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A Three-Phase Heuristic Approach for Reverse Logistics Network Design Incorporating Carbon Footprint

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Abstract

Reverse logistics (RL) is emerging as a significant area of activity for business and industry, motivated by both commercial profitability and wider environmental sustainability factors. However, planning and implementing an appropriate RL network within existing supply chains for product recovery that increases customer satisfaction, decreases overall costs, and provides a competitive advantage over other companies is complex. In the current study, we developed a mixed integer linear programming (MILP) model for a reverse logistics network design (RLND) in a multi-period setting. The RL network consists of collection centres, capacitated inspection and remanufacturing centres and customer zones to serve. Moreover, the model incorporates significant characteristics such as vehicle type selection and carbon emissions (through transportation and operations). Since the network design problems are NP-hard, we first propose a solution approach based on benders decomposition (BD). Then, based on the structure of the problem we propose a three-phase heuristic approach. Finally, to establish the performance and robustness of the proposed solution approach, the results are compared with benchmark results obtained using CPLEX in terms of both solution quality and computational time. From the computational results, we validated that the three-phase heuristic approach performs superior to the BD and Branch &Cut approach.

Keywords: Reverse Logistics, Carbon footprint, E-waste, Mixed Integer Linear Programming, Benders decomposition

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1. Introduction

Rapid pace technology development and population growth are driving the generation of waste at an alarming rate (Dwivedy and Mittal 2012). Among various types of waste generated, the electrical and electronic waste (e-waste) is one of the fastest growing waste streams in the world. E-waste typically consists of end-of-life computers, televisions, photocopiers, and mobile phones, whereas Waste Electrical and Electronic Equipment (WEEE) also includes non-electronic goods such as ovens and refrigerators, since all can be classed as discarded appliances that use electricity (Robinson 2009; Sthiannopkao and Wong 2013;Wong et al. 2007).

According to a report compiled by StEP (Solving the E-waste Problem), almost 48.9 Million Metric Tons (MMT) of e-waste was generated globally in 2013 (Coelho and Mateus 2017) and based on recent trends, StEP forecasts that the aggregate yearly volume of e-waste will increase by 33 percent by 2018 at 65.4 million tons.

Most E-waste is discarded household waste that ends up in landfill without any special treatment of items (Barba-Gutiérrez, Adenso-Díaz, and Hopp 2008; Ladou, MD, and Lovegrove 2007). It is estimated that eighty percent of untreated, discarded household E-waste from developed countries is exported to poorer countries (Schmidt 2006; Robinson 2009; Zhang, Schnoor, and Zeng 2012), including China, India, Pakistan, Vietnam, the Philippines, Malaysia, Nigeria, Ghana, Brazil and Mexico (Robinson 2009) where the industry can take advantage of less stringent environmental regulations and lower labour costs for processing items (Wong et al. 2007). The relatively high costs associated with disposal of items in developed countries has led to a growth in primitive and improper disposal methods (often with little to no proper pollution control equipment) being used in poorer nations, to attempt to recover valuable precious metals from the E-waste (Zhang, Schnoor, and Zeng 2012). However, these methods have been linked to serious environmental and human health risks due to the large number of toxicants released during the decomposition of E-waste (Zhang, Schnoor, and Zeng 2012; Leung et al. 2008).To alleviate, such undesirable consequences of E-waste, policymakers worldwide have implemented regulations and guidelines for the safe and sustainable disposal of E-waste, and firms are responding by increasingly adopting sustainable business practices. For instance, Original Equipment Manufacturers (OEMs) have implemented Extended Producer Responsibility (EPR) programs for the safe disposal of end-of-life (EOL) products (Nnorom and Osibanjo

2008). Whilst India is an established importer of E-Waste from developed countries (Sthiannopkao and Wong 2013), more recently it is evolving as one of the world's major generators of electronic waste (Dwivedy and Mittal 2012); thus the Government of India introduced an EPR rule under the Environment Protection Act (1986) for managing EOL electronic products in 2016.

In today’s global economy, increased consumerism has significantly increased demand for new products, leading to shorter Product Life Cycles, and greater consumption of raw materials. The scarcity of raw materials, economic issues and strict environmental regulations pertaining to waste management have made it imperative for firms to integrate used or returned products into the supply chain to recapture the valuable materials such as copper, gold and silver (Lee et al. 2004; Nnorom and Osibanjo 2008). Integrating RL activities into the existing SC network has become imperative for firms not only because it differentiates the firm from competitors through cost reduction but also by adding value to a firm’s supply chain and its end customers whilst incorporating the needs of environmental sustainability(Agarwal, Barari, and Tiwari 2012; Kumar, Chinnam, and Murat 2017). To enable this, firms usually engage downstream supply chain partners such as distributors and retailers by including RL activities in contractual agreements for product collections.

An OEM’s involvement with the RL process is typically a function of the financial value that can be captured by processing returned products (Dowlatshahi 2010). The OEM can create monetary value from product recovery; especially when establishing its own RL network that incorporates remanufacturing facilities becomes a viable option. However, planning and designing an efficient and suitable reverse logistics network (RLN) to facilitate product recovery is difficult. Network design is a crucial decision, as it constrains subsequent tactical and operational decisions.

Consideration of environmental impacts has become an integral part of the decision-making process at all levels of the organization (John, Sridharan, and Kumar 2017). By designing and planning an efficient RLN, firms can reduce their greenhouse gas emissions (GHG) along with overall operating costs, whilst achieving corporate social responsibility targets and increased competitive advantages (Y. Chen et al. 2017).

The aspects mentioned above motivated the consideration of a four-echelon, multi-period RLN involving product collection, inspection and remanufacturing centres in addition to markets/customer zones with the objective of simultaneously reducing costs and carbon emissions. The model described in this paper also considered a carbon tax policy for computing CO_2 emissions generated during core returns processing activities and their associated transportation. Thus, the model we developed incorporates carbon emission regulations, remanufacturing, transportation and technological factors within a unified framework.

The most widespread modelling approach to logistics network design problems in various contexts concerns facility location models based on mixed integer linear programming (MILP). Given this extensive body of research, MILP location models appear to be a natural starting point for quantitative approaches to RLN design. Several authors have followed this route and have presented MILP location models adapted to an RL context (Fleischmann, Nunen, and Gräve 2003).

Therefore, we outline four main contributions which from the focus of this paper:

1. Development of a MILP to model the problem of selecting optimal locations for inspection centres and remanufacturing plants while accounting for CO_2 emissions.
2. Selection of appropriate vehicle type for transportation across the reverse supply chain, again incorporating CO_2 emissions from vehicles.
3. Proposed Bender's Decomposition (BD) based method to solve the modelled problem setting. However, as the problem size increases with number of potential locations, length of the planning horizon, etc. the model becomes computationally intractable even for BD based methods. Hence, we have proposed a three-phase solution approach leveraging the dynamics of the problem setting to solve the model efficiently.
4. Proposed methods tested on a case study of Li-Ion battery for Electric Vehicles.

The remainder of this paper is organised as follows: Section 2 reviews the literature on RL, integrated forward/reverse logistics network, carbon emissions in RL and methodologies to solve problems. Section 3 presents a mathematical model to the multi-echelon RLN in a multi-period setting. Section 4 addresses a three-phase solution approach along with BD to alleviate the computational complexity of attaining a near-optimal solution. Section 5 presents the application of proposed model to the automotive industry. Section 6 addresses the effective performance of the proposed solution approach through the computational study. Finally, Section 7 concludes and suggests some future extensions of the model.

2. Literature Review

The most widespread modelling approach to logistics network design problems in various contexts concerns facility location models based on MILP. Given this extensive body of research, MILP location models appear to be a natural starting point for quantitative approaches to RLND. Several authors have followed this route and have presented MILP location models adapted to an RL context (Fleischmann, Nunen, and Gräve 2003). Further, a variety of modelling approaches including mixed integer location models, stochastic location models, and continuous approximation models have been proposed for solving the RLND (B. Fleischmann, Gnutzmann, and Sandvoß 2004).

2.1 Modelling approaches to solve the RLND

Y. T. Chen, Chan, and Chung (2015) established an integrated closed-supply chain model to recycle cartridges in Hong-Kong. A zero-one mixed integer programming (MIP) model for two-level location problem proposed with three types of the facility in an RL system (Lu and Bostel 2007). The model was solved and analyzed using an algorithm based on the Lagrangian heuristic approach and stated that reverse flows influenced location and allocation decisions. Coelho and Mateus (2017) proposed a model for locating facilities with a finite capacity for RL activities. Roghanian and Pazhoheshfar (2014) proposed a probabilistic MILP model for multi-product, multi-stage RLND and exploited a priority based genetic algorithm to find an optimal network to fulfil the demand with a minimum total cost under uncertainty condition. Where manufacturers are unable to incorporate RL into their operations, third-party logistics (3PL) service providers are utilised to recover used products. The remanufacturer may then satisfy the manufacturer's demand either by new components or by remanufacturing as considered in our model. Such a 3PL based RLN with integrated disassembly line balancing and recovery process was proposed by Kannan et al. (2016). To accomplish the aim, a MINLP was developed and validated using various products from the LCD industry. They found that there is a need to increase the awareness regarding the importance of product and component reuse among consumers to improve the cost-effectiveness of the recovery network. Likewise, Li, Guo, and Zhang (2018) studied the MINLP model for a closed-loop system with a 3PL and decided the location and inventory decisions together.

The complexity of the problem is amplified by uncertainty in logistics parameters such as capacity, demand, return quantity and quality. A generalized model for multi-product RLND with finite capacity was developed in a MIP structure under product demands and return uncertainty (Salema, Barbosa-Povoa, and Novais 2007). Lieckens and Vandaele (2012) presented a model for designing RLN by addressing the impact of lead times and the high level of uncertainty. Further, a generic multi-echelon, multi-product, and capacity constrained two-stage stochastic programming model is presented by considering uncertainties (returns rate, quality and transportation cost) in an RLN, it is solved using sample average approximation method and validated by applying to a real-world case study for a WEEE recycling firm in Turkey (Ayvaz, Bolat, and Aydın 2015). As conventional two-stage stochastic programming (2-SSP) considers the expectation of random variables in its objective function, it is risk neutral. A 2-SSP approach is developed to design and plan an RSC network with a risk evaluator (Soleimani and Govindan 2014). To make capacity, production and inventory decisions for modular products such as mobiles devices, Kaya, Bagci, and Turkay (2014) developed a large-scale mixed integer programming model and analyzed system behavior using two-stage stochastic optimization.

Soleimani, Seyyed-Esfahani, and Shirazi (2016) proposed a multi-product closed-loop supply chain network in a multi-period setting with stochastic demand and price in a MILP structure. The model applied to a plastic water cane manufacturer and analyzed results through a multi-criteria scenario based solution approach. Pishvaee, Jolai, and Razmi (2009) and Üster and Hwang (2016) developed stochastic MILP models for a closed-loop (integrated forward/reverse) logistics network design under the demand uncertainty of quantity and quality of returned products. Further, Easwaran and Üster (2009) proposed a new dual solution method associated with BD to solve a closed-loop logistics network. Interestingly, environmental concerns typically took a backseat to economic concerns in many of these modelling efforts. For example, Srivastava (2008) utilized combinatorial optimization to the solution and tried to determine different decisions like reuse, remanufacture, refurbish, etc., based on profit maximisation.

