

**TWO-ECHELON DISTRIBUTION NETWORK DESIGN WITH  
COLLABORATION AMONG CARRIERS**

by  
**İSMAİL GÖKAY DOĞAN**

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## ABSTRACT

# TWO-ECHELON DISTRIBUTION NETWORK DESIGN WITH COLLABORATION AMONG CARRIERS

İSMAİL GÖKAY DOĞAN

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Thesis Supervisor: Asst. Prof. Dr. Esra Koca

Keywords: distribution network design, two-echelon supply chain, collaborative supply chain, location-routing, mixed integer programming, cut-generation

Globalization, exponential growth of e-commerce and q-commerce industries, changing market habits and increased need of logistics services result in high competition among supply chain pillars. Collaboration is an effective strategy to pursue in this endeavour. We define a two-echelon distribution network design problem in which parties can collaborate to complete the last-mile delivery requests in the lower echelon. The objective is to minimize costs which arise from facility opening, transportation and transfer of goods between regional depots. In the upper echelon, goods are transferred from plants to regional depots via direct transportation. In the lower echelon, goods are delivered to the customers in a milk-run fashion from regional depots. We develop three mixed-integer linear programming models which differ in terms of modelling outbound routing decisions. Several valid inequalities are proposed to strengthen formulations. To solve a traditional vehicle-based formulation, a cut-generation based method is developed. For the path-based formulation, a heuristic route pool generation procedure which promotes collaboration is developed. Proposed models are tested with different problem sizes to examine solution qualities and computational times. Moreover, models are tested under different collaborative network settings in which main parameters of the problem such as number of common customers, demand amounts and number of common depots are varied in order to explore managerial insights such as savings due to collaboration.

## ÖZET

# TAŞİYİCİLAR ARASINDA İŞ BİRLİĞİ ALTINDA İKİ AŞAMALI DAĞITIM AĞI TASARIMI

İSMAİL GÖKAY DOĞAN

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Anahtar Kelimeler: dağıtım ağı tasarımı, iki kademeli tedarik zinciri, işbirlikçi tedarik zinciri, lokasyon-rotalama, tam sayılı doğrusal programlama, kesim üretimi

Küreselleşme, e-ticaret ve q-ticaret endüstrilerinin katlanarak büyümesi, değişen pazar alışkanlıklarını ve artan lojistik hizmetleri ihtiyacı, tedarik zinciri paydaşları arasında yüksek rekabete neden olmaktadır. İş birliği, bu rekabet ortamında maliyetleri azaltmak için izlenebilecek etkili bir stratejidir. Bu çalışmada, alt kademedeki son teslimat etaplarını tamamlamak için tarafların iş birliği yapabileceği iki kademeli bir dağıtım ağı tasarım problemi tanımlıyoruz. Problemin amaç fonksiyonun hedefi tesis açılışı, nakliye ve bölgesel depolar arası mal transferinden kaynaklanan maliyetleri en aza indirmektir. Üst kademedede mallar fabrikalardan doğrudan taşıma ile bölgesel depolara aktarılır. Alt kademedede mallar, bölgesel depolardan süt dağıtımını şemasıyla (depodan çıkışip tüm teslimat noktalarına uğradıktan sonra depoya geri donecek rotalarla) müşterilere teslim edilir. Alt kademedeki rotalama kararlarını modelleme açısından farklılık gösteren üç karma tam sayılı doğrusal programlama modeli geliştiriyoruz. Formülasyonları güçlendirmek için çeşitli geçerli eşitsizlikler önerilmiştir. Geleneksel araç bazlı formülasyonu çözmek için, kesim üretimi bazlı bir yöntem geliştirilmiştir. Rota tabanlı formülasyon için, iş birliğini destekleyecek türde rotalar oluşturan sezgisel bir prosedür geliştirilmiştir. Önerilen modeller, çözüm niteliklerini ve hesaplama sürelerini incelemek için farklı problem boyutlarıyla test edilmiştir. Ayrıca modeller, ortak müşteri sayısı, talep miktarları ve ortak depo sayısı gibi problemin ana parametrelerinin değiştirildiği farklı işbirlikçi dağıtım ağı senaryoları altında test edilerek, iş birliğinden kaynaklanan tasarruflar gibi yönetsel içgörüler keşfedilmiştir.

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*To my family...*  
*Aileme...*

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## LIST OF ABBREVIATIONS

FLP: Facility Location Problem .....	3
VRP: Vehicle Routing Problem .....	3
LRP: Location Routing Problem .....	3
2E-LRP: Two-Echelon Location Routing Problem .....	4
2E-CLRP: Two-Echelon Capacitated Location Routing Problem .....	4
MILP: Mixed-Integer Linear Programming .....	4
B&C: Branch and Cut .....	4
VNS: Variable Neighborhood Search .....	4
CVRP: Capacitated Vehicle Routing Problem .....	7
MIP: Mixed-Integer Programming .....	7
MD: Multi-depot .....	7
PDPTW: Pickup and Delivery with Time Windows .....	7
LTL: Less-Than-Truckload .....	8
WH: Warehouse .....	8
DC: Distribution Center .....	8
BR: Biased Randomization .....	8
ILS: Iterative Local Search .....	8
2E-FLP: Two-Echelon Facility Location Problem .....	8
SEC: Sub-tour Elimination Constraint .....	27
O: Original .....	29
ICC: Increased Common Customer .....	29
NCD: No Common Depot .....	29
HPC: High Performance Computing .....	31
GB: Gigabyte .....	31
RAM: Random Access Memory .....	31
IDE: Integrated Development Environment .....	31
VB: Vehicle-Based .....	31
VI: Valid inequality .....	32
LB: Load-Based .....	35
OFV: Objective Function Value .....	41

NNH: Nearest Neighborhood .....	57
PS: Parallel Savings .....	57
GS: Gaskell-Savings .....	57
CMT2P: CMT Two-Phase Heuristic .....	57
PB: Path-Based .....	58

## 1. INTRODUCTION

Network design is one of the key pillars of the modern supply chains. In addition to traditional supply requirements, exponential growth of e-commerce and q-commerce industries, changing market habits and increased need of micro logistics services promote competition among parties. Into the bargain, growing logistics needs also come along with social and environmental issues such as pollution, noise, traffic and congestion. Thus, promoting cost efficient supply networks become more important because of the increased competitiveness, and companies try to find new strategies for their logistics operations to cope with the sustainability issues and high competitiveness of the market (Aloui, Derrouiche, Hamani & Delahoche, 2020).

One strategy that can be followed by the parties of supply chains is collaboration. Collaboration between parties indeed promises positive outcomes such as decreased costs for businesses, companies, service providers, or increased environmental standards for community such as decreased pollution levels, noise and congestion. Hence, improving efficiencies via collaboration in logistics design and planning processes may have a great impact on environment and social welfare in society (Rao, Goh, Zhao & Zheng, 2015).

In this study, we address a two echelon centralized collaborative strategic network design problem in which companies are allowed to cooperate in the lower echelon within the scope of last mile delivery operations. The two echelon network consists of plants where products are produced, regional depots where goods are stored, and customers. Deliveries from plants to regional depots are conducted as direct transportation and called inbound transportation. Deliveries from regional depots to the customers are conducted in a milk-run fashion and called outbound transportation. Our goal is to determine the number and locations of regional depots, required inbound capacity and outbound routes as well as transfer lines between depots. Our problem includes strategic decisions such as facility decisions as well as tactical and operational decisions such as vehicle routing and transfer line construction decisions. The objective is to minimize total cost of the whole system due to both strategic, tactical and operational decisions.

To represent a collaborative distribution network, a single period strategic network design problem, in which parties can interchange demands, is defined.

We define a single period strategic network design problem in which parties can interchange demands to represent a collaborative distribution network. We develop three mathematical models which differ from each other in terms of modelling outbound routing operations.

Depending on the type and cause of computational challenges, the resulting mixed-integer linear programming formulations require different solution methods. We conduct computational experiments with different sizes of problem instances under three different collaborative network scenarios, and also two different demand settings. Our contributions can be summarized as follows:

- A centralized network design problem is defined in which parties can collaborate to satisfy other companies' demands in the outbound routing operations.
- Three mixed-integer linear programming formulations are proposed.
- A cut generation based method to solve one of the formulations is developed.
- Route pool generation procedure which employs five heuristic algorithms and promotes collaboration is proposed.
- Different valid inequalities are developed for each formulation in order to improve the solution performance.
- Impact of different collaborative network structures is investigated.

This thesis is organized as follows. Chapter 2 consists of a literature review. Problem definition and mathematical models are presented in Chapter 3. A vehicle-based formulation approach and related solution methodologies are presented in Chapter 4 together with computational results. Similarly, load-based and path-based formulation approaches and related solution methodologies as well as computational results are presented in Chapter 5 and Chapter 6, respectively. Finally, we conclude with our findings and future research directions in Chapter 7.

## 2. LITERATURE REVIEW

The literature review focuses on two aspects: strategic distribution network design problems and the effect of collaboration among parties that operate over the same network. Strategic distribution network design problems include two main decisions, locations of the facilities and transportation decisions. Both of these decisions can be presented under different optimization problem classes, such as facility location problems (FLP), and vehicle routing problems (VRP). Collaboration is a strategy that is utilized by the companies to increase service levels and decrease the costs. In the beginning of this literature review, we focus on FLP. In the later parts, collaborative approaches are explained.

Facility location problem is a combinatorial optimization problem, and its objective is to determine the number and locations of a set of facilities (warehouses, cross-docks, etc.) and assign customers to these facilities in such a way that the demands of the customers are satisfied, and the total cost is minimized (Wu, Zhang & Zhang, 2006). On the other hand, vehicle routing problem aims to decide on a set of vehicle routes to satisfy all or some transportation requests of the customers with the given vehicle fleet at minimum cost (Toth & Vigo, 2014).

In a distribution network, making location and routing decisions independently may lead to highly sub-optimal planning results (Salhi & Rand, 1989). Thus, making those decisions simultaneously pledges better outcomes. Location-routing problems (LRP) emerge from this basis. Given a set of possible depot locations, a set of vehicles, and a set of customers, LRP consists of simultaneous decision-making of opening a subset of depots, creating routes that depart from opened depots, and assigning customers to constructed routes of vehicles to minimize total cost including depot opening costs and transportation costs (Prodhon & Prins, 2014). The main difference between LRP and VRP is not only routing decisions, in addition to that, the optimal depot locations must be determined concurrently (Marinakis, 2009).

By the virtue of the complex logistics and distribution infrastructure requirements of modern-day supply chains, many distribution systems are designed as multi-echelon

systems. In multi-echelon distribution systems, delivery of the goods from origin to the final destination is extended through intermediate facilities such as warehouses, cross-docks, etc. where goods are stored, changed, packed, unpacked, merged, or consolidated. Every single level of the distribution network refers to an echelon (Cuda, Guastaroba & Speranza, 2015).

Two-echelon systems are very well studied in the literature because of their applicability to real-life instances and promising outcomes. Two-echelon distribution networks consist of three disjoint sets of nodes, depots (plants or origins), satellites which are intermediate facilities such as regional depots, consolidation points or cross docks, and customers (Cuda et al., 2015).

The two-echelon setting of LRPCs (2E-LRP) tries to answer, how many depots and/or intermediate facilities should be opened to which locations, and which routes should be constructed in both echelons according to the given network structure and parameters (Cuda et al., 2015). In terms of new problem structures and methodological works, numerous research has been conducted. Jacobsen & Madsen (1980) is one of the earliest studies on 2E-LRP which is motivated by a newspaper distribution problem which finds the best locations the satellite facilities, and routes to be created in both echelons. The authors propose three different heuristic approaches. Boccia, Crainic, Sforza & Sterle (2010) study a 2E-LRP where homogeneous vehicles in both echelons have fixed capacities. To the best of our knowledge, this study is one of the earliest examples of capacitated 2E-LRP, i.e., 2E-CLRP. They utilize a tabu search (TS) based heuristic algorithm.

Boccia, Crainic, Sforza & Sterle (2011) introduce three different mixed-integer linear programming (MILP) formulations for 2E-CLRP. They conduct computational experiments by solving two of those models with a commercial solver on a data set which is generated Boccia et al. (2011). Contardo, Hemmelmayr & Crainic (2012) propose a branch and cut (B&C) algorithm to solve 2E-LRP. They introduce a new two-index formulation that is used in B&C. They are able to solve small and medium-sized instances to optimality. Schwengerer, Pirkwieser & Raidl (2012) propose a Variable Neighborhood Search (VNS) for 2E-CLRP and conduct computational study on three sets of instances which are proposed by Contardo et al. (2012). The authors show that VNS is not able to outperform the B&C algorithm of Contardo et al. (2012).

Over the last few years, globalization changed logistics operations, as well as it has transformed many aspects of the modern world. Because of the exponential growth of e-commerce and q-commerce industries, micro logistics needs have been expanded and altered. Concerns about competitiveness and sustainability require reformer

methods and models for planning logistics operations (Aloui, Hamani, Derrouiche & Delahoche, 2021). Therefore, companies try to find new strategies for their logistics operations to cope with the sustainability issues and high competitiveness of the market (Aloui et al., 2020). In addition to these issues, inefficient logistics operations in urban areas also create congestion, carbon emission, noise, and space consumption problems (Cleophas, Cottrill, Ehmke & Tierney, 2019).

Collaboration may facilitate new approaches to cope with these new problems. In the context of supply chains, collaboration is realized when “two or more independent companies work jointly to plan and execute supply chain operations with greater success than when acting in isolation” (Simatupang & Sridharan, 2002). As Gonzalez-Feliu & Salanova (2012) suggest, logistics stakeholders have been led to examine collaborative strategies to curtail costs of the supply processes. Collaboration between the businesses or companies indeed promises positive outcomes for all pillars of the logistics industry such as service providers, customers, citizens, and the community itself. Collaboration among the parties may lead to more efficient transportation operations in terms of fewer vehicles, less pollution, decreased transportation costs, and lower prices for end products (Cleophas et al., 2019). Thus, increased efficiencies via collaboration in logistics design and planning processes may have a great impact on social welfare and peace in society (Rao et al., 2015).

In terms of collaboration, parties can collaborate on two dimensions: horizontal and vertical. In vertical scheme, different levels of the supply network cooperate such as manufacturers, customers, suppliers, and distributors (Saenz, Ubags & Cuevas, 2014). In horizontal collaboration, stakeholders acting at the same level of the supply chain cooperate. Those stakeholders may or may not be competitors of each other, i.e, they may be part of the same supply chain network or not (Soysal, Bloemhof-Ruwaard, Haijema & Vorst, 2018). Different types of collaboration can be seen in Figure 2.1.

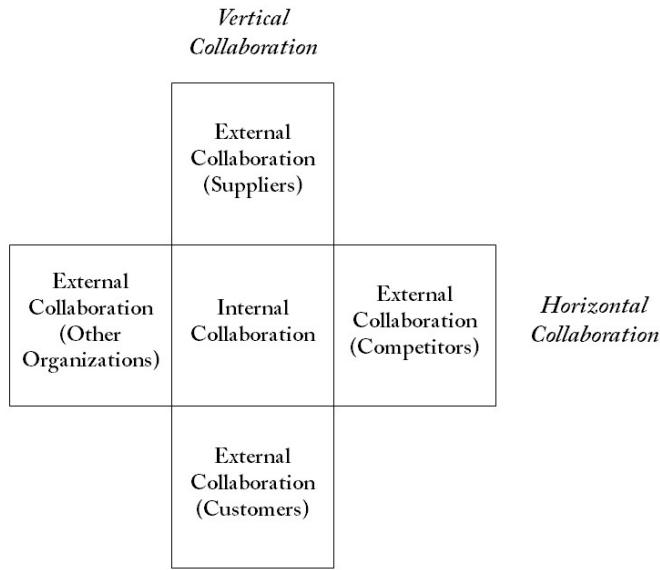


Figure 2.1 Collaboration Types (Barratt, 2004)

In the recent years, both academic research and professional practice have focused on horizontal collaboration in logistics systems because of the promised outcomes in terms of multiple benefits such as decreased costs and emissions, increased customer satisfaction rates, and profits (Pan, Trentesaux, Ballot & Huang, 2019). Horizontal collaboration can be utilized at different decision-making levels. As Defryns, Sørensen & Dullaert (2019) indicate, most of the previous work in the context of horizontal collaboration, focused on transportation optimization at the operational and tactical levels. According to Verdonck, Beullens, Caris, Ramaekers & Janssens (2016), research that focuses on the strategic level aims to design common supply networks to achieve economies of scale, but the number of such studies is not sufficient. The majority of the studies that focus on all different levels try to minimize costs or maximize profits.

Two common approaches are used for horizontal collaboration problems which focus on the operational level, capacity-sharing, and order-sharing (Verdonck, Caris, Ramaekers & Janssens, 2013). In the capacity sharing, stakeholders i.e., carriers or shippers, try to decide on whether they will share their vehicle capacities with the other parties or not (Defryns et al., 2019). In the second approach, all or some of the orders can be shared with the other parties so that they can satisfy those orders. According to Aloui et al. (2021), most of the studies at the operational level are related to variants of VRP. The main motivation behind those studies coincides with the findings of Chabot, Bouchard, Legault-Michaud, Renaud & Coelho (2018) who claim that outcomes of joint route planning or collaborative strategies through horizontal collaborative schemes pledge better economic benefits and environmental

gains.

In terms of collaborative vehicle routing (VRP-C), there exist different strategies to collaborate. Fusion or merging is one of those strategies in which two or more tasks are merged into one single task. According to Weng & Xu (2014), merging pledges lower costs. Exchanging demand is another method of collaboration; parties can swap, exchange, or transfer their demand requests to other carriers so that the overall cost of the network or single parties can be minimized. According to Pan et al. (2019), there exist two major approaches to exchange demand, auctions, and side payments. Berger & Bierwirth (2010) propose an arrangement mechanism-based MIP model for exchanging transportation requests to maximize the profit of the whole network without decreasing the individual profits of stakeholders and they report that in highly competitive environments, horizontal collaboration leads to increased profits. Özener, Ergun & Savelsbergh (2011) establish a lane exchange approaches for long-haul transportation problems to provide a decentralized demand transfer mechanism.

Hernández & Peeta (2011) focus on a time-dependent carrier collaboration problem where capacity varies over time so that carriers can utilize or provide capacity during routing. They model the problem as a minimum cost flow problem and use B&C to solve the problem. Another paradigm for collaboration is resource pooling where resources such as vehicles, warehouses, cross-docks etc., are pooled for the use of collaborators. Wang, Zhang, Guan, Peng, Wang, Liu & Xu (2020) solve a multi depot (MD) collaborative location network planning problem with time windows. They utilize a hybrid heuristic algorithm which consists of non-dominated sorting genetic algorithm, K-means clustering, and Clarke-Wright savings algorithm, to solve the problem and they conclude that the collaborative approach increase the efficiency. Lin (2008) studies a real-life problem of a multi-national logistics company and modeled their problem as an exact integer programming formulation. The model is based on classical pickup and delivery with time windows (PDPTW) in which a vehicle is allowed travel to transfer goods to another vehicle that returns to the depot if time window constraints are not violated. The authors compared proposed models with a new insertion-based construction heuristic and reported that cooperative scenarios are more cost-effective when compared to non-cooperative scenarios. Sprenger & Mönch (2014) establish a decision tool in which production companies can pool their vehicles to reduce transportation costs. Fernández, Roca-Riu & Speranza (2018) define a multi-depot VRP variant in which several carriers on the same horizontal level can satisfy other carriers' demands if a customer has demand from both carriers. They define two MILP formulations for a centralized approach and derive valid inequalities for each formulation. The authors proposed a branch and

cut algorithm to solve both formulations. They showed that collaboration among carriers leads to cost savings up to almost 21.2%.

Besides the operational and tactical levels, some studies focus on the strategic level as well. According to Aloui et al. (2021), strategic-level decisions are less studied in the context of collaborative planning despite the fact that they are the most essential part of supply chain management. The majority of the studies under the strategic-level section mainly focus on economic aspects. The number of studies that aim to optimize environmental or social aspects is narrow.

Hernández, Unnikrishnan & Awale (2012) define a multi-hub location problem with a centralized horizontal collaborative setting in which different Less-Than-Truckload (LTL) carriers can open joint consolidation transshipment points. The authors describe a new MILP which is a variant of  $p$ -hub location model and solved it via Lagrangian relaxation. They report that collaboration lead to cost savings, especially in small networks, and pledges more saving opportunities for small-sized LTL carriers. Pan, Ballot & Fontane (2013) investigate the environmental effect of the pooling of warehouses and distribution centers in a classical distribution network in which different companies shared their WHs and DCs for common usage. They provide a MILP formulation with two different objective functions depending on the transportation modes: road, and rail. They test their models with 2 real French companies' data. They report that pooling yields up to 14% savings in terms of carbon dioxide emissions. Fernández & Sgalambro (2020) define several models to investigate collaborative approaches for hub location problems in decentralized environments.

Nataraj et al. (2019), define a single echelon LRP in which the locations of urban consolidation centers and consequent routes are determined simultaneously. They utilized biased randomization (BR) technique to find good-quality solutions. They embedded BR into an Iterative Local Search (ILS) algorithm which they call BR-ILS. The authors investigate four different collaboration scenarios where collaboration level change. The results indicate that overall warehousing and maintenance costs decrease, service levels increase, and carbon emission levels decrease by the virtue of collaboration. Verdonck et al. (2016) describe a collaborative scheme and MILP for a 2E-FLP and takes into consideration that a carrier can prefer or not prefer to join cooperation. Only the carriers who are in cooperation can open joint depots. They conduct computational studies by using a commercial solver on a UK-based case study. They report that overall costs are decreased by 9.1% in average via collaboration. Tang, Lehuédé & Péton (2016) propose a MILP to solve a FLP for a centralized supply network to find the optimal locations for intermediate

storage facilities, i.e., regional depots. In other words, all resources are pooled, and decisions are made in a centralized context in which all pillars act like one single entity. Ouhader & Kyal (2017) define a collaborative 2E-LRP in a full centralized manner in which the demand of each customer can be met from any opened intermediate satellite. All satellites and routes are constructed jointly. The authors have proposed a MILP where the objective function consists of cost, carbon emissions, and created job opportunities that cover all pillars of sustainability. They showed that collaboration can lead to reduced costs and carbon emissions. However, as expected, collaboration can negatively affect the social aspects such as created job opportunities.

To the best of our knowledge, no work considers a two-echelon location routing problem in which carriers on the same horizontal level can complete other carriers' LTL delivery requests on the second echelon and first echelon deliveries are completed as direct shipments. Our goal is to provide a pragmatic definition of a distribution network design problem for a centralized collaborative scheme, present exact and matheuristic surrogate formulations as mixed integer-linear programming models, enhance those formulations with valid inequalities and solve them using a commercial solver. We examine the solutions not only in terms of computational aspects such as solution time and quality but also with respect to managerial insights like the effects of network structure, collaboration amount, joint facility decisions.

### 3. PROBLEM DEFINITION & MATHEMATICAL MODELS

We consider a distribution network design problem: multiple companies (carriers) operating over the same network are willing to collaborate to reduce costs. The network consists of plants where the goods are produced, regional depots where the goods are stored and customers which have demands from carriers. As Klibi, Martel & Guitouni (2016) indicate, w.l.o.g. goods are assumed to be aggregated as a single entity since they use same technology in terms of storing and handling.

Each company has one plant, numerous possible regional depot locations and customers. It is assumed that some of the customers have demand from multiple carriers; these customers are called *common* customers. In the context of collaboration, the demand of a common customer can be satisfied by one of the carriers which already has that customer in its own system. Demand from a customer can not be splitted among carriers. If a carrier is going to satisfy the demand of a customer which belongs to another carrier, then this carrier should satisfy the whole demand which emerges from other carrier. Goods are sent from plants to regional depots; then they are distributed from regional depots to customers. Transportation of the goods from plants to regional depots is direct and called inbound transportation. Transportation from regional depots to customers (outbound transportation) is conducted as milkrun shipments where vehicles follow routes in which several customers are visited in a specific order. For a carrier ( $A$ ) to satisfy another carrier's ( $B$ ) demand of a common customer from one of its depots, the goods should be sent from one of the regional depots of  $B$  to this specific regional depot of  $A$ .

#### 3.1 Problem Definiton

In the planning network,  $N$  denotes the set of customers.  $C$  represents the set of operating companies (i.e, carriers).  $D$  denotes the candidate regional depot locations

for the system where  $D_r$  is the possible depot locations for carrier  $r \in C$ .  $P$  is the set of all plants where  $P_r$  is the set of plants of carrier  $r$ .  $S_r$  is the set of carriers that has at least one common customer with carrier  $r$ , including  $r$ . In our case, each carrier  $r \in C$  has a single plant. Let  $G = (V, A)$  be the underlying network where  $V = N \cup D \cup P$  represents the set of all vertices and  $A = \{(V \times V) \setminus ((N \times P) \cup (P \times N))\}$  is the set of arcs connecting each pair of the vertices, except the ones which connect plant and customers. For each arc  $(i, j) \in A$ , there is a arc traversing cost  $c_{ij}$ . For each regional depot  $d \in D_r$  of each carrier  $r \in C$ , there is a homogeneous fleet of vehicles with capacity  $Q$ . For any customer  $i \in N$ ,  $d_i^r$  represents the amount of demand of customer  $i$  from carrier  $r$ . If  $d_i^r > 0$  then  $i$  is a customer of carrier  $r \in C$ .  $N_r$  represents the set of customers which belong to carrier  $r \in C$ . On the other hand,  $C_i$  is the set of carriers which has  $i$  as a customer. Undoubtedly, if a customer  $i \in N$  has a demand from carrier  $r \in C$ , then  $i \in N_r$  and  $r \in C_i$ . A customer  $i \in N$  can be visited in multiple routes. In other words, the demand that belong to a customer and emerge from different carriers can be satisfied by different routes.

If a customer only has a demand from one specific carrier (i.e  $|C_i| = 1$  and  $C_i = \{r^*\}$ ) than this demand should be satisfied in one of the routes which originates from one of depots of  $r^*$ :  $d^* \in D_{r^*}$ . In contrast, if a customer has demand from more than one carrier (i.e  $|C_i| > 1$ ), then  $d_i^r$  can be satisfied by one of the depots of these carriers  $r \in C_i$ . In other words, it can be satisfied from one of the depots of the carrier which demand is from, or it can be transferred to another carrier. For instance, carrier  $A$  can serve customer  $i$ 's demand  $d_i^B$  and carrier  $B$  can serve customer  $i$ 's demand  $d_i^A$ , which means carriers are allowed to interchange demands, assuming that customer  $i$  has demand from both carriers  $A$  and  $B$ . A specific demand can not be splitted among carriers. If there exist a demand  $d_i^r > 0$ , then it must be completely delivered in one the routes of carrier  $r \in C_i$ .

In our problem, a carrier  $r \in C$  can only visit the customers that already has demand from that carrier, i.e  $N_r$ . In any route which originates from any depot  $d \in D_r$  of carrier  $r$ , only arcs that can be traversed are  $A^{rd} = \{(i, j) \in A : i, j \in N_r, \text{ or } (i = d \text{ and } j \in N_r), \text{ or } (i \in N_r \text{ and } j = d)\}$ . If a demand is satisfied by another carrier, then this demand amount should be transferred between depots of those carriers. In order to transfer that amount, a transfer line between the corresponding depots must be established.

Among the strategic decisions involved in operating and managing such systems, we focus on determining number and location of regional depots and pairs of carrier depots between which transfer lines are to be established. In addition to that, direct transportation for inbound transportation and routing decisions for outbound

transportation are also considered. Flow of goods from plants to depots, depots to other carriers' depots and depots to customers are determined as well. A general representation of the network structure can be found in Figure 3.1.

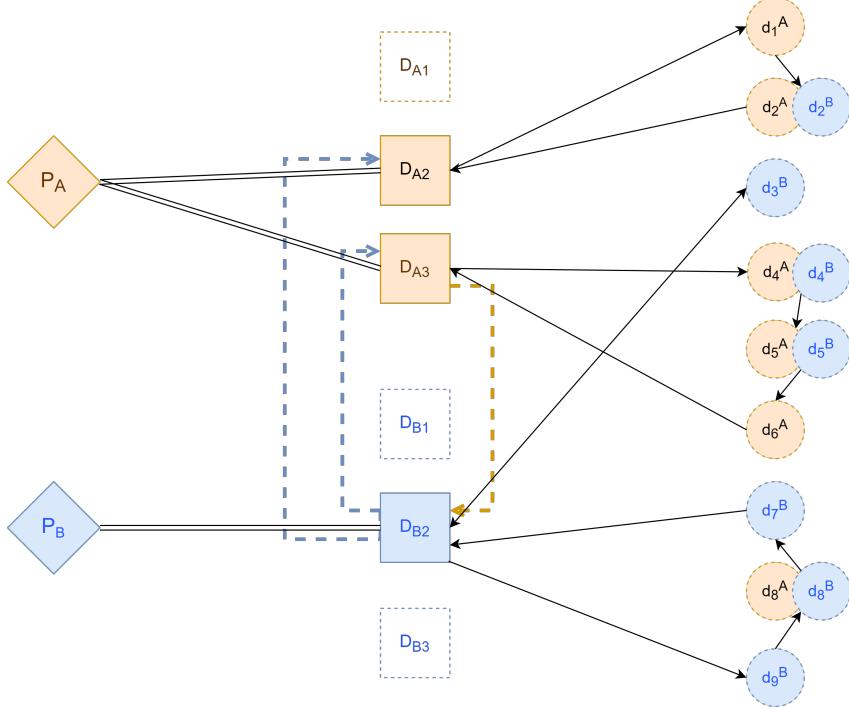


Figure 3.1 Sample network for two carriers

We illustrate the problem with an example and show how the carriers can collaborate. Figure 3.2 depicts a small example with 2 carriers:  $A$  and  $B$ . Each carrier has one plant:  $P_A$  and  $P_B$  for carriers  $A$  and  $B$ , respectively. Carrier  $A$  has two possible depot locations,  $D_A = \{1, 2\}$  and carrier  $B$  has only one possible depot location  $D_B = \{3\}$ . There are three customers,  $N = \{4, 5, 6\}$ . Customer 4 has only demand from carrier  $A$ , customers 5 and 6 have demand from both carriers. Related inbound line, transfer line and outbound route construction costs are depicted on arcs and based on distances between nodes. Regional depot opening and maintenance costs are shown above regional depots. Vehicle capacity  $Q$  is 20 units.

