European Journal of Operational Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing, Transportation and Logistics

Multi-period green reverse logistics network design: An improved Benders-decomposition-based heuristic approach

K. Nageswara Reddy[a], Akhilesh Kumar[b], Alok Choudhary[c,*], T. C. Edwin Cheng[d]

[a] Operations and Supply Chain, Indian Institute of Management Jammu (IIM Jammu), India
[b] Department of Industrial and Systems Engineering, Indian Institute of Technology, Kharagpur, West Bengal 721302, India
[c] Warwick Manufacturing Group (WMG), The University of Warwick, Coventry, CV4 7AL, United Kingdom
[d] Faculty of Business, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

A R T I C L E I N F O

Article history:
Received 12 December 2020
Accepted 8 March 2022
Available online xxx

Keywords:
Supply chain management
Reverse logistics
Carbon emissions
Vehicle fleet
Benders decomposition
Heuristic

A B S T R A C T

There has been extensive academic research on the optimisation of reverse logistics (RL) and closed-loop supply chain (CLSC) network design. However, the existing literature is lacking in several features of practical relevance, and the simultaneous consideration of dynamic characteristics, including the multi-period setting, inventory factors, environmental footprints, and scalability of the application. This shortcoming is primarily due to the challenges associated with computation complexity, mathematical formulation, and the need for a faster solution method to solve such large-scale problems in real-time. In this research, we address these challenges and investigate the multi-facility green RL network design problem, integrating carbon footprint and vehicle selection, entailing allocation between the facilities in the multi-period setting to incorporate the dynamic characteristics. We formulate a mixed-integer linear programming (MILP) model to minimise the total cost, comprising the carbon emission cost due to transport and production at the facilities. We also investigate the effects of carbon emissions and the choice of the vehicle fleet on the network's structure. The novelty of our research lies in the development and application of an exact solution method, namely "Improved Benders Decomposition (IBD)" with several algorithmic enhancements, including a strengthened master problem, valid inequalities, a heuristic, and a multi-stage strategy to accelerate the convergence of the Benders decomposition method. By combining these elements, the proposed IBD solves the MILP model, provides a faster solution methodology with improved convergence of the bounds, and addresses the inherent intractability of the existing problem. We apply our proposed heuristic on a set of 12 problem configurations under distinct scenarios. We show that the proposed IBD heuristic outperforms existing traditional methods in terms of solution quality, computational time, and robustness.

1. Introduction

The acceleration of climate change and the adverse environmental impact of waste related to end-of-life (EOL) durable products have forced governments in several countries to legislate industries to reduce their ecological footprints and to take back their EOL products. These EOL products include durable products such as aircraft, automobiles, large household appliances, and waste electrical and electronic equipment (WEEE), containing large quantities of precious and depletable raw materials (Jeihoonian, Zanjani & Gendreau, 2016; Lu & Bostel, 2007, Ayvaz, Bolat & Aydin 2015, Bing, Bloemhof-Ruwaard & Vorst 2014). It is now widely accepted that reverse logistics (RL) and closed-loop supply chains (CLSCs) are key drivers that enable and stimulate the diffusion of the circular economy (CE) business model (Lechner & Reimann, 2020). RL and CLSCs provide opportunities for industries to bring back used products (core returns), which can be reused via refurbishing or remanufacturing.

Several studies (Fleischmann, Nunen & Gräve, 2003; Üster & Hwang, 2016; Zhalechian, Tavakkoli-Moghaddam, Zahiri & Mohammadi, 2016) have considered the designing of a reverse supply chain (RSC), attempting to minimise the environmental footprint through the backward flow of products. Traditionally, RSCs concern decisions related to facility location, transport, and selection

* Corresponding author.
E-mail address: Alok.Choudhary@warwick.ac.uk (A. Choudhary).

https://doi.org/10.1016/j.ejor.2022.03.014
0377-2217/

of vehicles. A reverse logistic network (RLN) design is typically cast as a multi-echelon framework comprising the collection, inspection, and remanufacturing facilities (Fleischmann et al., 2003). Recently, many industries have been considering factors that influence the environmental footprint of their RL networks, such as the size of and emissions from facilities, fuel efficiency, and carbon emissions from the vehicles used (Cachon, 2014), and have thus started to promote a green reverse supply chain. An adequately designed green RLN helps a firm reduce carbon emissions from freight transport and facilities (Acquaye et al. 2018; Guo, Wang, Fan & Gen 2017). Furthermore, in the long run, it also reduces the total operating cost while meeting environmental standards. Optimisation models have been widely developed and employed to support the decision-making of an RLN design. However, despite extensive academic research in this area, the existing literature lacks several features of practical relevance with respect to the design of an RLN (Ghadimi, Wang & Lim, 2019; Reddy, Kumar & Ballantyne, 2019).

The design of such a green RLN faces three key challenges. First, a close-to-practical, i.e., incorporating several features of practical relevance, RLN design should consider the efficient flow of the returned products, including decisions related to the location and allocation of facilities (Chen, Chan & Chung, 2015), selection of vehicle type (Yang, Hu & Huang, 2020), operations such as testing and remanufacturing at facilities, and environmental footprint. Second, mathematical modelling is more complex in comparison with the traditional RLN design problem. The complexity increases with the constraints brought by consideration of the coordination of exogenous supply and demand. Several researchers (Fleischmann et al., 2003) have used MILP-based approaches to model the RLN design problem. However, the simultaneous consideration of such dynamic characteristics as the multi-period setting, inventory factors, environmental footprint, and scalability of the application increases the complexity of mathematical modelling (Jeihoonian, Kazemi Zanjani & Gendreau, 2020).

Third, solving such a large-scale network design problem under considerable time pressure becomes significantly difficult, given the *NP*-hardness nature of the problem (Santos, Coutinho-Rodrigues & Current, 2010; Sifaleras & Konstantaras, 2017). Many researchers have suggested Benders decomposition (BD) based approaches to solve such problems (Naderi, Govindan & Soleimani, 2019; Rahmaniani, Crainic, Gendreau & Rei, 2017). However, solving the problem (as detailed in the Literature Review section) directly using BD does not guarantee an optimal solution within a reasonable time limit. Therefore, the complex problem, as suggested in this research, requires an efficient solution methodology to address the inherent computational complexity. Such a methodology should have the properties of accelerating the convergence of the bounds. In line with the abovementioned challenges, we develop a set of research questions as follows:

- Q1: How to design an RLN design incorporating features of practical relevance, including decisions related to the location and allocation of facilities, selection of transport vehicle type, route options, operations including testing and remanufacturing at facilities, inventory at facilities environmental footprint, and activation of facilities?
- Q2: How does the carbon tax influence facility openings, production flows, and vehicle fleet choice?
- Q3: How to mathematically model such as a complex RLN design problem with dynamic characteristics including multi-period setting, inventory factors, environmental footprint, and ensuring scalability of the application?
- Q4: How to develop a novel BD-based heuristic to solve the proposed model effectively and demonstrate its robustness?

In this research, we address each decision-making challenge and develop a set of objectives to answer the research questions. To address the first challenge, our first objective is to design a four-echelon multi-period RLN. In this RLN, the used products are collected at collection facilities, processed at a testing facility where their yield factors are considered, and finally remanufactured at the remanufacturing centre. We consider several decisions, such as whether the returned product should be kept in the inventory, disposed, or forwarded to remanufacturing facilities or testing facilities. At the remanufacturing facilities, we consider decisions related to the quantities of new products required to fulfil the entire demand. At each echelon, we also consider decisions, including the selection of the transport vehicle and considering the costs and carbon emissions of the vehicles. To address the second challenge, our second objective is to develop a mathematical model using the MILP formulation and consider objectives including minimising the overall cost (comprising the setup cost, operating cost, transport cost, and emission costs, under several constraints). Finally, to address the third challenge, our third objective is to develop a novel BD-based heuristic, i.e. the IBD technique, to solve the proposed model. Through this technique, we modify the classical BD with several algorithmic enhancements, including a strengthened master problem, valid inequalities, a heuristic, and a multi-stage strategy to accelerate the convergence of the BD method. Finally, our last objective is to conduct exhaustive numerical studies on several instances of the problem to illustrate the applicability and effectiveness of the proposed IBD. We demonstrate the superior performance and robustness of the proposed IBD method over the classical branch-and-cut, traditional BD, and BD with the multi-stage strategy in terms of solution gap and computational time.

Our research contributes to the RL and CLSC network design literature by developing a novel mathematical model to mimic the plausible practical problem of green RLN design and proposing a robust and efficient optimisation method, i.e., IBD. Specifically, our contribution is threefold. First, we formulate a mathematical model (MILP) for the four-echelon green RLN to address both strategic and tactical decisions, including facilities location and allocation, inventory, and distribution decisions, as well as taking into account the environmental factors including carbon emissions from transport, production, and vehicle selection and allocation between facilities. Furthermore, we analyze the impacts of carbon emissions and the choice of vehicle fleet on the network. Second, we develop a novel improved BD-based heuristic, i.e., IBD, by enhancing the properties of the classical BD with several algorithmic enhancement strategies. These enhancements include partitioning into master- and sub-problems based on complex variables, proposing a novel algorithm to obtain an initial feasible solution, and strengthening the master problem using a multi-stage strategy based on the number of echelons in the network. These enhancements not only lead to an improved lower bound but also significantly accelerate the convergence of the bounds. Finally, we conduct exhaustive numerical studies on several benchmark instances of the problem to show the superior performance and robustness of the proposed approach over the existing methods applied in the relevant literature.

We organize the rest of the paper as follows. In the next section, we briefly review the relevant literature on the RLN design problem and the related solution methodologies. In Section 3, we present the problem's formulation, the related mathematical models, as well as assumptions. In Section 4, we explain the proposed IBD-based solution approach with algorithmic enhancements to improve convergence. In Section 5, we discuss the computational results, validation, and robustness checks using a comparative study and provide managerial insights. Finally, in Section 6, we conclude the paper and suggest some directions for future research.

2. Literature review

In this section, we review the relevant literature in two separate but complementary research streams. The first stream focuses on RLN design, and the complexity tackled by researchers in this area. For a detailed review of this area, we refer the reader to Alumur Sibel, Nickel, Saldanha-da-gama and Verter (2012), Chanintrakul, Mondragon, Lalwani and Wong (2009), Govindan, Soleimani and Kannan (2015), Govindan & Soleimani (2017) and Govindan and Bouzon (2018). The second stream of research focuses on solution methodologies, including relevant algorithmic refinements for BD methods. Finally, we summarise our findings from the literature review and highlight the existing research gaps.

2.1. RL network design

RLN design is much more complex than a forward logistics network with the operations such as examining and sorting return products, addressing return products in terms of quantity, quality, supply timing, etc. (Chanintrakul et al., 2009; Reddy, Kumar, Sarkis & Tiwari, 2020). Table 1 presents a comprehensive review of research papers investigating reverse supply chain (RSC) design models during 2016–2021. Consequently, modelling methods are categorized into two parts:

(1) MILP models without uncertain factors.
(2) MILP models, which dealt with any of the uncertain factors.

In the first group i.e., MILP models without uncertainty, Diabat and Jebali (2021) proposed a MILP model for CLSC network design with the assumption of a 100% recovery target. Tadaros, Migdalas, Samuelsson and Segerstedt (2020) developed a MILP model to decide where to locate facilities for inspection and recycling of lithium-ion batteries in the Swedish market. Govindan and Bouzon (2018) presented a framework for RL from the perspectives of multiple stakeholders. They identified that customers demand that the supply chain partners follow green standards, including in RL operations. Trochu, Chaabane and Ouhimmou (2018) developed a model to re-design the RLN for the construction, renovation, and demolition (CRD) industry and formulated a MILP for locating sorting facilities and measuring their capacity. Coelho and Mateus (2017) proposed a plant location model for RL with limited capacity. Meanwhile, Amin and Baki (2017) developed a facility location model for CLSC design with global aspects and validated it by applying a CLSC network in Canada. However, they did not incorporate inventory factors, and the model thus lacks applicability concerning larger problems.

Alshamsi and Diabat (2015) and Alumur Sibel et al. (2012) presented MILP models for designing the RLN and validated the models for large household appliances. They also mentioned that priority is given to locating inspection and remanufacturing centres ahead of the in-house fleet. Mutha and Pokharel (2009) developed a MILP model for an RLN to maximise the reuse and recycling of used products. They incorporated suppliers as an echelon to provide new models on a need basis when remanufactured product demand increases. Furthermore, Pishvaee, Jolai and Razmi (2009) used a MILP model for an integrated logistics (FL and RL) network design and applied a scenario-based stochastic approach to handle uncertainty. The results showed that demand has more influence on the total cost than the return ratio.

In general, most of these models only consider the economic aspect of supply chain sustainability. However, due to the growing awareness and regulation of environmental issues, researchers have focused on integrating economic and environmental aspects. Govindan, Paam and Abtahi (2016) addressed the significance of economic, social, and environmental aspects while designing a sustainable RLN over a finite planning horizon applied to a medical syringe recycling system. Brandenburg and Rebs (2015), Brandenburg, Govindan, Sarkis and Seuring (2014), and Seuring (2013) reviewed the literature on quantitative models that address the environmental and social issues in supply chains. Fahimnia, Sarkis, Dehghanian, Banihashemi and Rahman (2013) designed a CLSC network in Australia by considering carbon costs and suggested that the government provide subsidies on carbon costs to promote decarbonization, especially for RSC operations. Kannan, Diabat, Alrefaei, Govindan and Yong (2012) proposed a model combining location and transport problems to minimise the carbon footprint in an RLN for plastic industries. To find the trade-off between environmental and economic objectives, Chaabane, Ramudhin and Paquet (2012) proposed a sustainable framework for a supply chain with the help of life-cycle assessment principles. They also presented various efficient carbon management strategies to achieve long-term sustainability. Paksoy, Bektaş and Özceylan (2011) investigated the environmental and operational performance measures in CLSCs and observed that the operational costs dominated the environmental costs under extreme emissions scenarios.

Zhalechian et al. (2016) designed a CLSC network to make location-routing-inventory decisions with an emphasis on the importance of waiting times of vehicles, using queuing models. They observed that CLSC network costs are influenced more significantly by transport costs than inventory costs. Qiu et al. (2018) discussed the production routing problem with simultaneous pickups and deliveries in RL with remanufacturing. They interestingly found that the location of the remanufacturing depot does not affect the optimal decisions. They also mentioned that it is essential to consider emissions in vehicle routing. Kim, Yang and Lee (2009) presented a MILP model for a vehicle routing problem (VRP) in RL and applied it to recycle electronic products in South Korea. They investigated that a VRP is more significant when there is an increase in both the EOL of consumer electronic goods and the corresponding collection centres.