2.2 Sustainability in Supply Chain Network Design models

In recent years, the growing concern for sustainability has forced researchers and managers to incorporate environmental and social factors along with economic factors in the design of supply chains. Thus, developing a model that can simultaneously consider the environmental, social, and economic aspects and their indicators is an important problem for both researchers and practitioners to address. While most of the papers in the field of supply chain network design focus on economic performance, some recent studies have considered environmental dimensions. For instance, John, Sridharan, and Kumar (2017) developed a MILP model for a multi-period, multi-product reverse supply chain (RSC) by integrating emission cost from transportation activities into the model. Similarly, Kannan et al. (2012) presented a MILP model for RLND to minimize CO2 footprints, validated by a case study from the plastics industry. To enhance the consumers' environmental consciousness and to increase both the profits and the return of past-sold products, Giovanni (2017) developed two incentive games for closed loop supply chain coordination through a profit-sharing contract between manufacturer and retailer. Jindal and Sangwan (2016) presented fuzzy MILP for a multi-objective closed-loop supply chain considering the economic and environmental factors together and solved using an interactive ε-constraint method.

Besides environmental and social concerns, legislation in some countries also forces the recycling of products such as end-of-life vehicles (ELVs). Hence, (Özceylan et al. (2017) presented a closed-loop supply chain (CLSC) network for ELVs treatment in Turkey. For example, Choudhary et al. (2015) proposed a carbon market sensitive optimization model for integrated forward–reverse logistics, by integrating the carbon emissions with facility location decisions into quantitative operational decision-making. A multi-objective closed-loop supply chain design (MCSCD) model with cost and environmental concerns was developed from sustainability perspectives for the solar energy industry (Y. Chen et al. 2017). The trade-off between the total cost and total CO2 emissions has been captured to address the effect of CO2 emissions on the proposed model. They found that a firm needs to apply an adequate recycling strategy or energy-saving technology to achieve better economic effectiveness if the carbon emission regulation is applied. Devika, Jafarian, and Nourbakhsh (2014) developed a MIP model for a sustainable closed-loop supply chain network in the glass industry that considers social, economic and environmental issues simultaneously. The effects of environmental policies on a closed loop supply chain were evaluated using a variational inequality approach by Allevi et al. (2017). Finally, Rezaee et al. (2017) presented a model for a supply chain network by considering both environmental impacts and demand uncertainty to an Australian manufacturer of office furniture. They found that the supply chain configuration can be highly sensitive to the probability distribution of the carbon credit price, and observed that carbon price and budget availability have a positive nonlinear relationship in greening the supply chain.

To summarize, it is undeniable that RLND needs to move from its' traditional objective of minimizing total operational costs to a broader picture of sustainability. Therefore, it is imperative to develop models which embrace good business sense while catering for the needs of people, prosperity, environment and sustainability. Table 1 shows the modelling literature in this field that has been reviewed, and thus identifies the research gap that this paper intends to fill. Motivated by such findings from previous academic research, this research presents a complete and integrated consideration of these parameters and this decision environment through a MILP model for a carbon-footprint based RLND with vehicle type selection in a multi-period environment that can prove to be more valuable to practitioners. It also provides researchers insights into how to model and evaluate results in this environment.

Table 1: Summary of Literature Review

Author	Network structure	Model type	Objective function	Period	Product	Recovery Options	Facilities to be located	Returns quality	Carbon footprint	Vehicle type Selection	Solution Method	Case Study
Ayvaz, Bolat, and Aydın (2015)	Reverse	2SSP	MP	S	M	R	CC, SC, RC	×	×	×	Sample average approximation	WEEE
Y. T. Chen, Chan, and Chung (2015)	Closed	IP	MP	S	S	R	W, CC, RC	✓	×	×	Modified two-stage genetic algorithm	Cartridge recycling
Y. Chen et al. (2017)	Closed	MILP	MC, ME	S	S	R	PC, RC	×	P	×	Multi-objective PSO	Solar cell industry
Easwaran and Üster (2009)	Closed	MILP	MC	S	M	RM	CC, RMC	✓	×	×	Tabu Search and Benders Decomposition (BD)	-----
Jeihoonian, Zanjani, and Gendreau (2016)	Closed	MILP	MP	S	S	R, RM	DC, RC, CC, RMC	✓	×	×	Accelerating BD	Durable products
Jindal and Sangwan (2016)	Closed	FMILP	MP, ME	S	M	R, RU, RF	CC,DC, RFC	×	T	×	Interactive ε-constraint method	----
John, Sridharan, and Kumar (2017)	Reverse	MILP	TP	M	M	R,RP,RM	CC,SC,RC,R PC,RMC	×	T	×	LINGO	-----
Kannan et al. (2012)	Reverse	MILP	MC, ME	S	S	-----	CC,IC	×	T	×	LINGO	Plastic sector
Özceylan et al. (2017)	Closed	MILP	MP	M	M	R	-----	×	×	×	GAMS-CPLEX	Automotive industry
Pishvaee, Jolai, and Razmi (2009)	Integrated	SMILP	MC	S	S	----	PC, HDC	×	×	×	LINGO	------
Pishvaee, Farahani, and Dullaert (2010)	Integrated	MILP	MC, MR	S	S	-----	PC, DSC, CC	×	×	×	Memetic algorithm	----
Santibanez-Gonzalez and Diabat (2013)	Reverse	MILP	MC	S	S	-----	PC	×	×	×	Improved BD	----
Our Work	Reverse	MILP	MC	M	S	RM	IC, RMC	✓	P,T	✓	Three Phase Solution Approach, BD	Automotive Industry

2SSP – Two-Stage Stochastic Programming, IP – Integer Programming, MILP - Mixed Integer Linear Programming, FMILP – Fuzzy MILP, SMILP – Stochastic MILP
MP - Maximize Profit, MC – Minimize Costs, ME – Minimize Emissions/environmental impact, MR – Maximize Responsiveness
S – Single, M – Multi, I – Infinite/Single, F – Finite, P - Production, T – Transportation, R – Recycling, RM – Remanufacturing, RU – Reuse, RF – Refurbish, RP - Repair
CC – Collection Centre, SC – Sorting Centre, RC – Recycling Centre, W – Warehouse, PC – Production/Recovery Centre, RMC – Remanufacturing Centre, DC – Disassembly Centre, RFC – Refurbish Centre, RPC – Repair Centre, IC – Inspection Centre, DSC – Distribution Centre, HDC - Hybrid distribution–collection Centre

3. Mathematical Model

3.1 Problem Description

In this study, we consider an RSC that is multi-echelon, single-product, and multi-period. A typical reverse process flow consists of: collection of end-of-life products from the collection centres, shipment of these products to test centres, consolidation of the products that are recoverable and disposable, thereafter and shipment of the recoverable products to remanufacturing facilities.

In this setting, we make the following assumptions:

- The number of collection centres is equal to the number of markets (i.e., products sold in market i are collected at collection centre i);
- Demand information is present only at the market level (i.e., the customer-facing or demand nodes);
- Product returns depend on previous demand;
- Returned product quality is measured by an associated yield-factor at an inspection centre;
- The inventory holding, as well as the disposal decisions are determined only at the inspection centre with a given inventory holding cost and disposal cost respectively.

We also note that yield issues are typical in most remanufacturing industries given that not all items are viable candidates for remanufacturing, this is attributable to such factors as use or abuse of the product by the original customer and the nature of the product. The firm can, to some extent, control yield thus for our evaluations it is a product characteristic, deterministic, and known. Although, it is recognised that yield varies from inspection centre to inspection centre depending on the kind of technologies used for the inspection process. Based on this definition of yield, we have considered a yield factor as the portion of the returns that can be remanufactured. Operational decisions at the BOM (bill of materials) level are not introduced since the focus of this study is on strategic level decisions.

3.2 Model Formulation

In this section, we introduce a MILP model for the design of carbon emissions based, multi-period RLND with vehicle type selection. The proposed model incorporates many features of practical significance such as a multi-period setting, carbon emissions, returns percentage, returns yield, inventory holding, disposal and purchase decisions, vehicle type selection to present a holistic framework (Figure 1). The notation sets, parameters and decision variables used in the model are presented below.

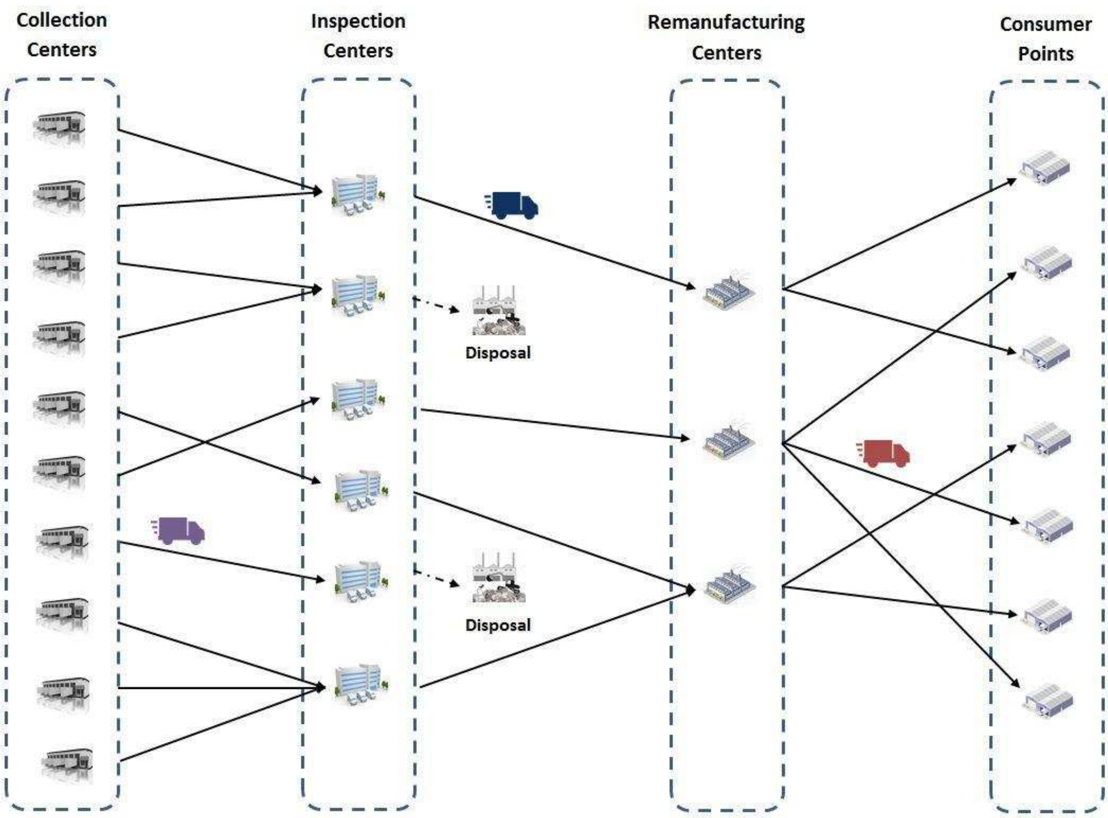

Figure 1: Reverse Logistics Network

Notations:

Sets

C - Fixed set of collection centres, indexed by “c”.