Figure 3.3 (b) shows the result for the non-collaborative scenario. For the non-collaborative scenario, carrier  $A$  opens depot 1 and constructs 2 routes from this depot. One route only serves to customer 4; another route serves customers 5 and 6. Carrier  $B$  opens depot 3 and creates 2 routes for two customers, 5 and 6. Since  $Q = 20$ ,  $d_5^B = 11$  and  $d_6^B = 14$  have to be delivered in different routes. In non-collaborative scenario, inbound line cost for carrier  $A$  is 16, regional depot cost is 17, and outbound routing costs are 53; total cost of carrier  $A = 16 + 17 + 53 = 86$ . For carrier  $B$ , inbound line cost is 10, regional depot cost is 25, and outbound routing costs are 66; total cost of carrier  $B = 10 + 25 + 66 = 101$ . Therefore, total cost for

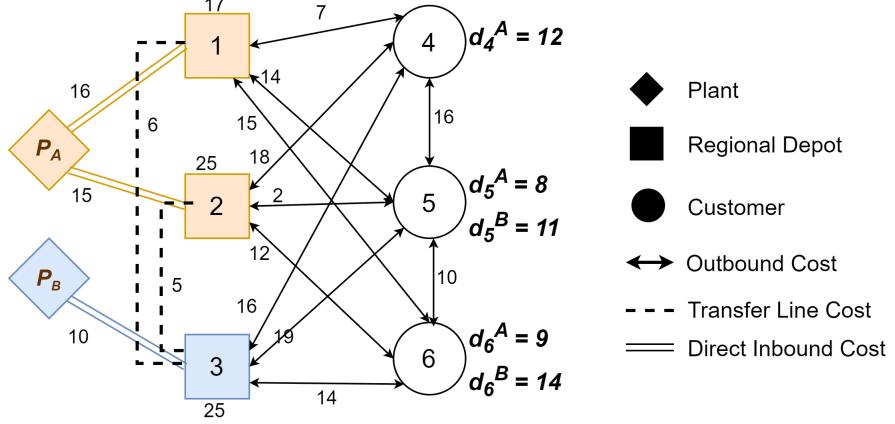


Figure 3.2 A small instance

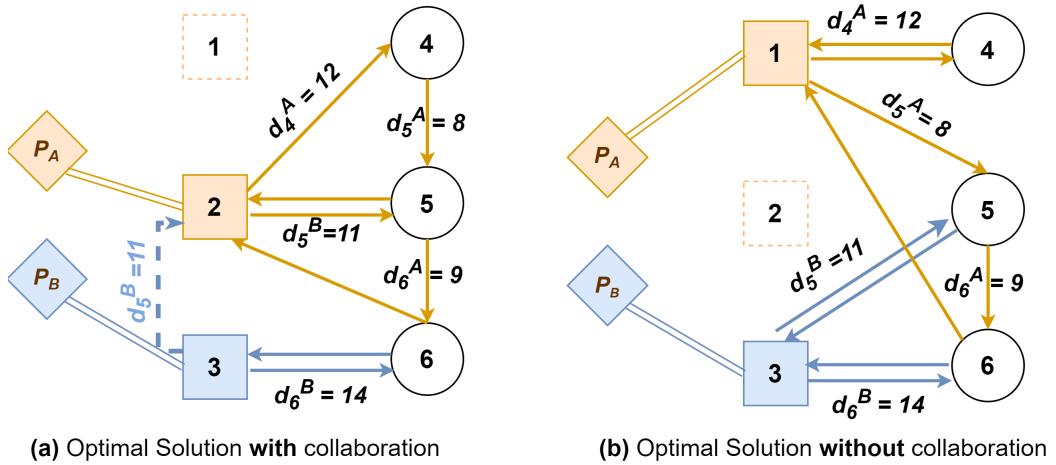


Figure 3.3 Results for collaborative and non-collaborative scenarios

non-collaborative scenario is 187.

Figure 3.3 (a) shows the result for a collaborative scenario. In this scenario carrier A opens depot 2. Carrier B opens depot 3 and creates a transfer line between depots 3 and 2. B transfers  $d_5^B$  to carrier A and sends this amount to depot 2 which belongs to carrier A. Carrier A constructs two routes from depot 2. In the first route, it serves its own demands for customers 4 and 5;  $d_4^A$  and  $d_5^A$ . In the second route, it serves its own demand for customer 6 and customer 5's demand which is transferred from carrier B; i.e  $d_6^A$  and  $d_5^B$ . Carrier B constructs only one route to serve demand  $d_6^B$ . In collaborative scenario, for carrier A inbound line cost is 15, regional depot cost is 25, and outbound routing costs are 60; total cost for carrier A =  $15 + 25 + 60 = 100$ . For carrier B, inbound line cost is 10, regional depot cost is 25, and outbound routing costs are 28. In addition to that, transfer line cost is incurred to carrier B since it constructed a transfer line between depots 3 and 2, which is equal to 5. Total cost of carrier B =  $10 + 25 + 28 + 5 = 68$ . Therefore, total cost for collaborative scenario is 168. In this instance, collaboration led to cost

savings up to approximately 10% for centralized system: 187 vs 168.

For the problem setting, we make the following assumptions:

- There are enough items in plants to satisfy demand.
- Regional depots has unlimited capacity for handling goods, but once one depot is used, opening and maintenance costs are incurred.
- All the locations for plants, candidate regional depots and customers and distances between those locations are known in advance.
- Demand for each customer is known in advance.
- Demand of each customer from each carrier is less than  $Q$ .
- Homogeneous vehicle fleets are used.
- The set of common customers is known in advance.
- There is a centralized decision making process.

The objective of this collaborative goods distribution network design problem is to minimize the costs which arise from regional depot opening and maintenance, direct inbound transportation, outbound transportation and transfer line construction between regional depots. Alternative mathematical models are proposed to solve this strategic network design problem. Mathematical models differ in terms of formulating outbound transportation operations.

### 3.2 Mathematical Models

Parameters and sets which are common for all models are defined in Table 3.2.

Table 3.1 Common notation for all three models

Set	Definition	
$C$	set of carriers	
$N$	set of customers	
$P$	set of plants	
$D$	set of possible regional depot locations	
$D_r$	set of possible regional depot locations for carrier $r$	$\forall r \in C$
$P_r$	set of plants that belong to carrier $r$	$\forall r \in C$
$N_r$	set of customers that have demand from carrier $r$	$\forall r \in C$
$C_i$	set of carriers that have $i$ as a customer	$i \in N$
$d_i^r$	demand of customer $i$ from carrier $r$	$i \in N, r \in C$
$S_r$	set of carriers that has at least one common customer with carrier $r$ , including $r$	$r \in C$
$V$	vertex set including regional depots and customers $V = N \cup D \cup P$	
$A$	arcs in the network: $A = \{(V \times V) \setminus ((N \times P) \cup (P \times N))\}$	
$c_{ij}$	cost of traversing arc $(i, j)$	$(i, j) \in A$
$B_{rd}$	cost of opening and operating regional depot $d$ of the carrier $r$	$\forall r \in C, d \in D_r$
$\Delta_{prd}$	inbound transfer line construction cost from plant $p$ to depot $d$ of carrier $r$	$\forall r \in C, d \in D_r$ $p \in P_r$
$F_{d,d'}$	cost of constructing a transfer line between regional depots $d$ to $d'$	$\forall r \in C, d \in D_r, s \in S_r, d' \in D_s, r \neq s$
$A^{rd}$	possible arcs that can be traversed in a route that is assigned to carrier $r$ 's depot $d$ $A^{rd} = \{(i, j) \in A : i, j \in N_r, \text{ or } (i = d \text{ and } j \in N_r)$ $(i \in N_r \text{ and } j = d)\}$	$\forall r \in C, d \in D_r$

In all models  $y_{rd}$ ,  $v_{d'd}$ ,  $\delta_{prd}$ ,  $\pi_{d'd}$ ,  $u_{prd}$  and  $w_{srd}$  are common decision variables. The binary decision variable  $y_{rd}$  is equal to 1 if regional depot  $d$  which belongs to carrier  $r$  is opened; 0, otherwise,  $\forall r \in C, d \in D_r$ . Binary decision variable  $v_{d'd}$  is equal to 1 if a transfer line established between depots  $d'$  and  $d$  that belong to different carriers; 0, otherwise. The binary decision variable  $\delta_{prd}$  is equal to 1 if a inbound transfer line is constructed between plant  $p$  and regional depot  $d$  of carrier  $r$ ; 0, otherwise. Continuous decision variable  $\pi_{d'd}$  represents the amount of goods transferred between regional depots  $d'$  and  $d$ ,  $u_{prd}$  represents the amount of goods sent from plant  $p$  to regional depot  $d$  of carrier  $r$ .  $w_{srd}$  denotes a continuous auxiliary decision variable used to calculate amount of demand of carrier  $s$  which is satisfied by carrier  $r$ 's regional depot  $d$ . In the subsequent sections, additional new decision variables and parameters are defined depending on the mathematical model.

Table 3.2 Common decision variables for all three models

Dec. Var.	Definition
$y_{rd}$	1 if regional depot $d$ which belongs to carrier $r$ is opened
$v_{d'd}$	1 if a transfer line established between depots $d'$ and $d$ that belong to different carriers; 0, otherwise
$\delta_{prd}$	1 if a inbound transfer line is constructed between plant $p$ and regional depot $d$ of carrier $r$ ; 0, otherwise
$\pi_{d'd}$	amount of goods transferred between regional depots $d'$ and $d$
$u_{prd}$	amount of goods sent from plant $p$ to regional depot $d$ of carrier $r$
$w_{srd}$	amount of demand of carrier $s$ which is satisfied by carrier $r$ 's regional depot $d$

### 3.2.1 Model 1: Vehicle-Based Formulation

In the first mathematical model, outbound routing decisions are denoted by decision variables which are representing arc traversals by vehicles. This model yields an exact solution to the problem. We define an additional parameter  $K_{rd}$  for each depot  $d \in D_r$  of carrier  $r \in C$  which represents the set of vehicles that belong to depot  $d$ . We define two additional binary decision variables  $z$  and  $x$ .  $z_{irs}^k$  is equal to 1 if demand  $d_i^r$  is assigned to vehicle  $k$  of depot  $d$  which belongs to carrier  $s$ , for  $i \in N, r \in C_i, s \in C_i, d \in D_s, k \in K_{sd}$ ; 0, otherwise. For each carrier  $r \in C$  and depot  $d \in D_r, k \in K_{rd}, (i, j) \in A^{rd}$ ,  $x_{ij}^k$  is equal to 1, if arc  $(i, j)$  is traversed by vehicle  $k$ , 0

otherwise. The resulting formulation becomes

$$(3.1) \quad \text{minimize} \quad \sum_{r \in C} \sum_{d \in D_r} \sum_{k \in K_{rd}} \sum_{(i,j) \in A^{rd}} c_{ij} x_{ij}^k + \sum_{r \in C} \sum_{d \in D_r} B_{rd} y_{rd} \\ + \sum_{r \in C} \sum_{d \in D_r} \sum_{\substack{s \in S_r \\ s \neq r}} \sum_{d' \in D_s} F_{dd'} v_{dd'} + \sum_{r \in C} \sum_{d \in D_r} \sum_{p \in P_r} \Delta_{prd} \delta_{prd}$$

subject to

$$(3.2) \quad \sum_{s \in C_i} \sum_{d \in D_s} \sum_{k \in K_{sd}} z_{irs}^k = 1 \quad \forall i \in N, r \in C_i$$

$$(3.3) \quad \sum_{j \in N_r} x_{d,j}^k \leq 1 \quad \forall r \in C, d \in D_r, k \in K_{rd}$$

$$(3.4) \quad \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} x_{j,i}^k - \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} x_{i,j}^k = 0 \quad \forall r \in C, d \in D_r, k \in K_{rd}, i \in N_r$$

$$(3.5) \quad \sum_{i \in N_r} \sum_{s \in C_i} z_{isrd}^{k-1} \geq \sum_{i \in N_r} \sum_{s \in C_i} z_{isrd}^k \quad \forall r \in C, d \in D_r, k \in K_{rd} \setminus \min\{k : k \in K_{rd}\}$$

$$(3.6) \quad \sum_{i \in W} \sum_{\substack{j \in N_r \setminus W \\ \cup \{d\}, i \neq j}} x_{i,j}^k \geq z_{isrd}^k \quad \forall r \in C, d \in D_r, k \in K_{rd}, s \in S_r, W \subset N_r, i \in W \cap N_s$$

$$(3.7) \quad \sum_{i \in N_r} \sum_{s \in C_i} d_i^s z_{isrd}^k \leq Q \quad \forall r \in C, d \in D_r, k \in K_{rd}$$

$$(3.8) \quad y_{rd} \sum_{i \in N} \sum_{r \in C} d_i^r \geq \sum_{i \in N_r} \sum_{s \in C_i} \sum_{k \in K_{rd}} z_{isrd}^k \quad \forall r \in C, d \in D_r$$

$$(3.9) \quad w_{srd} = \sum_{i \in N_s \cap N_r} \sum_{k \in K_{rd}} d_i^s z_{isrd}^k \quad \forall r \in C, d \in D_r, s \in S_r$$

$$(3.10) \quad \sum_{i \in N} \sum_{r \in C} d_i^r \sum_{d' \in D_s} v_{d',d} \geq w_{srd} \quad \forall r \in C, d \in D_r, s \in S_r, r \neq s$$

$$(3.11) \quad \sum_{d' \in D_s} v_{d',d} \leq 1 \quad \forall r \in C, d \in D_r, s \in S_r, r \neq s$$

$$(3.12) \quad \sum_{d' \in D_s} \pi_{d',d} = w_{srd} \quad \forall r \in C, d \in D_r, s \in S_r, r \neq s$$

$$(3.13) \quad v_{d',d} \sum_{i \in N} \sum_{r \in C} d_i^r \geq \pi_{d',d} \quad \forall r \in C, d \in D_r, s \in S_r, d' \in D_s, r \neq s$$

$$(3.14) \quad |D||D|y_{rd} \geq \sum_{d' \in D_s} v_{d,d'} \quad \forall r \in C, d \in D_r, s \in S_r, r \neq s$$

$$(3.15) \quad \delta_{prd} \sum_{i \in N} \sum_{r \in C} d_i^r \geq u_{prd} \quad \forall r \in C, d \in D_r, p \in P_r$$

$$(3.16) \quad \sum_{p \in P_r} u_{prd} + \sum_{\substack{s \in S_r \\ s \neq r}} w_{srd} - \sum_{s \in S_r} \sum_{\substack{d' \in D_s \\ s \neq r}} \pi_{d,d'} = \sum_{i \in N_r} \sum_{s \in C_i} \sum_{k \in K_{rd}} d_i^s z_{isrd}^k \quad \forall r \in C, d \in D_r$$

$$(3.17) \quad x_{ij}^k \in \{0, 1\} \quad \forall r \in C, d \in D_r, k \in K_{rd}, (i, j) \in A^{rd}$$

$$(3.18) \quad z_{irs}^k \in \{0, 1\} \quad \forall i \in N, r, s \in C_i, d \in D_s, k \in K_{sd}$$

$$(3.19) \quad y_{rd} \in \{0, 1\} \quad \forall r \in C, d \in D_r$$

$$(3.20) \quad v_{d',d} \in \{0, 1\} \quad \forall r \in C, d \in D_r, s \in S_r, d' \in D_s, r \neq s$$

$$(3.21) \quad \delta_{prd} \in \{0, 1\} \quad \forall r \in C, d \in D_r, p \in P_r$$

$$(3.22) \quad u_{prd} \in \mathbb{R}_+ \quad \forall r \in C, d \in D_r, p \in P_r$$

$$(3.23) \quad \pi_{d',d} \in \mathbb{R}_+ \quad \forall r \in C, d \in D_r, s \in S_r, d' \in D_s, r \neq s$$

$$(3.24) \quad w_{srd} \in \mathbb{R}_+ \quad \forall r \in C, d \in D_r, s \in S_r$$

The objective function (3.1) minimizes total cost which arise from outbound transportation, opening and operating depots, inbound transportation and transfer line construction between depots. Constraints (3.2) guarantee that each demand that a customer has from its own carriers, is satisfied by a possible carrier (any carrier that has this customer) once. Constraints (3.3) guarantee that each vehicle can leave a depot at most one time. Constraints (3.4) ensure that a vehicle visiting a customer should leave that customer. Moreover, constraints (3.3) and (3.4) work together to describe flow equality in the vehicle routes. Constraints (3.5) depict that a vehicle with a higher index can not be utilized if another vehicle with a lower index is not utilized from a depot of the same carrier. In other words, the model orders used vehicles in ascending order. Constraints (3.6) guarantee two restrictions. For  $W = \{i\}$ , they ensure that if the demand  $d_i^s$  is assigned to any vehicle  $k \in K_{rd}$  of depot  $d \in D_r$  of carrier  $r \in C_i$ , then this vehicle visits customer  $i$ . Moreover, they ensure that subtours are not generated since if a customer in set  $W$  is visited by a vehicle  $k \in K_{rd}$  then that vehicle use at least one arc which leaves set  $W$ . Constraints (3.7) guarantee that vehicle capacities is not exceeded. Constraints (3.8) indicate that demand can not be satisfied from a depot if the depot is not opened. Constraints (3.9) are used to calculate amount of demand that originally belongs to carrier  $s \in C$  but satisfied from carrier  $r$ 's depot  $d$ . Constraints (3.10) guarantee that a transfer line

should be constructed from one of the depots of the other carrier to the that depot if a carrier satisfied another carrier's demand from its depot. Constraints (3.11) work with constraints (3.10) to ensure that at most one transfer line can be constructed from a carrier's depots to another carriers' one specific depot. Constraints (3.12) calculates the amount that should be transferred between depots. Constraints (3.13) guarantee that there can not be any flow of goods between different carriers' depots if transfer line among these depots is not constructed. Constraints (3.14) ensure that a transfer line can not be constructed which originates from that depot if the depot is not opened. Constraints (3.15) guarantee that goods can not be transferred between a plant and a depot if inbound line is not constructed between a plant and a depot. Constraints (3.16) guarantee the flow balance of goods and ensure the enough amount of goods are transferred from plants to depots. Constraints (3.17), (3.18), (3.19), (3.20), (3.21), (3.22), (3.23) and (3.24) define the domains and ranges of the decision variables.

### 3.2.2 Model 2: Load-Based Formulation

In the second mathematical model, outbound routing decisions are modeled with decision variables representing amount of loads carried. Main motivation is to decrease high number of binary variables that are used to define outbound routing decisions (i.e.,  $x_{ij}^k$ ). Instead of using a binary decision variable to determine whether a vehicle which belongs to a depot of a carrier is using an arc or not, we define a new arc variable which uses an aggregated form of using arcs originating from a depot. If route originating from depot  $d$  of carrier  $r$ ,  $r \in C, d \in D_r$ , uses arc  $(i, j) \in A^{rd}$ , binary decision variable  $x_{ij}^{rd}$  takes value 1; otherwise, it takes 0. Decreased number of binary variables  $x$  is traded with new defined continuous variables  $l$  which are used to control overall load of the routes on the traversed arcs.  $l_{ij}^{rdh}$  represents the load carried on arc  $(i, j) \in A^{rd}$  to serve customer  $h \in N_r$  on a route originating from depot  $d \in D_r$  of carrier  $r \in C$ . Lastly, as in the  $x$  variables, vehicle index is dropped for allocation variable  $z$  as well. New binary allocation variable  $z_{irsds}$  is equal to 1 if  $d_i^r$  is assigned to any route which originates from depot  $d \in D_s$ ,  $s \in C_i$ ; 0, otherwise. The resulting formulation becomes

$$(3.25) \quad \text{minimize} \quad \sum_{r \in C} \sum_{d \in D_r} \sum_{(i,j) \in A^{rd}} c_{ij} x_{ij}^{rd} + \sum_{r \in C} \sum_{d \in D_r} B_{rd} y_{rd} \\ + \sum_{r \in C} \sum_{d \in D_r} \sum_{\substack{s \in S_r \\ s \neq r}} \sum_{d' \in D_s} F_{dd'} v_{dd'} + \sum_{r \in C} \sum_{d \in D_r} \sum_{p \in P_r} \Delta_{prd} \delta_{prd}$$

subject to

$$(3.26) \quad \sum_{s \in C_i} \sum_{d \in D_s} z_{irs} = 1 \quad \forall i \in N, r \in C_i$$

$$(3.27) \quad \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} x_{j,i}^{rd} - \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} x_{i,j}^{rd} = 0 \quad \forall r \in C, d \in D_r, i \in N_r$$

$$(3.28) \quad \sum_{\substack{j \in N_s \cup \{d\} \\ i \neq j}} x_{i,j}^{sd} \geq z_{irs} \quad \forall i \in N, r, s \in C_i, d \in D_s$$

$$(3.29) \quad \sum_{j \in N_r} l_{d,j}^{rdi} = \sum_{s \in C_i} d_{is} z_{irs} \quad \forall r \in C, d \in D_r, i \in N_r$$

$$(3.30) \quad \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} l_{i,j}^{rdh} - \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} l_{j,i}^{rdh} = \begin{cases} -\sum_{s \in C_i} d_{is} z_{irs} & \text{if } i = h \\ 0 & \text{if } i \neq h \end{cases} \quad \forall r \in C, d \in D_r, i, h \in N_r$$

$$(3.31) \quad \sum_{h \in N_r} l_{i,j}^{rdh} \leq Q x_{i,j}^{rd} \quad \forall r \in C, d \in D_r, (i,j) \in A^{rd}$$

$$(3.32) \quad y_{rd} \sum_{i \in N} \sum_{r \in C} d_i^r \geq \sum_{i \in N_r} \sum_{s \in C_i} z_{irs} \quad \forall r \in C, d \in D_r$$

$$(3.33) \quad w_{srd} = \sum_{i \in N_s \cap N_r} d_i^s z_{irs} \quad \forall r \in C, d \in D_r, s \in S_r$$

$$(3.10) - (3.15)$$

$$(3.34) \quad \sum_{p \in P_r} u_{prd} + \sum_{\substack{s \in S_r \\ s \neq r}} w_{srd} - \sum_{\substack{s \in S_r \\ s \neq r}} \sum_{d' \in D_s} \pi_{d,d'} = \sum_{i \in N_r} \sum_{s \in C_i} d_i^s z_{irs} \quad \forall r \in C, d \in D_r$$

$$(3.35) \quad x_{ij}^{rd} \in \{0, 1\} \quad \forall r \in C, d \in D_r, (i,j) \in A^{rd}$$

$$(3.36) \quad z_{irs} \in \{0, 1\} \quad \forall i \in N, r, s \in C_i, d \in D_s$$

$$(3.37) \quad l_{ij}^{rdh} \in \mathbb{R}_+ \quad \forall r \in C, d \in D_r, (i,j) \in A^{rd}, h \in N_r$$

$$(3.19) - (3.24)$$

Constraints (3.26) ensure that demand of each customer is satisfied by a possible carrier. Constraints (3.27) guarantee the flow equality of incoming and outgoing arcs to customers in an aggregated route which belongs to depot  $d$  of carrier  $r$ . Constraints (3.28) ensure that at least one arc must be activated if any of that customer's demand is assigned to any route of depot  $d$  of carrier  $s$ . In other words, if a demand is assigned to a route which originates from depot  $d$ , then the customer must be visited at least once. Constraints (3.29) ensure that amount of satisfied demand which belongs to customer  $h$  in a route of depot  $d$  leaves that depot  $d$ . Constraints (3.30) guarantee that required amount of assigned demands are delivered by the routes of depot  $d$  to customer  $h$  if  $i = h$ . They also guarantee that no load is served if  $i \neq h$ . Constraints (3.31) depicts that amount of load served in a route can not exceed the vehicle capacity. They also relate the variables  $l$  and  $x$  and ensure that any load can not be carried on an arc if the arc is not used. Constraints (3.32) indicate that any demand can not be satisfied from a regional depot if the depot is not opened. Constraints (3.33) are used to calculate amount of demand that originally belongs to carrier  $s \in C$  but is satisfied from carrier  $r$ 's depot  $d$ . Constraints (3.34) guarantee the flow balance of goods and ensure that a sufficient amount of goods are transferred from plants to depots. Constraints (3.35), (3.36) and (3.37) define the domains and ranges of the decision variables.

### 3.2.3 Model 3: Path-Based Formulation

In the path-based formulation, outbound routes are not constructed within by the formulation. Instead, they are selected among heuristically pre-generated routes. We define an additional parameter  $R$  which denotes the set of pre-generated routes. For the heuristic route creation, problem is decomposed for each carrier  $r \in C$  and solved as a single depot VRP for each depot of each carrier  $d \in D_r$ . Then all routes in each solution are united into a master route list. Parameter  $R_d$  represents the set of routes which belongs to depot  $d \in D_r$ .  $\alpha_{ird}^t$  is the assignability parameter; it is equal to 1 if demand  $d_i^r$  can be assigned to route  $t \in R_d$ ,  $r \in C, d \in D_r$ ; 0, otherwise. In other words,  $\alpha_{ird}^t$  is 1 if customer  $i$  is included in route  $t$  and  $i$  has demand from the carrier who owns this route. In this respect, we define the binary decision variable  $x^t$  is equal 1 if route  $t \in R$  is used and 0 otherwise. Binary allocation variable  $z_{irs}^t$  is equal to 1 if demand  $d_i^r$  is assigned to route  $t \in R_s$  which originates from depot

$d \in D_s$  of carrier  $s \in C$ . The cost parameter  $c$  is altered as  $c^t$  and denotes the length of route  $t$ .

$$(3.38) \quad \begin{aligned} \text{minimize} \quad & \sum_{t \in R} x^t c^t + \sum_{r \in C} \sum_{d \in D_r} B_{rd} y_{rd} + \sum_{r \in C} \sum_{d \in D_r} \sum_{s \in S_r} \sum_{\substack{d' \in D_s \\ s \neq r}} F_{dd'} v_{dd'} \\ & + \sum_{r \in C} \sum_{d \in D_r} \sum_{p \in P_r} \Delta_{prd} \delta_{prd} \end{aligned}$$

subject to

$$(3.39) \quad \sum_{s \in C_i} \sum_{d \in D_s} \sum_{t \in R_d} z_{irsrd}^t = 1 \quad \forall i \in N, r \in C_i$$

$$(3.40) \quad x^t \geq z_{irsrd}^t \quad \forall i \in N, s, r \in C_i, d \in D_r, t \in R_d$$

$$(3.41) \quad z_{irsrd}^t \leq \alpha_{ird}^t \quad \forall i \in N, s, r \in C_i, d \in D_r, t \in R_d$$

$$(3.42) \quad \sum_{i \in N_r} \sum_{s \in C_i} d_i^s z_{irsrd}^t \leq Q \quad \forall r \in C, d \in D_r, t \in R_d$$

$$(3.43) \quad y_{rd} \sum_{i \in N} \sum_{r \in C} d_i^r \geq \sum_{i \in N_r} \sum_{s \in C_i} \sum_{t \in R_d} z_{irsrd}^t \quad \forall r \in C, d \in D_r$$

$$(3.44) \quad w_{srd} = \sum_{i \in N_s \cap N_r} \sum_{t \in R_d} d_i^s z_{irsrd}^t \quad \forall r \in C, d \in D_r, s \in S_r$$

$$(3.10) - (3.15)$$

$$(3.45) \quad \sum_{p \in P_r} u_{prd} + \sum_{\substack{s \in S_r \\ s \neq r}} w_{srd} - \sum_{\substack{s \in S_r \\ s \neq r}} \sum_{d' \in D_s} \pi_{d,d'} = \sum_{i \in N_r} \sum_{s \in C_i} \sum_{t \in R_d} d_i^s z_{irsrd}^t \quad \forall r \in C, d \in D_r$$

$$(3.46) \quad x^t \in \{0, 1\} \quad \forall r \in C, d \in D_r, t \in R_d$$

$$(3.47) \quad z_{irsrd}^t \in \{0, 1\} \quad \forall i \in N, r, s \in C_i, d \in D_s, t \in R_d$$

$$(3.19) - (3.24)$$

Constraints (3.39) guarantee that demand of each customer is satisfied by a possible carrier. Constraints (3.40) relate variables  $x$  and  $z$  and ensure that a route is used if a demand is assigned to that route. Constraints (3.41) ensure that a demand from a customer can be assigned to a route if and only if that route contains that customer. Constraints (3.42) guarantees that vehicle capacities are not exceeded. Constraints

(3.43) indicates any demand can not be satisfied from a regional depot if the depot is not opened. Constraints (3.44) are used to calculate amount of demand that originally belongs to carrier  $s$  but it is satisfied from carrier  $r$ 's depot  $d$ . Constraints (3.45) guarantee the flow balance of goods and ensure that a sufficient amount is transferred from plants to depots. Constraints (3.46) and (3.47) define the domains and ranges of the decision variables.

