly on real-world data in Norway. With the help of the experimental results, we compare our findings with the previous research to obtain valuable implications for both management and future research.

The results showcase the strength and applicability of our proposed method. They also emphasize the significant influence of digitalization and Industry 5.0 in transforming analytical approaches and decision-support systems for future reverse logistics planning. On the one hand, digitalization provides new tools to seamlessly connect different analytical models, which drastically simplifies model building and execution and also improves decisions and analysis. Furthermore, reverse logistics flows, operations, and experimental results are presented in a highly visualized and interactive way to better communicate with decision-makers. However, from another perspective, the technology adoption may also bring some new challenges. For example, some operating parameters may change significantly by adopting cutting-edge technologies. These need to be considered and comprehensively evaluated at the initial network design stage, otherwise, the reliability of decisions may be compromised. Moreover, the facility upgrades may cause disruptions and reduced service levels throughout the entire reverse logistics system, so managers need to make collaborative decisions to minimize the adverse impact.

This research opens avenues for further exploration and refinement of digitalized analytical approaches to reverse logistics network design. One possible direction is to incorporate AI-based predictive analysis for some key parameters in the digitalized and integrated architecture, which may help minimize uncertainty and continuously evaluate network decisions and operational policies. Another potential approach is to undertake a thorough examination of how technology adoption impacts dynamic parameter configuration. Besides, the human factors and behavioral aspects need to be incorporated, analyzed, and better understood in decision-making to promote a smooth transition of human-centric smart reverse logistics systems. Last but not least, exploring the use of the proposed methodological architecture in solving the decision-making challenges in other complex logistics systems with high uncertainty and conflicting planning objectives, e.g., humanitarian logistics (Ali et al., 2020; Eligüzel et al., 2023), emergency response logistics (Pouraliakbarimamaghani et al., 2018), blood supply chain (Khalilpourazari et al., 2020), and vaccine logistics (Tirkolaee et al., 2023; Lotfi et al., 2023) is a promising direction for future research.

CRediT authorship contribution statement

Hao Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xu Sun:** Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.engappai.2024.108578.

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