I - Set of potential locations for inspection centres, indexed by “i”.

R - Set of potential locations for remanufacturing centres, indexed by “r”.

M - Fixed set of markets, indexed by “m”.

T - Set of periods in planning the horizon, indexed by “t”.

V - Set of different types of vehicles available for transport, indexed by “v”.

Parameters

f_c^t - Return percentage at collection centre “c” in period “t”.

λ_i^t - Yield factor at inspection centre “i” in period “t”.

D_m^t - Demand at market “m” in period “t”.

S_c^t - Supply of core returns to collection centre “c” in period “t”.

CAP_i - Capacity level of an inspection centre “i”.

CAP_r - Capacity level of a remanufacturing centre “r”.

SCI_i^t - Setup cost for opening an inspection centre “i” at the beginning of period “t”.

SCR_r^t - Setup cost for opening a remanufacturing centre “r” at the beginning of period “t”.

OCI_i^t - Cost of inspecting one unit of product at inspection centre “i” in period “t”.

OCR_r^t - Cost of remanufacturing one unit of product at remanufacturing centre “r” in period “t”.

IC_i^t - Inventory holding cost per unit at inspection centre “i” in period “t”.

DC_i^t - Disposal cost per unit at inspection centre “i” in period “t”.

PC^t - Purchasing cost per unit in period “t”.

Ω – Cost of carbon credits per unit ton of CO_2.

EI_i - CO_2 emissions at the inspection centre “i” while operating on one unit of product.

ER_r - CO_2 emissions at the remanufacturing centre “r” while processing one unit of a product.

dC_{ci} - Distance from collection centre “c” to inspection centre “i”.

dI_{ir} - Distance from inspection centre “i” to remanufacturing centre “r”.

dR_{rm} - Distance from remanufacturing centre “r” to market “m”.

FTC_v - Fixed transportation cost of the vehicle of type “v”.

VTC_v - Variable transportation cost of the vehicle of type “v” per unit distance of travel.

CAP_v - Capacity level of a vehicle of type “v”.

E_v - CO_2 emissions factor of vehicle type “v” per unit distance.

M_v - Minimum flow through vehicle “v” if selected.

Decision variables

y_i^t equal to 1, if inspection centre is open at location “i” in period “t”, otherwise 0.

z_r^t equal to 1, if the remanufacturing centre is open at location “r” in period “t”, otherwise 0.

yC^t_{civ} equal to 1, if vehicle type "v" is selected between collection centre "c" and inspection centre "i" in period "t", otherwise 0.

yI^t_{irv} equal to 1, if vehicle type "v" is selected between inspection centre "i" and remanufacturing centre "r" in period "t", otherwise 0.

yR^t_{rmv} equal to 1, if vehicle type "v" is selected between remanufacturing centre "r" and market "m" in period "t", otherwise 0.

xC^t_{civ} - Product quantity shipped from collection centre "c" to inspection centre "i" using vehicle type "v" in period "t".

xI^t_{irv} - Product quantity shipped from inspection centre "i" to remanufacturing centre "r" using vehicle type "v" in period "t".

xR^t_{rmv} - Product quantity shipped from remanufacturing centre "r" to market "m" using vehicle type "v" in period "t".

IQ^t_i - Inventory quantity at inspection centre "i" at the end of period "t".

DQ^t_i - Disposal quantity at inspection centre "i" at the end of period "t".

PQ^t_r - Purchase quantity at remanufacturing centre "r" in period "t".

NC^t_{civ} - Number of vehicles of type "v" used to ship products from collection centre "c" to inspection centre "i" in period "t".

NI^t_{irv} - Number of vehicles of type "v" used to ship products from inspection centre "i" to remanufacturing centre "r" in period "t".

NR^t_{rmv} - Number of vehicles of type "v" used to ship products from remanufacturing centre "r" to market "m" in period "t".

Objective function

The objective function is minimizing the total cost, which mainly includes setup, operating, purchase, inventory, transportation, and emission costs.

Setup Cost (for locating facilities):

$$\sum_{t\in T}\left[\sum_{i\in I} SCI^t_i CAP_i\left(y^t_i - y^{t-1}_i\right) + \sum_{r\in R} SCR^t_r CAP_r\left(z^t_r - z^{t-1}_r\right)\right] \tag{1.1}$$

In equation (1.1), the first term represents the setup cost for locating inspection centres and the second term represents the setup cost for locating remanufacturing centres.

Operating cost (for inspecting and remanufacturing used products)

$$\sum_{t\in T}\left[\sum_{c\in C}\sum_{i\in I}\sum_{v\in V} OCI_i^t xC_{civ}^t + \sum_{i\in I}\sum_{r\in R}\sum_{v\in V} OCR_r^t xI_{irv}^t\right] \tag{1.2}$$

In the above equation (1.2), the first term is the operating cost at inspection centres to test/sort the returned products and the second term is the operating cost at remanufacturing centres to process the returns.

Inventory holding cost

$$\sum_{t\in T}\sum_{i\in I} IQ_i^t IC_i^t \tag{1.3}$$

Disposal cost

$$\sum_{t\in T}\sum_{i\in I} DQ_i^t DC_i^t \tag{1.4}$$

Purchase cost

$$\sum_{t\in T}\sum_{r\in R} PQ_r^t PC^t \tag{1.5}$$

Fixed Transportation cost

$$\sum_{t\in T}\sum_{c\in C}\sum_{i\in I}\sum_{v\in V} NC_{civ}^t FTC_v + \sum_{t\in T}\sum_{i\in I}\sum_{r\in R}\sum_{v\in V} NI_{irv}^t FTC_v + \sum_{t\in T}\sum_{r\in R}\sum_{m\in M}\sum_{v\in V} NR_{rmv}^t FTC_v \tag{1.6}$$

In the above equation (1.6), the first term represents the fixed transportation cost to hire a vehicle from collection centres to inspection centres, the second term represents the fixed transportation cost to hire a vehicle from inspection centres to remanufacturing centres, and last term represents the fixed transportation cost for hiring a vehicle to operate between remanufacturing centres and markets.

Variable transportation cost

$$\sum_{t\in T}\left[\sum_{c\in C}\sum_{i\in I}\sum_{v\in V} xC_{civ}^t dC_{ci}\left(VTC_v/CAP_v\right) + \sum_{i\in I}\sum_{r\in R}\sum_{v\in V} xI_{irv}^t dI_{ir}\left(VTC_v/CAP_v\right)\right.$$

$$\left. + \sum_{r\in R}\sum_{m\in M}\sum_{v\in V} xR_{rmv}^t dR_{rm}\left(VTC_v/CAP_v\right)\right] \tag{1.7}$$

In the above equation (1.7) representing variable transport costs, the first term denotes this cost between collection centres and inspection centres, the second term represents it between inspection centres and remanufacturing centres, and the third term represents it between remanufacturing centres and markets.

Emission cost due to production

$$\Omega\left[\sum_{t\in T}\left(\sum_{c\in C}\sum_{i\in I}\sum_{v\in V}EI_i\,xC_{civ}^{t}+\sum_{i\in I}\sum_{r\in R}\sum_{v\in V}ER_r\,xI_{irv}^{t}\right)\right] \tag{1.8}$$

In the above equation (1.8), the first term is the emission cost due to production at inspection centres to test/sort the returned products and the second term is the emission cost from production activities at remanufacturing centres to process returns.

Emission cost due to transportation

$$\Omega\sum_{t\in T}\left(\sum_{c\in C}\sum_{i\in I}\sum_{v\in V}dC_{ci}\,NC_{civ}^{t}E_v+\sum_{i\in I}\sum_{r\in R}\sum_{v\in V}dI_{ir}\,NI_{irv}^{t}E_v+\sum_{r\in R}\sum_{m\in M}\sum_{v\in V}dR_{rm}NR_{rmv}^{t}E_v\right) \tag{1.9}$$

In equation (1.9), the first term represents the emission cost associated with transportation between collection centres and inspection centres, the second term represents the emission cost associated with transportation between inspection centres and remanufacturing centres, and final term represents the emission cost associated with transportation between remanufacturing centres and markets.

Constraints

$$S_c^t = f_c^t D_m^{t-1} \qquad \forall t\in T, \forall c\in C, \forall m\in M \tag{1.a}$$

$$\sum_{i\in I}\sum_{v\in V}xC_{civ}^{t} = S_c^t \qquad \forall c\in C, \forall t\in T \tag{1.b}$$

$$\lambda_i^t\sum_{c\in C}\sum_{v\in V}xC_{civ}^{t}+IQ_i^{t-1}=\sum_{r\in R}\sum_{v\in V}xI_{irv}^{t}+DQ_i^t+IQ_i^t \qquad \forall t\in T, \forall i\in I \tag{1.c}$$

$$PQ_r^t+\sum_{i\in I}\sum_{v\in V}xI_{irv}^{t}=\sum_{m\in M}\sum_{v\in V}xR_{rmv}^{t} \qquad \forall t\in T, \forall r\in R \tag{1.d}$$

$$\sum_{r\in R}\sum_{v\in V}xR_{rmv}^{t}=D_m^t \qquad \forall t\in T, \forall m\in M \tag{1.e}$$

$$\sum_{c\in C}\sum_{v\in V}xC_{civ}^{t}\le y_i^tCAP_i \qquad \forall t\in T, \forall i\in I \tag{1.f}$$

$$\sum_{i\in I}\sum_{v\in V}xI_{irv}^{t}\le z_r^tCAP_r \qquad \forall t\in T, \forall r\in R \tag{1.g}$$

$$NC_{civ}^t\ge\left(xC_{civ}^t/CAP_v\right) \qquad \forall t\in T, \forall c\in C, \forall i\in I, \forall v\in V \tag{1.h}$$

$$NI_{irv}^t\ge\left(xI_{irv}^t/CAP_v\right) \qquad \forall t\in T, \forall i\in I, \forall r\in R, \forall v\in V \tag{1.i}$$

$$NR_{rmv}^t\ge\left(xR_{rmv}^t/CAP_v\right) \qquad \forall t\in T, \forall r\in R, \forall m\in M, \forall v\in V \tag{1.j}$$

$$IQ_i^t=0 \qquad \forall t\in\{1,T\}, \forall i\in I \tag{1.k}$$

$$NC_{civ}^t\le y_i^tM \qquad \forall t\in T, \forall c\in C, \forall i\in I, \forall v\in V \tag{1.l}$$

$$NI_{irv}^{t} \leq y_{i}^{t} M \qquad \forall t \in T, \forall i \in I, \forall r \in R, \forall v \in V \qquad (1.m)$$

$$NI_{irv}^{t} \leq z_{r}^{t} M \qquad \forall t \in T, \forall i \in I, \forall r \in R, \forall v \in V \qquad (1.n)$$

$$NR_{rmv}^{t} \leq z_{r}^{t} M \qquad \forall t \in T, \forall r \in R, \forall m \in M, \forall v \in V \qquad (1.o)$$