## 4. VEHICLE-BASED FORMULATION

In the vehicle-based formulation, the number of sub-tour elimination constraints is exponential and the number of required binary variables for outbound routing is excessive. For the outbound routing decision variables,  $x$ , it is required to define  $\sum_{r \in C} \sum_{d \in D_r} |K_{rd}| |A^{rd}|$  many variables. This number is polynomial but increases the size significantly. In the original formulation, number of required constraints are polynomial except constraints (3.6). For the vehicle-based formulation, we propose an exact method for handling exponentially many constraints. The corresponding exact method is based on a cut generation scheme for sub-tour elimination constraints.

### 4.1 Cut generation for sub-tour elimination

Constraints (3.6) can be separated into two different constraints, one for connecting variables  $x$  and  $z$ , and the other one to ensure that there are no sub-tours.

$$(4.1) \quad \sum_{\substack{j \in N_r \cup \{d\} \\ i \neq j}} x_{i,j}^k \geq z_{isrd}^k \quad \forall i \in N, s \in C_i, r \in C_i, d \in D_r, k \in K_{rd}$$

$$(4.2) \quad \sum_{i \in W} \sum_{\substack{j \in W \\ j \neq i}} x_{i,j}^k \leq |W| - 1 \quad \forall r \in C, d \in D_r, k \in K_{rd}, W \subseteq N_r$$

Constraints (4.1) ensure that a vehicle must visit a customer at least once if any demand of this customer is assigned to that vehicle. Constraints (4.2) guarantee that there is at least one arc which leaves customer set  $W$  for each vehicle  $K_{rd}$  so that it is ensured that no sub-tours are generated. Constraints (3.6) can be replaced with constraints (4.1) and (4.2).

We propose an exact method for handling exponentially many sub tour elimination constraints with the updated constraints (4.1) and (4.2). Initially, all sub-tour elimination constraints proposed in (4.2) are relaxed. Then, the relaxed version of the problem is solved. Using the active routing variables  $\{x : x = 1\}$ , a sub-graph  $\bar{G}_x$  is constructed; all cycles in  $\bar{G}_x$  are detected using the algorithm in Johnson (1975). Johnson's algorithm is used to detect all simple cycles in a graph since it has a time complexity of  $\mathcal{O}((|V| + |E|)(C + 1)$ ,  $C$  indicating all cycles in a given graph, which is polynomial. If there are no sub-tours in the solution, the method aborts the execution and reports the optimum solution. If there are sub-tours, current solution for variables  $x$  is decomposed for each depot  $d \in D_r, \forall r \in C$  while  $x_d$  represents the active arcs which belong to any route of depot  $d$ . For each depot  $d$ , a sub-graph  $\bar{G}_x^d$  is constructed. All simple cycles for each sub-graph  $\bar{G}_x^d, \forall d \in D$ , are identified using Johnson's algorithm. If any simple cycle includes depot  $d$  itself, then nothing is identified. If there are sub-tours which do not include the depot, they are appended to a set  $\Gamma$  which includes all sub-tours to be eliminated for the given depot  $d$  in the current solution. Then sub-tour elimination constraints used to eliminate the sub-tours that are specific to the given depot are generated as in (4.3) and added to the model. Then, the model is resolved. As the iterations proceed, given solutions converges to a state in which no sub-tours are found. Flowchart of the method is represented in Figure 4.1.

$$(4.3) \quad \sum_{i \in \gamma} \sum_{\substack{j \in \gamma \\ j \neq i}} x_{ij}^k \leq |\gamma| - 1 \quad \forall \gamma \in \Gamma$$

## 4.2 Valid Inequalities for Vehicle-Based Formulation

Number of required binary variables in the vehicle-based formulation is excessive. In order to strengthen the formulation and tighten the solution space several valid inequalities are proposed.

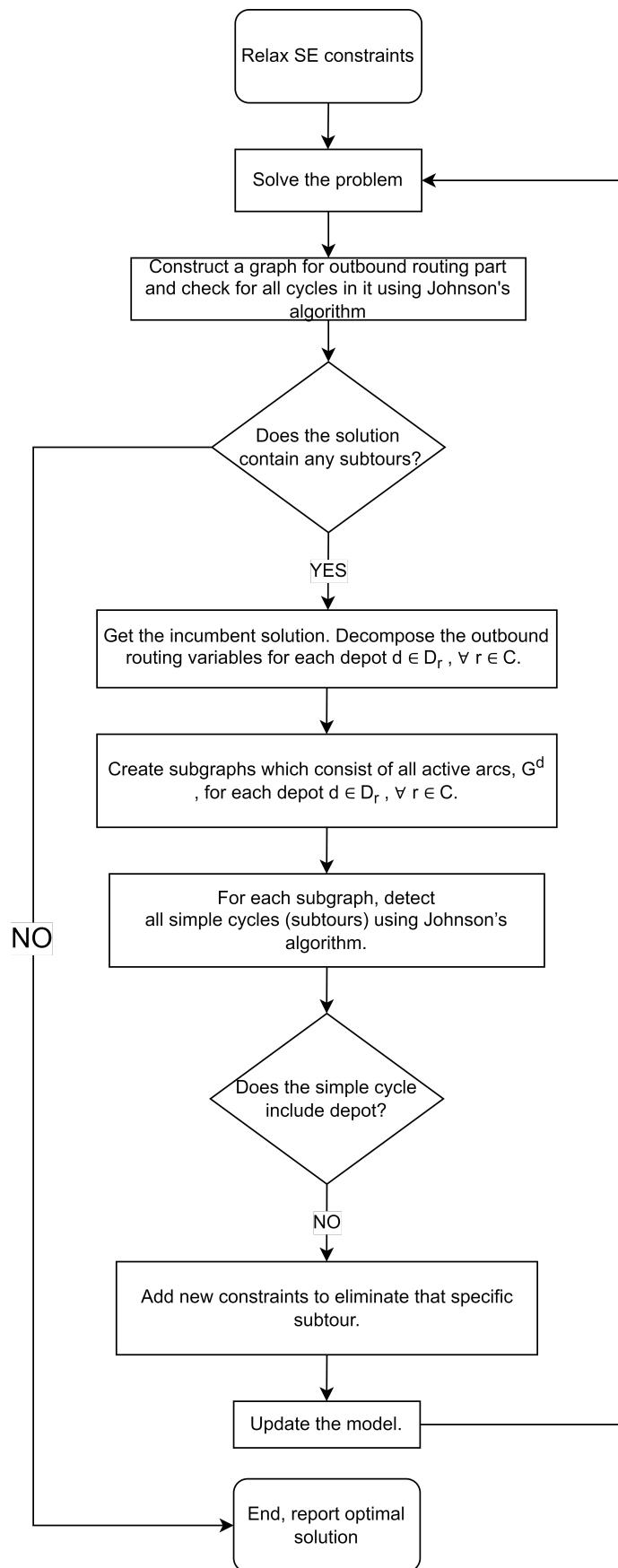


Figure 4.1 Cut generation method

#### 4.2.1 Minimum Depot Valid Inequalities

For any instance, first echelon transportation operations are executed in a direct manner. In other words, inbound deliveries are conducted as direct transportation in which trucks do not ramble around depots. If there is collaboration among carriers than that collaboration must take place at the second echelon including transfer among depots and mutual routing. Consequently, each company has to open and operate at least one regional depot in the system, whether it participates in a collaboration or not. Therefore, inequalities (4.4) are valid for the vehicle-based formulation and impose that each carrier  $r \in C$  must open at least one depot.

$$(4.4) \quad \sum_{d \in D_r} y_{rd} \geq 1 \quad \forall r \in C$$

#### 4.2.2 Two-Size Simple SEC Valid Inequalities

Sub-tour elimination is controlled by the constraints (3.6) in the original vehicle based formulation; they generate all constraints which eliminate all possible sub-tours. However, exponentially many constraints are required and a lower bound for required number of constraints is equal to  $\sum_{r \in C} 2^{|N_r|}$  in the original formulation. So a cut generation based method proposed in Section 4.1 and in this method, sub-tour elimination constraints are relaxed; in each iteration, only required sub-tour elimination constraints are added to the model. In the early iterations, models are tend to create sub-tours of size 2. Inequalities (4.5) eliminate all two-size sub-tour possibilities. Thus, they also eliminate unnecessary iterations which are only conducted to eliminate two-size sub-tours.

$$(4.5) \quad x_{i,j}^k + x_{j,i}^k < 2 \quad \forall r \in C, d \in D_r, k \in K_{rd}, i, j \in N_r, i < j$$

#### 4.2.3 Two-Size SEC Valid Inequalities

(4.6)

$$x_{i,j}^k + x_{j,i}^k \leq 2 - \lceil \frac{\sum_{s \in C_i} d_i^s z_{isrd}^k + \sum_{s \in C_j} d_j^s z_{jsrd}^k}{Q} \rceil \quad \forall r \in C, d \in D_r, k \in K_{rd}, i, j \in N_r, i < j$$

Extended version of (4.5) is proposed in (4.6) inequalities. If any demand of a customer  $i$  or  $j$  is assigned to a vehicle  $k$ , than this vehicle can travel only in one way among two different customer nodes i.e,  $i$  and  $j$ . SECs are activated for customer pairs if some demand of these customers is assigned to a vehicle. The total amount of demand that is assigned to a vehicle can not exceed vehicle capacity  $Q$ . Inside of ceiling operator can take values between 0 and 1. If any demand which emerge from customers  $i$  and  $j$  are not assigned to vehicle  $k$ , then no SECs are generated; otherwise, required two-size SECs are added to model. The ceiling operator breaks the linear structure of the model. So inequalities (4.6) can be replaced with inequalities (4.7).

(4.7)

$$x_{i,j}^k + x_{j,i}^k \leq 2 - \frac{\sum_{s \in C_i} d_i^s z_{isrd}^k + \sum_{s \in C_j} d_j^s z_{jsrd}^k}{Q} \quad \forall r \in C, d \in D_r, k \in K_{rd}, i, j \in N_r, i < j$$

#### 4.2.4 Symmetry Breaking Valid Inequalities

Distances and incurred cost for traversing arcs  $(i, j) \in A$  between nodes (i.e plants, depots and customers) are symmetrical such that  $c_{ij} = c_{ji}$ . As a consequence, model produces two identical solutions for two different outbound routes, one for normal order, one for reversed order. In order to brake that symmetry to some extent, Archetti, Fernández & Huerta-Muñoz (2017)'s inequalities are adopted for the vehicle-based formulation.

(4.8)

$$x_{j,d}^k \leq \sum_{\substack{i \in N_r \\ i < j}} x_{d,i}^k \quad \forall r \in C, d \in D_r, k \in K_{rd}, j \in N_r$$

#### 4.2.5 Outgoing Flow Valid Inequalities

Total amount of products shipped from the plants must be equal to the total amount of demand to conserve flow balance.

$$(4.9) \quad \sum_{r \in C} \sum_{p \in P_r} \sum_{d \in D_r} u_{prd} = \sum_{i \in N} \sum_{r \in C} d_i^r$$

#### 4.2.6 Carrier Inbound Flow Valid Inequalities

For each carrier, amount of products shipped from plants to depots must be equal to the total amount of demand of that carrier which ensures the inbound flow balance for each carrier  $r \in C$ .

$$(4.10) \quad \sum_{p \in P_r} \sum_{d \in D_r} u_{prd} = \sum_{i \in N_r} d_i^r \quad \forall r \in C$$

#### 4.2.7 One Enterance Valid Inequalities

$$(4.11) \quad \sum_{i \in N_r} x_{i,d}^k \leq 1 \quad \forall r \in C, d \in D_r, k \in K_{rd}$$

Those inequalities are the counterpart of (3.3) constraints. These inequalities impose that a vehicle can enter a depot at most once. Constraints (3.4) guarantee that a vehicle can enter a depot at most one time by controlling entering and leaving arc numbers. However, inequalities (4.11) strengthen the formulation.

### 4.3 Experimental Design

Since we focus on a strategic model, computational experiments do not only aim to evaluate the computational challenges of the models and solution methods but also managerial aspects of the proposed centralized collaboration schema. Experimental design lies at the heart of the computational experiments and directly affects the results. Thus, it is of great importance to design experiments carefully.

In order to explore the impact of the problem size on given solution techniques and formulations, three different problem sets are used by (Ercan, 2019). The three data sets differ in terms of number of possible regional depots and customers as follows:

- 30 customers and 10 possible depot locations,
- 50 customers and 15 possible depot locations, and
- 100 customers and 30 possible depot locations

Each instance is constructed on a 100x100 coordinate system in which each carrier in the system  $r \in C$  has one plant at the center of the coordinate system, (50,50). Customers are randomly distributed on the grid and candidate depot locations are determined using a k-means algorithm. Ten different instances are created for each problem size; locations of customers, candidate depot locations, and demand amounts differ in each problem instance. All distances between all nodes (plants, depots, customers) are calculated as Euclidean distances. Regional depot opening and maintenance costs are between 3000 and 6000. The cost of inbound transportation is a function of distance between plant and the regional depot. The outbound routing costs are calculated as a function of distance between travelled nodes. The transfer line cost is a function of distance between depots. Vehicle capacity  $Q$  is set to 1000 for each instance and problem size.

Ercan (2019) provides a problem set for a single carrier. For our computational experiments, we use two carriers. In each instance, we distribute the customers and candidate depot locations among two carriers while some customers and some depot locations are common. Depending on the problem size and experimental setup, number of customers and depot locations change in three different scenarios as

- Original (O),
- Increased Common Customer (ICC), and

- No Common Depot (NCD).

Three different scenarios are used to observe the effect of parameters on the computational behaviour and collaboration activities. In the Original scenario, we have a moderate number of common customers and common depot locations to represent an average collaboration schema. In the Increased Common Customer scenario, in addition to the original common customers, we declare several other customer as "common" while keeping the original common customers. In the No Common Depot scenario, we do not declare any of the possible depot locations as common; in other words, each carrier has to open their depots to the unique locations in the coordinate system.

For each combination of problem size and scenario, the corresponding numbers of customers, depot locations, common depot locations, common customers and total depot locations are shown in Table 4.1.

Table 4.1 Experimental setup parameters

	30 Customers			50 Customers			100 Customers		
	O	ICC	NCD	O	ICC	NCD	O	ICC	NCD
# Customers	30	30	30	50	50	50	100	100	100
# Depot Locations	10	10	10	15	15	15	30	30	30
# Common Depot Locations	4	4	0	4	4	0	8	8	0
# Common Customers	8	14	8	10	18	10	20	40	20
# Total Depot Locations	14	14	10	19	19	15	38	38	30

An example to the proposed instances can be found in Figure 4.2 with 30 customers and 10 candidate depot locations.

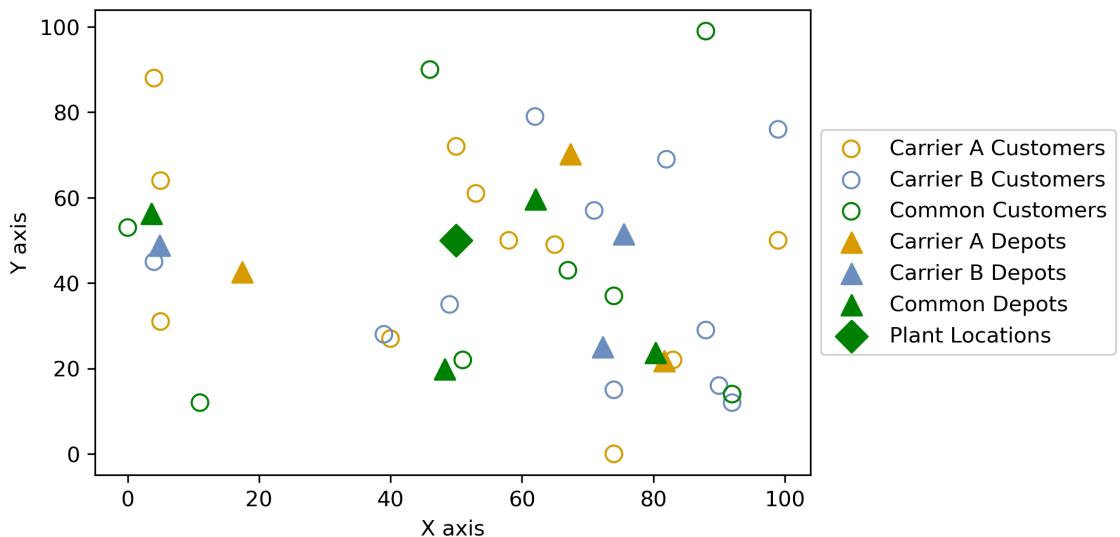


Figure 4.2 Instance 1 with 30 customers and 10 total candidate depot locations

The third dimension of our experimental setting is on the demand density. We conduct our experiments in two different demand settings: "Low Demand" and "High Demand". "Low Demand" setting depicts the initial demand setting in Ercan (2019) since we already divide demand of common customers between the two carriers. In the "High Demand" setting, we multiply all the demand by 2 to achieve a setup with higher demand density.

#### 4.4 Computational Experiments

For the computational experiments, we utilize the commercial solver Gurobi. Since Gurobi or any commercial solver has limited capabilities to solve large instance problems, we apply different solution methodologies for each formulation approach. We utilized the High Performance Computing (HPC) server of the Sabancı University. HPC servers are equipped with Intel(R) Xeon(R) Gold 6140 CPU @ 2.30GHz X2 processors in each node. For each run, a partition from any node of the HPC is created with 4 cores, and 64 GBs of RAM and the partition had an 64 bit Linux operating system. Data manipulation and preparation is conducted through Python 3.8 using PyCharm and Spyder IDE's. Gurobi 9.1.2 is used throughout gurobipy API. The computational time limit is set to 8 hours for 30 customer instances, 16 hours for 50 customer instances and 48 hours for 100 customer instances.

Our computational experiments started with the most simple setup, original VB formulation of vehicle-based (VB) formulation we were not able to solve any of the instances with 30 customers in the original scenario since they did not fit into random access memory. Main reason is the number of constraints in (3.6) which eliminates sub-tours and couples variables  $x$  and  $z$ . At least  $2^{|N_r|} |K_{rd}|$  many constraints are generated which directly exceeds several million constraints.

Because of the space complexity of the original VB formulation, a cut generation procedure to eliminate sub-tours is proposed in Section 4.1. We repeat all the tests indicated above with the cut generation method in order to avoid out of memory issues and results of those runs can be found in Table 4.2.

Table 4.2 Results using the cut generation method with VB formulation for the instances with 30 customers

Ins.	$F_A$	$F_B$	$T_A$	$T_B$	$Obj$	$Obj_A$	$Obj_B$	$T(s)$	Gap
<b>1</b>	1	2	2	1	66085	25145	40940	28800	25.5%
<b>2</b>	1	2	2	0	69977	27532	42445	28800	29.6%
<b>3</b>	-	-	-	-	-	-	-	28800	-
<b>4</b>	-	-	-	-	-	-	-	28800	-
<b>5</b>	-	-	-	-	-	-	-	28800	-
<b>6</b>	2	1	1	2	67788	42946	24842	28800	30.7%
<b>7</b>	-	-	-	-	-	-	-	28800	-
<b>8</b>	-	-	-	-	-	-	-	28800	-
<b>9</b>	-	-	-	-	-	-	-	28800	-
<b>10</b>	1	2	2	1	76991	34032	42959	28800	36.8%

Using the cut generation method, we are able to create and run all the instances for the original scenario of 30 customers without having any memory related issues.

In Table 4.2,  $F_A$  and  $F_B$  show how many facilities opened by carriers  $A$  and  $B$ , respectively.  $T_A$  and  $T_B$  indicate how many transfer lines are constructed by carriers  $A$  and  $B$ , respectively. While  $Obj$  shows the objective function value,  $Obj_A$  and  $Obj_B$  depict the cost separately for each carrier.  $T(s)$  indicates the run time in seconds and  $Gap$  indicates the percentage optimality gap reported by the solver. Rows with –’s represent that no feasible solution found within given time limit.

Within 8 hours of time limit, only 4 instances obtained a solution and the average gap for those four instances is 30.6%. For the rest of the instances, Gurobi was not able to find any feasible solution. Thus, in order to shrink the solution space and lower the gaps, several valid inequalities are proposed in Section 4.2. The valid inequalities (VI) are systematically added to the model in order to see the effect on the solution time and quality. Run results with different combinations of VIs can be found in Table 4.3. For all runs, time limit is set to 8 hours which is same with the previous tests.

Table 4.3 Effect of different combinations of valid inequalities to VB formulation

Ins.	(4.8)		(4.5) + (4.8)		(4.7) + (4.8)		(4.5) + (4.7) + (4.8)		All	
	Obj	Gap	Obj	Gap	Obj	Gap	Obj	Gap	Obj	Gap
1	68814	28.3%	68664	28.4%	69287	28.1%	68008	27.7%	67683	27.4%
2	-	-	-	-	72223	31.2%	-	-	-	-
3	76424	37.8%	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-
6	-	-	-	-	73753	36.7%	-	-	-	-
7	-	-	-	-	-	-	-	-	-	-
8	-	-	-	-	-	-	-	-	-	-
9	81462	36.3%	-	-	-	-	-	-	-	-
10	-	-	-	-	-	-	-	-	-	-

Different combinations of VIs yield different results when compared to the results indicated in Table 4.2. In the first column, only symmetry braking inequalities (4.8) are added to the model. With those inequalities, solver found feasible results for instances 3 and 9. Without those inequalities, it was not able to find any solutions for these instances. However, solver could not find any solution for instances 2, 4 and 10. Nonetheless, it found solutions without those inequalities. Then two-size simple SEC inequalities (4.5) are added in addition to symmetry braking inequalities; only one instance was solved. Then, two-size simple SECs are swapped with two-size SEC inequalities (4.7); instance 6 was solved with this combination but solver was not able to find solutions for other instances which it found solutions before. Then both two-size SEC inequalities are added to the model in addition to the symmetry braking inequalities. With these 3 additional inequalities, only instance 1 is solved. For the last test, all proposed VIs in Section 4.2 is added to the model; the solver

reported a solution for only instance 1.

While adding new inequalities, the model size is increasing and solver behaviour is changing. The solver was able to find new solutions which are previously not attained. On the other hand, since new constraints are added to the model, model size increases and search behaviour of the solver changes. Depending on the instance, solver may or may not be able to find good or any solutions when compared to cases in which no VIs are added. Also there is no significant change in the optimality gaps and still all the reported gaps are not close to 0.

As mentioned earlier , there are two main drivers which increase problem complexity in the VB formulation; number of binary variables for outbound routing decisions and handling sub-tour elimination constraints. To cope with those challenges, several methods are experimented with. In terms of space complexity issues, all the difficulties are solved. However, solution times still remain too high.

Consequently, a new load-based formulation is proposed in Section 3.2.2 in which outbound operations are controlled with continuous variables instead of a high number of binary variables. Details of load-based approach discussed in Section 5.

## 5. LOAD-BASED FORMULATION

In the load-based formulation, many continuous load variables are defined in the exchange of decreased number of binary variables. New valid inequalities are proposed for load-based formulation and their effects on solution times investigated. Then since instances become solvable, strategic analysis performed using load-based formulation.

### 5.1 Valid Inequalities for Load Based Formulation

For the load-based formulation, inequalities (4.4),(4.9) and (4.10) that are proposed in Section 4.2 are valid as well. Two different valid inequalities are proposed below for the load-based formulation.

#### 5.1.1 Capacity Cut Valid Inequalities

In the load-based formulation, amount of load that leaves a depot for a customer is controlled by variables  $l$  and constraints (3.28). Therefore, minimum number of arcs that must be used can be limited as well using inequalities (5.1) with a similar motivation that is proposed by Fernández et al. (2018).

$$(5.1) \quad \sum_{j \in N_r} x_{d,j}^{rd} \geq \lceil \frac{\sum_{i \in N_r} \sum_{s \in C_i} d_i^s z_{isrd}}{Q} \rceil \quad \forall r \in C, d \in D_r$$

By the same convergence with (4.6), inequalities (5.1) destruct linear structure of

the load based model. They can be replaced with (5.2).

$$(5.2) \quad \sum_{j \in N_r} x_{d,j}^{rd} \geq \frac{\sum_{i \in N_r} \sum_{s \in C_i} d_i^s z_{isrd}}{Q} \quad \forall r \in C, d \in D_r$$

### 5.1.2 Symmetry Breaking Valid Inequalities

As indicated in Section 4.2.4, arc traversing costs for outbound routing are symmetric, i.e  $c_{ij} = c_{ji}$ . Model becomes indifferent between choosing a specific route and its reversely ordered form which lead to same objective function value. To break this tie, inequalities (5.3) are proposed.

$$(5.3) \quad x_{j,d}^{rd} \leq \sum_{\substack{i \in N_r \\ i < j}} x_{d,i}^{rd} \quad \forall r \in C, d \in D_r, j \in N_r$$

## 5.2 Computational Experiments

Load-based (LB) formulation comes with the additionally defined continuous variables in exchange for binary variables and reduced number of indices on different variables as explained in Section 3.2.2. For 30, 50, and 100 customer instances we set the time limit to 8, 16, and 48 hours, respectively.

In the tables given below,  $F_A$  and  $F_B$  show how many facilities opened by carriers  $A$  and  $B$ , respectively.  $T_A$  and  $T_B$  indicate how many transfer lines are constructed by carriers  $A$  and  $B$ , respectively as well. While  $Obj$  shows the objective function value,  $Obj_A$  and  $Obj_B$  depict the cost for each carrier.  $T(s)$  indicates the run time in seconds and  $Gap$  indicates the percentage optimality gap reported.

We first consider the original scenario and low demand setting of 30 customers instances. Results can be found below in Table 5.1.

Within the given time limit, all instances were solved to reasonable gaps when compared to VB formulation and obtained a solution for each instance. Gaps deviate

Table 5.1 Summary of LB Formulation results with 30 customers and original scenario in low demand setting

Ins.	$F_A$	$F_B$	$T_A$	$T_B$	$Obj$	$Obj_A$	$Obj_B$	$T(s)$	$Gap$
<b>1</b>	1	1	1	1	58449	26680	31769	28800	7.5%
<b>2</b>	1	1	1	1	61095	29329	31766	28800	6.1%
<b>3</b>	1	1	1	1	61527	30436	31091	28800	4.0%
<b>4</b>	1	1	1	1	52444	27409	25035	28800	4.2%
<b>5</b>	1	1	1	1	57824	20603	37221	28800	8.5%
<b>6</b>	1	1	1	1	59213	33838	25376	28800	7.6%
<b>7</b>	1	1	1	1	57160	28020	29140	28800	5.0%
<b>8</b>	1	1	1	1	56851	29001	27850	28800	5.3%
<b>9</b>	1	1	1	1	66783	36342	30441	28800	8.8%
<b>10</b>	1	1	1	1	61442	26724	34718	28800	8.1%

between 4.0% and 8.5%. Average gap is 6.5% for the original scenario and low demand setting of 30 customer instances. In all the instances each carrier chose to open one facility and create one transfer line. In order to see the behaviour of the LB formulation with different data sets of different sizes, LB formulation is tested with the original scenario and high demand setting of 30 customer instances and the original scenario and high demand setting of 50 customer instances. Results can be found in Table 5.2.

Table 5.2 LB Formulation results with original scenario under high demand setting for 30 & 50 customers

Ins.	30 Customers High Demand					50 Customers High Demand				
	$Obj$	$Obj_A$	$Obj_B$	$T(s)$	$Gap$	$Obj$	$Obj_A$	$Obj_B$	$T(s)$	$Gap$
<b>1</b>	82893	36519	46374	28800	11.4%	110487	54658	55829	57600	9.3%
<b>2</b>	86373	40967	45405	28800	8.9%	116145	60624	55522	57601	10.1%
<b>3</b>	87266	42203	45063	28800	8.0%	115178	57232	57945	57600	12.7%
<b>4</b>	69866	34477	35389	28800	8.6%	113827	57719	56107	57600	11.4%
<b>5</b>	78676	32031	46645	28800	8.5%	119793	53929	65863	57600	10.9%
<b>6</b>	81847	46273	35575	28800	7.8%	115084	56188	58897	57600	10.5%
<b>7</b>	77987	38321	39666	28800	10.1%	116067	48423	67644	57600	10.8%
<b>8</b>	75652	33655	41998	28801	8.7%	131233	67436	63797	57600	9.9%
<b>9</b>	88638	42530	46108	28800	10.2%	111844	59768	52076	57600	11.1%
<b>10</b>	80652	35424	45229	28800	6.1%	132865	62753	70112	57600	11.0%

Once problem size increases or problem instance gets harder because of increased demand structure, gaps increase on average. For the original scenario and high demand setting of 30 customer instances, gaps deviate between 6.1% and 11.4%. Average gap for ten instances is 8.8%. In the low demand setting average gap was 6.5%. For the original scenario and high demand setting of 50 customer instances, gaps deviate between 9.3% and 11.4%. Average gap for ten instances for this setup is 10.8%. Average gap was 8.8% in the 30 customer instances of this setting. As problem size increases, gaps increase as well.