In the second group i.e., MILP model with uncertain factors, some authors (Antucheviciene, Jafarnejad, Mahdiraji, Hajiagha & Kargar, 2020; Shahparvari et al., 2021) provided MILP models that dealt with uncertainty for RLN Design. Baptista, Barbosa-Póvoa, Escudero, Gomes and Pizarro (2019) introduced a two-stage stochastic linear model to address CLSC design and production planning under the returns quantity and quality uncertainties along the time horizon. Further, they applied their model for efficient waste management of the demolition industry in Quebec's Canadian province. Similarly, few papers have considered two-stage stochastic MILP models for tackling uncertainty in CLSCs (Fattahi & Govindan, 2017; Jerbia, Kchaou Boujelben, Sehli & Jemai, 2018; Trochu, Chaabane & Ouhimmou, 2019; Üster & Hwang, 2016).

Overall, our review of this stream of research reveals three key aspects relevant to our study. First, the existing literature is lacking in practical relevance and fails to simultaneously consider the dynamic characteristics, including the multi-period setting, inventory factors, environmental footprint, and the scalability of the application. The extent to which we propose the model in this research goes beyond the existing literature and takes into account return ratio, quality levels of used products, along with the demand for a new and recoverable inventory. Though demand and return quantities are uncertain in reality, we consider them as deterministic and known since they are estimated for strategic-level decisions. Second, these research shortfalls may be partially due to the challenges associated with computational complexity, mathematical formulation, and the need for a faster method to solve such large-scale problems in real-time using commercial solvers. Hence, it is essential to pursue the application of heuristics. From the methodological perspective, compared with the BD-based approaches applied in earlier research, the complex nature of the problem considered in this research requires the development of a novel, efficient, and exact methodology to handle large-sized problems and solve the resulting MILP model.

2.2. Solution approaches and algorithmic enhancements made to Benders decomposition

The network design problem is complex and an *NP*-hard combinatorial optimisation problem. The complexity increases significantly when the practical aspects, as well as size, are taken into consideration. The existing research is broadly classified into exact methods (which provide an optimal solution) and heuristic approaches (which provide a near-optimal solution) to solve the complex network problem. Most solution methods employ standard commercial packages such as CPLEX to solve the MILP formulations (Farrokh, Azar, Jandaghi & Ahmadi 2018; Jiang et al., 2020). When the number of discrete variables is large, the resulting model can be solved only using heuristic or metaheuristic approaches to obtain a near-optimal solution. However, RLN design involves a large investment, which greatly influences the operational and tactical costs and service efficiency (Keyvanshokooh, Ryan & Kabir, 2016). Therefore, it is imperative to develop an efficient exact solution methodology to solve large-scale and more realistic cases (De Sá, De Camargo & De Miranda, 2013). While the focus of our research is on exact methods and, more precisely, algorithmic refinements of the BD method, we also acknowledge the relevant research on heuristic methods.

For the first category (exact methods), various researchers have suggested a BD-based approach to solve the network problem (Naderi et al., 2019; Rahmaniani et al., 2017). Fontaine and Minner (2018) converted a bi-level formulation into a mixed-integer linear program using the Karush-Kuhn-Tucker (KKT) conditions. They applied the multi-cut BD method to solve the Hazmat Transport Network Design problem optimally. Easwaran and Üster (2009) presented a MILP model for the multi-product CLSC and solved it using a BD-based approach. They used neighbourhood functions as a heuristic to enhance the BD method, which improves the convergence of the bounds. Santibanez-Gonzalez and Diabat (2013) applied IBD schemes such as valid inequalities and quasi Pareto-optimal cuts to solve the reverse supply chain (RSC) design problem.

Similarly, Jeihoonian, Zanjani and Gendreau (2016b) enhanced the performance of BD by implementing valid inequalities, Pareto-optimal cuts, and local branching to solve a CLSC for durable products. Elsewhere, Tang, Jiang & Saharidis (2013) proposed a high-density Pareto-cut generation approach to accelerate BD to solve a facility location problem. In Table 2 (Appendix 1), we summarise and compare various algorithmic enhancements used for BD to solve complex models in the existing research. Badri, Fatemi Ghomi and Hejazi (2017) applied a two-stage stochastic programming approach to solve a value-based CLSC network problem and make decisions in a stochastic environment. Similarly, Lee and Dong (2008) used a two-stage heuristic approach to solve a logistics network design problem by dividing it into two areas: a revised network flow problem; and a location-allocation problem. Reddy et al. (2019) presented a three-phase heuristic method to solve an RLN design. Although the three-phase heuristic is very efficient, it may lead to a sub-optimal solution because information flows in one direction, so there is no scope for feedback.

In the second category (heuristics), some researchers have applied heuristics to solve the network design problem. For instance, Antucheviciene et al. (2020) presented an NSGA-II algorithm to optimize the flow of materials in an RSC for the steel industry. Li, Guo and Zhang (2018) proposed a novel, improved hybrid differential evolution (IHDE) algorithm for the closed-loop supply chain to study location-inventory decisions with third-party logistics. Similarly, a hybrid genetic algorithm (GA) was developed by Aravendan and Panneerselvam (2016); Liao (2018) to solve the RL problem with product recovery via remanufacturing and tested for bulk waste recycling in Taiwan. Alshamsi and Diabat (2017) formulated a MILP model to design an RLN, and they implemented an efficient genetic algorithm to solve the MILP. In the interim, Cui et al. (2017) proposed a genetic artificial bee colony algorithm approach for designing an optimal CLSC network. Similarly, an improved genetic algorithm was presented to solve the multi-objective CLSC network design problem in China (Shi, Liu, Tang & Xiong, 2016).

Similarly, Chen, Wang, Wang and Chen (2017) presented a multi-objective PSO (MOPSO) algorithm to address the sustainable CLSC problem for the solar energy industry considering economic and environmental concerns. Zohal and Soleimani (2016) developed an ant colony approach to solve integrated forward RLN. Tiwari, Chang, Tiwari and Kandhway (2016) applied a hybrid territory-defined evolutionary algorithm to solve semiconductor industries' green CLSC network problem. Similarly, Cardona-Valdés, Álvarez and Pacheco (2014) and Devika, Jafarian and Nourbakhsh (2014) presented metaheuristics to solve the supply chain network design problem.

Among all the exact methods and heuristics, BD and its extensions are widely used to solve various complex problems optimally. However, several researchers have reported issues in relation to problem size, feasibility, cyclical behavior, and slow convergence in the traditional BD algorithm. These issues have been taken into account here while developing a solution approach.

Several researchers have extensively used heuristics/metaheuristics to produce an initial feasible solution with good quality, which provides a better set of initial cuts for solving a master problem or sub-problem. For example, Taskin and Cevik (2013) found an initial feasible solution using a greedy heuristic and used a heuristic to handle infeasibility in the BD-based approach. Randazzo, Luna and Mahey (2001) found an initial solution using the shortest path algorithm, and Easwaran and Üster (2009), and Jiang, Tang and Xue (2009) used a Tabu search to yield an initial feasible solution. Correspondingly, Belieres, Hewitt, Jozefowiez, Semet and Van Woensel (2020) proposed a new primal heuristic to enhance the Benders decomposition method along with valid inequalities and a strengthened master problem for large-sized industrial problems. Lai, Sohn, Tseng and Chiang (2010) and Poojari and Beasley (2009) used a genetic algorithm to obtain a (sub-optimal) solution for the master problem in the BD approach. Furthermore, to address the convergence issue, Lusby, Range and Larsen (2016) and Boschetti and Maniezzo (2009) developed a BD-based heuristic to solve the problem with a good-quality solution. Üster and Hwang (2016) and Easwaran and Üster (2010) strengthened Benders' cuts using algorithms such as the two-phase method and the Tabu approach.

On the other hand, many researchers have introduced valid inequalities, Pareto-optimal cuts, and induced constraints to significantly improve the quality of the lower bounds found by the master problem (in the case of minimisation) and also to accelerate the convergence of the bounds by restricting the solution space. For example,Jeihoonian et al. (2016b) and Saharidis, Boile and Theofanis (2011), Naderi et al. (2019) added valid inequalities to the master problem to reduce the number of feasibility cuts. Moreover, Jeihoonian et al. (2016b) put forward a local branching search to improve both lower and upper bounds concurrently during the execution of the BD algorithm. Alshamsi and Diabat (2018), De Sá et al. (2013), Santibanez-Gonzalez and Diabat (2013), and Tang et al. (2013) generated Pareto-optimal cuts to enhance the algorithm by excluding a larger space of the master problem.

The extant literature has proposed various acceleration techniques to speed up the classical BD to resolve the slow convergence issues in logistics network design. As presented earlier, these

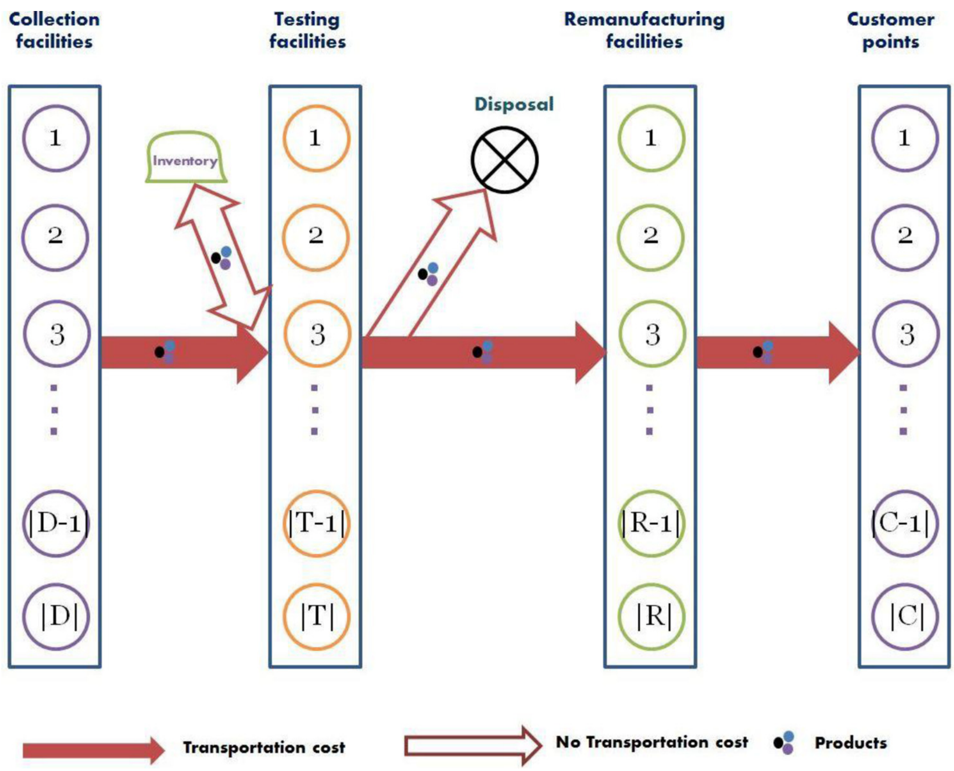

Fig. 1. RLN structure.

techniques range from improvement in the initial feasible solution to Pareto-optimal cuts. However, given the topology of RLNs, it is promising to explore the acceleration of BD by differentiating between the strategic and tactical decision variables. Thereafter, algorithmic enhancements are applied to accelerate the convergence of the bounds. This research proposes modelling and algorithmic enhancements, including a strengthened master problem, valid inequalities, a heuristic, and a multi-stage strategy. By combining these, the proposed IBD solves the MILP model, provides a faster solution methodology with improved convergence of the bounds, and addresses the inherent intractability of the present problem.

3. Mathematical model and formulation

We consider a multi-period and a single-product RLN. The primary setting of our problem spans both strategic and operational levels. At the strategic level, the RLN (as shown in Fig. 1) consists of four types of facilities, namely collection, testing, remanufacturing, and customer points.

In an RLN, the first step is to collect the available core returns from customers with a return policy and store them at the collection facilities. The collected core returns are then transferred to the testing facilities for testing and sorting. Depending upon the technology and location, these testing facilities can have different yields. After testing, depending upon their conditions, the cores are sent for either remanufacturing or disposal. The testing facilities can also keep the returned products to be used subsequently as core inventory. Finally, the remanufactured products are used to satisfy the demand at customer points.

In an RLN design, the objective is to minimise the total cost, which consists of carbon emission costs, transport costs, and fixed costs. Establishing and operating facilities implies the associated fixed costs and also variable operating costs for the returned products. Furthermore, the product flow between facilities entails variable transport costs. In reality, it is not possible to recover all the core returns via the remanufacturing activities because of quality issues. Thus, we consider the yield to represent the percentage of returned products that are remanufactured. The following assumptions support our model presented in this section:

- Demand and returns quantity and quality are deterministic.
- Potential locations for the testing and remanufacturing facilities are known.
- At each facility, a fixed and sufficient number of vehicles is available to serve all customers.
- New products are used as substitutes for a remanufactured product to meet the total demand.

3.1. Key objectives

The key objectives of our study are summarised below:

- To determine the testing and remanufacturing facilities' location(s).
- To determine the amount of the flow among the facilities of the network to minimise the cost.
- To determine the type and quantity of vehicle(s) in each arc between the facilities.
- To determine the amounts of inventory, disposals, and purchases.

3.2. Notation

We introduce the notation, including the sets, parameters, and decision variables used to design the RLN under the above-described characteristics. *Sets*

T	Set of potential testing facilities
C	Set of customer points
D	Set of collection facilities
R	Set of potential remanufacturing facilities
V	Types of vehicles

P	Length of the planning horizon

Parameters

S_i^p	Returns Supply to collection facility $i\epsilon D$ in period $p\epsilon P$.
b_t^p	Quality level (yield) of core returns at testing facility $t\epsilon T$ in period $p\epsilon P$
D_c^p	Demand at customer point $c\epsilon C$ in period $p\epsilon P$
Q_d^p	Returns quantity at collection facility $d\epsilon D$ in period $p\epsilon P$
H_j	Capacity limit of a facility $j\epsilon\{T,R\}$
H_v	Capacity of vehicle $v\epsilon V$
FC_j	Fixed cost for establishing a facility $j\epsilon\{T,R\}$
PC_j^p	Unit processing cost at a facility $j\epsilon\{T,R\}$ in period $p\epsilon P$
HC_t^p	Unit inventory holding cost at testing facility $t\epsilon T$ in period $p\epsilon P$
DC_t^p	Unit disposal cost at testing facility $t\epsilon T$ in period $p\epsilon P$
BC^p	Unit purchase cost in period $p\epsilon P$
E_v	Emissions generated by vehicle $v\epsilon V$ per unit distance
PE_j	Emissions generated by facility $j\epsilon\{T,R\}$ for processing unit product
Ω	Cost of carbon credits
d_{ij}	Distance between facilities $i\epsilon\{D,T,R\}$ and $j\epsilon\{T,R,C\}$
FTC_v	Fixed cost for using a vehicle $v\epsilon V$
VTC_v	Variable cost for using vehicle $v\epsilon V$ for travelling unit distance
M	A big number

Decision variables

q_{ijv}^p	Flow quantity between facilities $i\epsilon\{D,T,R\}$ and $j\epsilon\{T,R,C\}$ in period $p\epsilon P$ through vehicle $v\epsilon V$
x_j^p	1 if a facility is established at location $j\epsilon\{T,R\}$ in period $p\epsilon P$, otherwise 0
y_{ijv}^p	1 if vehicle type $v\epsilon V$ is selected on an arc between facilities $i\epsilon\{D,T,R\}$ and $j\epsilon\{T,R,C\}$ in period $p\epsilon P$, 0 otherwise
I_t^p	Inventory quantity at testing facility $t\epsilon T$ in period $p\epsilon P$
DQ_t^p	Disposal quantity at testing facility $t\epsilon T$ in period $p\epsilon P$
B_r^p	Purchase quantity at remanufacturing facility $r\epsilon R$ in period $p\epsilon P$
N_{ijv}^p	Vehicle quantity of type $v\epsilon V$ required to transport products between facilities $i\epsilon\{D,T,R\}$ and $j\epsilon\{T,R,C\}$ in period $p\epsilon P$

Based on the notation listed above, the mathematical formulation for the multi-period RLN design with carbon footprint is presented below.