$$NC_{civ}^{t} \geq yC_{civ}^{t} \qquad \forall t \in T, \forall c \in C, \forall i \in I, \forall v \in V \qquad (1.p)$$

$$NI_{irv}^{t} \geq yI_{irv}^{t} \qquad \forall t \in T, \forall i \in I, \forall r \in R, \forall v \in V \qquad (1.q)$$

$$NR_{rmv}^{t} \geq yR_{rmv}^{t} \qquad \forall t \in T, \forall r \in R, \forall m \in M, \forall v \in V \qquad (1.r)$$

$$NC_{civ}^{t} \leq yC_{civ}^{t} M \qquad \forall t \in T, \forall c \in C, \forall i \in I, \forall v \in V \qquad (1.s)$$

$$NI_{irv}^{t} \leq yI_{irv}^{t} M \qquad \forall t \in T, \forall i \in I, \forall r \in R, \forall v \in V \qquad (1.t)$$

$$NR_{rmv}^{t} \leq yR_{rmv}^{t} M \qquad \forall t \in T, \forall r \in R, \forall m \in M, \forall v \in V \qquad (1.u)$$

$$y_{i}^{t-1} \leq y_{i}^{t} \qquad \forall t \in T, \forall i \in I \qquad (1.v)$$

$$z_{i}^{t-1} \leq z_{i}^{t} \qquad \forall t \in T, \forall r \in R \qquad (1.w)$$

$$y_{i}^{1} = 0 \qquad \forall i \in I \qquad (1.x)$$

$$xC_{civ}^{t}, xI_{irv}^{t}, xR_{rmv}^{t}, IQ_{i}^{t}, DQ_{i}^{t}, PQ_{r}^{t}, NC_{civ}^{t}, NI_{irv}^{t}, NR_{rmv}^{t} \geq 0 \qquad (1.y)$$

$$y_{i}^{t}, z_{r}^{t}, yC_{civ}^{t}, yI_{irv}^{t}, yR_{rmv}^{t} \in \{0,1\} \qquad (1.z)$$

Constraint (1.a) represents the portion of products sold in earlier periods that will be returned in later periods. Constraints (1.b) - (1.e) are flow balance constraints related to collection, inspection, remanufacturing centres and customer zones (markets) respectively. These constraints guarantee the equality of all flows entering a network entity and all outward flows of the same entity. Constraints (1.f) - (1.g) are capacity constraints at inspection and remanufacturing centres and ensure that all flows entering into a network entity are less than their capacities. Constraints (1.h) - (1.j) are related to vehicle quantity of each type in an arc, based on the flow in that arc. Constraint (1.k) assures that no inventory is held in initial and final periods in a planning horizon. Constraints (1.l) - (1.o) are flow constraints depending on potential locations, i.e., there is a flow to a network entity if that entity is located. Constraints (1.p) - (1.u) are vehicle selection constraints in an arc, thus if no arc is selected between network entities, there would be no flows between them. Otherwise, there should be flow between network entities. Constraints (1.v) – (1.w) are constraints related to the location of inspection and remanufacturing facilities respectively. These constraints ensure that once a facility has located in a period, it should remain open until the end of the planning horizon. In addition, constraint (1.x) represents there being no location of inspection centres in the initial period since core returns are not available. However, a remanufacturing centre (assumed as a hybrid facility) is located in the initial period to fulfil the demand of customers using new products. Finally, constraints (1.y) and (1.z) are related to the nature of variables and should be held for all entities in all periods.

4. Solution Approach

Network design problems are known for their complexity (Johnson, Lenstra, and Kan 1978), and RLND is no different. Further, the addition of multi-period, vehicle type selection makes it more difficult to solve with commercially available solvers (such as CPLEX) for even moderate-sized problems as the model becomes computationally intractable. There is a plethora of literature that advocates a BD based approach can be an efficient framework to solve MILP problem, and the structure of the model motivates us to solve the problem using BD algorithm (Conejo et al. 2006; Castro, Nasini, and Saldanha-da-Gama 2017). However, it is widely known that owing to the special structure of the problem, applying a BD algorithm directly may lead to slow convergence (Tang, Jiang, and Saharidis 2012). Hence, to leverage on the special structure of the problem, we propose a heuristic solution method: a three-phase solution approach to solve the model efficiently. In the following subsections, we present, the BD framework followed by a three-phase solution approach.

4.1 Bender's Decomposition Framework

In BD, complicating variables are used to divide the master and sub-problems. The complicated variables associated with the current model are variables related to location decisions, vehicle type selection, and number of vehicles on an arc. Therefore, the master problem contains complicated variables, and the sub-problem contains the remaining variables of the model.

Primal Sub Problem (PSP)

$$\mathrm{PSP}\left(xC^{t}_{civ}, xI^{t}_{irv}, xR^{t}_{rmv}, IQ^{t}_{i}, DQ^{t}_{i}, PQ^{t}_{r} \mid \hat{y}^{t}_{i}, \hat{z}^{t}_{r}, N\hat{C}^{t}_{civ}, N\hat{I}^{t}_{irv}, N\hat{R}^{t}_{rmv}\right)$$

Minimize Z_{PSP} = (1.2) + (1.3) + (1.4) + (1.5) + (1.7) + (1.8) (2)

Subject to constraints (1a) to (1e) and (1k) and

$$\sum_{c\in C}\sum_{v\in V} xC^{t}_{civ} \le \hat{y}^{t}_{i}CAP_{i} \qquad \forall t \in T, \forall i \in I \qquad (2.a)$$

$$\sum_{i\in I}\sum_{v\in V} xI^t_{irv} \le \hat{z}^t_r CAP_r \qquad \forall t\in T, \forall r\in R \qquad (2.b)$$

$$xC^t_{civ} \le N\hat{C}^t_{civ} CAP_v \qquad \forall t\in T, \forall c\in C, \forall i\in I, \forall v\in V \qquad (2.c)$$

$$xI^t_{irv} \le N\hat{I}^t_{irv} CAP_v \qquad \forall t\in T, \forall i\in I, \forall r\in R, \forall v\in V \qquad (2.d)$$

$$xR^t_{rmv} \le N\hat{R}^t_{rmv} CAP_v \qquad \forall t\in T, \forall r\in R, \forall m\in M, \forall v\in V \qquad (2.e)$$

$$xC^t_{civ}, xI^t_{irv}, xR^t_{rmv}, IQ^t_i, DQ^t_i, PQ^t_r \ge 0$$

In PSP, objective function is minimization of cost which includes operating costs at facilities, inventory holding cost, disposal cost, purchase cost, variable transportation cost and carbon emission cost due to the production operations. PSP has identical constraints as in original problem from (1a) to (1e) and (1k), and also contains constraints (2.a) - (2.e) which formed by fixing complicated variables in constraints (1f) – (1j). In the current study we solve the dual sub problem (DSP) and use the DSP solution to generate cuts.

The dual variables $u^1_{tc}, u^2_{ti}, u^3_{tr}, u^4_{tm}, u^5_{ti}, u^6_{tr}, u^7_{tciv}, u^8_{tirv}, u^9_{trmv}, u^{10}_{ti}, u^{11}_{ti}$ are associated with constraints (1b) – (1e), (2.a) - (2.e) and (1k) respectively. Now, the dual subproblem can be formulated as follows:

Dual Sub Problem (DSP)

$$DSP\left(u^1_{tc}, u^2_{ti}, u^3_{tr}, u^4_{tm}, u^5_{ti}, u^6_{tr}, u^7_{tciv}, u^8_{tirv}, u^9_{trmv}, u^{10}_{ti}, u^{11}_{ti} \mid \hat{y}^t_i, \hat{z}^t_r, N\hat{C}^t_{civ}, N\hat{I}^t_{irv}, N\hat{R}^t_{rmv}\right)$$

Maximize

$$Z_{DSP} = \sum_{t\in T}\sum_{c\in C} u^1_{tc} S^t_c + \sum_{t\in T}\sum_{m\in M} u^4_{tm} D^t_m + \sum_{t\in T}\sum_{i\in I} u^5_{ti}\hat{y}^t_i CAP_i + \sum_{t\in T}\sum_{r\in R} u^6_{tr}\hat{z}^t_r CAP_r + \sum_{t\in T}\sum_{c\in C}\sum_{i\in I}\sum_{v\in V} u^7_{tciv} N\hat{C}^t_{civ}$$
$$+\sum_{t\in T}\sum_{i\in I}\sum_{r\in R}\sum_{v\in V} u^8_{tirv} N\hat{I}^t_{irv} + \sum_{t\in T}\sum_{r\in R}\sum_{m\in M}\sum_{v\in V} u^9_{trmv} N\hat{R}^t_{rmv} \qquad (3)$$

Subject to

$$u^1_{tc} + \lambda^t_i u^2_{ti} + u^5_{ti} + \left(u^7_{tciv}/CAP_v\right) \le OCI^t_i + EI_i\Omega + \left(VTC_v dC_{ci}\right)/CAP_v$$
$$\forall t\in T, \forall c\in C, \forall i\in I, \forall v\in V \qquad (3.a)$$

$$-u^2_{ti} + u^3_{tr} + u^6_{tr} + \left(u^8_{tirv}/CAP_v\right) \le OCR^t_r + ER_r\Omega + \left(VTC_v dI_{ir}\right)/CAP_v$$
$$\forall t\in T, \forall i\in I, \forall r\in R, \forall v\in V \qquad (3.b)$$

$$-u^3_{tr} + u^4_{tm} + \left(u^9_{trmv}/CAP_v\right) \le \left(VTC_v dR_{rm}\right)/CAP_v$$
$$\forall t\in T, \forall r\in R, \forall m\in M, \forall v\in V \qquad (3.c)$$

$$-u_{ti}^2 + u_{(t+1)i}^2 + u_{ti}^{10} \le IC_i^t \qquad \forall t = 1, \forall i \in I \qquad (3.d)$$

$$-u_{ti}^2 + u_{(t+1)i}^2 \le IC_i^t \qquad \forall t \in [2, T-1], \forall i \in I \qquad (3.e)$$

$$-u_{ti}^2 + u_{ti}^{10} \le IC_i^t \qquad \forall t = T, \forall i \in I \qquad (3.f)$$

$$-u_{ti}^2 \le DC_i^t \qquad \forall t \in T, \forall i \in I \qquad (3.g)$$

$$u_{tr}^3 \le PC^t \qquad \forall t \in T, \forall r \in R \qquad (3.h)$$

$u_{tc}^1, u_{ti}^2, u_{tr}^3, u_{tm}^4, u_i^{10}, u_i^{11}$ are unrestricted

$u_{ti}^5, u_{tr}^6, u_{tciv}^7, u_{tirv}^8, u_{trmv}^9 \le 0$

Now, the master problem can be formulated as follows:

Master Problem (MP)

$$MP\left(y_i^t, z_r^t, yC_{civ}^t, yI_{irv}^t, yR_{rmv}^t, NC_{civ}^t, NI_{irv}^t, NR_{rmv}^t \mid \hat{u}_{tc}^1, \hat{u}_{ti}^2, \hat{u}_{tr}^3, \hat{u}_{tm}^4, \hat{u}_{ti}^5, \hat{u}_{tr}^6, \hat{u}_{tciv}^7, \hat{u}_{tirv}^8, \hat{u}_{trmv}^9, \hat{u}_{ti}^{10}, \hat{u}_{ti}^{11}\right)$$