Even though solutions are found for the 30 and 50 customer instances with optimality gaps, several other runs are completed to see the behaviour of the formulation with 100 customers. For this purpose, runs are completed with the 100 customer instances with original scenario and low demand setting. The time limit is set as 48 hours for each run. Results can be found in Table 5.3. In Table 5.3, M indicates that server run out of memory during branching or model creation phase and -1 indicates that no solution found within given time limit. As it can be interpreted from Table 5.3, with 100 customers problem grows exponentially and half of the instances do not fit into 64 gigabytes of random access memory because of the increased number of variables and size of the branching tree. Solutions are reported for only three instances within 48 hours of time limit, and the reported gaps are above 55% on average.

Table 5.3 LB Formulation results with original scenario and low demand setting of 100 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>T(s)</i>	<i>Gap</i>
<b>1</b>	8	7	5	5	191879	97503.25	94375	172801	55.4%
<b>2</b>	M	M	M	M	M	M	M	M	M
<b>3</b>	6	9	5	5	196658	92681.9	103976	172801	65.7%
<b>4</b>	M	M	M	M	M	M	M	M	M
<b>5</b>	M	M	M	M	M	M	M	M	M
<b>6</b>	-	-	-	-	-	-	-	172801	
<b>7</b>	M	M	M	M	M	M	M	M	M
<b>8</b>	M	M	M	M	M	M	M	M	M
<b>9</b>	-	-	-	-	-	-	-	172800	
<b>10</b>	8	7	6	3	194335	98975.15	95360	172801	63.4%

In order to tighten solution space and reduce gaps, valid inequalities are proposed in Section 5.1. There exists five different valid inequalities (VI) which applies to LB formulation. In favor of examining the effect of VIs on different data sets of different sizes, we conduct three experiments. In all three experiments, we utilize the original scenario of 30 and 50 customer data sets in both low and high demand environments to see the behaviour of VIs. First experiments are conducted with no additional VIs to have a basis for the comparison. Then, (5.2) and (5.3) added and experiments are repeated. Lastly, all proposed VIs in the Section 5.1 are added to the formulation and the experiments are repeated again. Results in which gaps of first and second experiments are compared, can be found in Table 5.4.

In the Table 5.4, columns  $\Delta_O$  indicates original optimality gaps without any valid inequalities. Columns  $\Delta_{VI}$  indicates the optimality gaps with the added VIs (5.2) and (5.3). A cell is highlighted with a green color if VIs yield a better solution in terms of lower gaps, highlighted with a red color otherwise. In the 30 customer instances, 17 out of 20 instances are solved with lower gaps with activated VIs. In 50 customer instances, 13 out of 20 instances are solved with lower gaps. In total,

Table 5.4 Gap comparison for LB Formulation with original formulation and additional (5.2) and (5.3) valid inequalities

Ins.	30 Customer				50 Customer			
	Low Demand		High Demand		Low Demand		High Demand	
	$\Delta_O$	$\Delta_{VI}$	$\Delta_O$	$\Delta_{VI}$	$\Delta_O$	$\Delta_{VI}$	$\Delta_O$	$\Delta_{VI}$
1	7.5%	8.4%	11.4%	11.1%	11.7%	11.4%	9.3%	9.5%
2	6.1%	4.8%	8.9%	8.3%	10.6%	10.6%	10.1%	9.2%
3	4.0%	4.8%	8.1%	8.0%	14.4%	13.7%	12.7%	12.0%
4	4.2%	3.4%	8.6%	7.8%	12.2%	11.3%	11.4%	10.9%
5	8.5%	8.1%	8.5%	9.0%	10.5%	10.6%	10.9%	11.5%
6	7.6%	6.0%	7.8%	7.0%	11.1%	10.2%	10.5%	10.0%
7	5.0%	4.4%	10.1%	10.0%	13.2%	11.4%	10.8%	10.8%
8	5.3%	4.9%	8.7%	7.9%	12.6%	12.5%	9.9%	9.0%
9	8.8%	7.3%	10.2%	9.4%	14.1%	14.4%	11.1%	10.4%
10	8.1%	6.8%	6.1%	5.9%	12.8%	12.5%	11.0%	11.8%

30/40 instances are solved with lower gaps when the (5.2) and (5.3) VIs are added to the model. In some samples, the improvement is 0.1 percent, while in some samples, up to 1.8 percent improvement is observed.

To investigate the effect of all VIs, all proposed VIs in Section 5.1 are added to the model and experiments are repeated. Results can be found in Table 5.5 and Table 5.6 for 30 and 50 customers, respectively.  $\Delta_O$  indicates original gaps without any valid inequalities.  $\Delta_{(5.2)+(5.3)}$  demonstrates optimality gaps when only (5.2) and (5.3) VIs were added to the model.  $\Delta_{All}$  indicates gaps when all valid inequalities are added to the model. Green cells report the best gap found, orange cells indicate medium gap and red cells report the worst gap found for the given instance.

Table 5.5 Gap comparison for LB Formulation with original formulation, (5.2) and (5.3) VIs, and all VIs for 30 customers in original scenario

Ins.	30 Customers					
	Low Demand			High Demand		
	$\Delta_O$	$\Delta_{(5.2)+(5.3)}$	$\Delta_{All}$	$\Delta_O$	$\Delta_{(5.2)+(5.3)}$	$\Delta_{All}$
1	7.5%	8.4%	8.8%	11.4%	11.1%	11.4%
2	6.1%	4.8%	5.9%	8.9%	8.3%	9.0%
3	4.0%	4.8%	4.3%	8.1%	8.0%	8.2%
4	4.2%	3.4%	3.6%	8.6%	7.8%	7.6%
5	8.5%	8.1%	9.3%	8.5%	9.0%	9.6%
6	7.6%	6.0%	6.6%	7.8%	7.0%	7.8%
7	5.0%	4.4%	4.5%	10.1%	10.0%	11.0%
8	5.3%	4.9%	5.1%	8.7%	7.9%	8.8%
9	8.8%	7.3%	8.1%	10.2%	9.4%	9.8%
10	8.1%	6.8%	6.7%	6.1%	5.9%	6.1%

For the 30 customer instances, it is observed that still the best gaps are reported when only inequalities (5.2) and (5.3) are added to the model. When the other

two experiments are compared in which no VIs are added or all VIs are added, in high demand environments, original formulation is solved with lower gaps. However, in low demand environments, formulation with all added VIs reported lower gaps. Nonetheless, there is not a strict distinction between those since still exceptional instances are observed.

Table 5.6 Gap comparison for LB Formulation with original formulation, (5.2) and (5.3) VIs, and all VIs for 50 customers in original scenario

Ins.	50 Customers					
	Low Demand			High Demand		
	$\Delta_O$	$\Delta_{(5.2)+}$ (5.3)	$\Delta_{All}$	$\Delta_O$	$\Delta_{(5.2)+}$ (5.3)	$\Delta_{All}$
1	11.7%	11.4%	11.9%	9.3%	9.5%	9.1%
2	10.6%	10.6%	10.7%	10.1%	9.2%	11.6%
3	14.4%	13.7%	15.3%	12.7%	12.0%	12.6%
4	12.2%	11.3%	12.7%	11.4%	10.9%	12.4%
5	10.5%	10.6%	10.9%	10.9%	11.5%	11.6%
6	11.1%	10.2%	10.9%	10.5%	10.0%	10.4%
7	13.2%	11.4%	17.1%	10.8%	10.8%	10.7%
8	12.6%	12.5%	12.0%	9.9%	9.0%	9.5%
9	14.1%	14.4%	13.1%	11.1%	10.4%	10.5%
10	12.8%	12.5%	13.1%	11.0%	11.8%	11.5%

Once the results for 50 customer instances are evaluated, again best gaps are resulted with inequalities (5.2) and (5.3). For the low demand setting, original formulation reported better results in terms of gaps when compared to all VIs added. On the other hand, in the high demand setting, formulation with all added VIs reported lower gaps.

When all results indicated above considered, best results are obtained when inequalities (5.2) and (5.3). As mentioned in earlier sections, this study proposes a new collaboration schema for a strategic network design problem. Despite the models are not solved to the optimality, with the LB formulation and proposed VIs, reasonable solutions are reported. So we investigated the strategic outcomes of the proposed models and collaboration schema using those results in the following Section 5.3. All runs are completed using LB formulation + inequalities (5.2) & (5.3) for the strategic analysis since this formulation reported best gaps as discussed above.

### 5.3 Managerial Insights

Proposed models comprise managerial aspects in addition to mathematical approaches. Given an instance, companies make decisions about number and place of the facilities, which routes and transportation lines should be defined, and which and how many transfer lines should be constructed under collaborative schema. As it is proposed in former sections, collaboration leads to cost savings. And the above decisions directly affect the cost realization of the whole system. In order to investigate strategic decisions which are given under collaboration, effect of different parameters such as common customer number or common depot number and effect of those parameters on collaboration amounts and gains come from collaboration, experiments are conducted under three different scenarios as explained in Section 4.3.

First set of experiments are conducted with *original* scenario setup for 30 customers in both low and high demand environments. The results can be found Table 5.7. Explanations of abbreviations of column names from  $F_A$  to  $Gap$  is explained at the beginning of Section 5.2. Only four new columns added to new tables, namely,  $RC$ ,  $FC$ ,  $TC$ ,  $IC$ .  $RC$  indicates outbound routing cost,  $FC$  indicates facility opening and maintenance cost,  $TC$  describes transfer line construction cost and lastly  $IC$  defines inbound transportation line construction cost.

Table 5.7 LB Formulation results of original scenario and low demand setting of 30 customer instances

<i>Ins.</i>	$F_A$	$F_B$	$T_A$	$T_B$	$Obj$	$Obj_A$	$Obj_B$	$Gap$	$RC$	$FC$	$TC$	$IC$
<b>1</b>	1	1	1	1	59178	26722	32457	8.4%	49059	7029	0	3090
<b>2</b>	1	1	1	1	61095	27447	33648	4.8%	49314	7029	0	4752
<b>I</b>	1	1	1	1	61527	30436	31091	4.8%	46250	9413	452	5412
<b>4</b>	1	1	1	1	52444	27409	25035	3.4%	39391	7065	522	5466
<b>5</b>	1	1	1	1	57719	26702	31017	8.1%	44046	7065	259	6350
<b>6</b>	1	1	1	1	59213	33838	25376	6.0%	46029	8334	298	4552
<b>7</b>	1	1	1	1	57181	28020	29161	4.4%	44474	7065	478	5164
<b>8</b>	1	1	1	1	56851	29001	27850	4.9%	42153	8530	523	5645
<b>9</b>	1	1	1	1	66615	34664	31951	7.3%	51795	7669	614	6538
<b>10</b>	1	1	1	1	61106	29232	31875	6.8%	47922	7065	522	5597

In the original scenario of 30 customer instances with low demand setting, each carrier chooses to open and maintain one facility in all instances. Also in each instance, transfer lines are constructed between opened depots for each carrier, which means collaboration exists. In instances 1 and 2, model chose to declare depots on same locations and create transfer line between them with no cost, which advances collaboration. Next, same experiments are conducted for high demand environment.

Results can be found in Table 5.8.

Table 5.8 LB Formulation results of original scenario and high demand setting of 30 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	1	2	2	1	82554	39774	42780	11.1%	64073	10995	368	7118
<b>2</b>	1	1	1	1	86145	40060	46085	8.3%	70892	8731	384	6139
<b>3</b>	1	2	2	1	87266	42203	45063	8.0%	65143	12739	325	9059
<b>4</b>	1	1	1	1	69007	34748	34260	7.8%	55954	7065	522	5466
<b>5</b>	1	2	2	1	78874	31340	47534	9.0%	57403	10995	561	9915
<b>6</b>	2	1	1	2	81847	46273	35575	7.0%	62660	10266	368	8553
<b>7</b>	2	1	1	1	78808	39394	39415	10.0%	60127	10266	282	8133
<b>8</b>	1	1	1	1	75266	38078	37188	7.9%	60568	8530	523	5645
<b>9</b>	2	2	2	1	88562	42584	45978	9.4%	59361	15663	463	13074
<b>10</b>	1	2	2	1	80652	35424	45229	5.9%	56439	12460	886	10867

Once the demand increased, carriers chose to open new facilities in order to deal with increased routing costs. Overall, costs are increased since number of routes should be created to satisfy increased demand is increased as well. Depending on the instance, number of constructed transfer lines is also increased. Augmentation rate of *RC* is higher than other costs since increased demand mainly affects number of routes that must be constructed to satisfy increased demand. In high demand setting, instances 1 and 2, depots are opened in different locations as well in contrast to low demand setting.

In order to see how much gains are achieved through collaboration, above instances are solved in individual environments in which no collaboration exists between carriers. To solve instances, individual load based formulation is used which is proposed in Appendix A which is formulated for a single carrier. For each carrier, time limit is set to 4 hours for 30 customer instances and 8 hours for 50 customer instances to equate total run times with collaborative scenarios. In the individual run results, *Obj* shows the sum of separate objectives of each carrier *Obj<sub>A</sub>* and *Obj<sub>B</sub>* for carriers *A* and *B*, respectively. *BB<sub>A</sub>* and *BB<sub>B</sub>* indicates the best bounds of the objective function value that is found by the solver for carriers *A* and *B*, respectively and *BB<sub>Obj</sub>* indicates the sum of those value which is the OFV of integrated problem. *T<sub>A</sub>(s)* and *T<sub>B</sub>(s)* reports the run time for the given instance and *Gap<sub>A</sub>* and *Gap<sub>B</sub>* illustrates the reported lowest gap within given time limit for each carrier. Results for the 30 customer instances with original setting under low demand environment can be found in Table 5.9.

Instances which are solved until optimality are indicated with red color in Table 5.9. Five instances are solved to optimality. Rest is solved with lower gaps when compared to collaborative versions. However, in order to conduct an accurate comparison, best bounds are also compared with the collaborative solutions. Since best

Table 5.9 Individual LB Formulation results for original scenario and low demand setting of 30 customer instances

<i>Ins.</i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>BB<sub>Obj</sub></i>	<i>BB<sub>A</sub></i>	<i>BB<sub>B</sub></i>	<i>T<sub>A</sub>(s)</i>	<i>T<sub>B</sub>(s)</i>	<i>Gap<sub>A</sub></i>	<i>Gap<sub>B</sub></i>
<b>1</b>	65225	32188	33037	65225	32188	33037	1080	9587	0.0%	0.0%
<b>2</b>	67980	35502	32478	67980	35502	32478	3773	1312	0.0%	0.0%
<b>3</b>	70869	34267	36603	66351	32108	34244	14400	14400	6.3%	6.4%
<b>4</b>	58522	29866	28657	58522	29866	28657	2180	4372	0.0%	0.0%
<b>5</b>	65900	31679	34221	65511	31290	34221	14400	13516	1.2%	0.0%
<b>6</b>	66274	35616	30658	65133	34476	30658	14400	5907	3.2%	0.0%
<b>7</b>	63901	32540	31362	63901	32540	31362	9910	9916	0.0%	0.0%
<b>8</b>	61667	28201	33467	61667	28201	33467	2441	7336	0.0%	0.0%
<b>9</b>	73648	35447	38201	70154	33465	36689	14400	14400	5.6%	4.0%
<b>10</b>	65438	31330	34109	63361	31330	32031	3724	14400	0.0%	6.1%

bounds indicates the best achievable results for given individual instance, if the collaborative solutions with gaps still reports a better outcome against best bound of individual scenario, it means collaborative model indeed promises gains. Gains are identified in Figure 5.1 via comparing objective function values of non-collaborative and collaborative scenarios. In Figure 5.1, green bars indicate overall gain of the system, where orange and blue bars indicate gains of carrier *A* and carrier *B*, respectively. Gains can be realized with – coefficients which indicates loss.

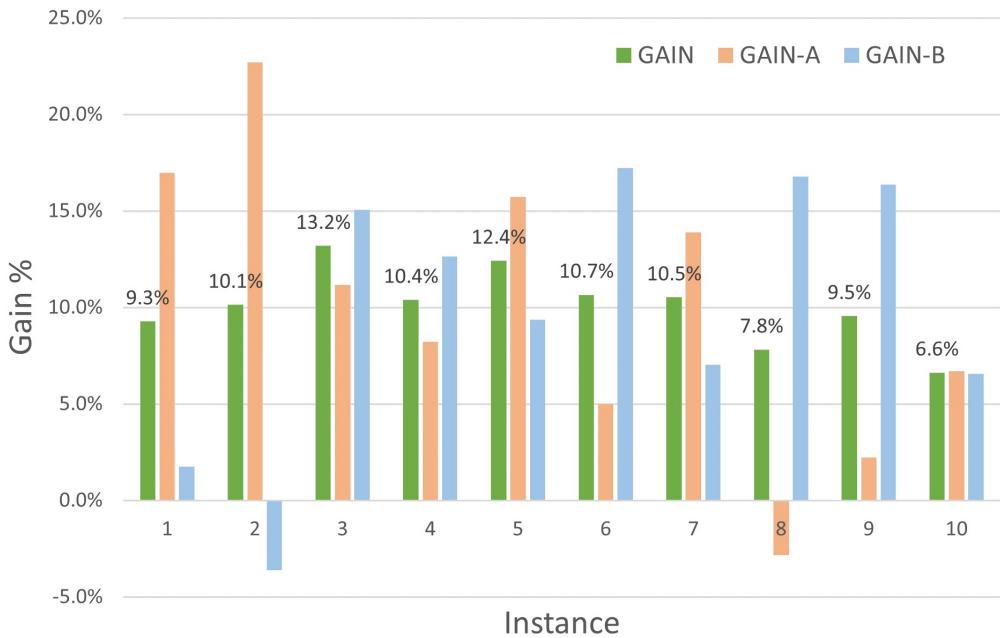


Figure 5.1 Gain comparison through OFVs for original scenario and low demand setting of 30 customer instances

When OFVs are compared in the low demand setting of original scenario with 30 customers, magnitude of the gains which arise from collaboration deviates between 6.6% and 13.2%. In average, overall gain of the whole system is 10.1%. As mentioned in earlier sections, proposed model assumes that there is a centralized decision

making mechanism so that they minimize the total cost of the all network. So that individual carriers may suffer and worse cost realizations may occur when compared to individual scenarios. For the given examples, gains for carrier  $A$  deviate between -2.8% and 22.7% where average gain for carrier  $A$  is 10%. Gains for carrier  $B$  deviate between -3.6% and 17.2% where average gain for carrier  $B$  is 9.9%. In instance 2, carrier  $B$  had a worse outcome when compared to individual scenario but gain of integrated system is 10.1%. On the contrary, in the instance 8, carrier  $A$  had a worse outcome where overall gain realization was 7.8%. As mentioned in Table 5.9, not all individual instances are solved to optimality. Therefore, best bounds are also compared with the collaborative results to ensure and investigate the minimum amount of gains. Results are presented in Figure 5.2.

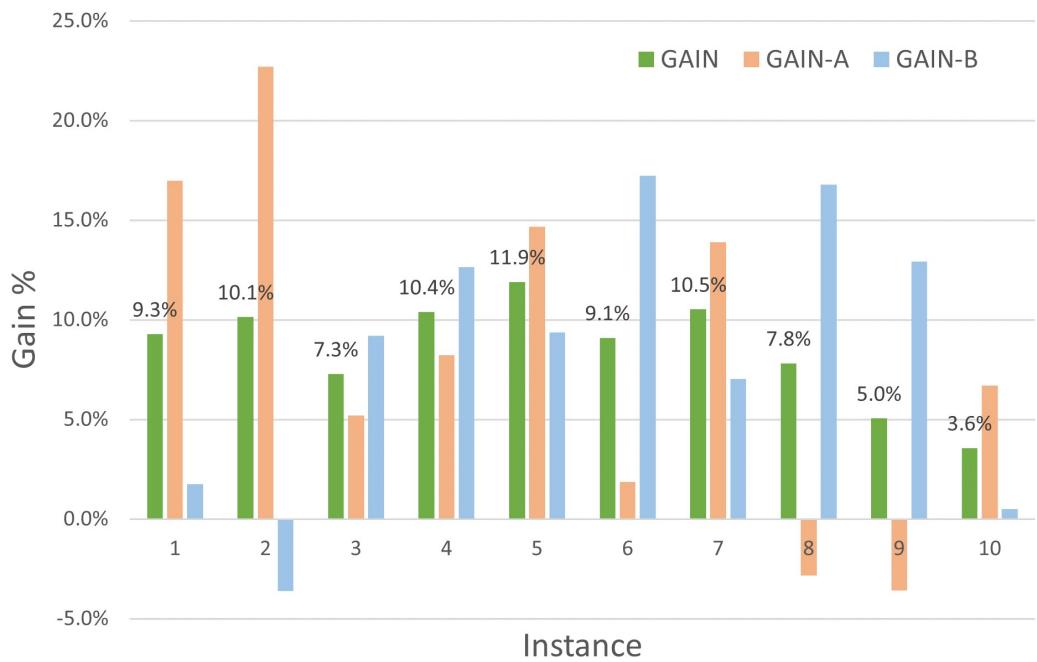


Figure 5.2 Gain comparison through best bounds for original scenario and low demand setting of 30 customer instances

Indeed gains reported in Figure 5.1 state an upper bound for the best bound results. On the other hand, gains reported in the best bound results hold a lower bound for the "real" gains since best bound represent the best theoretical results that can be achieved. Since some instances are solved with higher gaps, reported best bound may be far away from real optimum solution and OFV. When the best bounds of the individual scenario are compared with the collaborative solution, it is observed that gains deviate between 3.6% and 11.9% which indicates that despite gaps, collaborative scenario still provides a better cost realization. Average gain is 8.5%. For the given examples, gains for carrier  $A$  deviate between -3.6% and 22.7% where average gain for carrier  $A$  is 8.4%. Gains for carrier  $B$  deviate between -3.6% and 17.2% where average gain for carrier  $B$  is 8.4%.

In order to see the effect of demand on problem and collaboration, same experiments are conducted for high demand environment of original scenario with 30 customers. Results can be found in Table 5.10

Table 5.10 Individual LB Formulation results for original scenario and high demand setting of 30 customers instances

Ins.	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	BB <sub>Obj</sub>	BB <sub>A</sub>	BB <sub>B</sub>	T <sub>A(s)</sub>	T <sub>B(s)</sub>	Gap <sub>A</sub>	Gap <sub>B</sub>
1	89531	42193	47338	84942	41280	43663	14400	14400	2.2%	7.8%
2	91773	49064	42709	90047	47339	42709	14400	2491	3.5%	0.0%
3	92738	46788	45951	90634	44684	45951	14400	4814	4.5%	0.0%
4	77789	38617	39173	73886	36798	37088	14400	14400	4.7%	5.3%
5	87299	40988	46312	82738	39351	43388	14400	14400	4.0%	6.3%
6	90180	47948	42233	84576	45397	39179	14400	14400	5.3%	7.2%
7	84438	43178	41260	79481	40536	38945	14400	14400	6.1%	5.6%
8	84637	38809	45828	79355	36768	42587	14400	14400	5.2%	7.1%
9	94613	43824	50789	91511	43824	47687	5261	14400	0.0%	6.1%
10	88344	43196	45148	85843	40695	45148	14400	6838	5.8%	0.0%

When high demand scenarios are compared with the low demand scenarios, it is observed that the average gaps for individual scenarios are higher. None of the problems for both carriers solved to optimality. Individual results again compared with the collaborative scenario to see how much gains are obtained.

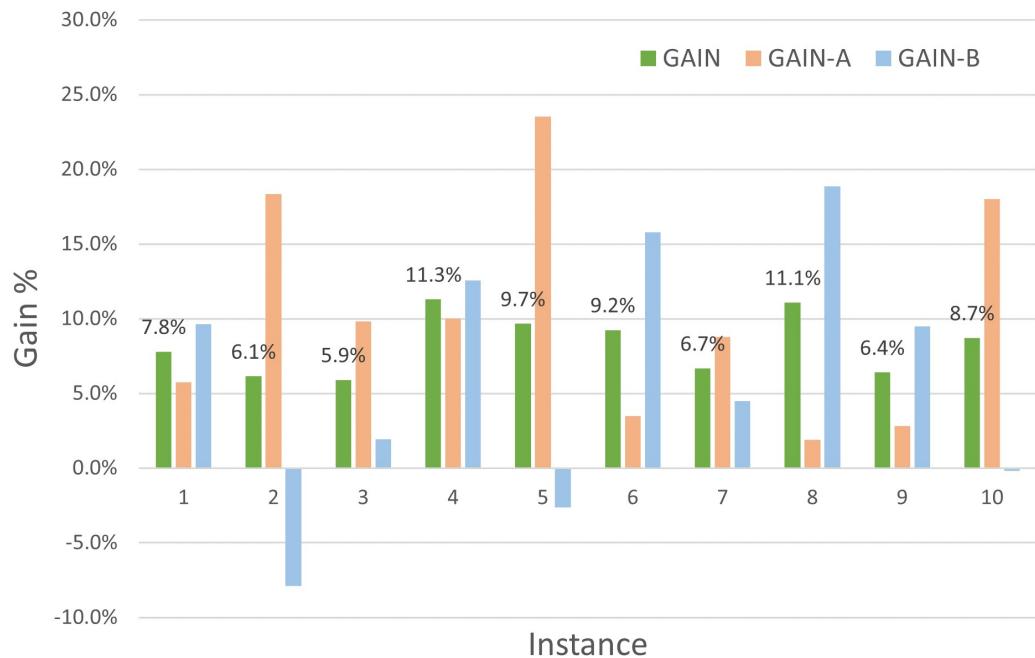


Figure 5.3 Gain comparison through OFVs for original scenario and high demand setting of 30 customer instances

When OFVs are compared for the centralized system, it is seen that gains deviate between 5.9% and 11.3% where average is 8.3%. In none of the instances, carrier A reported a loss for the collaborative schema and reported gains deviate between

1.9% and 23.5%. Average gain amount for the carrier  $A$  is 10.2%. For the carrier  $B$ , collaborative setup reported worse cost realizations for three instances. Gains for carrier  $B$  deviate between -7.9% and 18.9% where average gain for  $B$  is 6.2%. In order to see the lower bound of the gains, best bounds of reported individual scenarios are also compared and the results can be found in Figure 5.4.

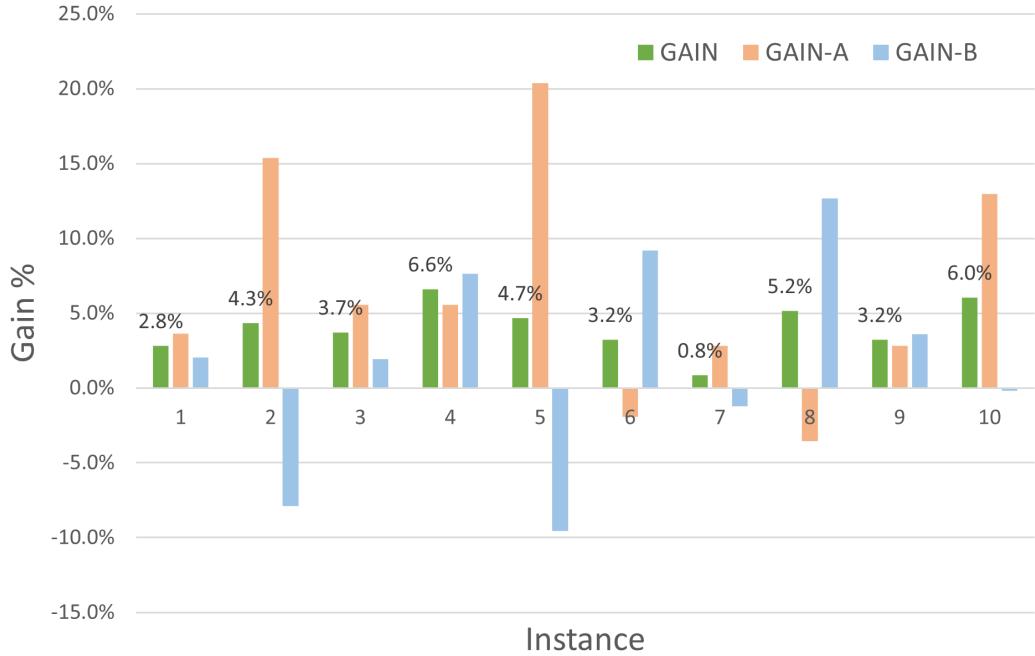


Figure 5.4 Gain comparison through best bounds for original scenario and high demand setting of 30 customer instances

When the gains are compared through best bounds for high demand setting of original scenario with 30 customers, it is seen that gains are lowered but still in all collaborative scenarios, a positive gain is reported. Gains for whole system vary between 0.8% and 6.6% and the average gain amount is 4.1%. For carrier  $A$ , average gain percentage is 6.4 where gains differ between -3.6% and 20.4%. For the carrier  $B$ , average gain percentage is 1.8 in which gains deviate between -9.6% and 12.7%.