3.3. Objective function

We formulate the problem mentioned above as a MILP with the objective of cost minimisation and considering the costs related to carbon emissions. The model objective is to minimise the overall cost correspondingly by determining the optimal location and allocation of facilities, the flows between the facilities, and the selection and allocation of the vehicles. The total cost includes the fixed cost for locating the facilities, processing costs at facilities, and disposal, inventory holding, transport, emissions, and purchase costs.

Minimise Z

$$
\begin{aligned}
&= \sum_{j\epsilon T}\sum_{p\epsilon P} FC_j\left(x_j^p - x_j^{p-1}\right) + \sum_{j\epsilon R}\sum_{p\epsilon P} FC_j\left(x_j^p - x_j^{p-1}\right) \\
&+ \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} PC_j^p q_{ijv}^p + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} PC_j^p q_{ijv}^p \\
&+ \sum_{t\epsilon T}\sum_{p\epsilon P} I_t^p HC_t^p + \sum_{t\epsilon T}\sum_{p\epsilon P} DQ_t^p DC_t^p + \sum_{r\epsilon R}\sum_{p\epsilon P} B_r^p BC^p \\
&+ \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v \\
&+ \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v \\
&+ \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v) \\
&+ \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v) \\
&+ \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v) \\
&+ \Omega\sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij}N_{ijv}^p E_v + \Omega\sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij}N_{ijv}^p E_v \\
&+ \Omega\sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij}N_{ijv}^p E_v \\
&+ \Omega\sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} PE_j q_{ijv}^p + \Omega\sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} PE_j q_{ijv}^p
\end{aligned} \tag{1}
$$

The first and second terms represent the total fixed cost for establishing the testing and remanufacturing facilities, respectively. Meanwhile, the third and fourth terms constitute the total processing cost of the used products at the testing and remanufacturing facilities, respectively. The fifth term indicates the total inventory cost for holding products until the next period, and the sixth term represents the total disposal cost at the testing facilities. The seventh term represents the total purchase cost of meeting the remaining demand after remanufacturing. Terms eight, nine, and ten represent the total fixed transport costs to carry products between the collection facility to the testing facility, the testing facility to the remanufacturing facility, and the remanufacturing facility to a customer point, respectively. Similarly, terms eleven, twelve, and thirteen represent the total variable transport costs of moving products from the collection facility to the testing facility, the testing facility to the remanufacturing facility, and the remanufacturing facility to a customer point, respectively. Terms fourteen, fifteen, and sixteen represent the total emissions costs of transport from the collection facility to the testing facility, the testing facility to the remanufacturing facility, and the remanufacturing facility to a customer point, respectively. Finally, the seventeenth and eighteenth terms represent the total emissions from the processing of used products at the testing and remanufacturing facilities, respectively.

3.4. Constraints

The proposed model contains the following constraints:

$$\sum_{j\epsilon T}\sum_{v\epsilon V} q_{ijv}^p = S_i^p \qquad \forall i\epsilon D, \forall p\epsilon P \tag{1.i}$$

$$b_j^p \sum_{i\epsilon D}\sum_{v\epsilon V} q_{ijv}^p + I_j^{p-1} = \sum_{r\epsilon R}\sum_{v\epsilon V} q_{jrv}^p + DQ_j^p + I_j^p \qquad \forall p\epsilon\{2..P\}, \forall j\epsilon T \tag{1.ii}$$

$$I_j^p = 0 \qquad p = 1,\ \forall j\epsilon T \tag{1.iii}$$

$$I_j^P = 0 \qquad \forall j\epsilon T \tag{1.iv}$$

$$B_j^p + \sum_{i\epsilon T}\sum_{v\epsilon V} q_{ijv}^p = \sum_{i\epsilon C}\sum_{v\epsilon V} q_{ijv}^p \qquad \forall p\epsilon P, \forall j\epsilon R \tag{1.v}$$

$$\sum_{i\epsilon R}\sum_{v\epsilon V} q_{ijv}^p = D_j^p \qquad \forall p\epsilon P,\ \forall j\epsilon C \tag{1.vi}$$

$$\sum_{i\epsilon D}\sum_{v\epsilon V} q_{ijv}^p \le x_j^p H_j \qquad \forall p\epsilon P,\ \forall j\epsilon T \tag{1.vii}$$

$$\sum_{i\epsilon T}\sum_{v\epsilon V} q_{ijv}^{p} \le x_j^p H_j \qquad \forall p\epsilon P, \forall j\epsilon R \qquad (1.\text{viii})$$

$$N_{ijv}^{p} \ge \left(q_{ijv}^{p}/H_v\right) \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{ix})$$

$$N_{ijv}^{p} \ge \left(q_{ijv}^{p}/H_v\right) \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{x})$$

$$N_{ijv}^{p} \ge \left(q_{ijv}^{p}/H_v\right) \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xi})$$

$$x_t^{p-1} \le x_t^p \qquad \forall t\epsilon T, \forall p\epsilon P \qquad (1.\text{xii})$$

$$x_t^1 = 0 \qquad \forall t\epsilon T \qquad (1.\text{xiii})$$

$$x_r^{p-1} \le x_r^p \qquad \forall r\epsilon R, \forall p\epsilon P \qquad (1.\text{xiv})$$

$$y_{ijv}^{p} \le x_j^p \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xv})$$

$$y_{ijv}^{p} \le x_i^p \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xvi})$$

$$y_{ijv}^{p} \le x_j^p \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xvii})$$

$$y_{ijv}^{p} \le x_j^p \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xviii})$$

$$N_{ijv}^{p} \le y_{ijv}^{p} M \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xix})$$

$$N_{ijv}^{p} \ge y_{ijv}^{p} \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xx})$$

$$N_{ijv}^{p} \le y_{ijv}^{p} M \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xxi})$$

$$N_{ijv}^{p} \ge y_{ijv}^{p} \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xxii})$$

$$N_{ijv}^{p} \le y_{ijv}^{p} M \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xxiii})$$

$$N_{ijv}^{p} \ge y_{ijv}^{p} \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \qquad (1.\text{xxiv})$$

$$x_j^p, y_{ijv}^{p} \epsilon \{0, 1\} \qquad (1.\text{xxv})$$

$$q_{ijv}^{p}, I_t^p, DQ_t^p, B_r^p \ge 0\ , \qquad N_{ijv}^{p} \ge 0 \text{ and int} \qquad (1.\text{xxvi})$$

Constraint (1.i) ensures that the outflow from the collection facility is equal to the inflow of the core returns collected from customers. Constraint (1.ii) balances the flow at the testing facility, i.e., the inflow and inventory of the previous year must be equal to the outflow as well as the disposal and inventory of the present period. Constraints (1.iii) and (1.iv) ensure that the inventory quantity is equal to zero at the beginning and end of the horizon. Constraint (1.v) ensures that the purchased quantity and the products being moved to a remanufacturing facility must be equal to the outflow from the remanufacturing facility. Constraint (1.vi) ensures that all the demand is satisfied at each customer point. Constraints (1.vii) and (1.viii) are capacity restrictions and limit the inflow at the testing facility and remanufacturing facility to their respective capacity. Constraints (1.ix), (1.x), and (1.xi) are associated with the vehicle quantity and assure that a sufficient number of vehicles is used to move products from one facility to another facility. Constraint (1.xii) is the location and allocation constraint related to testing facilities and ensures that once the facilities are installed at a location, they continue operating until the last period. Constraint (1.xiii) ensures that there is no installation of the testing facilities in the initial period. Constraint (1.xiv) is the remanufacturing facilities location constraint, which ensures that they continue operating until the last period once the remanufacturing facilities are established. Constraints (1.xv), (1.xvi), (1.xvii), and (1.xviii) are if-then constraints related to vehicle selection and facility location from the collection facility to the testing facility, the testing facility to the remanufacturing facility, and the remanufacturing facility to customer points, respectively. They ensure that a vehicle is selected and allocated between facilities if those are established. Constraints (1.xix) and (1.xx) are if-then constraints related to vehicle selection and quantity on an arc between the collection and testing facilities. Constraints (1.xxi) and (1.xxii) are if-then constraints related to vehicle selection and quantity on an arc between the testing and remanufacturing facilities. Similarly, constraints (1.xxiii) and (1.xxiv) are if-then constraints related to vehicle selection and quantity on an arc between the remanufacturing facilities and customer points. Constraints (1.xix)–(1.xxiv) ensure that at least one vehicle should be allocated on an arc between the facilities if the vehicle is selected, and constraints (1.xxv) and (1.xxvi) represent the non-negativity constraints.

4. Solution methodology

To solve the proposed complex RLN design problem, we develop a solution approach in this section. Specifically, we initially solve the model using the branch-and-cut method (referred to as the exact method) using the CPLEX software. However, the exact method is not able to provide a solution or takes long times to solve large-sized problems. Furthermore, we apply a decomposition technique, namely the classical BD, to solve the model (Costa, 2005; Fakhri & Ghatee, 2016). However, classical BD also fails to converge the bounds. Hence, we focus on developing an improved BD-based heuristic, i.e., IBD, to solve our model to enhance computational efficiency.

BD is a classical solution approach proposed by Benders (1962) to solve combinatorial optimization problems very quickly based on the divide-and-conquer strategy. In the BD approach, the original problem is divided into two interrelated problems, namely the master problem and the sub problem with complicated (integer and binary) variables and coupling constraints. The master problem is a relaxation of the original problem with complex variables and an auxiliary variable. In the minimisation problem, the optimal master solution provides a lower bound (LB), and the solution is transferred to the sub problem to obtain a new sub-solution. Solving the dual sub problem provides an upper bound (UB) and optimality, and feasibility cuts are also produced, which are added to the master problem.

The model presented above can be considered as a combination of two independent problem sets. The first can be seen as a problem related to the location and allocation of the testing and remanufacturing facilities along with the decision on the selection and allocation of the vehicles, while the second can be considered as a problem for the flow of products, inventory, and disposal under the specified network. This motivates to apply BD as it can provide an efficient framework to solve a MILP model.

4.1. Sub problem

4.1.1. . Primal sub problem

Following the BD approach presented above, the primal sub problem $SP(q_{ijv}^{p}, I_t^p, DQ_t^p, B_r^p | \hat{x}_j^p, \hat{y}_{ijv}^{p}, \hat{N}_{ijv}^{p})$ is derived by fixing the values of the design variables relating to the locations of testing and remanufacturing facilities as follows:

$$\begin{aligned}&\text{Minimise } Z_{SP}\\&= \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} PC_j^p q_{ijv}^p + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} PC_j^p q_{ijv}^p + \sum_{t\epsilon T}\sum_{p\epsilon P} I_t^p HC_t^p\\&\quad + \sum_{t\epsilon T}\sum_{p\epsilon P} DQ_t^p DC_t^p + \sum_{r\epsilon R}\sum_{p\epsilon P} B_r^p BC^p + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v)\\&\quad + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v) + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} q_{ijv}^p d_{ij}(VTC_v/H_v)\\&\quad + \Omega \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} PE_j q_{ijv}^p + \Omega \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} PE_j q_{ijv}^p\end{aligned} \tag{2}$$

Subject to constraints (1.i) to (1.vi) and

$$\sum_{i\epsilon D}\sum_{v\epsilon V} q_{ijv}^p \le \hat{x}_j^p H_j \qquad \forall p\epsilon P, \forall j\epsilon T \tag{2.i}$$

$$\sum_{i\epsilon T}\sum_{v\epsilon V} q_{ijv}^p \le \hat{x}_j^p H_j \qquad \forall p\epsilon P, \forall j\epsilon R \tag{2.ii}$$

$$q_{ijv}^p \le \hat{N}_{ijv}^p H_v \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \tag{2.iii}$$

$$q_{ijv}^p \le \hat{N}_{ijv}^p H_v \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{2.iv}$$

$$q_{ijv}^p \le \hat{N}_{ijv}^p H_v \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \tag{2.v}$$

$$q_{ijv}^p, I_t^p, DQ_t^p, B_r^p \ge 0$$

The optimal solution to the $SP(.)$ gives the product flows between the facilities (q_{ijv}^p), disposal, inventory, and purchasing quantities (I_t^p, DQ_t^p, B_r^p) by minimizing the overall cost.