Minimize $Z_{MP} = 1.1 + 1.6 + 1.9 + \alpha$ (4)

Subject to (1.l) to (1.x)

$y_i^t, z_r^t, yC_{civ}^t, yI_{irv}^t, yR_{rmv}^t \in \{0,1\}$

$NC_{civ}^t, NI_{irv}^t, NR_{rmv}^t \ge 0$

To improve the solution quality, a series of valid inequalities are developed to narrow the master problem solution space and to improve bounds (Tang, Jiang, and Saharidis 2012; Üster and Hwang 2016).

$$\sum_{i \in I} y_i^t \ge 1 \qquad \forall t \in T \qquad (4.a)$$

$$\sum_{r \in R} z_r^t \ge 1 \qquad \forall t \in T \qquad (4.b)$$

$$\sum_{i \in I}\sum_{v \in V} NC_{civ}^t CAP_V \ge S_c^t \qquad \forall t \in T, \forall c \in C \qquad (4.c)$$

$$y_i^t CAP_i \ge \sum_{c \in C}\sum_{v \in V} NC_{civ}^t CAP_v \qquad \forall t \in T, \forall i \in I \qquad (4.d)$$

$$z_r^t CAP_r \ge \sum_{i \in I}\sum_{v \in V} NI_{irv}^t CAP_v \qquad \forall t \in T, \forall r \in R \qquad (4.e)$$

$$\sum_{r \in R}\sum_{v \in V} NI_{irv}^t CAP_v \ge \lambda_i^t \sum_{c \in C}\sum_{v \in V} NC_{civ}^t CAP_v \qquad \forall t \in T, \forall i \in I \qquad (4.f)$$

$$\sum_{i \in I}\sum_{v \in V} NI_{irv}^t CAP_v \le \sum_{m \in M}\sum_{v \in V} NR_{rmv}^t CAP_v \qquad \forall t \in T, \forall r \in R \qquad (4.g)$$

$$\sum_{r \in R}\sum_{v \in V} NR_{rmv}^t CAP_V \ge D_m^t \qquad \forall t \in T, \forall m \in M \qquad (4.h)$$

Benders optimality cut (BOC) set related to α

$$\alpha \geq \sum_{t\in T}\sum_{c\in C}\hat{u}_{tc}^{1(k)}S_c^t + \sum_{t\in T}\sum_{m\in M}\hat{u}_{tm}^{4(k)}D_m^t + \sum_{t\in T}\sum_{i\in I}\hat{u}_{ti}^{5(k)}y_i^t CAP_i + \sum_{t\in T}\sum_{r\in R}\hat{u}_{tr}^{6(k)}z_r^t CAP_r + \sum_{t\in T}\sum_{c\in C}\sum_{i\in I}\sum_{v\in V}\hat{u}_{tciv}^{7(k)}NC_{civ}^t$$
$$+\sum_{t\in T}\sum_{i\in I}\sum_{r\in R}\sum_{v\in V}\hat{u}_{tirv}^{8(k)}NI_{irv}^t + \sum_{t\in T}\sum_{r\in R}\sum_{m\in M}\sum_{v\in V}\hat{u}_{trmv}^{9(k)}NR_{rmv}^t \qquad (4.i)$$

<u>Benders *feasibility cut (BFC) set related to α*</u>

$$\sum_{t\in T}\sum_{c\in C}\hat{u}_{tc}^{1(k)}S_c^t + \sum_{t\in T}\sum_{m\in M}\hat{u}_{tm}^{4(k)}D_m^t + \sum_{t\in T}\sum_{i\in I}\hat{u}_{ti}^{5(k)}y_i^t CAP_i + \sum_{t\in T}\sum_{r\in R}\hat{u}_{tr}^{6(k)}z_r^t CAP_r + \sum_{t\in T}\sum_{c\in C}\sum_{i\in I}\sum_{v\in V}\hat{u}_{tciv}^{7(k)}NC_{civ}^t$$
$$+\sum_{t\in T}\sum_{i\in I}\sum_{r\in R}\sum_{v\in V}\hat{u}_{tirv}^{8(k)}NI_{irv}^t + \sum_{t\in T}\sum_{r\in R}\sum_{m\in M}\sum_{v\in V}\hat{u}_{trmv}^{9(k)}NR_{rmv}^t \leq 0 \qquad (4.j)$$

A new auxiliary variable α is introduced in the master problem. The objective is to minimize α which also represents the lower bound to the original problem. Constraint (4.i) and (4.j) are the optimality and feasibility cuts generated from DSP solution and added to the master problem respectively.

4.2 Three – Phase solution approach

Solving the large-scale instances for exact solutions via proposed MILP is a challenging task. Thus, to solve the model effectively with less computational time, we presented a three-phase solution approach in this section. In the first phase, the model solved with a single type of vehicle (probably small vehicles) for the location decisions. Consecutively, the model solved for selection and allocation of vehicles in an arc in the second phase. Finally, in the third phase, the model solved for product flows between facilities, inventory, disposal and purchase quantities. The formulation is presented below.

Phase 1:

In this phase, we assume that only one type of vehicle is used for transmitting products between facilities. Here, the objective function $SP_1(y_i^t, z_r^t)$is to minimise the cost which includes (1.1) to (1.9).

Minimise $SP_1(y_i^t, z_r^t)$ = (1.1) + (1.2) +…+ (1.9) (5)

Subject to (1.a) to (1.x) and (1.y) to (1.z).

The optimal solution of $SP_1(y_i^t, z_r^t)$ provides the location and number of inspection and remanufacturing facilities. These decisions are used as input in forthcoming phases.

Phase 2:

In this phase, it assumed that various types of vehicle are present to move products between facilities. The objective function $SP_2\left(yC^t_{civ}, yI^t_{irv}, yR^t_{rmv}, NC^t_{civ}, NI^t_{irv}, NR^t_{rmv} \mid \hat{y}^t_i, \hat{z}^t_r, x\hat{C}^t_{civ}, x\hat{I}^t_{irv}, x\hat{R}^t_{rmv}\right)$ is obtained as follows for given values of design decisions involving location of facilities and product flows between facilities from the first phase.

Minimise $SP_2\left(yC^t_{civ}, yI^t_{irv}, yR^t_{rmv}, NC^t_{civ}, NI^t_{irv}, NR^t_{rmv} \mid \hat{y}^t_i, \hat{z}^t_r, x\hat{C}^t_{civ}, x\hat{I}^t_{irv}, x\hat{R}^t_{rmv}\right) =$

(1.6) + (1.9)

$$+\sum_{t\in T}\left[\sum_{c\in C}\sum_{i\in I}\sum_{v\in V} NC^t_{civ} dC_{ci} VTC_v + \sum_{i\in I}\sum_{r\in R}\sum_{v\in V} NI^t_{irv} dI_{ir} VTC_v + \sum_{r\in R}\sum_{m\in M}\sum_{v\in V} NR^t_{rmv} dR_{rm} VTC_v\right] \quad (6)$$

Subject to (1.l) to (1.u) and

$$\sum_{v\in V} NC^t_{civ} \geq \sum_{v\in V}\left(x\hat{C}^t_{civ} / CAP_v\right) \qquad \forall t\in T, \forall c\in C, \forall i\in I \qquad (6.a)$$

$$\sum_{v\in V} NI^t_{irv} \geq \sum_{v\in V}\left(x\hat{I}^t_{irv} / CAP_v\right) \qquad \forall t\in T, \forall i\in I, \forall r\in R \qquad (6.b)$$

$$\sum_{v\in V} NR^t_{rmv} \geq \sum_{v\in V}\left(x\hat{R}^t_{rmv} / CAP_v\right) \qquad \forall t\in T, \forall r\in R, \forall m\in M \qquad (6.c)$$

$$NC^t_{civ}, NI^t_{irv}, NR^t_{rmv} \geq 0 \quad \text{and} \quad \text{int}$$

$$yC^t_{civ}, yI^t_{irv}, yR^t_{rmv} \in \{0, 1\}$$

Constraints (6.a) to (6.b) are some valid inequalities developed in the current phase to solve the model. The optimal solution of $SP_2(yC^t_{civ}, yI^t_{irv}, yR^t_{rmv}, NC^t_{civ}, NI^t_{irv}, NR^t_{rmv} \mid .)$ provides the information regarding vehicle type selection and number of vehicles between facilities on a arc.

Phase 3:

The objective function $SP_3\left(xC^t_{civ}, xI^t_{irv}, xR^t_{rmv}, IQ^t_i, DQ^t_i, PQ^t_r \mid \hat{y}^t_i, \hat{z}^t_r, y\hat{C}^t_{civ}, y\hat{I}^t_{irv}, y\hat{R}^t_{rmv}, N\hat{C}^t_{civ}, N\hat{I}^t_{irv}, N\hat{R}^t_{rmv}\right)$ is obtained as follows for given values of design decisions involving location of facilities, number and type of vehicles between facilities from first and second phases respectively.

Minimise

$$SP_3\left(xC^t_{civ}, xI^t_{irv}, xR^t_{rmv}, IQ^t_i, DQ^t_i, PQ^t_r \mid \hat{y}^t_i, \hat{z}^t_r, y\hat{C}^t_{civ}, y\hat{I}^t_{irv}, y\hat{R}^t_{rmv}, N\hat{C}^t_{civ}, N\hat{I}^t_{irv}, N\hat{R}^t_{rmv}\right)$$

$$= (1.2) + (1.3) + (1.4) + (1.5) + (1.7) + (1.8) \qquad (7)$$

Subject to (1.a) to (1.k) and

$$xC^t_{civ}, xI^t_{irv}, xR^t_{rmv}, IQ^t_i, DQ^t_i, PQ^t_r \geq 0 \quad \text{and} \quad \text{int}$$

The optimal solution of $SP_3(xC_{civ}^t, xI_{irv}^t, xR_{rmv}^t, IQ_i^t, DQ_i^t, PQ_r^t \mid .)$ provides the decisions related to product flows between facilities on each selected arc, amount of inventory held for the next period, the amount of disposal and purchase quantity.

The steps for the solution approach are presented below.

- First, the model solved as simple LP problem with availability of one type of vehicle and the optimal decisions related facilities location (y_i^t, z_r^t) are reported and recorded.
- Second, the decision variables such as vehicle selection and number of vehicles in the corresponding arc $(yC_{civ}^t, yI_{irv}^t, yR_{rmv}^t, NC_{civ}^t, NI_{irv}^t, NR_{rmv}^t)$ are determined with various types of vehicles and their optimal values are recorded.
- Third, based on the first and second phase decisions, decision variables (product flows, purchase decisions) $(xC_{civ}^t, xI_{irv}^t, xR_{rmv}^t, IQ_i^t, DQ_i^t, PQ_r^t)$ are specified in order to minimize the objective function value.
- Finally, the best solution is selected based on the analyses of three criteria.

To conclude, the best solution of the overall problem includes location decisions from the first phase, vehicle type selection and number of vehicles of each type in an arc from the second phase and lastly, product flows between facilities, inventory, disposal and purchase quantities from the third phase.