Overall, in all experiments based on original scenario of 30 customers, proposed models report positive acquisitions. In most cases, both carriers benefit from the collaboration. However, there exist some instances in which one carrier reports a worse outcome when compared to individual scenario in favor of better outcome for whole system. To see the effect of common customer number on collaboration, above experiments, which are conducted to identify gain structure, are repeated. The setup, in which common customer numbers are increased, is called "Increased Common Customer" as mentioned in Section 4.3 and abbreviated as *ICC*. Collaboration occur if a customer is called *common*. If it is a common customer, then the demand which arise from this customer can be satisfied from either one of the

carriers. When the number of common customers increase in the system, number of opportunities increase as well. On the contrary, once the number of common customer increases, complexity of problem increases as well since the number of possible opportunities to complete deliveries increase as well.

First experiments of ICC scenario is conducted with 30 customers and low demand environment. Results can be found in Table 5.11.

Table 5.11 LB Formulation results with ICC scenario and low demand setting of 30 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	1	1	1	1	59139	28287	30852	8.2%	45771	9111	158	4099
<b>2</b>	1	1	1	1	60859	24108	36750	6.4%	45895	8441	384	6139
<b>3</b>	1	1	1	1	62598	29455	33143	7.6%	47356	9378	452	5412
<b>4</b>	1	1	1	1	49296	22490	26805	5.9%	36191	7456	492	5157
<b>5</b>	1	1	1	1	57451	20065	37385	8.8%	41731	9111	259	6350
<b>6</b>	1	1	1	1	55410	33115	22295	7.1%	43104	7456	298	4552
<b>7</b>	1	1	1	1	56382	26823	29558	6.3%	43440	7456	419	5067
<b>8</b>	1	1	1	1	52368	26016	26352	6.7%	38905	7892	428	5144
<b>9</b>	1	1	1	1	65171	34556	30615	10.2%	51047	7456	512	6156
<b>10</b>	1	1	1	1	62071	25848	36223	10.7%	47630	7456	244	6741

In all instances all carriers chose to open one depot and construct one transfer line. Reported optimality gaps are higher when compared the low number of customers on average. To see the effect of high demand on this setup, same experiments are repeated for high demand environment. Results can be found in Table 5.12.

Table 5.12 LB Formulation results with ICC scenario and high demand setting of 30 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	1	3	3	1	82197	28165	54032	12.7%	52235	16672	651	12639
<b>2</b>	2	1	1	2	81755	36503	45252	8.1%	57605	13572	690	9888
<b>3</b>	2	3	3	2	85123	36376	48747	8.8%	45362	19888	625	19247
<b>4</b>	1	1	1	1	65385	27469	37916	8.8%	52280	7456	492	5157
<b>5</b>	1	2	2	1	76175	32307	43869	8.3%	55266	10772	497	9640
<b>6</b>	2	2	2	2	75411	42314	33096	7.5%	47368	14965	697	12380
<b>7</b>	1	1	1	1	77186	38752	38434	11.2%	64244	7456	419	5067
<b>8</b>	1	2	2	1	65896	30849	35047	4.6%	42350	13292	731	9523
<b>9</b>	2	2	2	2	85490	41236	44255	10.1%	55448	14984	729	14329
<b>10</b>	1	2	2	1	80933	38737	42196	9.3%	55631	13409	868	11025

Once the demand setting is switched to high, number of opened facilities and constructed transfer lines increased. Total costs are increased when compared to low demand setting. To see the effect of increased number of common customers on collaboration and identify gains from that collaboration, non-collaborative scenario experiments are completed for 30 customer ICC setting as well. Results can be found in Table 5.13.

Table 5.13 Individual LB Formulation results for ICC scenario and low demand setting of 30 customer instances

<i>Ins.</i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>BB<sub>Obj</sub></i>	<i>BB<sub>A</sub></i>	<i>BB<sub>B</sub></i>	<i>T<sub>A</sub>(s)</i>	<i>T<sub>B</sub>(s)</i>	<i>Gap<sub>A</sub></i>	<i>Gap<sub>B</sub></i>
<b>1</b>	69703	35091	34612	69703	35091	34612	4559	2895	0.0%	0.0%
<b>2</b>	72538	37847	34691	69846	35155	34691	14400	8310	7.1%	0.0%
<b>3</b>	71499	33590	37909	65414	30885	34529	14400	14400	8.1%	8.9%
<b>4</b>	59526	30338	29188	59526	30338	29188	1256	1356	0.0%	0.0%
<b>5</b>	70753	35529	35224	68143	34207	33936	14400	14400	3.7%	3.7%
<b>6</b>	65553	35590	29964	63709	33746	29964	14400	2410	5.2%	0.0%
<b>7</b>	68737	34698	34040	65284	32538	32747	14400	14400	6.2%	3.8%
<b>8</b>	65577	31011	34566	61674	29324	32350	14400	14400	5.4%	6.4%
<b>9</b>	75511	36010	39501	70839	34215	36624	14400	14400	5.0%	7.3%
<b>10</b>	69502	35046	34456	65782	33681	32101	14400	14400	3.9%	6.8%

We compare the results of collaborative scenario with best reported objective function value of individual runs as well as best bounds found. Gains that are identified through the comparison of OFVs can be found in Figure 5.5.

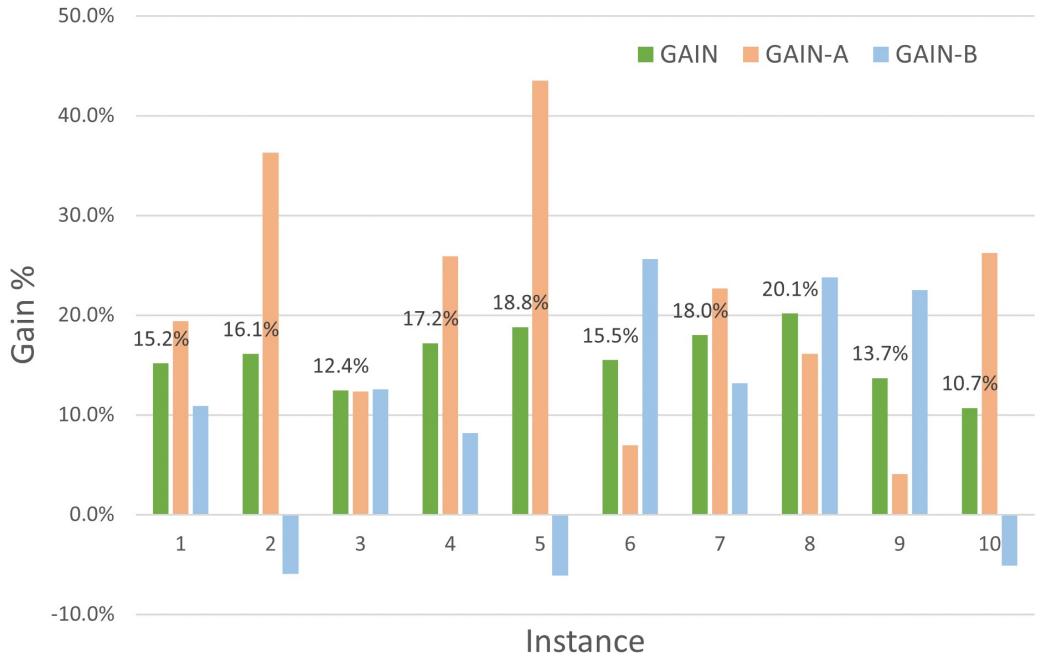


Figure 5.5 Gain comparisons through OFVs for ICC scenario and low demand setting of 30 customer instances

When the non-collaborative and collaborative scenarios are compared for low demand setting of ICC scenario with 30 customers, in all instances, collaborative scenario reports positive gains. For centralized system, gains deviate between 10.7% and 20.1% where average gain amount is 15.8%. For carrier *A*, average gain percentage is 21.3 where gains differ between 4% and 43.5%. 43.5% is an extreme example in which a carrier is decreased its cost almost by half with reported solutions. Carrier *A* benefits from collaboration in all instances and reports a positive gain for each instance. For the carrier *B*, average gain percentage is 9.9 in which gains deviate

between -6.1% and 25.6%. In three instances, carrier *B* suffer from collaboration and reports increased cost. In order to see the lower bound of the gains, best bounds of reported individual scenarios are also compared and the results can be found in Figure 5.6.

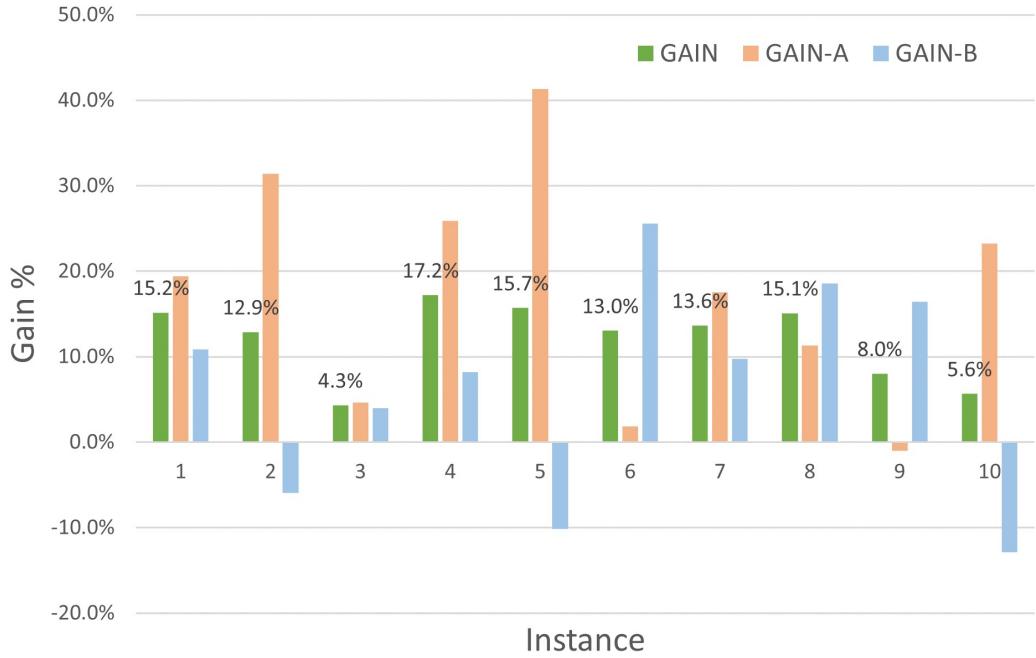


Figure 5.6 Gain comparisons through best bounds for ICC scenario and low demand setting of 30 customer instances

When the gains are compared through best bounds for low demand setting of ICC scenario with 30 customers, again in all instances, collaborative scenario yields better outcomes when contrasted with individual scenarios. Gains for whole system deviate between 4.3% and 17.2%. Average gain amount is 12.1%. Carrier *A* reports positive gains for 9 out of 10 instances with an average of 17.6%. Gain percentages vary between -1% and 41.3% for carrier *A*. For carrier *B* average gain is 6.4% where gains deviate between -12.8% and 25.6%.

The gains with ICC scenario with low demand are higher when compared to original scenario with low demand in average. To evaluate the effect of demand on collaboration levels, same experiments are conducted for high demand environment of ICC scenario with 30 customers. Results can be found in Table 5.14.

Similar to what we did for low demand instances of ICC, we compare the results of collaborative scenario with best reported OFV of individual runs as well as best bounds found. Gains that are identified through the comparison of OFVs can be found in Figure 5.7

When collaboration results are compared with individual results through best found

Table 5.14 Individual LB Formulation results for ICC scenario and high demand setting of 30 customer instances

<i>Ins.</i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>BB<sub>Obj</sub></i>	<i>BB<sub>A</sub></i>	<i>BB<sub>B</sub></i>	<i>T<sub>A</sub>(s)</i>	<i>T<sub>B</sub>(s)</i>	<i>Gap<sub>A</sub></i>	<i>Gap<sub>B</sub></i>
<b>1</b>	95724	44646	51078	88974	42116	46859	14400	14400	5.7%	8.3%
<b>2</b>	97506	50609	46898	90242	47136	43106	14400	14400	6.9%	8.1%
<b>3</b>	93483	46193	47290	87853	42151	45702	14400	14400	8.8%	3.4%
<b>4</b>	78934	39894	39040	74652	37587	37066	14400	14400	5.8%	5.1%
<b>5</b>	92166	45135	47031	86278	43818	42460	14400	14400	2.9%	9.7%
<b>6</b>	89378	48610	40768	83216	44074	39142	14400	14400	9.3%	4.0%
<b>7</b>	90706	45668	45039	83603	42033	41571	14400	14400	8.0%	7.7%
<b>8</b>	84769	40685	44085	78787	37157	41630	14400	14400	8.7%	5.6%
<b>9</b>	99234	45922	53312	91314	43898	47416	14400	14400	4.4%	11.1%
<b>10</b>	95170	46892	48279	87907	43623	44284	14400	14400	7.0%	8.3%

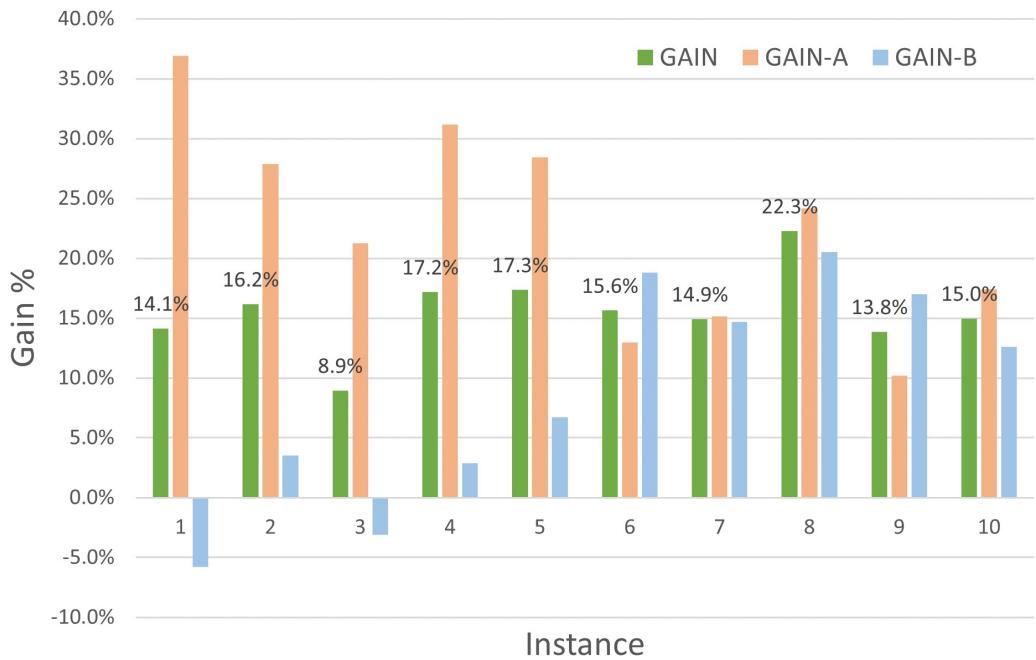


Figure 5.7 Gain comparisons through OFVs for ICC scenario and high demand setting of 30 customer instances

objective function values to evaluate gains for the high demand setup of ICC setting for 30 customers, it is seen that there is an average gain of 15.5%. For the integrated system gains vary between 8.9% and 22.3%. Carrier *A* benefited from collaboration in all instances with an average gain amount of 22.3%. Carrier *A* gained at least 10.2% from collaboration and 36.9% at most. On the other hand, carrier *B* reported worse outcomes for 2 instances but for the rest of the instances it reported positive gains as well. Average gain of carrier *B* is 8.8% where gains deviate between -5.8% and 20.5%.

Next, best bounds of individual scenarios are compared with the collaborative scenario results to asses lower bound on gains and the results can be found in Figure

## 5.8.

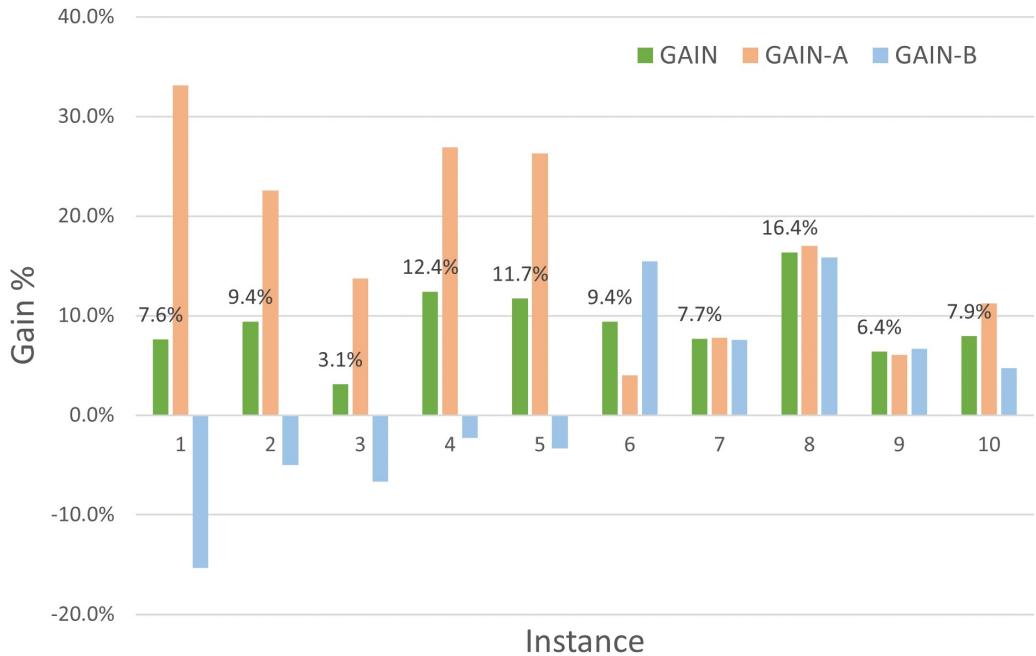


Figure 5.8 Gain comparisons through best bounds for ICC scenario and high demand setting of 30 customer instances

When the individual results are compared with collaborative results for the high demand setup of ICC scenario for 30 customers through best bounds, again all instances with collaboration reported a lower cost and more gains. Centralized system has a gain of 9.2% on average where gains vary between 3.1% and 16.4%. Carrier *A* reported better outcomes in all cases which means collaboration was beneficial for carrier *A* in all cases. Carrier *A* gained 16.9% on average where gains of *A* deviate between 4% and 33.1%. On the other hand, carrier *B* realized higher costs in five instances with an average gain of 1.8%. Minimum gain of carrier *B* is -15.3% and maximum gain of carrier *B* is 15.8%.

When the results of high demand ICC setting is compared with high demand original scenario results, it is observed that gain percentages are higher in ICC scenarios. Those results overlap with the expected outcomes since increased number of common customers increase the collaboration possibility which may yield lower costs. In original scenario's best bound comparisons, average gains was reported as 4.1%, but in ICC setting it is reported as 9.2%.

Overall, all experiments which are conducted with ICC setting of 30 customers yielded positive gains. As explained in Section 4.3, in the original scenarios, carriers declare some of the possible regional depot locations as *common* and no cost incurred if a transfer line is constructed between two depots which share same location. Main

Table 5.15 LB Formulation results for NCD scenario and low demand setting of 30 customer instances

<b><i>Ins.</i></b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b><i>Gap</i></b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b><i>1</i></b>	1	1	1	1	60011	30863	29147	6.8%	48222	7532	158	4099
<b><i>2</i></b>	1	1	1	1	64459	26433	38026	6.4%	51165	7532	284	5478
<b><i>3</i></b>	1	1	1	1	63377	31338	32039	5.9%	51274	7424	313	4366
<b><i>4</i></b>	1	1	1	1	54967	28233	26733	4.0%	41837	6794	66	6270
<b><i>5</i></b>	1	1	1	1	58945	31605	27339	6.1%	44804	7532	259	6350
<b><i>6</i></b>	1	1	1	1	61669	35543	26125	6.8%	49183	7226	406	4854
<b><i>7</i></b>	1	1	1	1	61605	31436	30169	5.9%	48431	7532	478	5164
<b><i>8</i></b>	1	1	1	0	58964	26534	32430	5.2%	46263	7730	57	4915
<b><i>9</i></b>	1	1	1	1	62428	32707	29720	5.2%	48825	6992	485	6126
<b><i>10</i></b>	2	1	1	2	63145	33361	29784	9.3%	39776	10457	805	12107

motivation behind this is to incentivize collaboration between carriers. To see the effect of not opening depots on same locations, runs are repeated with "No Common Depot" (NCD) setting. When the number of common depots are decreased in the system, number of collaboration opportunities decrease as well.

Initial experiments of NCD scenario are conducted with 30 customers and low demand environment. Results can be found in Table 5.15.

Both carriers chose to open regional depot and create transfer lines even though the depots are not located in same geographical locations to promote collaboration. In order to evaluate the effect of high demand density on NCD setup, same experiments are conducted in high demand setting. Results can be found in Table 5.16.

Table 5.16 LB Formulation results for NCD scenario and high demand setting of 30 customer instances

<b><i>Ins.</i></b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b><i>Gap</i></b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b><i>1</i></b>	1	1	1	1	84202	43080	41122	9.4%	69948	8999	361	4894
<b><i>2</i></b>	2	2	2	2	86447	40889	45558	5.8%	57741	14396	920	13389
<b><i>3</i></b>	2	1	1	2	90193	48824	41369	8.2%	68118	12525	552	8998
<b><i>4</i></b>	2	2	1	2	75341	39598	35742	9.1%	49606	14524	82	11129
<b><i>5</i></b>	2	1	1	2	80076	47109	32967	8.5%	57934	11767	489	9886
<b><i>6</i></b>	2	2	2	2	81810	43024	38785	7.2%	55812	13658	665	11675
<b><i>7</i></b>	2	1	1	2	81736	42321	39415	8.5%	62153	11125	326	8133
<b><i>8</i></b>	2	1	1	1	79613	39707	39905	8.1%	60084	11017	213	8299
<b><i>9</i></b>	2	1	1	2	83058	39650	43407	8.6%	61614	10457	815	10172
<b><i>10</i></b>	3	1	1	2	82731	45746	36984	8.4%	53536	15150	546	13499

Once total demand in the system increases, carriers prefer to open more depots to cope with routing costs. And still, despite the fact that depots are not located in same locations, they prefer to establish transfer lines. To investigate the effect of decreased number of common depots to the gains, individual runs are completed in which carriers act as individuals and do not collaborate. Results for the individual runs of NCD setting for 30 customers with low demand density setting can be found

in Table 5.17.

Table 5.17 Individual LB Formulation for NCD scenario and low demand setting of 30 customer instances

<i>Ins.</i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>BB<sub>Obj</sub></i>	<i>BB<sub>A</sub></i>	<i>BB<sub>B</sub></i>	<i>T<sub>A</sub>(s)</i>	<i>T<sub>B</sub>(s)</i>	<i>Gap<sub>A</sub></i>	<i>Gap<sub>B</sub></i>
<b>1</b>	62972	30239	32734	62972	30239	32734	345	2805	0.0%	0.0%
<b>2</b>	69764	31921	37843	69764	31921	37843	5683	9589	0.0%	0.0%
<b>3</b>	69981	37386	32595	68092	35497	32595	14400	2238	5.1%	0.0%
<b>4</b>	57514	29861	27654	57139	29861	27279	1322	14400	0.0%	1.4%
<b>5</b>	65043	34757	30287	63759	33472	30287	14400	2896	3.7%	0.0%
<b>6</b>	67162	36233	30930	66141	35211	30930	14400	939	2.8%	0.0%
<b>7</b>	67295	34859	32437	66097	33661	32437	14400	1341	3.4%	0.0%
<b>8</b>	62871	33044	29827	62298	32472	29827	14400	1273	1.7%	0.0%
<b>9</b>	70567	36683	33884	69610	35726	33884	14400	734	2.6%	0.0%
<b>10</b>	67898	36593	31306	67529	36224	31306	14400	3282	1.0%	0.0%

As we did in ICC and original scenario instances, we compare the results of collaborative scenario with best reported objective function value of individual runs as well as best bounds found. Gains that are identified through the comparison of OFVs for NCD setting in low demand environment of 30 customers can be found in Figure 5.9.

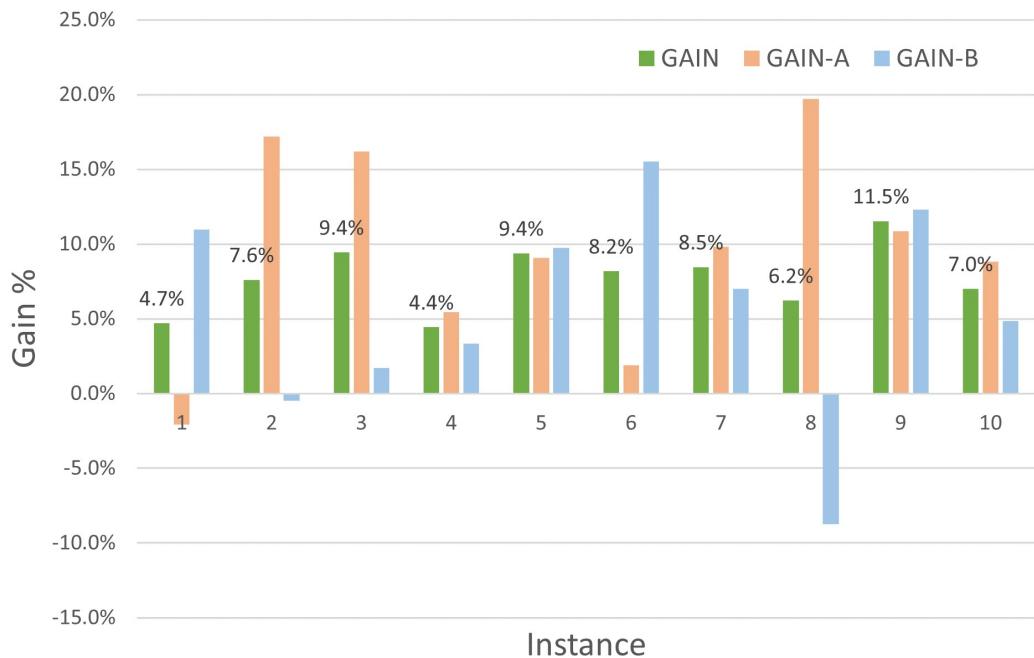


Figure 5.9 Gain comparisons through OFVs for NCD scenario and low demand setting of 30 customer instances

When costs of collaborative scenarios are compared with individual scenarios through OFVs, it is observed that all instances of NCD setting of low demand setup for 30 customers lead to positive gains. Gain amounts are lower than both original and ICC scenarios. Average gain percentage for centralized network is 7.7%

where gains deviate 4.4% and 11.5%. Carrier *A* reported worse outcome for only one instance and average gain of carrier *A* from collaboration is 9.7%. Gain percentages of carrier *A* vary between -2.1 and 19.7. Carrier *B* reports negative gains only for two instances. Gains for carrier *B* deviate between -8.7% and 15.5% where average gain for *B* is 5.6%. Best bounds of individual scenarios are also compared with the collaborative scenarios to investigate lower bounds on gains. Results can be found in figure 5.10.

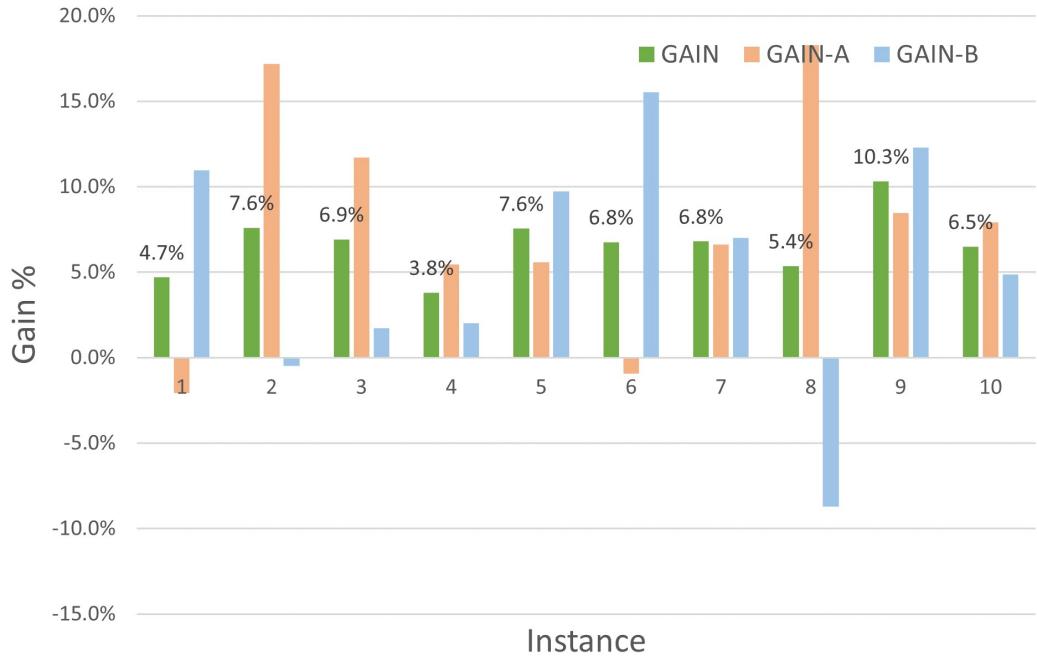


Figure 5.10 Gain comparisons through best bounds for NCD scenario and low demand setting of 30 customer instances

When the gains are compared through best bounds for NCD scenario of 30 customers with low demand setting, a similar outcome is observed with the comparison that is conducted through OFVs. In all instances, collaboration is beneficial for centralized system. Average gain through collaboration is 6.6%. Gains for collaborative system vary between 3.8% and 10.3%. For two instances carrier *A* reported increased costs when compared with the individual scenario. Average gain of carrier *A* is 7.8% where gains deviate between -2.1% and 18.3%. For carrier *B*, two instances resulted with worst outcomes but average gain of carrier *B* is 5.5% where gains of *B* deviate between -8.7% and 15.5%.