4.1.2. . Dual sub problem (DSP)

To get an upper bound for the original problem early, here we solve the dual sub problem. The dual variables $\upsilon_{pi}^1, \upsilon_{pj}^2, \upsilon_{pj}^{10}, \upsilon_{pj}^{11}, \upsilon_{pj}^3, \upsilon_{pj}^4, \upsilon_{pj}^5, \upsilon_{pj}^6, \upsilon_{pijv}^7, \upsilon_{pijv}^8, \upsilon_{pijv}^9$ are considered for constraints (1.i)–(1.vi) and (2.i)–(2.v), respectively. The dual sub-problem (DSP) of our model is as follows:

Objective function.

$$\begin{aligned}&\text{Minimise } Z_{DSP}\\&= \sum_{i\epsilon D}\sum_{p\epsilon P} \upsilon_{pi}^1 S_i^p + \sum_{j\epsilon C}\sum_{p\epsilon P} \upsilon_{pj}^4 D_j^p + \sum_{j\epsilon T}\sum_{p\epsilon P} \upsilon_{pj}^5 \hat{x}_j^p H_j + \sum_{p\epsilon P}\sum_{j\epsilon R} \upsilon_{pj}^6 \hat{x}_j^p H_j\\&\quad + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{p\epsilon P}\sum_{v\epsilon V} \upsilon_{pijv}^7 \hat{N}_{ijv}^p H_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{p\epsilon P}\sum_{v\epsilon V} \upsilon_{pijv}^8 \hat{N}_{ijv}^p H_v\\&\quad + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{p\epsilon P}\sum_{v\epsilon V} \upsilon_{pijv}^9 \hat{N}_{ijv}^p H_v\end{aligned} \tag{3}$$

Constraints. Constraint associated with variable $q_{ijv}^p (i\epsilon D, j\epsilon T)$

$$\upsilon_{pi}^1 + b_j^p \upsilon_{pj}^2 + \upsilon_{pj}^5 + \upsilon_{pijv}^7 \le PC_j^p + \Omega PE_j + d_{ij}(VTC_v/H_v) \qquad \forall p\epsilon P, \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V \tag{3.i}$$

Constraint associated with variable $q_{ijv}^p (i\epsilon T, j\epsilon R)$

$$-\upsilon_{pj}^2 + \upsilon_{pj}^3 + \upsilon_{pj}^6 + \upsilon_{pijv}^8 \le PC_j^p + \Omega PE_j + d_{ij}(VTC_v/H_v) \qquad \forall p\epsilon P, \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V \tag{3.ii}$$

Constraint associated with variable $q_{ijv}^p (i\epsilon R, j\epsilon C)$

$$-\upsilon_{pj}^3 + \upsilon_{pj}^4 + \upsilon_{pijv}^9 \le d_{ij}(VTC_v/H_v) \quad \forall p\epsilon P, \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V \tag{3.iii}$$

Constraint associated with variable I_t^1

$$-\upsilon_{pj}^2 + \upsilon_{(p+1)j}^2 + \upsilon_{pj}^{10} \le HC_j^p \qquad \forall j\epsilon T, p = 1 \tag{3.iv}$$

Constraint associated with variable I_t^p

$$-\upsilon_{pj}^2 + \upsilon_{(p+1)j}^2 \le HC_j^p \qquad \forall j\epsilon T, \forall p\epsilon[2, P-1] \tag{3.v}$$

Constraint associated with variable I_t^P

$$-\upsilon_{pj}^2 + \upsilon_{pj}^{11} \le HC_j^p \qquad \forall j\epsilon T, p = P \tag{3.vi}$$

Constraint associated with variable DQ_t^p

$$-\upsilon_{pj}^2 \le DC_j^p \qquad \forall p\epsilon P, \forall j\epsilon T \tag{3.vii}$$

Constraint associated with variable B_r^p

$$\upsilon_{pj}^3 \le BC^p \qquad \forall p\epsilon P, \forall j\epsilon R \tag{3.viii}$$

$$\upsilon_{pi}^1, \upsilon_{pj}^2, \upsilon_{pj}^3, \upsilon_{pj}^4, \upsilon_{pj}^{10}, \upsilon_{pj}^{11} \textbf{ are unrestricted} \tag{3.ix}$$

$$\upsilon_{pj}^5, \upsilon_{pj}^6, \upsilon_{pijv}^7, \upsilon_{pijv}^8, \upsilon_{pijv}^9 \ge 0 \tag{3.x}$$

The constraints of the dual sub problem are given by (3.i)–(3.x), which constitute a polyhedron. For fixed values of the design variables ($\hat{x}_j^p$), if the subproblem is feasible, then the DSP has a bounded solution, and an optimality cut is generated. At the same time, if the subproblem is infeasible, then the DSP has an unbounded solution, and a feasibility cut will be constructs.

4.2. Benders master problem

We solve the master problem $MP(x_j^p, y_{ijv}^p, N_{ijv}^p | \hat{q}_{ijv}^p, \hat{I}_t^p, \widehat{DQ}_t^p, \hat{B}_r^p)$ by transferring the subproblem solution to the original problem given below. We add the Benders' optimality and feasibility cuts to the master problem in each iteration.

$$\begin{aligned}&\text{Minimise } Z_{MP}\\&= \sum_{j\epsilon T}\sum_{p\epsilon P} FC_j\left(x_j^p - x_j^{p-1}\right) + \sum_{j\epsilon R}\sum_{p\epsilon P} FC_j\left(x_j^p - x_j^{p-1}\right)\\&\quad + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v\\&\quad + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v\\&\quad + \Omega \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij} N_{ijv}^p E_v\\&\quad + \Omega \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij} N_{ijv}^p E_v + \Omega \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij} N_{ijv}^p E_v + \alpha\end{aligned} \tag{4}$$

Subject to

$$x_t^{p-1} \le x_t^p \qquad \forall p\epsilon P, \forall t\epsilon T \tag{4.i}$$

$$x_t^1 = 0 \quad \forall t\epsilon T \tag{4.ii}$$

$$x_r^{p-1} \le x_r^p \qquad \forall r\epsilon R, \forall p\epsilon P \tag{4.iii}$$

$$y_{ijv}^p \le x_j^p M \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \tag{4.iv}$$

$$y_{ijv}^p \le x_i^p M \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{4.v}$$

$$y_{ijv}^p \le x_j^p M \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{4.vi}$$

$$y_{ijv}^p \le x_j^p M \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \tag{4.vii}$$

$$N_{ijv}^p \le y_{ijv}^p M \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \tag{4.viii}$$

$$N_{ijv}^p \ge y_{ijv}^p \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \tag{4.ix}$$

$$N_{ijv}^p \le y_{ijv}^p M \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{4.x}$$

$$N_{ijv}^p \ge y_{ijv}^p \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{4.xi}$$

$$N_{ijv}^{p} \leq y_{ijv}^{p} M \qquad \forall i \epsilon R, \forall j \epsilon C, \forall v \epsilon V, \forall p \epsilon P \tag{4.xii}$$

$$N_{ijv}^{p} \geq y_{ijv}^{p} \qquad \forall i \epsilon R, \forall j \epsilon C, \forall v \epsilon V, \forall p \epsilon P \tag{4.xiii}$$

and

$$x_j^p, y_{ijv}^p \epsilon \{0, 1\}, \qquad N_{ijv}^p \geq 0 \text{ and int}$$

Now, the Benders cut set (optimality and feasibility) related to α is as follows:

Benders optimality cut:

$$\begin{aligned}\alpha \geq & \sum_{i\epsilon D}\sum_{p\epsilon P} \hat{\upsilon}_{pi}^{1(k)} S_i^p + \sum_{j\epsilon C}\sum_{p\epsilon P} \hat{\upsilon}_{pj}^{4(k)} D_j^p + \sum_{j\epsilon T}\sum_{p\epsilon P} \hat{\upsilon}_{pj}^{5(k)} x_j^p H_j \\ & + \sum_{p\epsilon P}\sum_{j\epsilon R} \hat{\upsilon}_{pj}^{6(k)} x_j^p H_j \\ & + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{7(k)} N_{ijv}^p H_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{8(k)} N_{ijv}^p H_v \\ & + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{9} N_{ijv}^p H_v \end{aligned} \tag{4.xiv}$$

Benders feasibility cut:

$$\begin{aligned} & \sum_{i\epsilon D}\sum_{p\epsilon P} \hat{\upsilon}_{pi}^{1(k)} S_i^p + \sum_{j\epsilon C}\sum_{p\epsilon P} \hat{\upsilon}_{pj}^{4(k)} D_j^p + \sum_{j\epsilon T}\sum_{p\epsilon P} \hat{\upsilon}_{pj}^{5(k)} x_j^p H_j + \sum_{p\epsilon P}\sum_{j\epsilon R} \hat{\upsilon}_{pj}^{6(k)} x_j^p H_j \\ & + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{7(k)} N_{ijv}^p H_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{8(k)} N_{ijv}^p H_v \\ & + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{9} N_{ijv}^p H_v \leq 0 \end{aligned} \tag{4.xv}$$

We present the algorithm for BD below.

4.3. Enhancing the Benders algorithm

Though BD is a finite scheme, the iterations required for convergence may be too large, or the algorithm fails to converge within a set time limit for many cases. For practical adoption of BD, researchers have proposed many acceleration strategies, as well as valid inequalities and heuristic methods.

With reference to the literature mentioned in Section 2.2, in the current research, initially, we present three valid inequalities to a better set of initial cuts by improving the quality of the lower bound. Furthermore, we present an algorithm to produce an initial feasible solution. Finally, we develop a multi-stage strategy for obtaining a (sub-optimal) solution to the master problem and attain quick convergence.

4.3.1. Valid inequalities

Aside from the produced Benders cuts, Saharidis et al. (2011) found that one of the reasons for slow convergence is that the lower bound has no strong valid inequalities (for the minimization case). Hence, to improve the lower bound and narrow the solution space, we propose the following valid inequalities for our problem.

a) Inequalities related to the location decision

$$\sum_{j\epsilon T} x_j^p \geq 1 \qquad \forall p \epsilon P \tag{4.xvi}$$

$$\sum_{j\epsilon R} x_j^p \geq 1 \qquad \forall p \epsilon P \tag{4.xvii}$$

Valid inequalities (4.xvi) and (4.xvii) ensure that at least one facility has to be located for processing the core returns in each period. Constraints (4.xvi) and (4.xvii) are associated with the testing and remanufacturing centers, respectively.

a) Supply inequality at the collection facility

$$\sum_{j\epsilon T}\sum_{v\epsilon V} N_{ijv}^p H_v \geq S_i^p \qquad \forall p \epsilon P, \forall i \epsilon D \tag{4.xviii}$$

Valid inequality (4.xviii) ensures that the total core returns available at all the collection facilities should move to the testing facilities using a sufficient number of vehicles in each period $\forall p \epsilon P$.

a) The inequality for using a sufficient number of vehicles to move products between facilities

$$\sum_{i\epsilon R}\sum_{v\epsilon V} N_{ijv}^p H_v \geq b_j^p \sum_{i\epsilon D}\sum_{v\epsilon V} N_{ijv}^p H_v \qquad \forall p \epsilon P, \forall j \epsilon T \tag{4.xix}$$

$$\sum_{i\epsilon T}\sum_{v\epsilon V} N_{ijv}^p H_v \leq \sum_{i\epsilon C}\sum_{v\epsilon V} N_{ijv}^p H_v \qquad \forall p \epsilon P, \forall j \epsilon R \tag{4.xx}$$

Valid inequalities (4.xix) and (4.xx) guarantee that sufficient numbers of vehicles are used for the inflow and outflow of products at each facility.

4.3.2. Multi-stage strategy (MSS)

It is noted that the master solution has an adverse effect on the convergence of the bounds because of computational complexity. Therefore, we develop a three-stage approach (similar to dynamic programming) to solve the master problem in each iteration. We explain the stages in detail in the following.

Stage 1. This stage contains the decisions between the collection facilities and testing facilities. Here the decisions are the location of testing facilities, vehicle selection, and allocation between the collection and testing facilities, as well as the vehicle quantity between them. The mathematical model in this stage is as follows:

$$\begin{aligned} \text{Minimize } Z_{MP1} = & \sum_{j\epsilon T}\sum_{p\epsilon P} FC_j \left(x_j^p - x_j^{p-1}\right) + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v \\ & + \Omega \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij} N_{ijv}^p E_v + \alpha_1 \end{aligned} \tag{5}$$

Subject to (1.xii), (1.xiii), (1.xv), (1.xix), (1.xx), (4.iii), (4.v) and

$$\alpha_1 \geq \sum_{i\epsilon D}\sum_{p\epsilon P} \hat{\upsilon}_{pi}^{1(k)} S_i^p + \sum_{j\epsilon T}\sum_{p\epsilon P} \hat{\upsilon}_{pj}^{5(k)} x_j^p H_j + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{7(k)} N_{ijv}^p H_v. \tag{5.i}$$

Stage 2. In this stage, the decisions between testing and remanufacturing facilities are made, given the stage 1 decisions. Here, the decisions are the location of the remanufacturing facilities, vehicle selection, and allocation between the testing and remanufacturing facilities, along with the vehicle quantity between them. The mathematical model in this stage is as follows:

$$\begin{aligned} & \text{Minimize } Z_{MP2} \\ & = \sum_{j\epsilon R}\sum_{p\epsilon P} FC_j \left(x_j^p - x_j^{p-1}\right) + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} N_{ijv}^p FTC_v \\ & + \Omega \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij} N_{ijv}^p E_v + \alpha_2 \end{aligned} \tag{6}$$

Subject to (1.xiv), (1.xvi), (1.xvii), (1.xxi), (1.xxii), (4.iv), (4.vi) and

$$\alpha_2 \geq \sum_{p\epsilon P}\sum_{j\epsilon R} \hat{\upsilon}_{pj}^{6(k)} x_j^p H_j + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{p\epsilon P}\sum_{v\epsilon V} \hat{\upsilon}_{pijv}^{8(k)} N_{ijv}^p H_v \tag{6.i}$$

Stage 3. In this stage, decisions are made between the remanufacturing facilities and facilities, given the stage 2 decisions. Here the decisions are vehicle selection and allocation between the remanufacturing facilities and customer points as well as the vehicle quantity between them. The mathematical model in this stage is as follows:

$$Minimize\ Z_{MP3} = \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} N^p_{ijv}FTC_v + \Omega\sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P} d_{ij}N^p_{ijv}E_v + \alpha_3 \tag{7}$$

Subject to (1.xvii), (1.xxiii), (1.xxiv), (4.vii) and

$$\alpha_3 \geq \sum_{j\epsilon C}\sum_{p\epsilon P}\hat{\upsilon}^{4(k)}_{pj}D^p_j + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{p\epsilon P}\sum_{v\epsilon V}\hat{\upsilon}^9_{pijv}N^p_{ijv}H_v \tag{7.i}$$

We show the three-stage solution procedure in the form of a pseudo-code in Algorithm 3. Now, we present in Algorithm 3 the overall pseudo-code for BD with MSS combined with Algorithms 1 and 2.

4.3.3. Algorithm for initial feasible solution

Though we provide a multi-stage strategy to converge the bounds, the master solution in the initial iterations of the algorithm leads to a low-quality solution. Thus, we develop a simple two-step algorithm to provide an initial feasible solution for improving the overall BD approach. Then we solve the sub problem to build an optimal solution with this solution.

Step 1: In this step, consider that all the vehicles available for transporting goods between the facilities are homogeneous. Now, the objective function $P_1(x^p_j|.)$ in this step is as follows:

$$\begin{aligned}
&Minimse\ P_1\left(x^p_j|.\right)\\
&= \sum_{j\epsilon T}\sum_{p\epsilon P}FC_j\left(x^p_j - x^{p-1}_j\right)\\
&\quad + \sum_{j\epsilon R}\sum_{p\epsilon P}FC_j\left(x^p_j - x^{p-1}_j\right) + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}PC^p_j q^p_{ijv}\\
&\quad + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}PC^p_j q^p_{ijv} + \sum_{t\epsilon T}\sum_{p\epsilon P}I^p_t HC^p_t\\
&\quad + \sum_{t\epsilon T}\sum_{p\epsilon P}DQ^p_t DC^p_t + \sum_{r\epsilon R}\sum_{p\epsilon P}B^p_r BC^p\\
&\quad + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v\\
&\quad + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}q^p_{ijv}d_{ij}(VTC_v/H_v)\\
&\quad + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}q^p_{ijv}d_{ij}(VTC_v/H_v)\\
&\quad + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}q^p_{ijv}d_{ij}(VTC_v/H_v) + \Omega\sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v\\
&\quad + \Omega\sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v + \Omega\sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v\\
&\quad + \Omega\sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}PE_j q^p_{ijv} + \Omega\sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}PE_j q^p_{ijv}
\end{aligned} \tag{8}$$

Subject to (1.i) to (1.xvi)

We use the solution of $P_1(x^p_j|.)$ to make decisions on the locations of the testing and remanufacturing facilities, which are fixed in the next step.