5. The Case Study: Lithium-Ion Batteries

In India, electric vehicles account for only 1% of the total vehicles (International Energy Agency, 2016) as they are relatively new. The 'National Electric Mobility Mission Plan (NEMMP) 2020' was implemented by the Indian Government in 2013 to report on vehicular pollution, national energy security issues, and growth of domestic manufacturing capabilities. In addition, NITI Aayog motivated Electric Vehicle (EV) manufacturers by providing incentives to facilitate growth in the EV industry. According to reports, India can save $60 billion by 2030 with electric cars, buses, and metro trains; and CO_2 emissions could reduce by 37% if India succeeds in attaining its EV targets (NITI Aayog and the Rocky Mountain Institute, 2017).

As Li-Ion batteries are the major power source of modern EVs, we focused on their recovery in India under the Make-in-India initiative. In Li-Ion batteries, cells are a crucial component and begin to lose their capacity after a few years; however, remanufacturing can bring back these defective cells to full functionality. Creating a process to remanufacture battery packs can dramatically reduce warranty and replacement costs for end-users. Thus, replacing the battery pack with a remanufactured battery can reduce replacement costs by over 70%.

In the recovery process, the firm first inspects the battery pack and diagnoses defective cells within it. Then, defective cells are removed and replaced with recovered-healthy cells; and finally all the cells within the pack are balanced to ensure a good quality overall. Later, these remanufactured cells will be sold in markets like new products (Kampker et al. 2016).

Our proposed model has been applied to designing an RLN for ABC Pvt. Ltd (Battery manufacturer) to test its applicability. The firm is planning to locate inspection and remanufacturing centres in various locations across South India (Andhra Pradesh, Karnataka, Tamilnadu, and Telangana) to process product returns. In this case study, 16 cities will be used as collection centres and markets, eight potential locations for setting up inspection centres and four potential locations for remanufacturing plants have also been identified. All locations for collection, inspection, remanufacturing and markets are represented on the google map (Figure 2). The length of the planning horizon considered is five (T = 5 months).

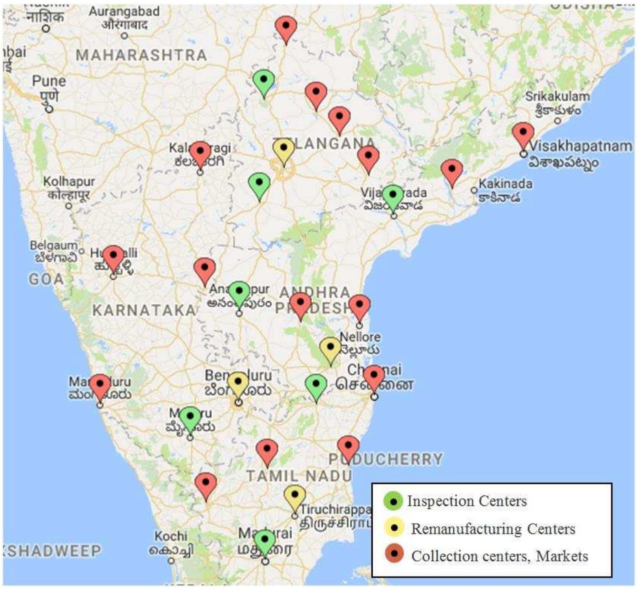

Figure 2: Locations of facilities of Reverse Logistics network

Transportation plays a key role in logistics as cities are far from each other and approximately 74% of goods are transported by trucks (Spangenberg 2017). Therefore, road transportation mode is the focus of this research. In the current study, carbon emissions and cost from transportation between facilities are considered proportional to the distance between the facilities. Carbon footprints are fixed at each location but vary between locations. Since ABC maintain the inspection centres and remanufacturing centres, the CO_2 emissions related to these are also included in the objective function.

Table 2: Product demand at markets and return rate at collection centres

	Time Period	Market/Collection Center 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Demand	1	407	311	358	410	351	462	445	448	338	283	415	380	324	180	126	279
	2	546	175	286	360	434	351	253	383	193	306	285	346	359	317	461	524
	3	403	331	432	398	413	441	231	288	228	466	389	419	407	458	313	363
	4	410	348	485	293	324	338	302	357	314	304	510	315	286	383	295	395
	5	490	165	352	143	148	455	134	356	380	263	283	253	309	489	436	199
Return rate	2	0.73	0.64	0.61	0.78	0.55	0.73	0.63	0.60	0.78	0.70	0.58	0.67	0.69	0.66	0.70	0.63
	3	0.73	0.57	0.60	0.76	0.80	0.61	0.62	0.65	0.63	0.69	0.58	0.61	0.73	0.61	0.66	0.70
	4	0.75	0.64	0.60	0.57	0.70	0.58	0.79	0.79	0.59	0.65	0.77	0.63	0.64	0.59	0.75	0.65
	5	0.59	0.71	0.69	0.67	0.57	0.75	0.66	0.66	0.58	0.71	0.62	0.58	0.70	0.61	0.67	0.80

The network is initialized with zero inspection/remanufacturing centres, and zero trucks at the start of the planning horizon. The distances between the locations have been measured using Google Maps. Table 2 presents the market demand and return rate in each period respectively.

In the current study, even though land and labour prices are unlikely to be the same from one location to another; we assume that set-up costs are equal at all locations. However, the set-up costs for inspection and remanufacturing plants will be higher where centres use advanced technology to process returns (Table 3). The operating cost at inspection and remanufacturing centres also presented in Table 3 along with carbon footprint at potential locations.

Table 3: Parameters for potential locations of Inspection and Remanufacturing Centers

Parameter	Period	Inspection Centers 1	2	3	4	5	6	7	Remanufacturing Centers 1	2	3	4
Setup Cost ($)		250	250	420	420	420	250	250	1200	700	700	1200
Carbon footprint (Kg CO_2 per unit)		3	3	0.5	0.5	0.5	3	3	0.5	3	3	0.5
Max. Capacity		1000	1000	1000	1000	1000	1000	1000	1400	1400	1400	1400
Operating cost ($)	2	0.34	0.29	0.25	0.35	0.26	0.38	0.40	0.89	0.63	0.87	0.96
	3	0.49	0.44	0.33	0.53	0.43	0.33	0.35	0.95	0.83	0.61	0.82
	4	0.48	0.34	0.40	0.25	0.27	0.49	0.28	0.69	0.78	0.90	0.74
	5	0.46	0.30	0.46	0.48	0.50	0.33	0.46	0.77	0.90	0.86	0.71

Assuming remanufactruing is an attractive option, the majority of demand in the market from period 2 will be fulfilled using remanufactured products. Any shortage will be fulfilled by either purchasing new/virgin products from forward manufacturing units (or potentially through a jobbers network) at the cost of $2.50. The carbon price for a kg of CO_2 is $0.0625 for transporting the products from one centre to another and production. In reality, there are different criterions used by the transport industry for transport pricing, usually, these are: vehicle/km, ton/km, and emissions. Currently, the company uses three types of vehicles to ship products between facilities. Table 4 presents costs and carbon footprint associated with each vehicle.

Table 4: Vehicle parameters data

Vehicle Type	Fixed Cost ($)	Variable Cost ($ per mile)	Carbon footprint (kg per mile)	Capacity
V_1	3.125	0.225	0.5	100
V_2	1.875	0.185	0.30	80
V_3	1.25	0.15	0.2	60

From the results it is observed that inspection centres are located at Zip codes: 520001, 632001, 503001, 515001 and remanufacturing centres are at 560001, 50000. The optimal locations of inspection and remanufacturing centres are represented in Figure 3.

Figure 3: Optimal facility locations

The total flow of items from collection centres to inspection centres, and inventory quantity held at each inspection centre in each period are presented in Table 5. Similarly, Table 6 shows the total flow of items from inspection centres to remanufacturing centres together with total purchase quantity of new products at all centres in each period.

Table 5: Total Flow of items from collection centres and inventory quantity at inspection centers

	Period	Inspection center							
		1	2	3	4	5	6	7	Total
Total Flow	**2**	796	0	961	964	959	0	0	**3680**
	3	987	0	986	811	960	0	0	**3744**
	4	958	0	1000	1000	1000	0	0	**3958**
	5	1000	0	1000	818	913	0	0	**3731**
Inventory Qty	**2**	0	0	0	0	89	0	0	**89**
	3	66	0	30	30	0	0	0	**126**
	4	161	0	0	0	0	0	0	**161**
	5	0	0	0	0	0	0	0	**0**

Table 6: Total Flow of items from inspection centers and purchase quantity at remanufacturing centers

Period	Total Flow					Purchase Qty				
	Remanufacturing center					Remanufacturing center				
	1	2	3	4	Total	1	2	3	4	Total
2	0	1190	0	1354	**2544**	0	1314	0	1554	**2868**
3	0	1300	0	1400	**2700**	0	1918	0	1342	**3260**
4	0	1400	0	1340	**2740**	0	1746	0	1113	**2859**
5	0	1400	0	1400	**2800**	0	1310	0	1154	**2464**

Various costs of the model including: setup cost ($3410), operation cost ($14374), transportation cost ($36174) and emission cost ($6336) were also calculated. Finally, the optimal arcs between facilities will vary in each period even though optimal facilities are fixed because of different supply and demand. Figure 4 represents the optimal RLN in each period.

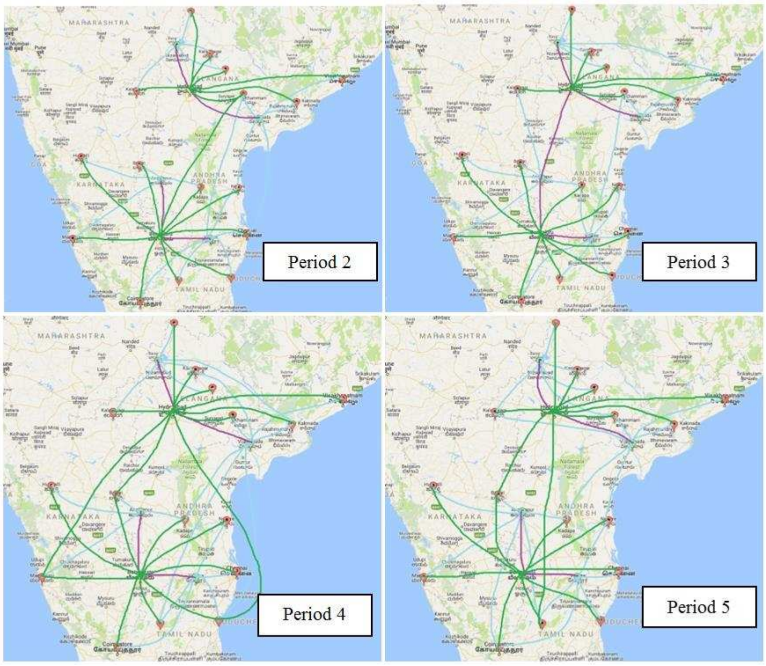

Figure 4: Optimal reverse logistics network

6. Computational Study

In this section, we present computational test and analysis results to validate the computational efficiency and effectiveness by evaluating the generalized performance of the proposed three-phase method. We further compare the results obtained with BD and CPLEX solution. All modelling and algorithm development has been done on CPLEX 12.5 through Microsoft Visual Studio 2010 on a PC with an Intel i5core processor (2.90 GHz) with 8.0 GB RAM. To help improve the scalability of the model we generated the model parameters randomly (see Table 7). The standard MILP was also solved using CPLEX solver on the same computer for easy comparison and validation reasons. The next section describes testbed of random test instances and is followed by a summary of computational results.