In order to see the effect of demand density on collaboration, NCD experiments with 30 customers are repeated under high demand environment. Results can be found in Table 5.18.

As we did in previous experiments, we compare gains for 30 customers and NCD

Table 5.18 Individual LB Formulation results for NCD scenario and high demand setting of 30 customer instances

<i>Ins.</i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>BB<sub>Obj</sub></i>	<i>BB<sub>A</sub></i>	<i>BB<sub>B</sub></i>	<i>T<sub>A</sub>(s)</i>	<i>T<sub>B</sub>(s)</i>	<i>Gap<sub>A</sub></i>	<i>Gap<sub>B</sub></i>
<b>1</b>	87660	43034	44626	83156	39841	43315	14400	14400	7.4%	2.9%
<b>2</b>	97832	43943	53890	92413	41787	50626	14400	14400	4.9%	6.1%
<b>3</b>	98572	53252	45320	92765	48858	43907	14400	14400	8.3%	3.1%
<b>4</b>	77764	40805	36960	74127	38593	35534	14400	14400	5.4%	3.9%
<b>5</b>	88225	49267	38959	82112	45469	36643	14400	14400	7.7%	5.9%
<b>6</b>	89788	47081	42707	87402	45673	41730	14400	14400	3.0%	2.3%
<b>7</b>	86779	44246	42533	84324	41791	42533	14400	10600	5.5%	0.0%
<b>8</b>	83816	44627	39189	80263	41868	38395	14400	14400	6.2%	2.0%
<b>9</b>	90951	46161	44791	90464	46161	44303	5409	14400	0.0%	1.1%
<b>10</b>	89321	45671	43651	87131	45671	41460	14244	14400	0.0%	5.0%

scenario in high demand setting through best found OFVs and best reported individual bounds. Gains that are identified through the comparison of OFVs can be found in figure 5.11.

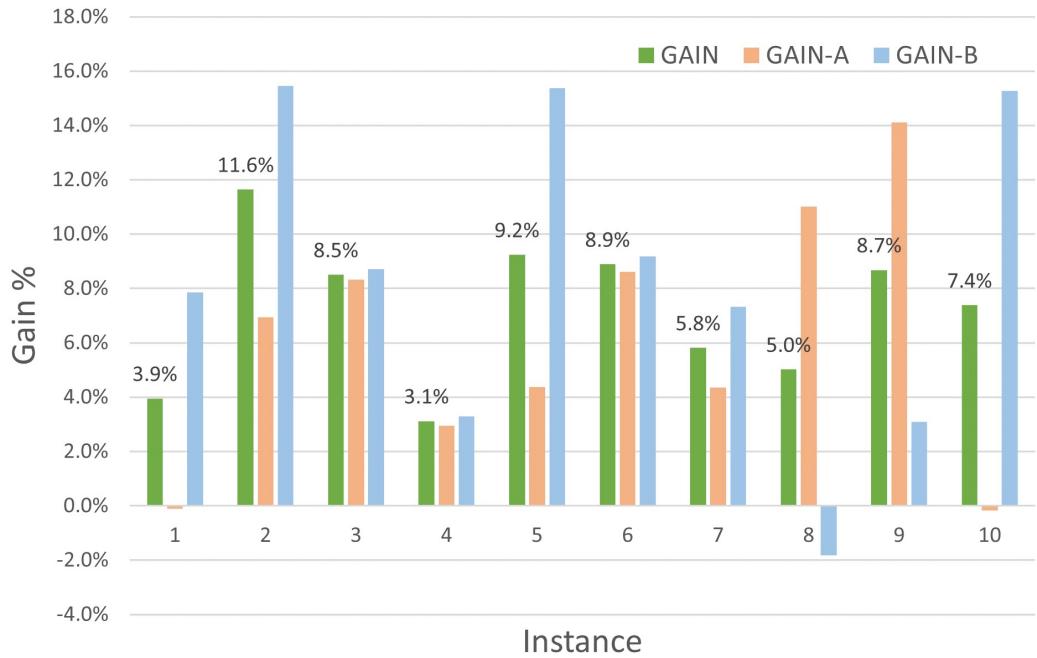


Figure 5.11 Gain comparisons through OFVs for NCD scenario and high demand setting of 30 customer instances

When the comparisons are through OFVs, in parallel of previous findings, all instances yielded better results under collaborative scenarios. Average gain amount is 7.2% for centralized system where gains differ between 3.1% and 11.6%. For carrier *A* all instances reported better values except for two instances. Average gain percentage for carrier *A* is 6%. For carrier *A*, gains deviate between -0.2% and 14.1%. For carrier *B* gains vary between -1.8% and 15.5% where average gain is 8.4%. Best bounds of individual scenarios are also compared with the collaborative scenarios to investigate lower bounds on gains. Results can be found in Figure 5.12

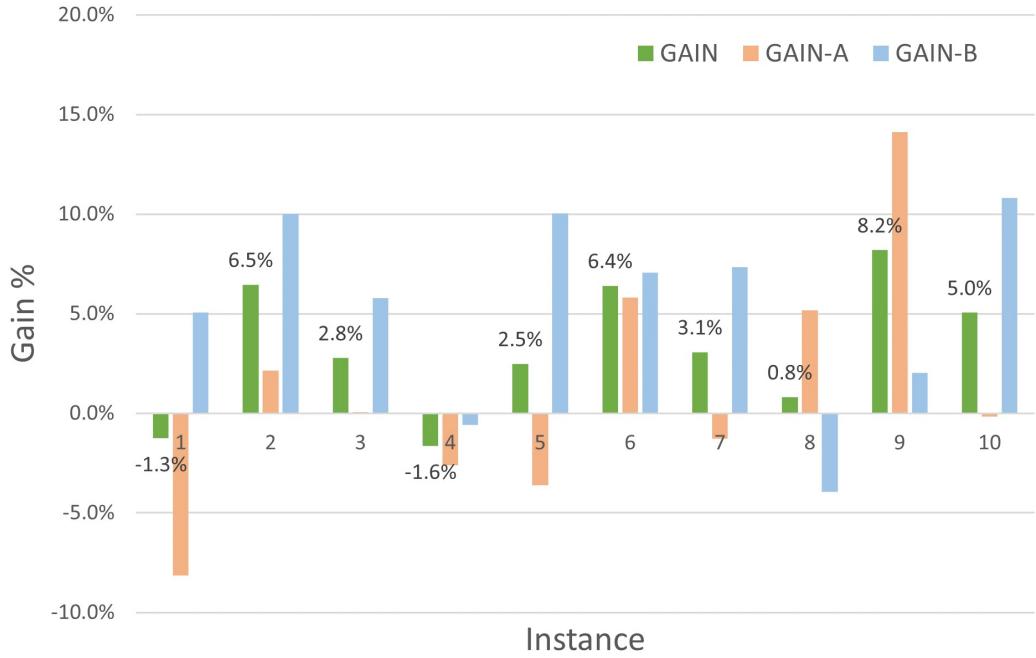


Figure 5.12 Gain comparison through best bounds for NCD scenario and high demand setting of 30 customer instances

When the comparison is conducted through best bounds for high demand setting of NCD scenario with 30 customers, all instances yielded better results under collaborative scenarios except for two scenarios. Since all the models are solved relatively higher gaps, these two cases are exceptions with only approximately -1% deviation. Average gain for collaborative scenarios is 3.2% where gains deviate between -1.6% and 8.2%. Carrier *A* reported an average of 1.1% gain where gains vary between -8.1% and 14.1%. Average gain of carrier *B* is 5.4% where gains of *B* deviate between -3.9% and 10.8%.

Overall, all instances of all scenarios are solved under both low demand and high demand environments. LB formulation was able to find solutions for all instances with deviating gaps. To lower gaps several valid inequalities are proposed and their effects are investigated. All tests are continued with best found combination of proposed valid inequalities. From the managerial perspective, it is observed that in all scenarios, collaboration yielded better solutions even though the collaborative scenario instances are solved with gaps. Collaboration behaviour tested with all three scenarios proposed in Section 4.3, namely; original, ICC and NCD. When the original and ICC scenarios are compared, ICC instances yielded higher gains in average, as expected because of the increased number of opportunities for collaboration. When the original and NCD scenarios are compared, NCD instances yielded lower gains than original instances, since the collaboration gains are restricted through distanced facility declaration. Same experiments are conducted with 50 customer

setups as well. Results can be found in Appendix A. However, since the reported gaps are higher in both collaborative and individual runs, comparing results do not promise reliable insights.

As indicated in previous sections, none of the collaborative instances solved until optimality. Moreover, solution times are 8 and 16 hours for 30 and 50 customer instances, respectively. 100 customer instances did not yield sensible results within 48 hour time limit.

Consequently, a new path-based formulation is proposed in Section 3.2.3 to solve problem with a path-based formulation approach in which outbound routes are selected pre-generated routes instead of creating optimum routes. As mentioned before, outbound routing decisions is one of the key reasons that increase time and space complexity of the problem. Via path-based method, time and space complexity of the model decreased in exchange of exact solutions. Details of path-based formulation approach discussed in Section 6.

## 6. PATH-BASED FORMULATION

The path-based formulation is different from the other two in the way routing decisions are modeled. Instead of constructing the routes through arc traversal decisions, the formulation selects a subset of the routes from a set of predetermined routes. As a matter of fact, the formulation requires these routes to be generated a priori, i.e., a pre-processing phase to generate routes is needed. Ideally, for the mathematical model to find the true optimal solution equivalent that can be found by either the VB formulation or the LB formulation, all possible feasible routes must have been generated by this pre-processing phase. Since the number of such routes are usually exponentially many, a possible approach is to generate a limited number of good routes.

In our approach, the set of routes are created by solving heuristically a series of single depot VRPs: a VRP for each depot  $d \in D_r$  of each carrier  $r \in C$ . For each depot, the problem is solved with several different heuristic algorithms and the resulting routes are added to route pool. Then, demands of common customers are merged as if they are a single customer of that carrier: the new version of the problem is solved with all heuristic algorithms again. These routes are also, added to route pool. Main motivation behind the repetition and merging demands is to mimic creation of joint routes when the carriers collaborate and transfer their demand among themselves. 5 different well known heuristics are utilized:

- *Nearest Neighborhood (NNH)* (Tyagi, 1968)
- *Sweep* (Gillett & Miller, 1974)
- *Parallel Savings (PS)* (Clarke & Wright, 1964)
- *Gaskell-Savings (GS)* (Gaskell, 1967)
- *CMT Two-Phase Heuristic (CMT2P)* (Christofides, Mingozzi & P.Toth, 1979)

The working mechanisms of the heuristics or heuristic algorithm development is beyond the scope of this study. Different heuristic algorithms are utilized to generate

different routes and increase the diversity among routes. Since demand transfer is allowed if vehicle capacity is not exceeded on that route, creation of sub-optimal routes in individual cases may be beneficial to incentivize collaboration as well. Flowchart of the route pool generation mechanism can be found in Figure 6.1.

During root pool generation, firstly an empty master route list  $R$  is defined. Then for each depot  $d \in D_r$  of each carrier  $r \in C$ , problem is reduced to a single depot VRP and a list  $R_d = \{\}$  is initialized which denotes the routes belong to depot  $d$  and a parameter  $iter = 1$ . Then problem is solved by NNH, Sweep, PS, GS and CMT2P heuristics separately and all found routes are appended to  $R_d$ . Then all generated identical routes eliminated from  $R_d$ , if there is any, to break possible symmetry. Append  $R_d$  to  $R$ . If  $iter = 1$ , then demand of other common customers which emerge from other carriers assigned to that customer and  $iter$  is updated to 2. All reduced problem steps are repeated for this depot. Then master route list  $R$  is used as "possible route list" for outbound routes in path-based formulation.

For the path-based formulation, inequalities (4.4),(4.9) and (4.10) that are proposed under Section 4.2 are valid as well. One extra valid inequality is proposed for path-based model.

$$(6.1) \quad \sum_{t \in R} x^t \geq \lceil \frac{\sum_{i \in N} \sum_{r \in C} d_i^r}{Q} \rceil$$

Since the total demand and vehicle capacities are known and vehicles are homogeneous, a lower bound on the number of routes that should be used can be forced by inequalities (6.1). Note that since (6.1) are non-linear, it can be replaced with (6.2).

$$(6.2) \quad \sum_{t \in R} x^t \geq \frac{\sum_{i \in N} \sum_{r \in C} d_i^r}{Q}$$

## 6.1 Computational Experiments

Path-based (PB) formulation reduces the problem size and consequently time and space complexity drastically. Therefore, for 30 customer instances, time limit is set

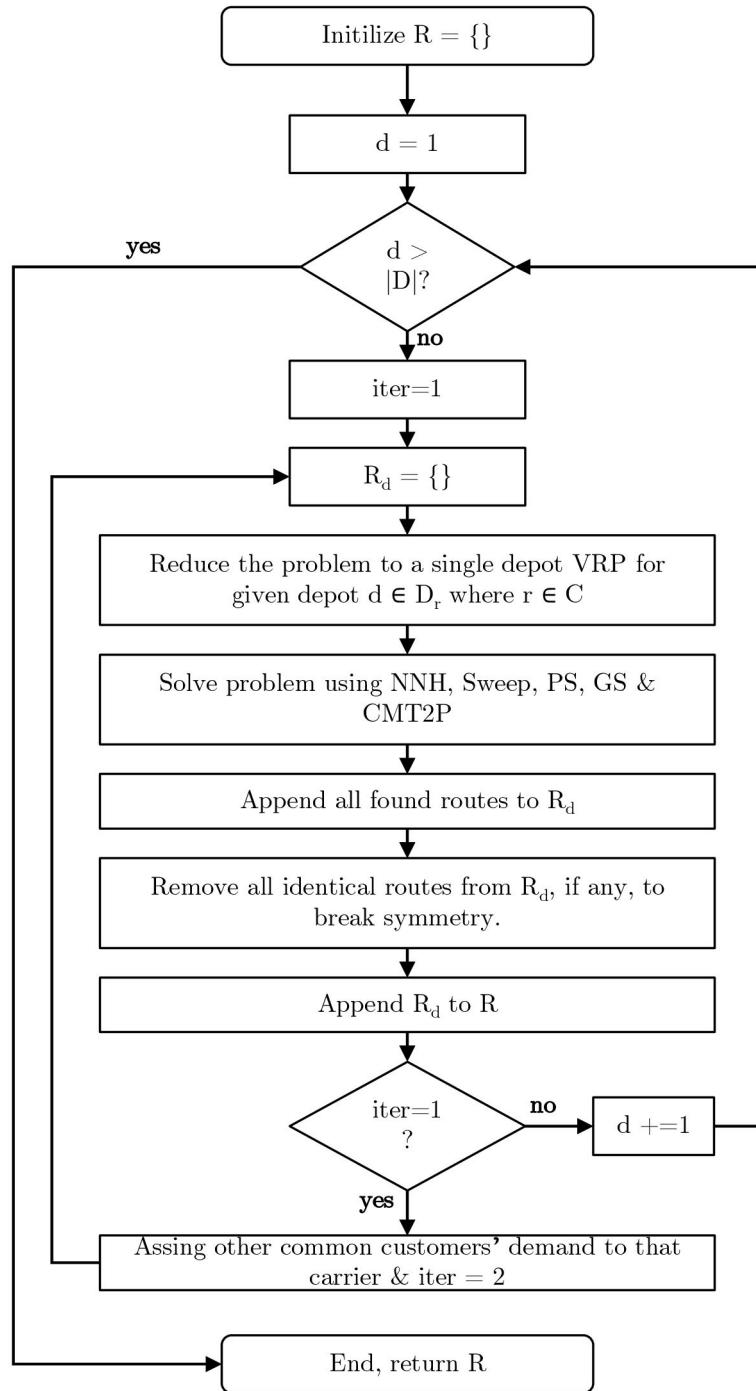


Figure 6.1 Heuristic route pool generation

as 2 hours, 50 customer instances 4 hours and 100 customer instances 16 hours. Note that route generation process takes no more than 2 minutes even for biggest instances, so they are not included in solution times.

For all results tables,  $R_A$  and  $R_B$  columns indicate the number of used routes in optimum solution. Rest of the column names explained at the beginning of Section 5.2.

In PB approach, computational experiments are started with original scenario and low demand setting of 30 customer instances. Before going into details of the run results, information on number of pre-generated routes in original scenarios presented in Table 6.1. As it can be interpreted from Table 6.1, number of possible routes per carrier deviate between 245 and 6344 depending on the problem size and demand structure. In Table 6.1,  $TR_A$  and  $TR_B$  depicts the number of pre-generated routes for each carrier, respectively.

Table 6.1 Pre-generated route numbers for original scenario

Ins.	30 Customer				50 Customer				100 Customer			
	Low Dem.	High Dem.	Low Dem.	High Dem.	Low Dem.	High Dem.	Low Dem.	High Dem.	Low Dem.	High Dem.	Low Dem.	High Dem.
	$TR_A$	$TR_B$	$TR_A$	$TR_B$	$TR_A$	$TR_B$	$TR_A$	$TR_B$	$TR_A$	$TR_B$	$TR_A$	$TR_B$
1	315	379	622	785	690	603	1265	1093	2819	2678	6177	5774
2	371	320	784	679	798	705	1489	1284	2780	2855	5466	5500
3	380	323	662	617	749	649	1389	1166	2627	2522	5708	5450
4	245	359	532	793	785	726	1405	1326	2672	2575	5286	4927
5	328	357	712	722	763	733	1400	1336	2619	2779	5652	6020
6	358	315	767	678	712	713	1312	1305	2836	2737	5485	5255
7	357	316	753	664	696	714	1338	1312	2838	2858	4618	4644
8	315	315	588	615	807	701	1570	1281	2769	2851	6156	6344
9	315	353	622	787	684	668	1479	1402	2814	2682	4582	4343
10	315	356	529	667	767	700	1416	1273	2870	2715	5573	5331

Results of the path-based formulation for 30 customers under original scenario and low demand setting can be found in Table 6.2.

Table 6.2 PB Formulation results for original scenario and low demand setting of 30 customer instances

Ins.	$F_A$	$F_B$	$T_A$	$T_B$	$R_A$	$R_B$	$Obj$	$Obj_A$	$Obj_B$	T(s)	$RC$	$FC$	$TC$	$IC$
1	1	1	1	1	4	5	59212	28374	30838	2	49093	7029	0	3090
2	1	1	1	1	9	4	63258	31251	32007	6	51477	7029	0	4752
3	1	1	1	1	9	4	66487	35099	31389	4	53486	9073	105	3928
4	1	1	1	1	3	5	56495	28600	27894	2	42512	8334	492	5157
5	1	1	1	1	4	5	59675	23104	36571	5	46002	7065	259	6350
6	1	1	1	1	4	4	62773	35704	27069	4	50294	7065	382	5033
7	1	1	1	1	5	4	60823	29770	31053	3	48116	7065	478	5164
8	1	1	1	1	3	4	59838	27162	32675	5	45140	8530	523	5645
9	1	1	1	1	4	4	71090	34649	36441	6	55295	8938	333	6525
10	1	1	1	1	4	5	63738	29752	33986	3	50554	7065	522	5597

Within seconds, all of the instances are solved with 0 gap. Maximum run time is

6 seconds. When the results are compared with the LB formulation results, both carriers open one depot and create one transfer line between depots. Number of total selected routes in PB formulation results deviate between 7 and 13. Same experiments are conducted for high demand environment as well. Results can be found in Table 6.3.

Table 6.3 PB Formulation results for original scenario and high demand setting of 30 customer instances

<b>Ins.</b>	<b><math>F_A</math></b>	<b><math>F_B</math></b>	<b><math>T_A</math></b>	<b><math>T_B</math></b>	<b><math>R_A</math></b>	<b><math>R_B</math></b>	<b><math>Obj</math></b>	<b><math>Obj_A</math></b>	<b><math>Obj_B</math></b>	<b>T(s)</b>	<b><math>RC</math></b>	<b><math>FC</math></b>	<b><math>TC</math></b>	<b><math>IC</math></b>
<b>1</b>	1	2	2	1	7	11	84655	37917	46738	10	66736	11299	181	6439
<b>2</b>	2	1	1	2	18	7	87762	49155	38607	6	66925	12130	192	8515
<b>3</b>	2	2	2	2	15	22	81829	41689	40140	2	50744	17032	362	13691
<b>4</b>	2	1	1	2	7	9	72874	35897	36977	5	53427	10266	327	8854
<b>5</b>	1	2	2	1	8	9	80099	33351	46748	7	59982	11440	448	8229
<b>6</b>	2	2	2	2	8	10	87084	44873	42211	8	59309	14641	692	12442
<b>7</b>	2	1	1	1	10	7	80806	44932	35874	15	62124	10266	282	8133
<b>8</b>	1	1	1	1	8	6	78296	42119	36177	18	63598	8530	523	5645
<b>9</b>	2	2	1	2	8	8	91513	46544	44970	29	62523	15967	166	12857
<b>10</b>	1	2	2	1	6	10	79527	37881	41646	4	55314	12460	886	10867

In high demand environment, all instances are solved under 30 seconds as well. Maximum solution time is 29 seconds and average solution time is 10 seconds. Number of selected routes deviate between 14 and 37.

Since outbound routes are created heuristically, results of exact solutions which are achieved through LB formulation, are compared with PB solutions in order to evaluate how much PB formulation deviate from optimality. Since not all LB formulation examples are solved to optimality, we compare both best found objective values within 8 hour limit and best bounds found by solver. Deviation amounts for original scenario of 30 customer instances can be found in Table 6.4.

Table 6.4 PB deviation percentages for original scenario of 30 customer instances

<b>Ins</b>	<b>Low Demand</b>		<b>High Demand</b>	
	<b><math>\Delta_{OFV}</math></b>	<b><math>\Delta_{BB}</math></b>	<b><math>\Delta_{OFV}</math></b>	<b><math>\Delta_{BB}</math></b>
<b>1</b>	0.1%	8.4%	2.5%	13.3%
<b>2</b>	3.4%	8.1%	1.8%	9.9%
<b>3</b>	7.5%	11.9%	-6.6%	7.0%
<b>4</b>	7.2%	10.3%	5.3%	12.7%
<b>5</b>	3.3%	11.1%	1.5%	10.4%
<b>6</b>	5.7%	11.3%	6.0%	12.6%
<b>7</b>	6.0%	10.1%	2.5%	12.2%
<b>8</b>	5.0%	9.6%	3.9%	11.4%
<b>9</b>	6.3%	13.1%	3.2%	12.3%
<b>10</b>	4.1%	10.7%	-1.4%	4.5%

In deviation tables,  $\Delta_{OFV}$  indicates the percentage difference between the objective function value of PB formulations run results and the best reported objective function value of LB formulation. In other words, it shows that how far PB solution is

away from the best found exact solution reported by LB model within 8 hours for 30 customer instances. Similarly,  $\Delta_{BB}$  reports the difference percentage between the objective function value of PB model results and the best reported bound by LB formulation. A negative sign (-) means that PB method reported a better solution.

In low demand environment of original scenario of 30 customer instances, PB formulation deviates 4.8% on average when comparison is conducted through best found OFVs of LB formulation. Minimum deviation is 0.1% which means that PB formulation found a solution almost as good as exact formulation, within seconds. On the other hand maximum deviation is 7.5%. When deviations compared through best bounds, average difference in 10.5% where minimum variance is 8.1% and maximum variance is 13.1%.

When best found OFVs are compared with PB formulation results for high demand environment of the original scenario of 30 customers, it is observed that PB model reported better outcomes for two instances. In average, PB formulation deviates 1.9% and deviation range is between -6.6% and 6%. When deviations compared through best bounds, average difference is 10.6% where minimum variance is 4.5% and maximum variance is 13.3%.

Overall, when the original setting of 30 customer instances investigated, PB approach deviates 3.4% in average when OFVs are compared and 10.5% on average when bests bounds are compared. Same experiments are repeated with 50 customer instances. PB formulation run results for low demand setting and original scenario of 50 customer instances can be found in Table 6.5.

Table 6.5 PB Formulation results for original scenario and low demand setting of 50 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	2	2	2	1	6	6	89476	43608	45868	12	58555	17069	147	13706
<b>2</b>	2	1	1	0	6	8	90619	44855	45764	21	67563	13406	239	9411
<b>3</b>	1	1	1	1	7	6	84881	40609	44273	37	70557	10386	285	3653
<b>4</b>	2	2	2	2	7	8	87623	42465	45158	29	60775	15664	396	10788
<b>5</b>	2	1	1	2	7	8	87197	46103	41094	13	68541	11894	370	6392
<b>6</b>	1	1	1	1	6	7	86500	43433	43067	22	75813	8590	181	1916
<b>7</b>	1	1	1	1	7	6	86940	46419	40521	21	76263	8032	223	2422
<b>8</b>	2	2	2	2	7	7	104264	50686	53579	44	72608	17306	584	13766
<b>9</b>	1	2	1	1	6	8	90836	45053	45783	92	69787	11430	43	9576
<b>10</b>	2	2	2	2	8	8	103262	51673	51589	32	71436	19049	692	12085

In low demand environment, all instances are solved under two minutes. Maximum solution time is 92 seconds and average solution time is 32 seconds. Number of selected routes deviate between 14 and 16.

The experiments are repeated for the for high demand environment and original

scenario setting of 50 customers. Results can be found in Table 6.6.

Table 6.6 PB Formulation results for original scenario and high demand setting of 50 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	2	2	2	2	11	12	107793	53111	54682	12	76724	17069	294	13706
<b>2</b>	2	2	2	2	13	13	112120	60779	51341	38	77212	19656	827	14424
<b>3</b>	2	2	1	2	13	11	111125	52967	58159	80	83610	17700	145	9671
<b>4</b>	2	3	1	2	14	12	108818	56296	52523	18	70451	22130	417	15820
<b>5</b>	2	3	2	2	12	13	115084	52583	62501	45	78273	20106	874	15832
<b>6</b>	3	3	2	2	10	14	110016	53199	56818	14	66996	23449	218	19353
<b>7</b>	2	2	2	2	12	15	114594	50365	64229	41	84984	17822	567	11222
<b>8</b>	3	2	2	3	16	11	129866	70035	59832	18	87191	21068	712	20896
<b>9</b>	3	3	2	3	14	13	116189	59813	56376	15	72337	22778	323	20751
<b>10</b>	3	2	1	2	14	13	128774	61819	66955	64	89393	22311	560	16510

In high demand environment, all instances are solved under two minutes as well. Maximum solution time is 80 seconds and average run time is 35 seconds. As we did in 30 customer setting, deviations are compared with the best reported OFVs and best bounds of LB formulation. Results can be found in Table 6.7

Table 6.7 PB deviations for original scenario of 50 customer instances

<b>Ins</b>	<b>Low Demand</b>		<b>High Demand</b>	
	$\Delta_{OFV}$	$\Delta_{BB}$	$\Delta_{OFV}$	$\Delta_{BB}$
<b>1</b>	1.4%	12.7%	-2.9%	6.9%
<b>2</b>	8.5%	18.2%	-3.3%	6.1%
<b>3</b>	3.5%	16.7%	-3.2%	9.2%
<b>4</b>	2.7%	13.7%	-4.4%	6.9%
<b>5</b>	2.6%	12.9%	-5.0%	7.1%
<b>6</b>	6.4%	15.9%	-4.3%	6.1%
<b>7</b>	2.1%	13.2%	-1.3%	9.7%
<b>8</b>	5.1%	17.0%	-0.3%	8.7%
<b>9</b>	3.6%	17.4%	4.0%	13.9%
<b>10</b>	3.2%	15.3%	-4.3%	7.9%

In low demand and original scenario of 50 customer instances, PB formulation results deviate 3.9% on average when comparisons are conducted through the best found OFVs of LB formulation's 16 hour runs. Average run time for PB formulation is in the order of seconds. Minimum deviation is 1.4% and maximum deviation is 8.5%. When deviations compared through best bounds, average deviation is 15.3% where minimum deviation is 12.7% and maximum deviation is 18.2%. Since LB formulations solved with optimality gaps for 50 customer instances, deviation rate  $\Delta_{BB}$  reports an upper bound for deviation amount.

In high demand environment, when the best OFVs are compared, average deviation turns out to be -2.5% where minimum deviation is -5% and maximum deviation is 4%. Furthermore, PB formulation found better results within seconds for 9 out of 10

instances. When deviations are compared through best bounds, average deviation is 8.2% where maximum deviation is 13.9%.

Overall, when the original setting of 50 customer instances investigated, PB approach deviates 0.7% in average when OFVs are compared and 11.8% in average when bests bounds are compared.

Since solution times decreased for 30 and 50 customer instances under original scenario, 100 customer instances are solved with PB formulation as well. For the 100 customer instances, only 3 solutions are found by LB formulation within 48 hours of run time, and average gap of those instances are 61.5%. Other instances were not be able to solved because of memory issues or no feasible solutions are reported within given time limit. Experiments are repeated with original scenario of 100 customer instances for PB formulation. PB formulation run results for low demand and original scenario of 100 customer instances can be found in Table 6.8.