Step 2: In step 2, consider that the vehicles available to move goods between the facilities are heterogeneous. Now, for known values of facility locations, product flows from the previous step, the objective function $P_2(y^p_{ijv},\ \ N^p_{ijv} \mid \hat{x}^p_j, \hat{q}^p_{ijv})$ is as follows:

Algorithm 1
Benders Decomposition Algorithm.

Initialise *LB*, *UB*, *Iteration*, *MaxIteration*, *gap* and set *BENDERS CUTSET* empty
Solve $MP(x^p_j, y^p_{ijv}, N^p_{ijv}|.)$
  Set $LB = Z_{MP}$
  While (*UB* - *LB*) $\leq$ *gap* and (*Iteration* $<$ *MaxIteration*) **do**
  Iteration = *Iteration* + 1
    Solve DSP to obtain $q^p_{ijv}, I^p_t, DQ^p_t, B^p_r$
    If (*DSP is feasible*)
      Calculate ***UB*** $= (Z_{DSP} + Z_{MP} - \Theta(CUTSET))$
      Add optimality cut to *BENDERS CUTSET*
    else if (DSP is Infeasible)
      Add feasibility cut to *BENDERS CUTSET*
    end if
    Solve $MP(x^p_j, y^p_{ijv}, N^p_{ijv}|\hat{q}^p_{ijv}, \hat{I}^p_t, \widehat{DQ}^p_t, \hat{B}^p_r)$
     Set $LB = Z_{MP}$
  end while
  Solve $SP(q^p_{ijv}, I^p_t, DQ^p_t, B^p_r|\hat{x}^p_j, \hat{y}^p_{ijv}, \hat{N}^p_{ijv})$
Report $\hat{x}^p_j, \hat{y}^p_{ijv}, \hat{N}^p_{ijv}, \hat{q}^p_{ijv}, \hat{I}^p_t, \widehat{DQ}^p_t, \hat{B}^p_r$ and objective function value

---

$$\begin{aligned}
&\mathbf{Minimise} P_2\left(y^p_{ijv},\ \ N^p_{ijv} \mid \hat{x}^p_j, \hat{q}^p_{ijv}\right)\\
&= \Omega\sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v\\
&\quad + \Omega\sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v + \Omega\sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}E_v\\
&\quad + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v\\
&\quad + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}N^p_{ijv}FTC_v\\
&\quad + \sum_{i\epsilon D}\sum_{j\epsilon T}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}VTC_v + \sum_{i\epsilon T}\sum_{j\epsilon R}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}VTC_v\\
&\quad + \sum_{i\epsilon R}\sum_{j\epsilon C}\sum_{v\epsilon V}\sum_{p\epsilon P}d_{ij}N^p_{ijv}VTC_v
\end{aligned} \tag{9}$$

Subject to (1.xv) to (1.xxiv) and

$$N^p_{ijv}H_v \geq \hat{q}^p_{ijv} \qquad \forall i\epsilon D, \forall j\epsilon T, \forall v\epsilon V, \forall p\epsilon P \tag{9.i}$$

$$N^p_{ijv}H_v \geq \hat{q}^p_{ijv} \qquad \forall i\epsilon T, \forall j\epsilon R, \forall v\epsilon V, \forall p\epsilon P \tag{9.ii}$$

$$N^p_{ijv}H_v \geq \hat{q}^p_{ijv} \qquad \forall i\epsilon R, \forall j\epsilon C, \forall v\epsilon V, \forall p\epsilon P \tag{9.iii}$$

$$y^p_{ijv} \in \{0, 1\}, \quad N^p_{ijv} \geq 0.$$

Constraints (9.i-9.iii) represent the inequalities added in this phase after fixing the product flows. The solution to $P_2(y^p_{ijv},\ \ N^p_{ijv} \mid \hat{x}^p_j, \hat{q}^p_{ijv})$ gives the vehicle selection and allocation along with the vehicle quantity among the facilities. We illustrate in Algorithm 4 the solution procedure in the form of a pseudo-code.

Now, we present in Algorithm 5 the overall pseudo-code for the improved BD (IBD) combined with Algorithms 2 and 4.

5. Results and discussion

5.1. Computational experiments

In this section, we report the results obtained by conducting exhaustive computational studies to assess IBD's performance. We also compare IBD with the exact method (classical branch-and-cut), classical BD, and BD-MSS. To provide managerial insights to practitioners, we present a case example to illustrate the impacts of carbon emissions and the choice of the vehicle fleet (e.g., homogeneous vs. heterogeneous).

For all our experiments, we employed ILOG CPLEX (version 12.5) using C++ API on a PC with an Intel Core i5 2.90 GHz processor and 16 Gigabyte RAM to solve the problems. We set the termination criterion for the CPLEX solution method at 10,800 s or

Algorithm 2
To find a master solution for BD.

Stage-1: Solve Master problem $MP1(x_i^p,\ y_{ijv}^t, N_{ijv}^p|\hat{\upsilon}_{pi}^1, \hat{\upsilon}_{pj}^5, \hat{\upsilon}_{pijv}^7)$ *for* $i \in D, j \in T$
    record $\hat{x}_i^p,\ \hat{y}_{ijv}^t, \hat{N}_{ijv}^p$
Stage-2: Solve Master problem $MP2(x_i^p,\ y_{ijv}^t, N_{ijv}^p|\hat{\upsilon}_{pj}^6, \hat{\upsilon}_{pijv}^8, \hat{x}_k^p, \hat{N}_{kiv}^p)$ *for* $i \in T, j \in R, k \in D$
    record $\hat{x}_i^p,\ \hat{y}_{ijv}^t, \hat{N}_{ijv}^p$
Stage-3: Solve Master problem $MP3(x_i^p,\ y_{ijv}^t, N_{ijv}^p|\hat{\upsilon}_{pj}^4, \hat{\upsilon}_{pijv}^9, \hat{x}_k^p, \hat{N}_{kiv}^p)$ *for* $i \in R, j \in C, k \in T$
    record $\hat{y}_{ijv}^t, \hat{N}_{ijv}^p$

Algorithm 3
Benders decomposition with Multi-Stage Strategy (BD-MSS).

Initialize UB=+∞, LB=-∞, Iterations, Gap=0, loop=0, ε;
Solve $MP(x_j^p, y_{ijv}^p, N_{ijv}^p|.)$
Evaluate $LB = Z_{MP}$
do {
  Solve dual sub problem
    $DSP\left(\begin{matrix}\upsilon_{pi}^1, \upsilon_{pj}^2, \upsilon_{pj}^3, \upsilon_{pj}^4, \upsilon_{pj}^5, \upsilon_{pj}^6, \upsilon_{pijv}^7, \upsilon_{pijv}^8, \upsilon_{pijv}^9, \upsilon_{pj}^{10}, \upsilon_{pj}^{11}| \\ \hat{x}_j^p,\ \hat{N}_{ijv}^p\end{matrix}\right)$
    record $\hat{\upsilon}_{pi}^1, \hat{\upsilon}_{pj}^2, \hat{\upsilon}_{pj}^3, \hat{\upsilon}_{pj}^4, \hat{\upsilon}_{pj}^5, \hat{\upsilon}_{pj}^6, \hat{\upsilon}_{pijv}^7, \hat{\upsilon}_{pijv}^8, \hat{\upsilon}_{pijv}^9, \hat{\upsilon}_{pj}^{10}, \hat{\upsilon}_{pj}^{11}$
  Evaluate $UB = Z_{DSP} + (Z_{MP} - \alpha(cutset))$
  If DSP is infeasible,
    generate Benders feasibility cut (BFC)
  else
    generate Benders optimality cut(BOC)
  $Gap = ((UB - LB)/LB) * 100$
  *Find **Master Solution** using* Algorithm 2
  Evaluate $LB = Z_{MP}$
  loop ++
} ***while*** *(loop ⟨ Iterations && Gap ⟩ ε)*
Solve $PSP(q_{ijv}^p,\ I_j^p, DQ_j^p, B_j^p|\hat{x}_j^p,\ \hat{N}_{ijv}^p)$
Report $\hat{q}_{ijv}^p,\ \hat{I}_j^p, \widehat{DQ}_j^p, \hat{B}_j^p, \hat{x}_j^p,\ \hat{N}_{ijv}^p$ *and*
The objective value Z^**=UB.*

Algorithm 4
An initial feasible solution for BD.

Phase 1: Set $V = 1$
    solve the $P_1(x_j^p|.)$
    record x_j^p, q_{ijv}^p *values*
Phase 2: solve the $P_2(y_{ijv}^p,\ \ N_{ijv}^p \mid \hat{x}_j^p, \hat{q}_{ijv}^p)$
    record $y_{ijv}^p,\ \ N_{ijv}^p$ *values*

0.1% optimality gap (Easwaran & Üster, 2009, 2010; Jeihoonian et al., 2016b). We terminated the BD, BD-MSS, and IBD algorithms if one of the following conditions was satisfied: the gap between the bounds was below the threshold value of 2, and the maximum number of iterations was fixed at 100.

5.1.1. Data generation

We used data from previously published research (Choudhary, Sarkar, Settur & Tiwari, 2015; Pishvaee et al., 2009), and emissions reports from the center for Science and Environment (CSE) and the Central Pollution Control Board (CPCB). Table 3 lists the different cost parameters (e.g., fixed costs for locating facilities and processing costs for testing and remanufacturing) and yields of core returns, along with the demand and capacity of facilities and the distances between the facilities. We consider three types of vehicles, namely petrol, diesel, and hybrid vehicles, each with different capacity levels, i.e., 60, 80, and 100.

5.2. Test instances

To assess the performance of the proposed solution approach, we generated a set of 12 problem configurations/classes (with five problem instances for each) (Soleimani & Govindan, 2014). Therefore, we generated a total of 60 problem instances from these problem configurations. We developed these problem classes by varying the planning horizon length (P), the number of potential locations for the testing facilities (T), and the remanufacturing facilities (R). The configurations range from networks of planning horizon lengths of six, ten potential locations for the testing facilities, and three potential locations for the remanufacturing facilities ($6 \times 30 \times 10 \times 3$) up to $12 \times 30 \times 20 \times 5$ (Table 4).

To explain the complexity of problem configurations, we present the number of constraints and variables in Table 4. For example, I12 has 92,641 (out of which around 60% are integer and binary variables) and 127,660 constraints. Table 3 shows that the problem complexity increases with the number of constraints and variables, which motivates us to implement IBD and solve the problems. In the following section, we present an analysis of the results for various configurations.

5.3. Computational results

As mentioned above, we solve each problem configuration using the branch-and-cut approach (known as the exact method), the BD approach, the BD approach with the multi-stage strategy, and the BD approach with heuristic improvements (IBD). To see the average behaviors of the solution methods, we present the resulting means and standard deviations (SD) in Table 5. We use the results obtained by the exact method using the CPLEX solver as the benchmark solutions for comparison and validation of the test results. We measure the performance of the proposed IBD mainly by the computational time and solution gap (%), which we present in the following sections.

5.3.1. A comparative study of the computational time

We compare the solution approaches with respect to the computational time. Table 6 represents the computational times for the instances using all solution methods. From Table 6, we observe that, initially, the classical BD finds the solutions for all the instances within a reasonable time. However, as the instance size increases, the classical BD and exact methods take more time to

Table 3
Input parameters data.

Parameter	Value	Units	Parameter	Value	Unit
D_c^p	~U(350, 100)	Units of Product	FC_t	Carbon inefficient: 0.16 Carbon efficient: 0.32	$ per unit capacity
H_t	1000	Units of products	FC_r	Carbon inefficient: 0.24 Carbon efficient: 0.40	$ per unit capacity
PE_j	Carbon inefficient: 0.5 Carbon-efficient: 3.0	Kilos of CO_2 per product	PC_t^p	~U (0.24, 0.55)	$ per unit
Ω	0.0625	$ per kilo of CO_2	PC_r^p	~U (0.40, 0.78)	$ per unit
b_t^p	~U (0.6, 0.9)	––	HC_t^p	~U (0.1, 0.2)	$ per unit per period
d_{dt}	~U (20, 50)	km	DC_t^p	~U (0.05, 0.10)	$ per unit
d_{tr}	~U (40, 90)	km	BC^p	1.78	$ per unit
d_{rc}	~U (30, 70)	km			

Table 4
Problem configurations.

		Variables				
Testconfiguration	**(P x D x T x R)**	**Binary**	**Integer**	**Continuous**	**Total**	**Constraints**
I1	6 × 30 × 10 × 3	7638	7560	7699	22,897	31,394
I2	6 × 30 × 10 × 5	9090	9000	9151	27,241	37,550
I3	6 × 30 × 15 × 3	10,638	10,530	10,729	31,897	43,644
I4	6 × 30 × 15 × 5	12,270	12,150	12,361	36,781	50,700
I5	6 × 30 × 20 × 3	13,638	13,500	13,759	40,897	55,894
I6	6 × 30 × 20 × 5	15,450	15,300	15,571	46,321	63,850
I7	12 × 30 × 10 × 3	15,276	15,120	15,397	45,793	62,768
I8	12 × 30 × 10 × 5	18,180	18,000	18,301	54,481	75,080
I9	12 × 30 × 15 × 3	21,276	21,060	21,457	63,793	87,258
I10	12 × 30 × 15 × 5	24,540	24,300	24,721	73,561	101,370
I11	12 × 30 × 20 × 3	27,276	27,000	27,517	81,793	111,748
I12	12 × 30 × 20 × 5	30,900	30,600	31,141	92,641	127,660

Table 5
Comparison of the solution approaches in terms of the objective function value.

	Exact		BD		BD-MSS		IBD	
Testconfiguration	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
I1	155,382	3862.31	158,658	3735.06	161,613	3335.63	159,352	3619.71
I2	153,234	1583.27	156,151	1429.13	159,497	1311.73	157,386	2256.97
I3	155,213	943.147	159,538	943.568	161,899	2103.59	161,327	1079.05
I4	153,479	1489.37	157,808	1965.73	161,254	1863.18	157,243	1594.32
I5	156,973	2140.44	163,186	3051.46	164,952	2256.67	162,497	2291.5
I6	153,903	3963.41	160,590	3214.39	161,122	4291.56	158,175	4470.95
I7	307,553	5419.99	313,011	4974.61	320,452	4697.32	319,622	7673.33
I8	303,612	847.72	309,502	829.402	327,305	17,370.7	313,628	1251.82
I9	307,999	2641.85	315,434	2814.16	321,957	4242.53	315,492	4536.61
I10	302,592	5253.24	309,483	5357.36	316,992	5214.24	310,506	3180.3
I11	307,434	2072.05	314,827	1726.51	325,628	3291.14	315,934	4420.3
I12	302,124	5624.5	311,303	4798.87	319,912	6343.99	311,965	4823.65

solve the problem. For example, for the I11 and I12 instances, both the exact and BD-based methods take more than 10,800 seconds, whereas IBD requires around 60 seconds. In general, IBD requires 30 seconds, on average, to produce a near-optimal solution. Fig. 2 presents the box plot for a comparison of the computational times among the solution methods. From Fig. 2, we see that BD-MSS and IBD require very little time to find solutions for the test instances.