Here, "U" denotes the uniform distribution. Note that setup costs of opening facilities in the reverse network are generated considering the carbon footprint of facilities. More specifically, larger infrastructural costs will require carbon-efficient facilities, while conversely, carbon emissions generated while operating facilities is more for carbon-inefficient facilities.

Table 7: Values of input parameters

Parameter	Value	Parameter	Value
λ_i^t	~U (0.6, 0.9)	PC_r^t	$2.5 per unit
f_c^t	~U (0.3, 0.8)	DC_i^t	~U ($ 0.05, $0.10) per unit
D_m^t	~U(350, 100) units	CAP_i	500 units
SCI_i^t	$ 0.16 (or) 0.32 per unit capacity	Ω	$ 0.0625 per kilo of CO_2
SCR_r^t	$ 0.24 (or) 0.40 per unit capacity	EI_i&ER_r	1.5 (or) 3.0 Kilos of CO_2 per product
OCI_i^t	~U ($ 0.24, $ 0.55) per unit	dC_{ci}	~U (20, 50) miles
OCR_r^t	~U ($0.40, $0.78) per unit	dI_{ir}	~U (40, 90) miles
IC_i^t	~U ($ 0.1, $ 0.2) per unit	dR_{rm}	~U (30, 70) miles

Vehicle selection depends on various parameters like fixed, variable costs, carbon emission and capacity (these values are identical to those presented in the case study in section 5) etc.

6.1.Random test instance generation

Two sets of test instances that are of realistic size are generated (set I—small test instances and set II—medium test instances) by altering the planning horizon length |T|, as well as the number of collection centres |C|, the number of potential inspection locations |I|, the number of potential remanufacturing locations |R| and the number of markets/customer zones |M|, and shown in Table 8. A total of 12 random instances for set I and nine instances for set II are generated.

Table 8: Instances used in computational testing with problem size

	Class	|T|	|C=M|	|I|	|R|	|V|	Constraints	Variables		
								Binary	Integer	Continuous
Set I: Small Instances	CS1	6	30	10	3	3	31394	7638	7560	7699
	CS2	6	30	10	5	3	37550	9090	9000	9151
	CS3	6	30	15	3	3	43644	10638	10530	10729
	CS4	6	30	15	5	3	50700	12270	12150	12361
	CS5	6	30	20	3	3	55894	13638	13500	13759
	CS6	6	30	20	5	3	63850	15450	15300	15571
	CS7	12	30	10	3	3	62768	15276	15120	15397
	CS8	12	30	10	5	3	75080	18180	18000	18301
	CS9	12	30	15	3	3	87258	21276	21060	21457
	CS10	12	30	15	5	3	101370	24540	24300	24721
	CS11	12	30	20	3	3	111748	27276	27000	27517
	CS12	12	30	20	5	3	127660	30900	30600	31141
Set II: Medium Instances	CM1	3	60	25	10	3	87575	21255	21150	21331
	CM2	3	60	40	10	3	126890	30750	30600	30871
	CM3	3	60	50	10	3	153100	37080	36900	37231
	CM4	3	80	25	10	3	112895	27555	27450	27631
	CM5	3	80	40	10	3	163010	39750	39600	39871
	CM6	3	80	50	10	3	196420	47880	47700	48031
	CM7	3	100	25	10	3	138215	33855	33750	33931
	CM8	3	100	40	10	3	199130	48750	48600	48871
	CM9	3	100	50	10	3	239740	58680	58500	58831

The size and complexity of the problem instances are described by number of variables and the average number of constraints. Table 8 present the size of instances for both small and medium size test instances respectively.

6.2. Algorithmic performance

The computational results of three-phase solution approach and BD along with exact method (Branch and Cut approach) for both set I and II are summarized in this section. Each problem instance is solved five times to compare the algorithms more effectively. We first solve each problem instance with the exact method to set benchmark results. Thereafter, each problem instance is solved using the three-phase solution approach and BD. The results reported in Tables 9 and 10 indicate a comparison of computational statistics obtained by the three-phase solution approach, BD and exact method after solving each test instance.

Results for Set – I:

Our initial set of experimentation suggested that working with an optimality gap below 0.1% requires extensive computational effort. Thus, we resort to moderate stopping criterion of a runtime of 10800 sec or a 0.1% optimality gap (whichever is early). Furthermore, the termination criteria for BD is maximum of 100 iterations as well as a relative optimality gap ε = 2%.

In Table 9, for each problem instance, we summarize minimum, maximum and average objective function values for the exact, BD and the three-phase solution approaches. As well, a comparison of computational times for all methods for each instance is presented in Table 9.

From the results, in general, we noticed that computational time increases with an increase in problem size, specifically with a number of potential locations. It is important to note that with growing problem size, the exact method exhibits high computational times. Additionally, the BD is taking more time to converge as problem size increases. While the computational time increases, implementing the solution approach to solve the problem within a reasonable time plays a vital role.

Table 9: Solution methods comparison – small instances

	Class	**Three – Phase**			**BD**			**Exact**		
		Min.	**Avg.**	**Max.**	**Min.**	**Avg.**	**Max.**	**Min.**	**Avg.**	**Max.**
Objective value ($)	**CS1**	150785.9	157786.4	161079.5	152384.3	158657.8	161946.6	148731.2	155381.5	158575.1
	CS2	152806.5	155419.0	156929.1	153808.6	156151.0	157643.8	150636.1	153234.2	154709.0
	CS3	156337.1	157890.7	158676.2	158532.1	159538.4	160775.6	153844.9	155213.0	155969.1
	CS4	154076.3	155949.0	158039.7	155568.4	157807.9	160159.2	151661.4	153478.8	155635.0
	CS5	157002.4	159456.3	161381.8	158663.2	163186.3	166365.6	154404.5	156973.0	159003.7
	CS6	151405.9	156343.7	160981.7	157173.3	160590.1	164336.8	148990.3	153902.6	158349.1
	CS7	307319.1	312442.7	319130.4	308393.7	313010.7	318863.4	302371.4	307553.4	314177.7
	CS8	307096.6	308242.1	309512.3	308242.7	309501.8	310342.9	302481.2	303611.9	304754.4
	CS9	309865.0	312823.6	316649.1	312017.8	315433.6	319846.3	304838.7	307999.3	312077.9
	CS10	301281.8	306637.3	314413.4	304289.4	309483.0	317473.8	296999.0	302592.1	309776.9
	CS11	309931.5	312249.8	315285.4	313223.6	314827.4	317266.4	305280.8	307434.0	310431.0
	CS12	299479.3	306686.1	313649.4	305981.9	311303.1	316554.7	295263.2	302123.8	309082.1
Computational time (sec)	**CS1**	1.2	1.8	2.1	75.5	187.3	435.3	162.3	1752.1	4057.6
	CS2	1.2	2.3	2.9	68.9	179.5	394.1	714.4	4032.0	10800.4
	CS3	2.2	6.0	9.8	200.7	1854.3	5911.9	1624.6	5256.4	10804.6
	CS4	4.4	6.3	9.6	258.7	977.7	2177.7	10800.3	10800.3	10800.4
	CS5	3.0	16.9	41.0	225.8	262.9	328.5	5069.5	8849.3	10805.1
	CS6	6.6	21.3	36.2	108.0	314.7	552.4	9411.1	10522.5	10800.4
	CS7	2.8	3.4	4.2	102.1	1046.6	2691.4	444.0	3348.4	6296.6
	CS8	3.7	5.0	6.2	429.6	823.3	1518.7	2501.2	6476.7	10800.4
	CS9	5.6	6.1	7.1	5118.9	8057.0	≥10800	5835.8	8037.7	10801.0
	CS10	6.4	8.3	13.7	3287.4	5625.3	10227.9	3862.1	8658.3	10800.6
	CS11	7.0	8.3	10.3	2930.5	≥10800	≥10800	3189.2	8397.8	10804.7
	CS12	12.0	19.7	33.0	≥10800	≥10800	≥10800	10800.8	10803.8	10811.6

It is clearly evident from Table 9 that the proposed three-phase method is much faster than exact and BD in solving all test instances. Among BD and exact method, we find that the BD is at least on average ten times faster than exact.

In addition to computational time, to compare the quality of optimal objective values obtained by three-phase solution approach and BD, we use the following criterion - the relative gap of the solution. Figure 5 illustrates the average relative gap percentage:

$$\%\ Relative\ gap = \frac{(Three\ phase_{sol} - Exact_{sol})}{Exact_{sol}} \text{ x } 100$$

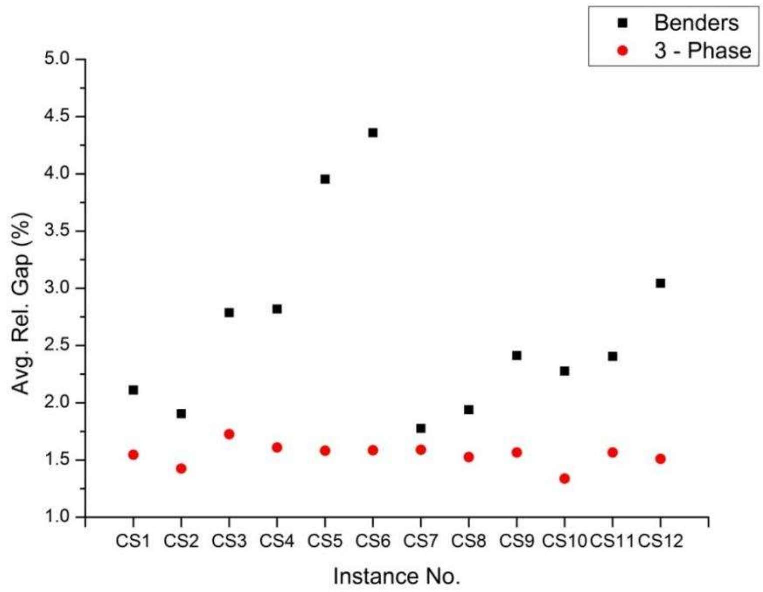

Figure 5: Solution gaps for small instances

From Figure 5, we observe that three-phase solution approach provides solutions with an average relative gap of 1.55% whereas BD provides solutions with 2.65% gap. Hence, we conclude that the three-phase solution approach is efficient and effective as it provides the better quality solution in most instances with less time.

Results for Set – II:

Similar to set – I, we study the performance of the proposed solution approach with an exact solution based on the solution times and the objective value in this section. We avoid the tail-off effect in the exact method by setting the tolerance for stopping criterion to a runtime of 10,800sec or a 0.1% gap whichever comes earlier.