Table 6.8 PB Formulation results for original scenario and low demand setting of 100 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	3	2	2	3	15	12	130086	67529	62556	676	98570	18080	413	13022
<b>2</b>	2	2	2	2	13	14	134553	65329	69224	4035	109531	15958	469	8595
<b>3</b>	2	3	3	2	12	13	134803	70106	64697	1955	95940	21309	674	16880
<b>4</b>	2	2	2	2	14	12	132917	66092	66826	1738	107289	14054	391	11183
<b>5</b>	2	2	2	2	13	13	139164	69815	69349	3543	118193	14318	247	6406
<b>6</b>	2	2	2	2	13	14	130353	64118	66236	730	109035	13525	307	7486
<b>7</b>	2	3	2	2	15	14	138534	69514	69020	1929	102812	21847	246	13629
<b>8</b>	2	3	3	2	14	13	135919	71045	64874	669	100961	17639	658	16661
<b>9</b>	3	2	2	3	14	14	138389	69475	68914	2698	104155	19929	705	13600
<b>10</b>	2	2	2	2	14	14	137148	71254	65894	1604	110825	15548	658	10118

Using PB formulation, all instances are solved to optimality. For original scenario and low demand setting of 100 customer instances, average run time turns out to be 1958 seconds which is approximately half an hour. Maximum run time is 3543 seconds and minimum run time is 669 seconds. Carriers started to open more depots and declare more transfer lines. Number of total selected routes increased either for both carriers. Since all instances are solved with no gaps, same experiments are repeated for the high demand setting. Results can be found in Table 6.9.

For original scenario and high demand setting of 100 customer instances, average run time is 1189 seconds which is under 20 minutes. Conversely, the deviation between max run time and min run time is higher when compared to low demand scenario. For the high demand scenario, minimum run time is 328 seconds and maximum run time is 6010 seconds. In the high demand scenario, carriers prefer to open more depot and transfer lines between depots. Number of used routes increased as well and deviate between 45 and 59.

Table 6.9 PB Formulation results for original scenario and high demand setting of 100 customer instances

<b><i>Ins</i></b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>R<sub>A</sub></i></b>	<b><i>R<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b>T(s)</b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b>1</b>	4	5	5	2	27	31	179192	81451	97741	358	117208	32436	383	29165
<b>2</b>	3	4	4	3	24	28	175510	82049	93461	921	124757	27080	770	22902
<b>3</b>	4	3	3	3	26	27	172583	89524	83059	495	117288	25220	659	29416
<b>4</b>	4	4	3	4	26	23	171736	90075	81661	535	113552	30924	814	26445
<b>5</b>	4	4	4	4	27	28	184279	93553	90726	350	128324	29172	842	25941
<b>6</b>	4	3	2	4	26	24	173623	89068	84555	1143	127297	26668	623	19035
<b>7</b>	3	3	3	2	24	21	165411	83634	81777	1298	122132	23824	427	19027
<b>8</b>	4	3	3	4	32	27	187854	99803	88052	446	136635	27551	852	22816
<b>9</b>	4	3	3	3	23	21	171977	84453	87524	6010	119259	26977	572	25170
<b>10</b>	4	4	4	3	25	29	174801	90015	84786	328	114162	32381	606	27651

All instances of original scenario are solved till optimality with PB formulation and therefore all experiments are repeated with ICC and NCD scenarios to see the effect of data structure on problem. Initially, experiments are started with the 30 customer and low demand setup of ICC scenario.

Before going into details of the experiment results, information on number of pre-generated routes in ICC scenarios presented in Table 6.10. As it can be concluded from the Table 6.10, number of possible routes per carrier deviate between 282 and 6682 depending on the problem size and demand structure.

Table 6.10 Pre-generated route numbers for ICC scenarios

<b>Ins.</b>	<b>30 Customer</b>				<b>50 Customer</b>				<b>100 Customer</b>			
	<b>Low Dem.</b>		<b>High Dem.</b>		<b>Low Dem.</b>		<b>High Dem.</b>		<b>Low Dem.</b>		<b>High Dem.</b>	
	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>	<b><i>TR<sub>A</sub></i></b>	<b><i>TR<sub>B</sub></i></b>
<b>1</b>	346	368	705	800	748	659	1384	1174	2978	2901	6525	6308
<b>2</b>	383	360	817	769	857	759	1841	1611	3054	3047	5950	5874
<b>3</b>	366	358	678	670	783	707	1696	1508	2842	2727	6110	5919
<b>4</b>	282	365	605	774	881	725	1617	1297	2835	2843	5452	5485
<b>5</b>	359	354	773	743	784	794	1440	1456	2804	3012	6080	6570
<b>6</b>	377	348	818	719	802	752	1457	1376	2995	3017	5801	5804
<b>7</b>	370	347	818	715	797	754	1476	1382	3036	3066	4899	4960
<b>8</b>	334	338	654	646	909	763	1702	1371	2967	3044	6540	6682
<b>9</b>	349	370	703	837	747	707	1598	1504	2985	2933	4844	4726
<b>10</b>	322	384	596	710	784	776	1471	1411	3096	2828	6119	5563

Results of PB formulation runs for 30 customer instances under original and low demand scenario can be found in Table 6.11.

Under two minutes, all of the instances all solved to optimality. Maximum run time is 98 seconds and minimum run time is 9 seconds. Average run time is 27 seconds for the PB formulation results with 30 customers and ICC scenario in low demand setting. In all instances, both carriers chose to open one depot and declare one transfer line. Number of total selected routes vary between 8 and 12. Same experiment is conducted for high demand environment as well. Results can be

Table 6.11 PB Formulation results for ICC scenario and low demand setting of 30 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	1	1	1	1	4	4	61617	30649	30968	18	48249	9111	158	4099
<b>2</b>	1	1	1	1	6	6	66917	28582	38335	27	51542	10623	0	4752
<b>3</b>	1	1	1	1	4	6	64793	30357	34436	9	50906	9208	313	4366
<b>4</b>	1	1	1	1	4	4	52718	28585	24133	19	39614	7456	492	5157
<b>5</b>	1	1	1	1	4	5	61008	24980	36028	25	45289	9111	259	6350
<b>6</b>	1	1	1	1	5	3	58756	37667	21089	22	46450	7456	298	4552
<b>7</b>	1	1	1	1	5	4	62069	32040	30029	17	49127	7456	419	5067
<b>8</b>	1	1	1	1	4	4	54596	27326	27270	16	39947	7963	594	6092
<b>9</b>	1	1	1	1	3	5	69495	30289	39206	98	52908	10005	237	6345
<b>10</b>	1	1	1	1	4	5	65380	31796	33584	19	50773	6929	606	7073

found in Table 6.12.

Table 6.12 PB Formulation results with 30 customers and ICC scenario in high demand setting

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	1	2	2	1	6	12	82493	29554	52939	27	60454	12973	449	8618
<b>2</b>	3	1	1	3	21	5	85637	51811	33825	20	53441	16324	1038	14834
<b>3</b>	1	2	2	1	12	22	80740	35753	44987	42	58286	12471	487	9497
<b>4</b>	1	1	1	1	6	10	68220	29142	39078	27	55116	7456	492	5157
<b>5</b>	1	2	2	1	6	11	77020	25294	51726	17	55371	12973	448	8229
<b>6</b>	2	2	2	2	9	9	77171	42707	34464	14	49129	14965	697	12380
<b>7</b>	1	2	2	1	9	9	79263	38681	40582	91	58602	11318	545	8798
<b>8</b>	1	2	2	1	7	8	68111	30198	37913	13	44566	13292	731	9523
<b>9</b>	2	2	2	2	9	10	88169	41383	46786	61	58127	14984	729	14329
<b>10</b>	2	2	2	2	7	9	79354	35915	43438	26	46707	15420	617	16610

Optimum results for PB formulation are reported under two minutes for high demand setting. Average run time is 34 seconds where run times deviate between 17 and 91 seconds. Once the demand setting switched to high, carriers started to open more depots and define more transfer lines. Number of total selected routes vary between and 16 and 34. When the ICC experiments with 30 customers compared with the original scenario experiments with 30 customers, it is observed that solution times increased with ICC setup. Run time comparisons can be found in Table 6.13. Run times are indicated in terms of seconds.

Table 6.13 Original vs ICC scenario run times with 30 customer instances under PB formulation

		<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Demand</b>	<b>Original</b>		2	6	4	2	5	4	3	5	6	3
	<b>ICC</b>		18	27	9	19	25	22	17	16	98	19
<b>High Demand</b>	<b>Original</b>		10	6	2	5	7	8	15	18	29	4
	<b>ICC</b>		27	20	42	27	17	14	91	13	61	26

When the results compared in Table 6.13, it is observed that ICC setting increases

solution times. Since number of possibilities for assignment and collaboration increases with the ICC scenario, solution times are increased as well.

As we did in original scenario instances, deviations are compared with the best reported OFVs and best bounds of LB formulation for ICC scenario. Results can be found in Table 6.14.

Table 6.14 PB deviations for ICC scenario of 30 customer instances

Ins	Low Demand		High Demand	
	$\Delta_{OFV}$	$\Delta_{BB}$	$\Delta_{OFV}$	$\Delta_{BB}$
<b>1</b>	4.0%	11.9%	0.4%	13.0%
<b>2</b>	9.1%	14.9%	4.5%	12.3%
<b>3</b>	3.4%	10.7%	-5.4%	3.9%
<b>4</b>	6.5%	12.0%	4.2%	12.6%
<b>5</b>	5.8%	14.1%	1.1%	9.3%
<b>6</b>	5.7%	12.4%	2.3%	9.6%
<b>7</b>	9.2%	14.9%	2.6%	13.6%
<b>8</b>	4.1%	10.5%	3.3%	7.7%
<b>9</b>	6.2%	15.8%	3.0%	12.8%
<b>10</b>	5.1%	15.2%	-2.0%	7.4%

In low demand environment of ICC scenario of 30 customer instances, PB model deviates 5.9% in average when comparison is conducted through best found OFVs. Minimum deviation is 3.4% and maximum deviation is 9.2%. When deviations compared through best bounds, average difference is 13.2% where minimum variance is 10.5% and maximum variance is 15.8%.

When best found OFVs are compared with PB formulation results for high demand environment of the ICC scenario of 30 customers, it is observed that PB model reported better outcomes for two instances; instance 3 and instance 10. On average, PB formulation deviates 1.4% and deviation range is between -5.4% and 4.5%. When deviations compared through best bounds, average difference in 10.2% where minimum variance is 3.9% and maximum variance is 13.6%.

Overall, when the ICC setting of 30 customer instances investigated, PB approach deviates 3.6% in average when OFVs are compared and 11.7% in average when bests bounds are compared. Same experiments are repeated with 50 customer instances. PB formulation run results for low demand and ICC scenario of 50 customer instances can be found in Table 6.15.

In low demand environment, all instances are solved under 360 seconds. Minimum run time is 29 seconds and maximum run time is 345 seconds where average run time is 186 seconds. Number of selected routes deviate between 13 and 17. In order to see the effect of demand, experiments are repeated under high demand setup. Results can be found in Table 6.16.

Table 6.15 PB Formulation results for ICC scenario and low demand setting of 50 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	2	2	2	2	7	6	85584	44174	41710	29	54284	17699	326	13575
<b>2</b>	2	1	1	2	9	6	92657	54120	38538	265	67974	12211	738	11734
<b>3</b>	1	1	1	1	7	6	82663	42731	39932	151	69393	9332	285	3653
<b>4</b>	2	1	1	2	8	7	88608	45647	42961	170	66577	12832	592	8607
<b>5</b>	2	1	1	2	7	7	86911	45951	40961	36	67778	12372	370	6392
<b>6</b>	1	1	1	1	7	6	84591	45736	38854	120	73652	8842	181	1916
<b>7</b>	1	1	1	1	6	8	90956	39374	51581	328	79345	8966	223	2422
<b>8</b>	2	2	2	2	9	8	100368	50299	50070	237	65580	17352	863	16574
<b>9</b>	2	2	1	2	7	7	89009	41119	47890	176	57755	18467	110	12677
<b>10</b>	2	1	1	2	8	7	101852	50555	51297	345	78985	14221	570	8076

Table 6.16 PB Formulation results for ICC scenario and high demand setting of 50 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	3	2	2	2	12	11	102624	50198	52426	61	63609	20525	560	17930
<b>2</b>	3	2	2	3	15	15	118839	63005	55833	51	76689	21427	929	19794
<b>3</b>	2	2	2	2	16	11	113558	60556	53002	128	84758	17668	532	10600
<b>4</b>	2	2	2	2	16	10	103221	58861	44360	51	73093	16999	701	12427
<b>5</b>	2	2	2	2	13	13	111538	54013	57525	159	78150	17162	977	15249
<b>6</b>	2	3	3	2	9	15	107299	48336	58964	136	72376	19854	615	14455
<b>7</b>	3	2	2	3	14	11	112998	58003	54995	174	74384	21660	797	16157
<b>8</b>	3	2	2	3	15	11	120297	64610	55687	42	77345	20598	656	21698
<b>9</b>	3	2	1	3	16	11	110823	55383	55441	88	70363	21726	834	17900
<b>10</b>	3	2	2	3	14	12	122948	63880	59069	146	79999	22598	910	19442

In high demand environment, all instances are solved under three minutes. Maximum solution time is 159 seconds and average run time is 104 seconds. When the demand setting is high, companies started to open more depots and transfer lines overall. Number of selected routes vary between 23 and 30. When the ICC experiments with 50 customers compared with the original scenario experiments with 50 customers, it is observed that solution times increased with ICC setup. Run-time comparisons can be found in Table 6.17. Run times are indicated in terms of seconds.

Table 6.17 Original vs ICC scenario run times with 50 customer instances under PB formulation

	<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Demand</b>	Original	12	21	37	29	13	22	21	44	92	32
	ICC	29	265	151	170	36	120	328	237	176	345
<b>High Demand</b>	Original	12	38	80	18	45	14	41	18	15	64
	ICC	61	51	128	51	159	136	174	42	88	146

When the results compared in Table 6.17, it is observed that ICC setting increases solution times which is get along with the findings in 30 customer experiments. Since number of possibilities for assignment and collaboration increases with the ICC scenario, solution times are increased as well.

As we did in 30 customer setting, deviation amounts from exact solutions are compared with the best reported OFVs and best bounds of LB formulation. Results can be found in Table 6.18.

Table 6.18 PB deviations for ICC scenario of 50 customers

Ins	Low Demand		High Demand	
	$\Delta_{OFV}$	$\Delta_{BB}$	$\Delta_{OFV}$	$\Delta_{BB}$
<b>1</b>	3.1%	13.9%	-0.8%	8.1%
<b>2</b>	8.9%	19.4%	4.4%	14.6%
<b>3</b>	0.6%	18.6%	3.8%	15.5%
<b>4</b>	8.5%	18.6%	-6.1%	6.5%
<b>5</b>	3.5%	13.4%	-2.7%	7.4%
<b>6</b>	5.7%	16.1%	-6.5%	6.8%
<b>7</b>	9.2%	19.0%	-6.8%	8.0%
<b>8</b>	6.7%	17.7%	-5.4%	8.0%
<b>9</b>	5.9%	18.5%	4.4%	13.6%
<b>10</b>	3.7%	18.2%	-3.2%	8.7%

PB formulation deviates 5.6% in average when ICC scenario of 50 customer instances are compared in low demand setup through best found OFVs. Minimum deviation is 0.6% and maximum deviation is 9.2%. When deviations compared through best bounds, average difference is 17.3% where minimum variance is 13.4% and maximum variance is 19.4%.

When best found OFVs are compared with PB formulation results for high demand environment of the ICC scenario of 50 customers, it is observed that PB formulation reported better outcomes for seven out of ten instances, except instances 2,3 and 9. PB formulation deviates -1.9% in average which means that PB formulation reported better outcomes than 16 hour exact LB formulation runs within few minutes. When deviations compared through best bounds, average difference in 9.7% where minimum variance is 6.5% and maximum variance is 15.5%.

Overall, when the ICC setting of 50 customer instances investigated, PB approach deviates 1.8% in average when OFVs are compared and 13.5% in average when best bounds are compared.

Experiments are continued with ICC setting of 100 customer instances in order to see the effect of number of increased customers to solution times and managerial aspects with the biggest available instances. PB formulation run results for low demand and ICC scenario of 100 customer instances can be found in Table 6.19.

All ICC and low demand scenario instances of 100 customer setting, are solved to optimality. With the increased number of common customers, problem became harder to solve and run times increase. Average run time for those instances is 14105 seconds which is approximately 4 hours. Minimum run time is 5335 seconds and

Table 6.19 PB Formulation results for ICC scenario and low demand setting of 100 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	2	2	2	2	12	15	128694	56056	72638	9604	101259	15477	758	11200
<b>2</b>	2	3	3	2	13	15	129742	57798	71945	14403	97217	19042	480	13004
<b>3</b>	2	3	3	2	12	14	127583	63829	63755	3010	90843	20495	810	15435
<b>4</b>	3	1	1	3	14	11	128180	69858	58322	7291	100630	15392	696	11462
<b>5</b>	3	1	1	3	14	12	136663	70309	66353	15057	113408	14004	484	8767
<b>6</b>	2	3	3	2	13	15	129174	55453	73721	15271	99443	18035	244	11452
<b>7</b>	2	2	2	2	15	13	132599	68772	63827	14852	105916	14650	183	11850
<b>8</b>	2	3	3	2	13	14	138466	67378	71088	5335	104122	21636	457	12252
<b>9</b>	3	2	2	3	15	12	138107	70187	67920	28791	100601	22208	657	14640
<b>10</b>	3	2	2	3	15	13	139141	75873	63268	27424	104668	20243	606	13624

maximum run time is 28791 seconds which is almost 8 hours. Genuinely run times increase with the ICC scenario. As it is anticipated, number of opened and created depots are increased as well. In order to see the effect of demand amount on the problem, same experiments are repeated under high demand setting. Results can be found in Table 6.20.

Table 6.20 PB Formulation results for ICC scenario and high demand setting of 100 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	4	4	4	4	29	27	171710	77686	94024	5044	112140	31268	938	27364
<b>2</b>	4	4	4	4	29	25	163346	79945	83401	1933	103554	33093	856	25843
<b>3</b>	4	3	3	4	25	28	162491	81949	80542	587	107552	26793	1023	27123
<b>4</b>	3	4	4	3	24	24	162973	80907	82066	4796	113570	26477	1045	21882
<b>5</b>	4	4	3	4	29	27	182783	95253	87531	5725	121098	32309	920	28457
<b>6</b>	5	3	3	5	27	24	165413	79464	85949	4175	110697	29908	733	24075
<b>7</b>	3	3	3	3	21	22	158518	75119	83399	2538	119674	23424	402	15018
<b>8</b>	5	3	3	5	36	25	185498	100967	84531	15071	125966	31420	955	27157
<b>9</b>	4	4	4	4	22	22	159548	79042	80505	7730	99803	32197	801	26747
<b>10</b>	5	3	3	5	29	22	175915	94526	81389	3938	114106	35257	964	25588

In high demand environment, all instances are solved to optimality. Maximum solution time is 15071 seconds and average run time is 5154 seconds. When the demand setting is high, companies started to open more depots and transfer lines overall. Number of selected routes vary between 43 and 61. When the ICC experiments with 100 customers compared with the original scenario experiments with 100 customers, it is observed that solution times increased with ICC setup. Runtime comparisons can be found in Table 6.21. Run times are indicated in terms of seconds.

When the run times compared in Table 6.21, it is observed that ICC setting increase run times which is also in parallel to previous findings in the 30 and 50 customer experiments. Consequently, it can be concluded that increased number of common customers increases the time complexity of the model.

As explained in Section 5.3, experiments are repeated with NCD setting with PB

Table 6.21 Original vs ICC scenario run times with 100 customer instances under PB formulation

	<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Dem.</b>	Original	676	4035	1955	1738	3543	730	1929	669	2698	1604
	ICC	9604	14403	3010	7291	15057	15271	14852	5335	28791	27424
<b>High Dem.</b>	Original	358	921	495	535	350	1143	1298	446	6010	328
	ICC	51	1933	587	4796	5725	4175	2538	15071	7730	3938

formulation in which carriers do not have any common depot declaration opportunities. Main motivation behind those experiments is to see the effect of opening depots on same location on collaboration and centralized gains as well as effect on problem complexity in terms of run times and gaps. Experiments started with the simplest setup again, 30 customers and low demand environment.

Before going into details of the experiment results, information on number of pre-generated routes in NCD scenarios presented in Table 6.22. As it can be interpreted from the Table 6.22, number of possible routes per carrier deviate between 179 and 4949 depending on the problem size and demand structure. When the total route numbers compared with original and ICC scenarios it is observed that total created route numbers under NCD setup is less because of the decreased amount of candidate depot locations.

Table 6.22 Pre-generated route numbers for NCD scenarios

Ins.	30 Customer				50 Customer				100 Customer			
	Low Dem.		High Dem.		Low Dem.		High Dem.		Low Dem.		High Dem.	
	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>	<i>TR<sub>A</sub></i>	<i>TR<sub>B</sub></i>
<b>1</b>	225	268	478	572	620	456	1334	922	2023	2194	4438	4798
<b>2</b>	262	225	554	505	639	561	1349	1188	2312	2125	4473	4055
<b>3</b>	267	252	462	461	588	523	1272	1137	1971	2075	4238	4434
<b>4</b>	179	240	396	513	671	506	1244	918	2106	2021	4043	3911
<b>5</b>	276	234	569	490	584	605	1055	1099	2062	2136	4461	4695
<b>6</b>	226	233	469	528	584	533	1034	1004	2151	2190	4180	4207
<b>7</b>	229	241	476	539	584	529	1047	1015	2254	2199	3694	3529
<b>8</b>	226	202	440	416	706	555	1345	977	2262	2139	4949	4761
<b>9</b>	225	229	481	510	602	487	1263	1040	2108	2239	3428	3566
<b>10</b>	235	231	469	436	620	529	1150	948	2149	2325	4109	4666

Run results of 30 customer instances in low demand and NCD setting can be found in Table 6.23.

Within 10 seconds, all instances are solved to optimality. Maximum run time is 6 seconds and average run time is 3 seconds for the PB Formulation results with 30 customers and NCD scenario in low demand setting. As it occurred in previous scenario settings, almost all carriers opened one depot. However, in one of the instances, instance 9, carrier *B* opened two depots. Moreover, in instance 4, carrier *B* does not prefer to create a transfer line. These results overlap with our motiva-

Table 6.23 PB Formulation results for NCD scenario and low demand setting of 30 customer instances

<b><i>Ins</i></b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>R<sub>A</sub></i></b>	<b><i>R<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b>T(s)</b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b>1</b>	1	1	1	1	4	4	62373	30610	31762	1	50584	7532	158	4099
<b>2</b>	1	1	1	1	5	4	68354	31458	36897	2	55060	7532	284	5478
<b>3</b>	1	1	1	1	5	6	69004	36390	32614	5	56901	7424	313	4366
<b>4</b>	1	1	1	0	3	5	56480	28615	27866	2	43383	6794	33	6270
<b>5</b>	1	1	1	1	5	4	62815	33996	28818	2	48674	7532	259	6350
<b>6</b>	1	1	1	1	4	4	63365	35077	28287	2	50879	7226	406	4854
<b>7</b>	1	1	1	1	4	4	66503	32122	34381	4	52825	7730	123	5825
<b>8</b>	1	1	1	1	4	4	63489	32684	30805	4	50925	6992	428	5144
<b>9</b>	1	2	1	1	4	4	67429	34404	33024	4	46650	10931	526	9322
<b>10</b>	1	1	1	1	4	4	66736	35860	30876	6	53085	7532	522	5597

tion in which it is assumed that NCD obstructs collaboration. Number of selected routes vary between 8 and 11. Same instances experimented under high demand environment as well. Results can be found in Table 6.24.

Table 6.24 PB Formulation results for NCD scenario and high demand setting of 30 customer instances

<b><i>Ins</i></b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>R<sub>A</sub></i></b>	<b><i>R<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b>T(s)</b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b>1</b>	1	1	1	1	8	8	86322	44535	41787	7	72068	8999	361	4894
<b>2</b>	2	2	2	2	10	8	89328	41463	47866	2	57931	15863	888	14647
<b>3</b>	2	1	1	2	9	12	85718	47741	37977	2	63643	12525	552	8998
<b>4</b>	2	2	2	2	7	9	76847	39792	37055	3	51097	14524	97	11129
<b>5</b>	2	1	1	2	10	8	81508	47715	33794	4	59367	11767	489	9886
<b>6</b>	2	2	2	2	8	10	83165	43643	39522	1	57168	13658	665	11675
<b>7</b>	1	2	2	1	8	10	82852	41615	41237	4	60759	12398	441	9254
<b>8</b>	2	1	1	1	7	8	81581	39435	42146	5	62053	11017	213	8299
<b>9</b>	2	1	1	2	9	8	85209	45088	40121	4	63765	10457	815	10172
<b>10</b>	3	1	1	3	10	6	82206	42062	40143	4	52217	14284	730	14975

Optimum results are found under 10 seconds for each instance of NCD and high demand setting of 30 customer instances. Maximum run time is 7 seconds and average run time is 4 seconds. As a result of increased demand density, carriers started to open more depots and construct more transfer lines. Number of total selected routes vary between 16 and 21. When the NCD experiments are compared with original scenario experiments, for the low demand setting, there is no distinct effect on run times. For the high demand setting, there exist some instances which are solved faster under NCD setting. Run time comparisons can be found in Table 6.25. Run times are indicated in terms of seconds.

When the run time results examined in Table 6.25, there is no solid distinction between low demand scenarios. In high demand setting, original scenario instances are solved with higher run times which may be explained by decreased number of possibilities for collaboration. But still, difference is not distinct.

Similar to what we did in original scenario and ICC scenario instances, deviations

Table 6.25 Original vs NCD scenario run times with 30 customer instances under PB formulation

		<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Demand</b>	<b>Original</b>	2	6	4	2	5	4	3	5	6	3	
	<b>NCD</b>	1	2	5	2	2	2	4	4	4	6	
<b>High Demand</b>	<b>Original</b>	10	6	2	5	7	8	15	18	29	4	
	<b>NCD</b>	7	2	2	3	4	1	4	5	4	4	

from the exact solutions are compared with the best reported OFVs and best bounds of LB formulation for NCD scenario. Results can be found in Table 6.26.

Table 6.26 PB deviations for NCD scenario of 30 customers

	<b>Low Demand</b>		<b>High Demand</b>	
<b>Ins</b>	$\Delta_{OFV}$	$\Delta_{BB}$	$\Delta_{OFV}$	$\Delta_{BB}$
<b>1</b>	3.8%	10.3%	2.5%	11.6%
<b>2</b>	5.7%	11.7%	3.2%	8.8%
<b>3</b>	8.2%	13.6%	-5.2%	4.8%
<b>4</b>	2.7%	6.6%	2.0%	10.9%
<b>5</b>	6.2%	11.9%	1.8%	10.1%
<b>6</b>	2.7%	9.3%	1.6%	8.7%
<b>7</b>	7.4%	12.8%	1.3%	9.7%
<b>8</b>	7.1%	11.9%	2.4%	10.4%
<b>9</b>	7.4%	12.3%	2.5%	11.0%
<b>10</b>	5.4%	14.2%	-0.6%	7.8%

When the deviations are compared through best OFVs in low demand environment for NCD scenario, it is observed that model deviates 5.6% on average. Minimum deviation is 2.7% and maximum deviation is 8.2%. When deviations compared through best bounds, average deviation is 11.5% where minimum deviation is 6.6% and maximum deviation is 14.2%. As mentioned before, since LB formulation instances are not solved to optimality, comparisons through  $\Delta_{BB}$  denotes an upper bound for deviation amount.

In high demand environment of NCD scenario of 30 customer instances, PB formulation deviates 4.8% in average when comparison is conducted through best found OFVs of LB formulation. For two instances, instance 3 and 10, PB formulation reported lower costs within seconds. In average, PB formulation deviates 1.1% and deviation range is between -5.2% and 3.2%. On the other hand, when deviations compared through best bounds, average deviation is 9.4% where minimum deviation is 4.8% and maximum variance is 11.6%. Same experiments for NCD scenario are repeated for 50 customer instances. PB formulation run results for low demand and NCD scenario of 50 customer instances can be found in Table 6.27.

Within a minute, all 50 customer instances with low demand scenario solved to optimality. Maximum solution time is 57 seconds where average is 19 seconds.

Table 6.27 PB Formulation results for NCD scenario and low demand setting of 50 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	2	2	2	1	7	7	87908	43486	44422	16	56711	17461	218	13518
<b>2</b>	2	2	2	1	7	9	92528	45972	46557	57	61754	15663	687	14424
<b>3</b>	1	1	1	1	7	6	82109	41232	40877	8	69605	8154	269	4081
<b>4</b>	2	1	1	2	8	7	88358	46828	41530	7	68300	12686	481	6891
<b>5</b>	1	1	1	1	7	8	93751	45423	48328	14	81762	9307	201	2481
<b>6</b>	1	1	1	1	7	7	85270	44321	40949	6	74134	9039	181	1916
<b>7</b>	1	1	1	1	7	7	90827	43085	47742	20	78875	9307	223	2422
<b>8</b>	2	1	1	2	7	7	102740	52825	49914	19	77749	14511	470	10009
<b>9</b>	2	2	2	1	6	8	89349	40514	48835	19	59126	17492	85	12646
<b>10</b>	2	1	1	2	7	7	103108	53742	49366	29	81728	11103	550	9728

The number of opened depots increased when compared to 30 customer instances. Moreover, they declared more transfer lines. Number of total selected routes change between 13 and 16. To see how increased demand density affect the outcomes, experiments are repeated under high demand setup. Results can be found in Table 6.28.