From the presented analysis, we conclude that BD-MSS and IBD perform better than the exact method and classical BD in terms of computational time. In the next section, we examine solution quality with respect to the exact method.

5.3.2. A comparative study of solution gap

In the last section, we established the efficient performance of IBD with respect to the computational time. To study the effectiveness of IBD, we compare the obtained objective values with those of the exact method for the test problems. We calculate the solution gap for each problem configuration as follows:

$$Solution\ gap\ (\%) = 100 * \left({}^{(Val_{SolMethod} - Val_{Exact})}/_{Val_{Exact}} \right)$$

Fig. 3 presents the solution gaps for BD, BD with MSS, and IBD for the generated test problems. From Fig. 3, we observe that BD and BD-MSS produce solutions with an average gap of 3.08% and 5.04%, respectively, whereas IBD produces solutions with an average gap of 2.65%. Therefore, we conclude that IBD is more efficient as it produces better solutions than the other methods in most instances in less time.

5.4. Managerial implications

To understand the effect of carbon emissions and choice of vehicle, we consider the following setting. Assuming that returns are collected from 16 collection facilities (also 16 customer points) located at various regions over a 5-year planning horizon. There are seven and four potential locations for testing and remanufacturing facilities, respectively. This setting results in a MILP formulation with 13.027 constraints and 9334 variables (3115 binary; 6219 continuous).

The product return data is generated uniformly based on the return rate in the range of 0.5–0.8 (Table 7). The data regarding

Table 6
Computational time comparison among the various solution methods.

Testconfiguration	Exact Mean	SD	BD Mean	SD	BD-MSS Mean	SD	IBD Mean	SD
I1	1752.06	1528.82	187.33	150.41	94.01	80.03	6.15	1.80
I2	4032.02	4123.69	179.48	133.73	95.49	131.67	29.03	51.36
I3	5256.44	3859.48	1854.29	2422.28	411.33	275.49	26.71	13.84
I4	10,800.32	0.03	977.73	787.69	178.37	123.62	20.10	13.66
I5	8849.32	2742.18	262.93	39.54	401.96	96.88	60.71	31.44
I6	10,522.53	621.33	314.68	185.06	273.01	76.08	38.77	18.09
I7	3348.45	2582.74	1046.62	1096.95	148.44	45.39	9.33	3.44
I8	6476.66	2975.22	823.26	422.99	432.58	634.80	9.77	1.88
I9	8037.68	2461.67	8056.97	5256.61	606.25	508.44	18.75	5.94
I10	8658.32	3139.66	5625.28	2773.65	757.97	274.45	22.83	6.87
I11	8397.80	3481.66	≥10,800	≥10,800	1297.92	650.35	64.44	20.27
I12	10,803.83	4.74	≥10,800	≥10,800	824.46	615.45	56.06	27.82

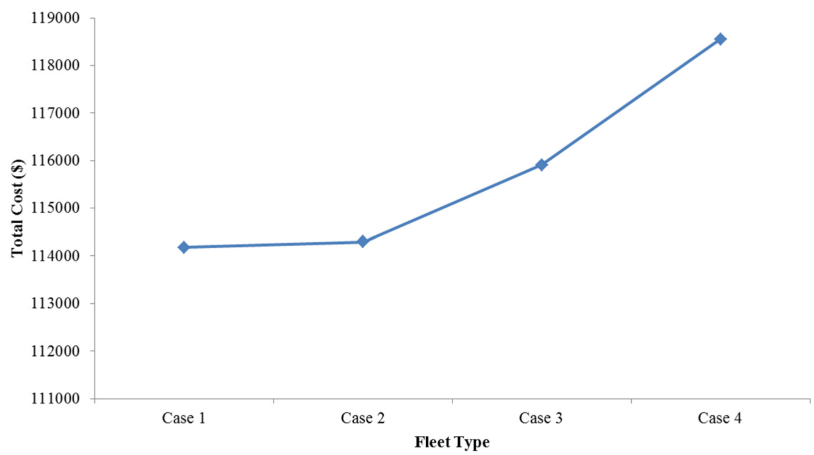

Fig. 2. Box Plot Showing comparison of average computational time for different solution methods.

Table 7
Product return data at collection facilities.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
T2	296	199	219	318	194	337	282	271	264	199	239	256	224	119	88	175
T3	396	100	172	275	347	213	156	250	123	212	165	210	263	195	302	365
T4	304	213	257	228	288	256	183	228	134	302	298	265	262	269	234	237
T5	243	247	336	196	184	253	199	234	181	216	316	181	199	234	198	314

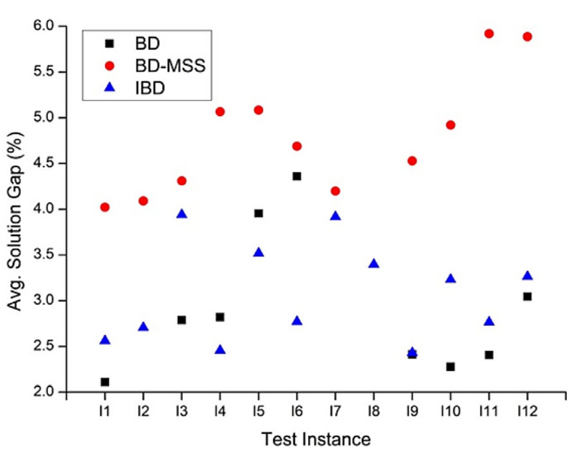

Fig. 3. Average Solution gap (%).

fixed costs, carbon footprint, capacity, and unit processing costs are presented in Table 8 for testing and remanufacturing facilities.

Furthermore, the emission costs are incurred through processing at facilities and transport. Transport costs are calculated based on the number of vehicles used and the distance between facilities. We have considered a heterogeneous vehicle fleet with different capacity levels. The fixed costs, variable costs, and capacities, along with CO_2 emissions for various vehicles, are presented in Table 9.

5.4.1. Impact of carbon emissions on the network

To understand the impact of emission costs on the formulated model, we tested our model on two cases, namely case 1 (RLN design model with emission costs) and case 2 (RLN design model without emission costs). The location decisions are different for both testing and remanufacturing facilities in these two cases. Testing facilities are located at potential locations 1, 3, 4, and 5 in case 1 vs potential locations 1, 2, 3, and 4 in case 2. In case 1, location 5 is preferred over location 2 because it is carbon-efficient, although it has a higher fixed cost than 2. It is interesting to note that the facility is not located at location 6 in both cases because it is carbon-inefficient (though it has a low fixed cost) but has a higher average distance from successive and preceding facilities.

Similarly, considerable changes are found in the location of remanufacturing facilities upon consideration of emission costs. Re-

Table 8
Capacity, carbon footprint, and cost parameters at facilities.

		Testing facilities							Remanufacturing Centers			
		1	2	3	4	5	6	7	1	2	3	4
Fixed Cost		250	250	420	420	420	250	250	1200	700	700	1200
Footprint		3	3	0.5	0.5	0.5	3	3	0.5	3	3	0.5
Max. Capacity		1000	1000	1000	1000	1000	1000	1000	1400	1400	1400	1400
Processing Cost	**T2**	0.34	0.29	0.25	0.35	0.26	0.38	0.40	0.89	0.63	0.87	0.96
	T3	0.49	0.44	0.33	0.53	0.43	0.33	0.35	0.95	0.83	0.61	0.82
	T4	0.48	0.34	0.40	0.25	0.27	0.49	0.28	0.69	0.78	0.90	0.74
	T5	0.46	0.30	0.46	0.48	0.50	0.33	0.46	0.77	0.90	0.86	0.71

Table 9
Cost, capacity, and CO2 emission parameters of different vehicles.

Parameter	Small (V_1)	Medium (V_2)	Large (V_3)
Fixed Cost ($)	1.5625	1.875	3.125
Variable Cost ($ per km)	0.185	0.185	0.185
Capacity	60	80	100
Carbon Footprint	0.25	0.30	0.45

Table 10
Various costs (in $) in the entire planning horizon.

Cost	Case 1	Case 2
Fixed Cost	3910	3240
Processing Cost	15,049	14,587
Disposal Cost	29	5
Inventory Cost	18	24
Fixed Transport Cost	1494	1614
Variable Transport Cost	45,188	42,548
Purchase Cost	41,000	41,400
Total (WoC)	**106,687**	**103,417**
Emission Cost - Production	1391	0
Emission Cost- Transport	6100	0
Total	**114,178**	**103,417**

manufacturing facilities are located at locations 1 and 4 in case 1 and locations 2 and 4 in case 2. In case 1, location 1 is preferred over location 4 due to its carbon efficiency, which leads to a reduction in emissions via production, although it has a higher fixed cost and a higher-than-average remanufacturing cost. The remanufacturing facility is not located at location 3 due to its carbon inefficiency as well as the high inbound and outbound distances from facilities.

Interestingly, the purchased quantity is less in case 1, although there is high disposal here compared to case 2; this is due to high recovery and effective utilisation of core returns. It has also been found that the decision on inventory and disposal was steered based on the limited capacity of remanufacturing facilities.

The total cost and other costs like fixed cost and processing costs related to the two cases are presented in Table 10. The fixed cost is higher in case 1 compared to case 2 due to the location of carbon-efficient facilities. Moreover, the processing costs are higher in case 1 compared to case 2 because of the high testing cost and the processing of more core returns. The purchase cost in case 1 is relatively low compared to case 2; this is due to the effective utilisation of core returns and low purchase quantity. Fixed transport cost in case 1 is relatively high compared to case 2; this is because of the need for more vehicles to move goods between facilities. However, the variable transport cost is high in case 1 because more distance is covered between its facilities.

Interestingly, the total cost in case 1 is only 2.5% higher than in case 2 when emissions are not considered. The total emissions cost (due to production and transport) for case 1 is found to be US$8244. It should be noted that overall emissions from production in case 2 are almost 2.5 times that of case 1 due to the installation of carbon-inefficient facilities (Table 11). Moreover, the emissions from transport in case 2 are 10% higher than case 1 because the former uses more vehicles to move products.

5.4.2. Choice of vehicle fleet

To observe the importance of heterogeneous vehicle fleets (large, medium, and small capacities) in the model, we compared the results against the homogeneous vehicle fleet for large, medium, and small capacities. In this regard, we presented four cases: case 1: heterogeneous vehicle fleet; case 2: homogeneous vehicle fleet with large capacity; case 3: homogeneous vehicle fleet with medium capacity; and case 4: homogeneous vehicle fleet with small capacity.

From Fig. 4, we see that taking into account the heterogeneous or homogeneous vehicle fleet does not affect the location of facilities. Moreover, there is not much variation in purchase quantity, disposal, and inventory quantities. However, the flow of products between facilities does change with the consideration of a homogeneous fleet. This happens mainly because of the requirement for more vehicles and higher fixed transport costs (Table 12). The fixed transport cost for all cases follows the following order: case $1 <$ case $2 <$ case $3 <$ case 4. From the results, it can be observed that the variable transport cost is greater for case 1. A comparison of overall total costs for all cases is presented in Fig. 4.

From Table 12, we can infer that the usage of a heterogeneous fleet reduces emissions while compromising cost in comparison to the homogeneous fleet. Essentially, the usage of a heterogeneous vehicle fleet significantly decreases the environmental and fixed transport cost but inversely impacts the variable transport cost. Within the homogeneous vehicle fleet, the use of large-capacity vehicles produces fewer emissions and costs compared to a homogeneous fleet with medium- and small-capacity vehicles. Another observation worth noting here is that flow routes/arcs for the network depend on the fleet's composition, which affects both economic and environmental costs. For instance, networks with a heterogeneous vehicle fleet help to optimise environmental aspects of a network such as emissions by selecting a suitable vehicle, depending on the quantities and distances involved.

5.4.3. Applicability of model to real-world case and managerial insights

Our research provides insights that various manufacturing industries could use to make decisions related to facilities location, vehicle selection, and allocation for product flow while achieving environmental sustainability. It is important to highlight that our research can be beneficial in modelling high volume, hyperlocal returns of small-size products such as household appliances (Alumur Sibel et al., 2012; Jeihoonian et al., 2016b), healthcare sector (Alizadeh, Makui & Paydar, 2020; Kargar, Paydar & Safaei, 2020), the fashion industry (Aravendan & Panneerselvam, 2016), electronic goods (John, Sridharan & Ram Kumar, 2018), and Battery industry (Reddy et al., 2019). Interestingly, we have considered a reverse logistics system with remanufacturing, but our solution approach, specifically a multi-stage strategy that divides the problem into various echelons, can suitably handle other reverse logis-

Table 11
Emissions due to production and transport.

		Case 1			Case 2		
		Cost ($)	Emissions (Kg of CO2)	Emission Cost ($)	Cost ($)	Emissions (Kg of CO2)	Emission Cost ($)
Production	**Testing facilities**	5915	16,651	1041	5755	36,142	2252
	Remanufacturing facilities	9134	5595	350	8616	18,617	1160
	Total	**15,049**	**22,246**	**1391**	**14,371**	**54,759**	**3411**
Transport	**D to T**	8662	16,740	1046	8651	22,451	1403
	T to R	5600	9115	570	5427	11,935	746
	R to C	32,420	71,742	4484	30,084	73,170	4573
	Total	**46,682**	**97,597**	**6100**	**44,162**	**107,556**	**6722**

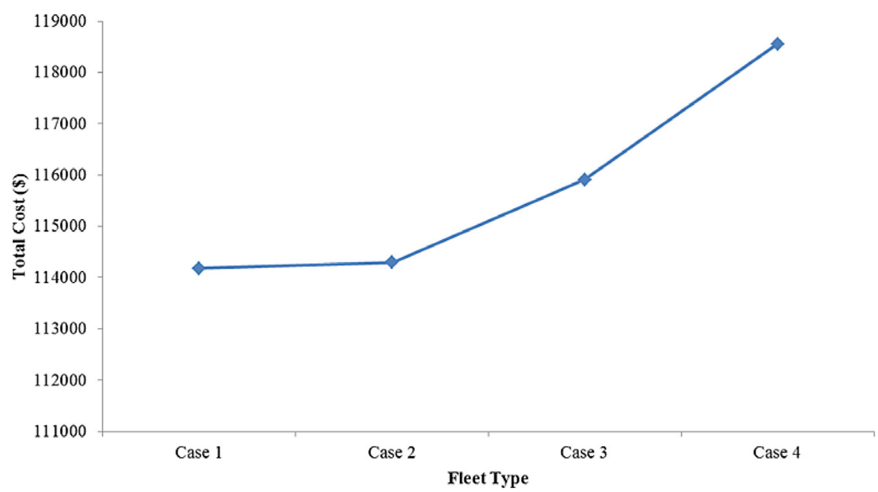

Fig. 4. Total cost comparison for heterogeneous vehicle fleet vs. homogeneous vehicle fleet.