The comparison of objective function values and computational times for all test instances using all methods is presented in Table 10. Results indicate that except test instance 1, all instances failed to reach optimality gap below 2% using BD method, this is due to failure in the convergence of upper and lower bounds.

Table 10: Solution methods comparison – Medium instances

	Class	**Three - Phase**			**BD**			**Exact**		
		Min.	**Avg.**	**Max.**	**Min.**	**Avg.**	**Max.**	**Min.**	**Avg.**	**Max.**
Objective value ($)	**CM1**	151409.0	154678.0	157110.6	156106.2	159277.9	161142.0	149211.3	152381.6	154993.9
	CM2	150037.9	153457.7	158317.8	152952.5	158040.1	165234.4	147960.2	151350.8	156365.2
	CM3	151253.6	153857.0	155872.2	159604.0	161506.8	164564.7	149546.7	151785.0	153813.6
	CM4	201424.2	204821.3	208105.6	205763.0	208345.3	210876.7	198564.3	202046.4	205343.6
	CM5	202197.9	204120.0	208752.1	210407.6	212982.2	216637.1	199241.7	201460.1	205827.8
	CM6	200711.7	205889.8	210599.8	208244.1	215338.9	217530.1	197834.7	203058.4	207770.1
	CM7	251342.7	254704.1	258430.2	252100.0	256523.8	259873.3	247635.4	251270.2	254827.7
	CM8	249789.2	254750.3	260711.0	257922.3	261624.0	264920.1	246584.9	251267.8	257199.6
	CM9	251875.9	255769.0	258514.1	260325.4	265645.5	268119.7	247911.4	252360.4	255077.4
Computational time (sec)	**CM1**	8.2	45.3	102.1	308.0	1098.2	2130.0	2796.1	9199.6	10800.6
	CM2	45.6	711.3	3274.5	≥10800	≥10800	≥10800	10800.6	10800.7	10800.8
	CM3	123.7	476.5	1137.9	≥10800	≥10800	≥10800	10800.7	10800.9	10801.2
	CM4	12.9	44.8	152.0	3213.8	9288.8	≥10800	10800.6	10806.0	10818.3
	CM5	30.8	289.0	1124.4	9717.5	≥10800	≥10800	10800.8	10801.1	10801.7
	CM6	80.5	159.3	393.2	≥10800	≥10800	≥10800	10801.0	10802.3	10806.8
	CM7	8.0	13.3	21.3	2239.9	7639.6	≥10800	10800.7	10802.4	10807.4
	CM8	74.4	207.4	347.2	≥10800	≥10800	≥10800	10801.0	10802.4	10805.4
	CM9	47.7	249.2	546.3	≥10800	≥10800	≥10800	10801.1	10802.3	10806.7

The solution quality of the three-phase solution approach is illustrated in Figure 6, where the solution gap varies from 1.32% to 1.51% using three-phase concerning exact method.

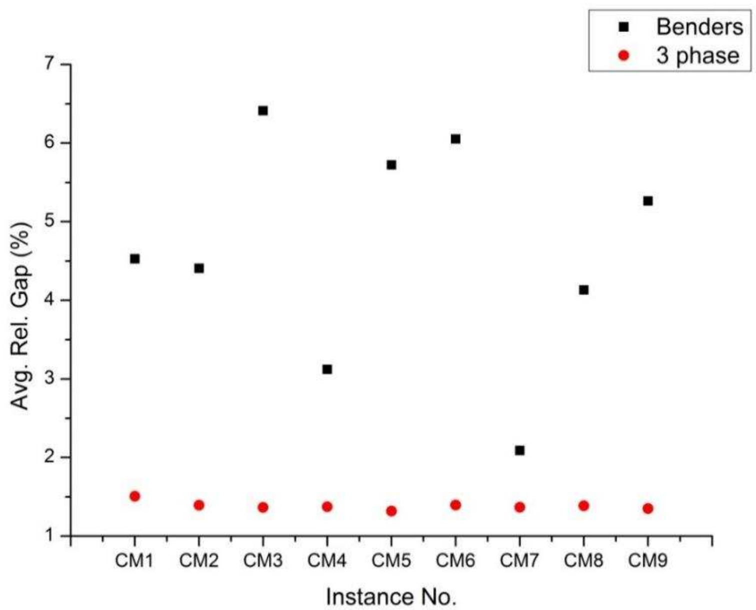

Figure 6: Solution gaps for medium instances

From the above results, we observed that the three-phase solution approach out-performs the others. It would appear that the computational statistics explain the use of three-phase solution approach rather than the BD and exact method in terms of both solution gap and runtime. Among all methods, poor performance was obtained by BD as problem size increases. Since the run times for the three-phase solution algorithm are significantly lower than the exact method and BD computation times, is quite acceptable in the case of both sets of problems.

6.3. Statistical analysis:

In this section, the t-test is used to make a significant comparison between quality of solutions obtained using solution methodologies for two sets. We also present the confidence intervals and significance level at $\alpha = 0.05$. For independent samples t-test,

Null hypothesis: $\mu_{\text{three-phase}} = \mu_{\text{exact}}$

Alternate Hypothesis: $\mu_{\text{three-phase}} \neq \mu_{\text{exact}}$

Since, the sample sizes are same ($n_1 = n_2 = 5$), the degree of freedom (df) is 8. The critical t-test statistic value from statistical table at df = 8 and alpha = 0.05 is 2.306. Table 11 represents the t-test statistic and hypothesis results for small and medium instances.

These results reveal that when the three-phase solution approach is compared with exact, the null hypothesis was not rejected in most cases. Thus, the mean for the three-phase and exact methods is equal in most cases. However, when we compare the three-phase results with BD, for 50% of instances Null hypothesis is rejected. That means there exists a significant difference between means of exact and BD, because of failure in the convergence of lower and upper bounds in BD as the problem size increases.

We can conclude that for three-phase solution approach with respect to the exact method, the hypothesis of equal means for all of the instances is not rejected. A 95% confidence interval (CI) of the means of small and medium instances illustrates that there is a significant difference between the performances of methods because none of the CIs includes zero in their intervals.

Summarizing the above results, it can be realized that three-phase solution approach is effective and statistically significantly different from the exact and BD methods. Thus, the three-phase solution approach, concerning their acceptable run times and solution gaps, is preferred to solve the large-scale problems. Our computational results demonstrate the superior performance of three-phase solution approach over the exact and BD methods.

Table 11: t-test values for small and medium instances

	Class	Three-Phase		BD		Exact		3 phase vs. Exact			Three-Phase vs. BD		
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**t-stat**	**p-value**	**Hypothesis**	**t-stat**	**p-value**	**Hypothesis**
Small Instances	**CS1**	157786.4	4029.3	158657.8	3735.1	155381.5	3862.3	-0.963	0.3635	Accept	0.355	0.732	Accept
	CS2	155419.0	1605.2	156151.0	1429.1	153234.2	1583.3	-2.167	0.0621	Accept	0.762	0.4682	Accept
	CS3	157890.7	1017.7	159538.4	943.6	155213.0	943.1	-4.315	0.0026	Reject	2.655	0.029	Reject
	CS4	155949.0	1471.3	157807.9	1965.7	153478.8	1489.4	-2.638	0.0298	Reject	1.693	0.1289	Accept
	CS5	159456.3	2157.0	163186.3	3051.5	156973.0	2140.4	-1.827	0.1051	Accept	2.232	0.0561	Accept
	CS6	156343.7	4098.1	160590.1	3214.4	153902.6	3963.4	-0.957	0.3664	Accept	1.823	0.1058	Accept
	CS7	312442.7	5411.3	313010.7	4974.6	307553.4	5420.0	-1.427	0.1913	Accept	0.173	0.8671	Accept
	CS8	308242.1	900.2	309501.8	829.4	303611.9	847.7	-8.373	< 0.0001	Reject	2.301	0.0504	Accept
	CS9	312823.6	2488.7	315433.6	2814.2	307999.3	2641.9	-2.972	0.0178	Reject	1.553	0.1589	Accept
	CS10	306637.3	5103.3	309483.0	5357.4	302592.1	5253.2	-1.235	0.2519	Accept	0.86	0.4148	Accept
	CS11	312249.8	2190.0	314827.4	1726.5	307434.0	2072.1	-3.572	0.0073	Reject	2.067	0.0726	Accept
	CS12	306686.1	5704.3	311303.1	4798.9	302123.8	5624.5	-1.273	0.2386	Accept	1.385	0.2035	Accept
Medium Instances	**CM1**	154678.0	2246.6	159277.9	1972.2	152381.6	2250.8	-1.615	0.1450	Accept	3.441	0.0088	Reject
	CM2	153457.7	3166.8	158040.1	4553.9	151350.8	3207.8	-1.045	0.3265	Accept	1.847	0.1019	Accept
	CM3	153857.0	1961.6	161506.8	2014.9	151785.0	1976.0	-1.664	0.1347	Accept	6.083	0.0003	Reject
	CM4	204821.3	3091.6	208345.3	2326.5	202046.4	2979.7	-1.445	0.1864	Accept	2.037	0.0761	Accept
	CM5	204120.0	2641.8	212982.2	2312.1	201460.1	2545.8	-1.621	0.1436	Accept	5.645	0.0005	Reject
	CM6	205889.8	3572.7	215338.9	3984.0	203058.4	3593.1	-1.249	0.2468	Accept	3.948	0.0042	Reject
	CM7	254704.1	2674.9	256523.8	2839.3	251270.2	2702.5	-2.019	0.0781	Accept	1.043	0.3274	Accept
	CM8	254750.3	4009.8	261624.0	2638.5	251267.8	3923.9	-1.388	0.2026	Accept	3.202	0.0126	Reject
	CM9	255769.0	2558.4	265645.5	3111.9	252360.4	2737.4	-2.034	0.0764	Accept	5.482	0.0006	Reject

7. Conclusion

In this paper, we consider a multi-echelon RLN incorporated with vehicle type selection, and carbon emissions simultaneously in a multi-period setting. We developed a MILP model for RLND to minimize the overall costs for the firm, including: fixed setup cost, transportation cost, operating cost and emission cost. The network presented in this study contains capacitated facilities such as collection, inspection, remanufacturing centres, and markets. The proposed model can help managers to decide facility (inspection/remanufacturing) locations, transportation of quantity of cores/remanufactured product between facilities and also routing of vehicles between facilities while accounting for carbon footprint.

Given the special structure of the problem, we proposed an efficient heuristic-three-phase method. Based on computational analysis, we established the superior performance of the proposed three-phase method over the exact method (branch and cut) and BD in terms of solution quality and computational time. We test our solution approach on a testbed corresponding to small and medium instances. Based on extended numerical testing using two set of benchmark problems with 21 instances, our approach is effective and efficient. As problem size increases, BD is unable to converge which results in a high solution gap and time. The use of the three-phase solution approach significantly reduces the computational times and improves the quality of the solutions.

This study has the potential for further extension in several directions. In this paper, both demand and returns are assumed to be known, in reality, this is difficult for businesses to forecast. Thus, to specify the problem for a more realistic scenario, the model has to incorporate the uncertainty of returns and demand. The model can be further extended by developing and incorporating a pricing policy based on the quality of returns; and by improving the convergence of bounds in BD by applying some heuristics to improve the solution.

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