Table 12
Fixed, variable, and emissions cost from transport for all cases.

Cost	Heterogeneous	Homogeneous- Large	Homogeneous- Medium	Homogeneous- Small
Case 1: Fixed Transport Cost	1494	1647	1829	2321
Case 2: Variable Transport Cost	45,188	44,386	44,974	45,078
Case 3: Emission Cost – Transport	6100	6854	7658	9809

Algorithm 5
Improved Benders decomposition (IBD).

Initialize UB=+∞, LB=-∞, Iterations, Gap=0, loop=0, ε;
Construct the ***initial feasible solution*** *using* Algorithm 4
Evaluate $LB = Z_{MP}$
do *{*
  Solve dual sub problem
  $DSP\left(v^1_{pi}, v^2_{pj}, v^3_{pj}, v^4_{pj}, v^5_{pj}, v^6_{pj}, v^7_{pijv}, v^8_{pijv}, v^9_{pijv}, v^{10}_{pj}, v^{11}_{pj} \middle| \hat{x}^p_j,\ \hat{N}^p_{ijv}\right)$
  record $\hat{v}^1_{pi}, \hat{v}^2_{pj}, \hat{v}^3_{pj}, \hat{v}^4_{pj}, \hat{v}^5_{pj}, \hat{v}^6_{pj}, \hat{v}^7_{pijv}, \hat{v}^8_{pijv}, \hat{v}^9_{pijv}, \hat{v}^{10}_{pj}, \hat{v}^{11}_{pj}$
  Evaluate $UB = Z_{DSP} + (Z_{MP} - \alpha(cutset))$
  If DSP is infeasible,
   generate Benders feasibility cut (BFC)
  else
   generate Benders optimality cut(BOC)
Gap $= ((UB - LB)/LB) * 100$
Find ***Master Solution*** *using* Algorithm 2
  Evaluate $LB = Z_{MP}$
  loop ++
} ***while*** *(loop* ⟨ *Iterations && Gap* ⟩ *ε)*
Solve $PSP(q^p_{ijv},\ I^p_j, DQ^p_j, B^p_j | \hat{x}^p_j,\ \hat{N}^p_{ijv})$
Report $\hat{q}^p_{ijv},\ \hat{I}^p_j, \widehat{DQ}^p_j, \hat{B}^p_j, \hat{x}^p_j,\ \hat{N}^p_{ijv}$ *and*
The objective value Z^**=UB.*

tics paradigms such as refurbishing, recycling, disposal, and repair. For example, an open box return from the e-commerce industry can easily be configured by removing the remanufacturing facility from the network. For the household appliances network, the remanufacturing centre is replaced by a repair centre. Our study helps decision-makers to quickly redesign their systems to respond to emergent policies anticipating new carbon emissions rules and regulations. Many countries across the world are planning to adopt a 100% electric vehicle policy by 2030. Our study can help organizations to carry out a feasibility study to realize the advantages of becoming an initial first mover in such a scenario. This internalization of externalities into the operations of systems provides a realistic view of the environmental and social costs of doing business. As mentioned earlier, while our model could apply to several industries, we use a specific example of the tire industry (Pedram et al., 2017; Sasikumar, Kannan & Haq, 2010). Table 13 in the appendix shows how different characteristics included in our model relate to the tire industry context and therefore demonstrate our model's real-world applicability.

6. Conclusion

In this paper, we present a MILP model to design RLN integrated with carbon footprint in which the facility location decisions are optimised, and the vehicle allocations in each arc between the facilities are made. We consider the carbon footprint from both processing at the facilities and distribution between the facilities. Considering a single objective type of optimisation provides the decision-makers with insights into the nature of the problem. We propose a BD-based heuristic, namely IBD, to find a quality solution within a reasonable time. This will help managers to find near-optimal solutions within a reasonable time for each instance. We illustrate all the solution approaches through 12 problem configurations of different sizes and compare their performance with the CPLEX solver.

Furthermore, to help managers, we examine the impacts of carbon emissions and the choice of the vehicle fleet. It is worth noting that the difference in the total cost between the cases where the carbon cost is and is not considered is a mere 2.5%. This increase in cost is attributed to investment in carbon-efficient technologies for the facilities as well as vehicles. Thus, it is not difficult to envisage that, in the long run, once the technology matures, sustainable practices are no more a burden but would result in a win-win situation for manufacturing industries with a lesser environmental impact and higher profits. Furthermore, our analysis asserts that the choice of the vehicle fleet affects the location decision in the network and noticeably reduces the carbon footprint.

This study provides improvements and extensions on previous remanufacturing network designs, but it has limitations and could be improved in several ways. First, the model can be extended by allowing inventory at different echelons and considering other pertinent operational decisions. Secondly, the model decisions could be examined considering different carbon policies such as carbon cap and trade. Furthermore, in line with Choudhary, De, Ahmed and Shankar (2021), we have considered various operational and tactical environmental key performance indicators (KPIs) in our modelling effort, including GHG emissions, waste management, resources utilization, risk management, etc. However, the present research explicitly doesn't model other key environmental performance indicators, including strategic level environmental KPIs related to innovation and improvement, government regulations, compliance to regulations, and quality management. Thus, incorporating other strategic KPIs into the modelling framework could be an interesting future research direction.

Acknowledgments

We would like to thank the European Union Commission for funding the research under the “EU – India Research and Innovation Partnership for Efficient and Sustainable Freight Transportation (REINVEST)” project (ICI + /2014/342–800).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.03.014.

References

Acquaye, A., Ibn-Mohammed, T., Genovese, A., Afrifa, G. A., Yamoah, F. A., & Oppon, E. (2018). A quantitative model for environmentally sustainable supply chain performance measurement. *European Journal of Operational Research, 269*(1), 188–205. https://doi.org/10.1016/j.ejor.2017.10.057.

Alizadeh, M., Makui, A., & Paydar, M. M. (2020). Forward and reverse supply chain network design for consumer medical supplies considering biological risk. *Computers and Industrial Engineering, 140*, Article 106229. https://doi.org/10.1016/j.cie.2019.106229.

Alshamsi, A., & Diabat, A. (2015). A reverse logistics network design. *Journal of Manufacturing Systems, 37*, 589–598. https://doi.org/10.1016/j.jmsy.2015.02.006.

Alshamsi, A., & Diabat, A. (2017). A genetic algorithm for reverse logistics network design: A case study from the GCC. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2017.02.096.

Alshamsi, A., & Diabat, A. (2018). Large-scale reverse supply chain network design: An accelerated Benders decomposition algorithm. *Computers and Industrial Engineering, 124*, 545–559. https://doi.org/10.1016/j.cie.2018.05.057.

Alumur Sibel, A., Nickel, S., Saldanha-da-gama, F., & Verter, V. (2012). Multi-period reverse logistics network design. *European Journal of Operational Research, 220*(1), 67–78. https://doi.org/10.1016/j.ejor.2011.12.045.

Amin, S. H., & Baki, F. (2017). A facility location model for global closed-loop supply chain network design. *Applied Mathematical Modelling, 41*, 316–330. https://doi.org/10.1016/j.apm.2016.08.030.

Antucheviciene, J., Jafarnejad, A., Mahdiraji, H. A., Hajiagha, S. H. R., & Kargar, A. (2020). Robust multi-objective sustainable reverse supply chain planning: An application in the steel industry. *Symmetry, 12*(4). https://doi.org/10.3390/SYM12040594.

Aravendan, M., & Panneerselvam, R. (2016). Application of hybrid genetic algorithm for CLSC network design problem in fashion footwear industry — a case study approach. *Journal of Service Science and Management, 9*, 195–210. https://doi.org/10.4236/jssm.2016.93024.

Ayvaz, B., Bolat, B., & Aydin, N. (2015). Stochastic reverse logistics network design for waste of electrical and electronic equipment. *Resources, Conservation and Recycling, 104*, 391–404. https://doi.org/10.1016/j.resconrec.2015.07.006.

Badri, H., Fatemi Ghomi, S. M. T., & Hejazi, T. H. (2017). A two-stage stochastic programming approach for value-based closed-loop supply chain network design. *Transportation Research Part E: Logistics and Transportation Review, 105*, 1–17. https://doi.org/10.1016/j.tre.2017.06.012.

Baptista, S., Barbosa-Póvoa, A. P., Escudero, L. F., Gomes, M. I., & Pizarro, C. (2019). On risk management of a two-stage stochastic mixed 0–1 model for the closed-loop supply chain design problem. *European Journal of Operational Research, 274*(1), 91–107. https://doi.org/10.1016/j.ejor.2018.09.041.

Belieres, S., Hewitt, M., Jozefowiez, N., Semet, F., & Van Woensel, T. (2020). A Benders decomposition-based approach for logistics service network design. *European Journal of Operational Research, 286*(2), 523–537. https://doi.org/10.1016/j.ejor.2020.03.056.

Bendres, J. F. (1962). Partitioning procedures for solving mixed-variables programming problems. *Numerische Mathematik, 4*, 238–252.

Bing, X., Bloemhof-Ruwaard, J. M., & van der Vorst, J. G. A. J. (2014). Sustainable reverse logistics network design for household plastic waste. *Flexible Services and Manufacturing Journal, 26*, 119–142. https://doi.org/10.1007/s10696-012-9149-0.

Boschetti, M., & Maniezzo, V. (2009). Benders decomposition, Lagrangean relaxation and metaheuristic design. *Journal of Heuristics, 15*, 283–312. https://doi.org/10.1007/s10732-007-9064-9.

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research, 233*(2), 299–312. https://doi.org/10.1016/j.ejor.2013.09.032.

Brandenburg, M., & Rebs, T. (2015). Sustainable supply chain management: A modelling perspective. *Annals of Operations Research*. https://doi.org/10.1007/s10479-015-1853-1.

Cachon, G. P. (2014). Retail store density and the cost of greenhouse gas emissions. *Management Science, 60*(8), 1907–1925. https://doi.org/10.1287/mnsc.2013.1819.

Cardona-Valdés, Y., Álvarez, A., & Pacheco, J. (2014). Metaheuristic procedure for a bi-objective supply chain design problem with uncertainty. *Transportation Research Part B: Methodological, 60*, 66–84. https://doi.org/10.1016/j.trb.2013.11.010.

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics, 135*, 37–49. https://doi.org/10.1016/j.ijpe.2010.10.025.

Chanintrakul, P., Mondragon, A. E. C., Lalwani, C., & Wong, C. Y. (2009). Reverse logistics network design: A state-of-the-art literature review. *International Journal of Business Performance and Supply Chain Modelling, 1*(1), 61–81.
Chen, Y. T., Chan, F. T. S., & Chung, S. H. (2015). An integrated closed-loop supply chain model with location allocation problem and product recycling decisions. *International Journal of Production Research, 53*(10), 3120–3140. https://doi.org/10.1080/00207543.2014.975849.
Chen, Y. W., Wang, L. C., Wang, A., & Chen, T. L. (2017). A particle swarm approach for optimizing a multi-stage closed loop supply chain for the solar cell industry. *Robotics and Computer-Integrated Manufacturing, 43*, 111–123. https://doi.org/10.1016/j.rcim.2015.10.006.
Choudhary, A., De, A., Ahmed, K., & Shankar, R. (2021). An integrated fuzzy intuitionistic sustainability assessment framework for manufacturing supply chain: A study of UK based firms. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03452-3.
Choudhary, A., Sarkar, S., Settur, S., & Tiwari, M. K. (2015). A carbon market sensitive optimization model for integrated forward-reverse logistics. *International Journal of Production Economics, 164*, 433–444. https://doi.org/10.1016/j.ijpe.2014.08.015.
Coelho, E. K. F., & Mateus, G. R. (2017). A capacitated plant location model for reverse logistics activities. *Journal of Cleaner Production, 167*, 1165–1176. https://doi.org/10.1016/j.jclepro.2017.07.238.
Costa, A. M. (2005). A survey on Benders decomposition applied to fixed-charge network design problems. *Computers and Operations Research, 32*(6), 1429–1450. https://doi.org/10.1016/j.cor.2003.11.012.
Cui, Y. Y., Guan, Z., Saif, U., Zhang, L., Zhang, F., & Mirza, J. (2017). Close loop supply chain network problem with uncertainty in demand and returned products: Genetic artificial bee colony algorithm approach. *Journal of Cleaner Production, 162*, 717–742. https://doi.org/10.1016/j.jclepro.2017.06.079.
De Sá, E. M., De Camargo, R. S., & De Miranda, G. (2013). An improved Benders decomposition algorithm for the tree of hubs location problem. *European Journal of Operational Research, 226*(2), 185–202. https://doi.org/10.1016/j.ejor.2012.10.051.
Devika, K., Jafarian, A., & Nourbakhsh, V. (2014). Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques. *European Journal of Operational Research, 235*, 594–615. https://doi.org/10.1016/j.ejor.2013.12.032.
Diabat, A., & Jebali, A. (2021). Multi-product and multi-period closed loop supply chain network design under take-back legislation. *International Journal of Production Economics, 231*(July 2020), Article 107879. https://doi.org/10.1016/j.ijpe.2020.107879.
Easwaran, G., & Üster, H. (2009). Tabu search and Benders decomposition approaches for a capacitated closed-loop supply chain network design problem. *Transportation Science, 43*(3), 301–320. https://doi.org/10.1287/trsc.1090.0267.
Easwaran, G., & Üster, H. (2010). A closed-loop supply chain network design problem with integrated forward and reverse channel decisions. *IIE Transactions (Institute of Industrial Engineers), 42*(11), 779–792. https://doi.org/10.1080/0740817X.2010.504689.
Fahimnia, B., Sarkis, J., Dehghanian, F., Banihashemi, N., & Rahman, S. (2013). The impact of carbon pricing on a closed-loop supply chain: An Australian case study. *Journal of Cleaner Production, 59*, 210–225. https://doi.org/10.1016/j.jclepro.2013.06.056.
Fakhri, A., & Ghatee, M. (2016). Application of Benders decomposition method in solution of a fixed-charge multicommodity network design problem avoiding congestion. *Applied Mathematical Modelling, 40*(13–14), 6468–6476. https://doi.org/10.1016/j.apm.2016.01.057.
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 and Systems, 341*, 69–91. https://doi.org/10.1016/j.fss.2017.03.019.
Fattahi, M., & Govindan, K. (2017). Integrated forward/reverse logistics network design under uncertainty with pricing for collection of used products. *Annals of Operations Research, 253*(1), 193–225. https://doi.org/10.1007/s10479-016-2347-5.
Fleischmann, M., Nunen, J. A. E. E. van, & Gräve, B. (2003). Integrating closed-loop supply chains and spare parts management at IBM. *Interfaces, 33*(6), 44–56. https://doi.org/10.1287/inte.33.6.44.25189.
Fontaine, P., & Minner, S. (2018). Benders decomposition for the Hazmat transport network design problem. *European Journal of Operational Research, 267*(3), 996–1002. https://doi.org/10.1016/j.ejor.2017.12.042.
Ghadimi, P., Wang, C., & Lim, M. K. (2019). Sustainable supply chain modeling and analysis: Past debate, present problems and future challenges. *Resources, Conservation and Recycling, 140*, 72–84. https://doi.org/10.1016/j.resconrec.2018.09.005.
Govindan, K., & Bouzon, M. (2018). From a literature review to a multi-perspective framework for reverse logistics barriers and drivers. *Journal of Cleaner Production, 187*, 318–337. https://doi.org/10.1016/j.jclepro.2018.03.040.
Govindan, K., Paam, P., & Abtahi, A. R. (2016). A fuzzy multi-objective optimization model for sustainable reverse logistics network design. *Ecological Indicators, 67*, 753–768. https://doi.org/10.1016/j.ecolind.2016.03.017.
Govindan, K., & Soleimani, H. (2017). A review of reverse logistics and closed-loop supply chains: A journal of cleaner production focus. *Journal of Cleaner Production, 142*, 371–384. https://doi.org/10.1016/j.jclepro.2016.03.126.
Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain : A comprehensive review to explore the future. *European Journal of Operational Research, 240*(3), 603–626. https://doi.org/10.1016/j.ejor.2014.07.012.
Guo, J., Wang, X., Fan, S., & Gen, M. (2017). Forward and reverse logistics network and route planning under the environment of low-carbon emissions: A case study of Shanghai fresh food E-commerce enterprises. *Computers and Industrial Engineering, 106*, 351–360. https://doi.org/10.1016/j.cie.2017.02.002.
Jeihoonian, M., Zanjani, M. K., & Gendreau, M. (2016). Accelerating Benders decomposition for closed-loop supply chain network design: Case of used durable products with different quality levels. *European Journal of Operational Research, 251*(3), 830–845. https://doi.org/10.1016/j.ejor.2015.12.052.
Jeihoonian, Mohammad, Kazemi Zanjani, M., & Gendreau, M. (2020). Dynamic reverse supply chain network design under uncertainty: Mathematical modeling and solution algorithm. *International Transactions in Operational Research, 00*, 1–29. https://doi.org/10.1111/itor.12865.
Jeihoonian, Mohammad, Zanjani, M. K., & Gendreau, M. (2016). *A decomposition algorithm for dynamic reverse supply chain network design under uncertainty*: 55. CIRRELT.
Jerbia, R., Kchaou Boujelben, M., Sehli, M. A., & Jemai, Z. (2018). A stochastic closed-loop supply chain network design problem with multiple recovery options. *Computers and Industrial Engineering, 118*(June 2017), 23–32. https://doi.org/10.1016/j.cie.2018.02.011.
Jiang, G., Wang, Q., Wang, K., Zhang, Q., Zhou, J., Gao, X., et al. (2020). Reverse supply chain management in manufacturing industry: A systematic review. *Journal of Cleaner Production, 0*(1), 1–20. https://doi.org/10.1016/j.apenergy.2020.115538.
Jiang, W., Tang, L., & Xue, S. (2009). A hybrid algorithm of tabu search and benders decomposition for multi-product production distribution network design. In *Proceedings of the IEEE International Conference on Automation and Logistics* (pp. 79–84). August.
John, S. T., Sridharan, R., & Ram Kumar, P. N. (2018). Reverse logistics network design: A case of mobile phones and digital cameras. *The International Journal of Advanced Manufacturing Technology, 94*, 615–631. https://doi.org/10.1007/s00170-017-0864-2.
Kannan, D., Diabat, A., Alrefaei, M., Govindan, K., & Yong, G. (2012). A carbon footprint based reverse logistics network design model. *Resources, Conservation and Recycling, 67*, 75–79. https://doi.org/10.1016/j.resconrec.2012.03.005.
Kargar, S., Paydar, M. M., & Safaei, A. S. (2020). A reverse supply chain for medical waste: A case study in Babol healthcare sector. *Waste Management, 113*, 197–209. https://doi.org/10.1016/j.wasman.2020.05.052.
Keyvanshokooh, E., Ryan, S. M., & Kabir, E. (2016). Hybrid robust and stochastic optimization for closed-loop supply chain network design using accelerated Benders decomposition. *European Journal of Operational Research, 249*(1), 76–92. https://doi.org/10.1016/j.ejor.2015.08.028.
Kim, H., Yang, J., & Lee, K. D. (2009). Vehicle routing in reverse logistics for recycling end-of-life consumer electronic goods in South Korea. *Transportation Research Part D: Transport and Environment, 14*(5), 291–299. https://doi.org/10.1016/j.trd.2009.03.001.
Lai, M. C., Sohn, H. S., Tseng, T. L., & Chiang, C. (2010). A hybrid algorithm for capacitated plant location problem. *Expert Systems with Applications, 37*(12), 8599–8605. https://doi.org/10.1016/j.eswa.2010.06.104.
Lechner, G., & Reimann, M. (2020). Integrated decision-making in reverse logistics: An optimisation of interacting acquisition, grading and disposition processes. *International Journal of Production Research, 58*(19), 5786–5805. https://doi.org/10.1080/00207543.2019.1659518.
Lee, D. H., & Dong, M. (2008). A heuristic approach to logistics network design for end-of-lease computer products recovery. *Transportation Research Part E: Logistics and Transportation Review, 44*(3), 455–474. https://doi.org/10.1016/j.tre.2006.11.003.
Li, Y., Guo, H., & Zhang, Y. (2018). An integrated location-inventory problem in a closed-loop supply chain with third-party logistics. *International Journal of Production Research, 56*(10), 3462–3481. https://doi.org/10.1080/00207543.2017.1338781.
Liao, T. Y. (2018). Reverse logistics network design for product recovery and remanufacturing. *Applied Mathematical Modelling, 60*, 145–163. https://doi.org/10.1016/j.apm.2018.03.003.
Lu, Z., & Bostel, N. (2007). A facility location model for logistics systems including reverse flows: The case of remanufacturing activities. *Computers and Operations Research, 34*, 299–323. https://doi.org/10.1016/j.cor.2005.03.002.
Lusby, R. M., Range, T. M., & Larsen, J. (2016). A benders decomposition-based matheuristic for the cardinality constrained shift design problem. *European Journal of Operational Research, 254*, 385–397. https://doi.org/10.1016/j.ejor.2016.04.014.
Mutha, A., & Pokharel, S. (2009). Strategic network design for reverse logistics and remanufacturing using new and old product modules. *Computers and Industrial Engineering, 56*(1), 334–346. https://doi.org/10.1016/j.cie.2008.06.006.
Naderi, B., Govindan, K., & Soleimani, H. (2019). A Benders decomposition approach for a real case supply chain network design with capacity acquisition and transporter planning: Wheat distribution network. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03137-x.
Paksoy, T., Bektaş, T., & Özceylan, E. (2011). Operational and environmental performance measures in a multi-product closed-loop supply chain. *Transportation Research Part E: Logistics and Transportation Review, 47*, 532–546. https://doi.org/10.1016/j.tre.2010.12.001.
Pedram, A., Yusoff, N. bin, Udoncy, O. E., Mahat, A. B., Pedram, P., & Babalola, A. (2017). Integrated forward and reverse supply chain: A tire case study. *Waste Management, 60*, 460–470. https://doi.org/10.1016/j.wasman.2016.06.029.
Pishvaee, M. S., Jolai, F., & Razmi, J. (2009). A stochastic optimization model for integrated forward/reverse logistics network design. *Journal of Manufacturing Systems, 28*(4), 107–114. https://doi.org/10.1016/j.jmsy.2010.05.001.

Poojari, C. A., & Beasley, J. E. (2009). Improving Benders decomposition using a genetic algorithm. *European Journal of Operational Research, 199*, 89–97. https://doi.org/10.1016/j.ejor.2008.10.033.

Qiu, Y., Ni, M., Wang, L., Li, Q., Fang, X., & Pardalos, P. M. (2018). Production routing problems with reverse logistics and remanufacturing. *Transportation Research Part E: Logistics and Transportation Review, 111*(January), 87–100. https://doi.org/10.1016/j.tre.2018.01.009.

Rahmaniani, R., Crainic, T. G., Gendreau, M., & Rei, W. (2017). The Benders decomposition algorithm: A literature review. *European Journal of Operational Research, 259*(3), 801–817. https://doi.org/10.1016/j.ejor.2016.12.005.

Randazzo, C. D., Luna, H. P. L., & Mahey, P. (2001). Benders decomposition for local access network design with two technologies. *Discrete Mathematics & Theoretical Computer Science, 4*(2), 235–246.

Reddy, K. N., Kumar, A., & Ballantyne, E. E. F. (2019). A three-phase heuristic approach for reverse logistics network design incorporating carbon footprint. *International Journal of Production Research, 57*(19), 6090–6114. https://doi.org/10.1080/00207543.2018.1526422.

Reddy, K. N., Kumar, A., Sarkis, J., & Tiwari, M. K. (2020). Effect of carbon tax on reverse logistics network design. *Computers and Industrial Engineering, 139*(March 2019), Article 106184. https://doi.org/10.1016/j.cie.2019.106184.

Saharidis, G. K. D., Boile, M., & Theofanis, S. (2011). Initialization of the Benders master problem using valid inequalities applied to fixed-charge network problems. *Expert Systems with Applications, 38*(6), 6627–6636. https://doi.org/10.1016/j.eswa.2010.11.075.

Santibanez-Gonzalez, E. D. R., & Diabat, A. (2013). Solving a reverse supply chain design problem by improved Benders decomposition schemes. *Computers and Industrial Engineering, 66*, 889–898. https://doi.org/10.1016/j.cie.2013.09.005.

Santos, L., Coutinho-Rodrigues, J., & Current, J. R. (2010). An improved ant colony optimization based algorithm for the capacitated arc routing problem. *Transportation Research Part B: Methodological, 44*(2), 246–266. https://doi.org/10.1016/j.trb.2009.07.004.

Sasikumar, P., Kannan, G., & Haq, A. N. (2010). A multi-echelon reverse logistics network design for product recovery-a case of truck tire remanufacturing. *International Journal of Advanced Manufacturing Technology, 49*(9–12), 1223–1234. https://doi.org/10.1007/s00170-009-2470-4.

Seuring, S. (2013). A review of modeling approaches for sustainable supply chain management. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2012.05.053.

Shahparvari, S., Soleimani, H., Govindan, K., Bodaghi, B., Fard, M. T., & Jafari, H. (2021). Closing the loop: Redesigning sustainable reverse logistics network in uncertain supply chains. *Computers & Industrial Engineering*, Article 107093. https://doi.org/10.1016/j.cie.2020.107093.

Shi, J., Liu, Z., Tang, L., & Xiong, J. (2016). Multi-objective optimization for a closed-loop network design problem using an improved genetic algorithm. *Applied Mathematical Modelling, 45*, 14–30. https://doi.org/10.1016/j.apm.2016.11.004.

Sifaleras, A., & Konstantaras, I. (2017). Variable neighborhood descent heuristic for solving reverse logistics multi-item dynamic lot-sizing problems. *Computers and Operations Research, 78*, 385–392. https://doi.org/10.1016/j.cor.2015.10.004.

Soleimani, H., & Govindan, K. (2014). Reverse logistics network design and planning utilizing conditional value at risk. *European Journal of Operational Research, 237*, 487–497. https://doi.org/10.1016/j.ejor.2014.02.030.

Tadaros, M., Migdalas, A., Samuelsson, B., & Segerstedt, A. (2020). Location of facilities and network design for reverse logistics of lithium-ion batteries in Sweden. *Operational Research*, Article 0123456789. https://doi.org/10.1007/s12351-020-00586-2.

Tang, L., Jiang, W., & Saharidis, G. K. D. (2013). An improved Benders decomposition algorithm for the logistics facility location problem with capacity expansions. *Annals of Operations Research, 210*(1), 165–190. https://doi.org/10.1007/s10479-011-1050-9.

Taskin, Z. C., & Cevik, M. (2013). Combinatorial Benders cuts for decomposing IMRT fluence maps using rectangular apertures. *Computers & Operations Research, 40*, 2178–2186. https://doi.org/10.1016/j.cor.2011.07.005.

Tiwari, A., Chang, P. C., Tiwari, M. K., & Kandhway, R. (2016). A hybrid territory defined evolutionary algorithm approach for closed loop green supply chain network design. *Computers and Industrial Engineering, 99*, 432–447. https://doi.org/10.1016/j.cie.2016.05.018.

Trochu, J., Chaabane, A., & Ouhimmou, M. (2018). Reverse logistics network redesign under uncertainty for wood waste in the CRD industry. *Resources, Conservation & Recycling, 128*, 32–47. https://doi.org/10.1016/j.resconrec.2017.09.011.

Trochu, J., Chaabane, A., & Ouhimmou, M. (2019). A two-stage stochastic optimization model for reverse logistics network design under dynamic suppliers' locations. *Waste Management, 95*, 569–583. https://doi.org/10.1016/j.wasman.2019.06.012.

Üster, H., & Hwang, S. O. (2016). Closed-loop supply chain network design under demand and return uncertainty. *Transportation Science* December, trsc.2015.0663. https://doi.org/10.1287/trsc.2015.0663.

Yang, L., Hu, Y., & Huang, L. (2020). Collecting mode selection in a remanufacturing supply chain under cap-and-trade regulation. *European Journal of Operational Research, 287*(2), 480–496. https://doi.org/10.1016/j.ejor.2020.04.006.

Zhalechian, M., Tavakkoli-Moghaddam, R., Zahiri, B., & Mohammadi, M. (2016). Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. *Transportation Research Part E: Logistics and Transportation Review, 89*, 182–214. https://doi.org/10.1016/j.tre.2016.02.011.

Zohal, M., & Soleimani, H. (2016). Developing an ant colony approach for green closed-loop supply chain network design: A case study in gold industry. *Journal of Cleaner Production, 133*, 314–337. https://doi.org/10.1016/j.jclepro.2016.05.091.

Further Reading

Bayley, T., Süral, H., & Bookbinder, J. H. (2018). A hybrid Benders approach for coordinated capacitated lot-sizing of multiple product families with set-up times. *International Journal of Production Research, 56*(3), 1326–1344. https://doi.org/10.1080/00207543.2017.1338778.

Yang, C., & Chen, J. (2020). Robust design for a multi-echelon regional construction and demolition waste reverse logistics network based on decision Maker's conservative attitude. *Journal of Cleaner Production, 273*. https://doi.org/10.1016/j.jclepro.2020.122909.

Shi, J., Liu, Z., Tang, L., & Xiong, J. (2017). Multi-objective optimization for a closed-loop network design problem using an improved genetic algorithm. *Applied Mathematical Modelling, 45*, 14–30. https://doi.org/10.1016/j.apm.2016.11.004.