Table 6.28 PB Formulation results for NCD scenario and high demand setting of 50 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	3	2	2	1	15	14	115718	58034	57685	9	75086	22861	374	17398
<b>2</b>	2	3	3	1	13	18	116431	54685	61746	5	73736	22010	892	19794
<b>3</b>	2	2	1	2	15	13	115473	55665	59808	19	87080	16217	243	11933
<b>4</b>	2	2	1	2	15	11	114511	61551	52960	7	86743	16385	321	11062
<b>5</b>	1	3	3	1	9	16	124417	53764	70653	17	92246	17861	752	13558
<b>6</b>	3	3	2	2	13	13	110843	57115	53729	13	66503	24343	385	19612
<b>7</b>	2	2	2	2	12	14	114360	51852	62509	8	84596	15878	682	13204
<b>8</b>	3	2	1	3	17	10	124894	72843	52052	12	81695	20982	687	21530
<b>9</b>	3	3	3	16	13	117288	59698	57590	7	68396	26772	691	21429	
<b>10</b>	2	2	1	2	15	11	126785	67859	58926	14	93700	15472	813	16799

In the high demand setting, all instances are solved under 20 seconds. Maximum solution time is 19 seconds and average is 11 seconds. Overall, number of opened depots, transfer lines and selected depots increased when compared to low demand setting. Number of selected routes vary between 25 and 31. When the NCD experiments with 50 customers compared with the original scenario experiments with 50 customers, it is observed that solution times of NCD scenarios are less than original scenarios. Run time comparisons can be found in Table 6.29. Note that run times are indicated in terms of seconds.

When run times examined in Table 6.29, it is observed that run times are shorter under NCD setting under both low and high demand environments. Since NCD eliminates the number of opportunities that can rise from joint depot opening decisions, instances may become more distinguishable from the perceptive of optimum

Table 6.29 Original vs NCD scenario run times with 50 customer instances under PB formulation

		<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Demand</b>	<b>Original</b>	12	21	37	29	13	22	21	44	92	32	
	<b>NCD</b>	16	57	8	7	14	6	20	19	19	29	
<b>High Demand</b>	<b>Original</b>	12	38	80	18	45	14	41	18	15	64	
	<b>NCD</b>	9	5	19	7	17	13	8	12	7	14	

depot locations. Next, deviations from exact solutions which are reported by LB formulation experiments are compared with the best reported OFVs and best bounds of LB formulation for NCD scenario. Results can be found in Table 6.30.

Table 6.30 PB deviations for NCD scenario of 50 customers

	<b>Low Demand</b>		<b>High Demand</b>	
<b>Ins</b>	$\Delta_{OFV}$	$\Delta_{BB}$	$\Delta_{OFV}$	$\Delta_{BB}$
<b>1</b>	0.5%	11.6%	3.9%	12.5%
<b>2</b>	5.0%	14.9%	2.9%	12.0%
<b>3</b>	5.7%	17.8%	5.1%	15.1%
<b>4</b>	3.8%	14.8%	-3.0%	9.8%
<b>5</b>	5.5%	14.6%	-6.0%	6.9%
<b>6</b>	4.0%	13.2%	-3.9%	6.2%
<b>7</b>	5.1%	16.5%	-4.5%	8.5%
<b>8</b>	2.6%	15.4%	-3.5%	7.9%
<b>9</b>	4.6%	16.2%	1.9%	13.5%
<b>10</b>	6.2%	16.9%	-4.9%	8.0%

When the deviations from exact solutions compared in low demand setting through best OFVs of LB formulation, PB formulation deviates 4.3% in average. Maximum deviation is 6.2% and minimum deviation is 0.5% which means that PB approach found a solution which is almost good as 16 hours of LB formulation within seconds. When deviations compared through best bounds, minimum deviation is 11.6% and maximum deviation is 17.8% where average deviation is 15.2%.

In high demand environment of NCD scenario of 50 customer instances, PB model deviates -1.2% in average when comparison is conducted through best found OFVs of LB formulation. In other words, PB formulation reports better outcomes when compared to 16 hour runs of exact LB formulation for five instances. Maximum deviation is 5.1% and minimum deviation is -6%. On the other hand, when deviations compared through best bounds, average deviation is 10.0% where minimum deviation is 6.2% and maximum variance is 15.1%.

Consequently, when the NCD setting of 50 customer instances investigated, PB formulation deviates 1.5% on average when OFVs are compared and 12.6% on average when best bounds are compared.

Experiments continued with 100 customer NCD instances in order to see the effect of number of customers to solution times and vital aspects of problem. PB formulation run results for low demand and NCD scenario of 100 customer instances can be found in Table 6.31.

Table 6.31 PB Formulation results for NCD scenario and low demand setting of 100 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	<b>2</b>	<b>3</b>	<b>2</b>	<b>2</b>	12	16	136420	62995	73425	628	100790	22870	133	12628
<b>2</b>	2	2	2	2	14	14	133221	62212	71008	1243	108422	15595	478	8726
<b>3</b>	2	3	2	2	12	13	134427	68625	65802	326	101546	20144	65	12672
<b>4</b>	2	2	2	2	13	12	134611	66603	68008	1697	113003	13596	459	7553
<b>5</b>	2	3	3	2	12	14	140476	70739	69737	2373	105887	20936	646	13007
<b>6</b>	2	2	2	2	14	14	133781	63293	70489	1372	110044	15437	371	7929
<b>7</b>	2	2	1	2	14	14	138358	67052	71305	696	112043	15950	241	10123
<b>8</b>	2	3	3	2	13	14	140567	64549	76019	1704	107112	18706	586	14163
<b>9</b>	3	2	2	2	14	14	141770	69315	72455	1716	104238	21249	491	15792
<b>10</b>	2	3	3	2	12	15	143327	67682	75645	1180	107312	20511	818	14686

All of the 100 customer instances are solved with no gap under NCD and low demand setting. Average run time is 1294 seconds where maximum run time is 2373 seconds and minimum run time is 326 seconds. Number of transfer lines, depots and selected routes increased when compared to 50 customer instances. Since all instances are solved with no gaps, same experiments are repeated for the high demand density setting. Results can be found in Table 6.32.

Table 6.32 PB Formulation results for NCD scenario and high demand setting of 100 customer instances

<i>Ins</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>R<sub>A</sub></i>	<i>R<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	T(s)	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b>1</b>	4	4	3	4	27	40	182381	84717	97663	135	122699	34744	535	24403
<b>2</b>	3	5	4	3	25	28	171402	76676	94726	331	110805	32665	918	27013
<b>3</b>	4	4	4	3	25	30	178360	90850	87510	288	117369	33478	860	26652
<b>4</b>	4	3	3	4	26	21	171617	86116	85501	585	121356	26729	783	22749
<b>5</b>	3	5	5	3	25	31	184627	89863	94764	388	123940	31495	1069	28123
<b>6</b>	3	4	4	2	24	28	172335	78350	93985	450	124531	27472	688	19643
<b>7</b>	4	3	3	3	23	21	169075	82562	86512	205	119725	26961	700	21689
<b>8</b>	3	5	5	2	26	32	193339	93195	100144	298	134502	32781	708	25348
<b>9</b>	3	3	2	3	20	22	167551	80449	87102	402	118269	27624	483	21174
<b>10</b>	3	5	4	3	25	27	182750	85297	97453	446	119823	33242	550	29135

In high demand environment, all instances are solved to optimality. Maximum solution time is 15071 seconds and average run time is 353 seconds. When the demand setting is high, companies started to open more depots and transfer lines overall. Number of selected routes vary between 42 and 67.

When the NCD experiments with 100 customers compared with the original scenario experiments with 100 customers, it is observed that solution times decreased with NCD setup. Run time comparisons can be found in Table 6.33. Run times are indicated in terms of seconds.

Table 6.33 Original vs NCD scenario run times with 100 customer instances under PB formulation

	<i>Instance</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Low Demand</b>	<b>Original</b>	676	4035	1955	1738	3543	730	1929	669	2698	1604
	<b>NCD</b>	628	1243	326	1697	2373	1372	696	1704	1716	1180
<b>High Demand</b>	<b>Original</b>	358	921	495	535	350	1143	1298	446	6010	328
	<b>NCD</b>	135	331	288	585	388	450	205	298	402	446

When the run times of 100 customer instances of original and NCD scenarios under low demand environment are compared, 8 out 10 instances are solved faster with NCD scenario which coincides with the finding in previous experiments. In average, NCD instances are solved 33% faster. When the run times compared for high demand setting experiments, similar behavior is observed, NCD instances get solved faster in average.

Overall, all instances of all scenarios are solved under both low demand and high demand environments to optimality with PB formulation. In some instances it reported better outcomes with the 8 or 16 hours of run results of LB formulation solutions with gaps, within seconds or few minutes. As mentioned in Section 5.2, this study focuses on joint strategic network design in which parties may collaborate. Consequently, we investigated managerial outcomes via PB formulation results in Section 6.2.

## 6.2 Managerial Insights

In order to investigate gains achieved thorough collaboration, to see how many percent of customers' demand is transferred among carriers and the effect of collaboration on the number of created routes, individual runs are completed with PB formulation. In the individual runs, both carriers act individually in which there is no possibility for collaboration. In other words, problem is solved as a traditional LRP for each carrier. Individual experiments started with original scenario of 30 customer instances. Results can be found in Table 6.34.

In both low demand and high demand settings, collaboration yield better solutions in terms of lower costs. Gain amounts in terms of percentages can be found in Table 6.35.

When the gains are compared for original scenario instances, in low demand envi-

Table 6.34 Individual PB Formulation results for original scenario of 30 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
1	66388	32595	33793	59212	28374	30838	90528	43009	47519	84655	37917	46738
2	68956	36256	32700	63258	31251	32007	95109	50647	44462	87762	49155	38607
3	71805	34816	36989	66487	35099	31389	89502	45145	44357	81829	41689	40140
4	59756	30425	29331	56495	28600	27894	81507	39854	41653	72874	35897	36977
5	67529	32644	34885	59675	23104	36571	91368	43381	47988	80099	33351	46748
6	66488	35616	30872	62773	35704	27069	92182	49204	42978	87084	44873	42211
7	64561	33172	31389	60823	29770	31053	86870	44286	42584	80806	44932	35874
8	63114	29647	33467	59838	27162	32675	85608	38881	46727	78296	42119	36177
9	74007	35668	38339	71090	34649	36441	96850	44863	51987	91513	46544	44970
10	65777	31669	34109	63738	29752	33986	86586	42803	43784	79527	37881	41646

Table 6.35 Gain comparison for original scenario of 30 customer instances

Ins	Low Demand				High Demand			
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>
1	10.8%	13.0%	8.7%	6.5%	11.8%	1.6%		
2	8.3%	13.8%	2.1%	7.7%	2.9%	13.2%		
3	7.4%	-0.8%	15.1%	8.6%	7.7%	9.5%		
4	5.5%	6.0%	4.9%	10.6%	9.9%	11.2%		
5	11.6%	29.2%	-4.8%	12.3%	23.1%	2.6%		
6	5.6%	-0.2%	12.3%	5.5%	8.8%	1.8%		
7	5.8%	10.3%	1.1%	7.0%	-1.5%	15.8%		
8	5.2%	8.4%	2.4%	8.5%	-8.3%	22.6%		
9	3.9%	2.9%	5.0%	5.5%	-3.7%	13.5%		
10	3.1%	6.1%	0.4%	8.2%	11.5%	4.9%		
Avg.	6.7%	8.8%	4.7%	8.0%	6.2%	9.7%		

ronment, collaboration yields 6.7% of savings on average for the centralized system. Minimum gain is 3.1% and maximum gain is 11.6%. For carrier *A*, average gain percentage is 8.8%. However, in two instances, carrier *A* reported higher costs but the difference is 0.8% at most. On the other hand, carrier *A*, benefits from collaboration in 8 out of 10 instances in which it benefited from collaboration with up to 29.2% gains in some instances. Carrier *B* reports worse outcomes only for once instance. Gains for carrier *B* deviate between -4.8% and 15.1% where average gain for *B* is 4.7%.

For the high demand setting of original scenario instances, average gain is 8% where gains deviate between 5.5% and 12.3%. Carrier *A* suffered from collaboration in terms of increased costs in 3 instances. For carrier *A*, average gain is 6.2%, minimum gain is -8.3% and maximum gain is 23.1%. For carrier *B*, average gain amount is 9.7%. For all instances, carrier *B* benefits from collaboration. Minimum saving amount is 1.6% and maximum saving amount is 22.6%.

Another managerial outcome is amount of transferred goods. It is important to

investigate how much of original demand is served by the other carriers in the system. In the transfer percentage comparison tables like Table 6.36, columns  $\%TD_A$  and  $\%TD_B$  indicates how much of the total demand which belongs to that carrier is transferred to other carriers, for carrier  $A$  and  $B$ , respectively. Columns  $\%TP_A$  and  $\%TP_B$  depicts how much of the total possible transferable amount is transferred to other carrier, for carrier  $A$  and  $B$ , respectively.

Table 6.36 Transfer percentages for original scenario of 30 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$
1	13.8%	11.4%	49.3%	50.7%	16.3%	6.2%	58.3%	27.6%
2	10.6%	9.4%	44.7%	35.4%	7.6%	17.9%	32.1%	67.9%
3	14.7%	14.7%	58.7%	52.7%	9.3%	14.5%	37.1%	52.0%
4	15.1%	6.9%	53.9%	36.8%	11.8%	10.9%	42.2%	57.8%
5	18.3%	5.5%	64.5%	20.2%	18.3%	9.6%	64.5%	35.5%
6	14.0%	10.4%	55.1%	35.9%	15.4%	8.8%	60.6%	30.5%
7	10.4%	9.8%	41.0%	33.7%	8.5%	15.3%	33.4%	52.7%
8	23.0%	10.0%	68.8%	31.2%	4.9%	17.2%	14.7%	53.6%
9	17.4%	15.1%	58.7%	61.8%	3.4%	13.8%	11.5%	56.5%
10	12.5%	7.6%	48.1%	35.8%	16.7%	10.0%	64.3%	46.9%
Avg	15.0%	10.1%	54.3%	39.4%	11.2%	12.4%	41.9%	48.1%

As Table 6.36 investigated, it is observed that for low demand setting, carrier  $A$  transfers 15% of its total demand in average and carrier  $B$  transfers 10.1% of its total demand on average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer more than half of shared demand on average. Carrier  $B$  transferred 39% percent of the possible transferable amount. Note that, in instance 8, carrier  $A$  transferred 68.8% of the total transferable amount, which means that model chose to serve most of common demand points by a route of carrier  $B$ .

For the high demand setting, carrier  $A$  transfers 11.2% of its total demand on average and carrier  $B$  transfers 12.4% of its total demand on average. When total possible transfer amounts are compared, carrier  $A$  prefers to transfer 41.9% of shared demand on average. Carrier  $B$  transferred 48.1% percent of the possible transferable amount. In some cases, model chose to transfer only 11.5% of transferable amount for a carrier. On the other hand, there are instances in which 67.9% of the transferable amount is transferred to other carrier.

Next, all those strategic aspects are investigated with 50 customer instances. Results of individual experiments with original scenario of 50 customer instances can be found in Table 6.37.

Gains which are calculated through comparison of OFVs of individual and collabora-

Table 6.37 Individual PB Formulation results for original scenario of 50 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
1	97095	50391	46704	89476	43608	45868	117833	59881	57952	107793	53111	54682
2	97762	54057	43705	90619	44855	45764	122749	68755	53994	112120	60779	51341
3	88869	40837	48032	84881	40609	44273	116031	52893	63138	111125	52967	58159
4	92287	46175	46112	87623	42465	45158	116826	57301	59526	108818	56296	52523
5	99933	49348	50585	87197	46103	41094	128829	61427	67402	115084	52583	62501
6	92755	45260	47495	86500	43433	43067	123198	63501	59697	110016	53199	56818
7	93369	44406	48963	86940	46419	40521	120204	56897	63308	114594	50365	64229
8	106786	53323	53464	104264	50686	53579	140040	68825	71215	129866	70035	59832
9	92756	46995	45762	90836	45053	45783	121594	60682	60912	116189	59813	56376
10	107412	53168	54244	103262	51673	51589	134679	65996	68684	128774	61819	66955

rative PB formulation experiments can be found in Table 6.38.

Table 6.38 Gain comparison for original scenario of 50 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
1	7.8%	13.5%	1.8%	8.5%	11.3%	5.6%
2	7.3%	17.0%	-4.7%	8.7%	11.6%	4.9%
3	4.5%	0.6%	7.8%	4.2%	-0.1%	7.9%
4	5.1%	8.0%	2.1%	6.9%	1.8%	11.8%
5	12.7%	6.6%	18.8%	10.7%	14.4%	7.3%
6	6.7%	4.0%	9.3%	10.7%	16.2%	4.8%
7	6.9%	-4.5%	17.2%	4.7%	11.5%	-1.5%
8	2.4%	4.9%	-0.2%	7.3%	-1.8%	16.0%
9	2.1%	4.1%	0.0%	4.4%	1.4%	7.4%
10	3.9%	2.8%	4.9%	4.4%	6.3%	2.5%
Avg	5.9%	5.7%	5.7%	7.0%	7.3%	6.7%

In low demand environment and original scenario setting of 50 customer instances, collaboration reduces costs of centralized system by 5.9% on average. For centralized system, minimum gain amount is 2.1% and maximum gain amount is 12.7%. For both carriers *A* and *B* average gain amount is 5.7%. Carrier *A* reports a worse outcome for only one instance where carrier *B* reports two.

In high demand environment and original scenario setting of 50 customer instances, average gain for collaborative schema is 7% in average. Gains deviate between 4.2% and 10.7%. For carrier *A*, only two instances reported a negative gain and on average carrier *A* gains 7.3% from collaboration. Carrier *B* reported a increased cost for only one instance and average gain of carrier *B* is 6.7%.

Transfer amounts in percentages for original scenario of 50 customer instances can be found in Table 6.39.

In low demand setting, carrier *A* transfers 8.5% of its total demand in average

Table 6.39 Transfer percentages for original setting of 50 customer instances of PB formulation experiments

Ins	Low Demand					High Demand			
	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>	
1	5.7%	5.1%	42.8%	38.0%	6.2%	7.2%	46.5%	53.5%	
2	14.8%	0.0%	71.4%	0.0%	10.8%	10.4%	51.9%	48.1%	
3	7.9%	11.9%	36.9%	53.6%	10.0%	13.9%	46.6%	62.7%	
4	14.3%	6.0%	67.2%	29.6%	4.6%	13.5%	21.8%	66.1%	
5	7.5%	13.9%	35.5%	71.1%	11.5%	8.9%	54.6%	45.4%	
6	9.9%	9.0%	49.8%	50.2%	15.6%	3.9%	78.3%	21.7%	
7	1.7%	13.8%	8.7%	77.4%	15.2%	4.3%	76.1%	23.9%	
8	9.2%	8.0%	55.3%	44.7%	2.5%	15.2%	15.0%	85.0%	
9	4.4%	2.3%	19.7%	10.9%	5.1%	16.3%	22.5%	77.5%	
10	9.9%	8.4%	45.5%	39.3%	5.9%	6.2%	27.0%	29.0%	
<b>Avg</b>	<b>8.5%</b>	<b>7.8%</b>	<b>43.3%</b>	<b>41.5%</b>	<b>8.7%</b>	<b>10.0%</b>	<b>44.0%</b>	<b>51.3%</b>	

and carrier  $B$  transfers 7.8% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 43.3% of shared demand in average. Carrier  $B$  transferred 41.5% percent of the possible transferable amount in average.

For the high demand setting, carrier  $A$  transfers 8.7% of its total demand in average and carrier  $B$  transfers 10% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 44% of shared demand in average. Carrier  $B$  transferred 51.3% percent of the possible transferable amount. In some cases, PB formulation can transfer up 85% of the transferable amount. However, it may also choose to only transfer 15% of the transferable amount is transferred to other carrier.

Same experiments are repeated for original scenario with 100 customer instances. Results of individual experiments with original scenario of 100 customer instances can be found in Table 6.40.

Table 6.40 Individual PB Formulation results for original scenario of 100 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>
1	138661	69258	69403	130086	67529	62556	193969	94953	99016	179192	81451	97741
2	140693	69394	71299	134553	65329	69224	188494	92613	95881	175510	82049	93461
3	140428	74080	66349	134803	70106	64697	185322	98405	86917	172583	89524	83059
4	140481	70747	69734	132917	66092	66826	186592	93513	93080	171736	90075	81661
5	145953	74726	71228	139164	69815	69349	198227	103262	94965	184279	93553	90726
6	140161	71179	68982	130353	64118	66236	186127	94872	91255	173623	89068	84555
7	148899	73072	75827	138534	69514	69020	176171	87883	88288	165411	83634	81777
8	145403	73370	72034	135919	71045	64874	202033	99887	102146	187854	99803	88052
9	143928	73783	70145	138389	69475	68914	184902	94211	90691	171977	84453	87524
10	143895	77077	66818	137148	71254	65894	187466	99056	88410	174801	90015	84786

Gains through collaboration for the 100 customer instances of original setting can be found in Table 6.41.

Table 6.41 Gain comparison for original scenario of 100 customer instances

Ins	Low Demand			High Demand		
	Gain	Gain <sub>A</sub>	Gain <sub>B</sub>	Gain	Gain <sub>A</sub>	Gain <sub>B</sub>
1	6.6%	2.5%	9.9%	7.6%	14.2%	1.3%
2	4.6%	5.9%	2.9%	6.9%	11.4%	2.5%
3	4.2%	5.4%	2.5%	6.9%	9.0%	4.4%
4	5.7%	6.6%	4.2%	8.0%	3.7%	12.3%
5	4.9%	6.6%	2.6%	7.0%	9.4%	4.5%
6	7.5%	9.9%	4.0%	6.7%	6.1%	7.3%
7	7.5%	4.9%	9.0%	6.1%	4.8%	7.4%
8	7.0%	3.2%	9.9%	7.0%	0.1%	13.8%
9	4.0%	5.8%	1.8%	7.0%	10.4%	3.5%
10	4.9%	7.6%	1.4%	6.8%	9.1%	4.1%
Avg	5.7%	5.8%	4.8%	7.0%	7.8%	6.1%

In low demand and original setting of 100 customer instances, average gain amount for centralized system is 5.7% where gains deviate between 4.2% and 7.5%. For carrier  $A$  and  $B$ , average gain percentages are 5.8 and 4.8, respectively. None of the carriers reported a loss. In high demand setting, for collaborative system, average gain amount is 7%. Carrier  $A$  and  $B$  have an average gain of 7.8% and 6.1%, respectively. Again, in all instances, both carriers benefited from the collaboration.

Transfer amounts in percentages for original scenario of 100 customer instances can be found in Table 6.42.

Table 6.42 Transfer percentages for original setting of 100 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>
1	6.7%	13.5%	33.7%	63.8%	13.1%	3.9%	65.5%	18.6%
2	10.4%	9.7%	50.1%	47.9%	10.6%	7.7%	50.9%	37.9%
3	12.9%	8.0%	64.4%	38.3%	11.4%	6.5%	56.9%	31.0%
4	11.0%	6.7%	49.6%	28.8%	9.2%	12.8%	41.5%	55.3%
5	9.7%	10.9%	43.7%	52.4%	11.0%	8.1%	49.8%	38.8%
6	12.7%	9.3%	55.2%	39.2%	7.8%	10.9%	33.8%	46.0%
7	9.2%	9.2%	42.2%	42.4%	10.8%	12.3%	49.4%	57.1%
8	8.1%	12.1%	37.6%	57.8%	5.5%	13.8%	25.5%	65.5%
9	9.7%	9.1%	50.9%	44.8%	10.0%	7.8%	52.3%	38.6%
10	8.5%	7.1%	51.0%	39.6%	9.9%	6.2%	59.4%	34.5%
Avg	9.9%	9.5%	47.8%	45.5%	9.9%	9.0%	48.5%	42.3%

In low demand setting, carrier  $A$  transfers 9.9% of its total demand in average and carrier  $B$  transfers 9.5% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer

47.8% of shared demand in average. Carrier  $B$  transferred 45.5% percent of the possible transferable amount in average.

For the high demand setting, carrier  $A$  transfers 9.9% of its total demand in average and carrier  $B$  transfers 9% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 48.5% of shared demand in average. Carrier  $B$  transferred 42.3% percent of the possible transferable amount. In some cases, PB formulation can transfer up 65.5% of the transferable amount. However, it may also choose to only transfer 18.6% of the transferable amount is transferred to other carrier.

In order to see the effect of common customer number on collaboration, above experiments, which are conducted to identify gain structure and transfer amounts, are repeated with ICC setting.

Initial individual experiments of ICC scenario is conducted with 30 customer instances. Results can be found in Table 6.43.

Table 6.43 Individual PB Formulation results for ICC scenario of 30 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
1	70328	35307	35021	61617	30649	30968	97998	45222	52776	82493	29554	52939
2	74657	39033	35625	66917	28582	38335	101297	52859	48438	85637	51811	33825
3	73008	34690	38318	64793	30357	34436	89891	45085	44807	80740	35753	44987
4	61915	32667	29248	52718	28585	24133	80651	40683	39968	68220	29142	39078
5	71877	35933	35944	61008	24980	36028	94990	47262	47729	77020	25294	51726
6	67086	36828	30258	58756	37667	21089	90078	49075	41003	77171	42707	34464
7	68922	34731	34192	62069	32040	30029	91384	46059	45325	79263	38681	40582
8	67771	31759	36012	54596	27326	27270	86110	42038	44072	68111	30198	37913
9	75577	36075	39503	69495	30289	39206	102797	47158	55639	88169	41383	46786
10	70475	35417	35058	65380	31796	33584	95391	47771	47620	79354	35915	43438

Identified saving amounts which are calculated through comparison of optimum solutions of individual and collaborative PB formulation experiments can be found in Table 6.44.

In low demand environment and ICC scenario setting of 30 customer instances, average gain amount is 12.1% for centralized system. Carrier  $A$  benefits an average gain amount of 14.1% where carrier  $B$  gains 10.3% on average. Carrier  $A$  reported increased costs only for one instance and loss percentage when compared to non-collaborative scenario is 2.3%. Maximum gain reported by carrier  $A$  is 30.5%. Carrier  $B$  suffered from collaboration in two instances. Maximum gain reported by

Table 6.44 Gain comparison for ICC scenario of 30 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
<b>1</b>	12.4%	13.2%	11.6%	15.8%	34.6%	-0.3%
<b>2</b>	10.4%	26.8%	-7.6%	15.5%	2.0%	30.2%
<b>3</b>	11.3%	12.5%	10.1%	10.2%	20.7%	-0.4%
<b>4</b>	14.9%	12.5%	17.5%	15.4%	28.4%	2.2%
<b>5</b>	15.1%	30.5%	-0.2%	18.9%	46.5%	-8.4%
<b>6</b>	12.4%	-2.3%	30.3%	14.3%	13.0%	15.9%
<b>7</b>	9.9%	7.7%	12.2%	13.3%	16.0%	10.5%
<b>8</b>	19.4%	14.0%	24.3%	20.9%	28.2%	14.0%
<b>9</b>	8.0%	16.0%	0.8%	14.2%	12.2%	15.9%
<b>10</b>	7.2%	10.2%	4.2%	16.8%	24.8%	8.8%
<b>Avg</b>	12.1%	14.1%	10.3%	15.5%	22.6%	8.8%

carrier *B* is 30.3%.

When gains are compared in high demand setting, average gain amount for collaborative schema turns out to be 15.5%, which is higher than the low demand environment. Average gain of carrier *A* is 22.6% and average gain of carrier *B* is 8.8%. For all instances, carrier *A* benefited from collaboration. Maximum gain amount reported by carrier *A* is 46.5% which means cost of carrier *A* is almost cut in half. On the contrary, carrier *B* reported worse outcomes for three instances. Maximum loss amount of carrier *B* is 8.4% and maximum gain amount is 30.2%.

Transfer amounts in percentages for ICC scenario of 30 customer instances can be found in Table 6.45.

Table 6.45 Transfer percentages for ICC setting of 30 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	<i>%TD<sub>A</sub></i>	<i>%TD<sub>B</sub></i>	<i>%TP<sub>A</sub></i>	<i>%TP<sub>B</sub></i>	<i>%TD<sub>A</sub></i>	<i>%TD<sub>B</sub></i>	<i>%TP<sub>A</sub></i>	<i>%TP<sub>B</sub></i>
<b>1</b>	17.1%	19.6%	36.5%	47.7%	32.6%	6.0%	69.6%	14.6%
<b>2</b>	38.1%	6.7%	79.1%	13.0%	7.0%	44.0%	14.6%	85.4%
<b>3</b>	24.2%	12.3%	60.8%	30.3%	30.1%	9.9%	75.6%	24.4%
<b>4</b>	15.4%	18.1%	33.0%	51.2%	30.2%	12.5%	64.6%	35.4%
<b>5</b>	23.3%	17.0%	54.6%	40.1%	36.8%	5.8%	86.4%	13.6%
<b>6</b>	15.3%	34.8%	35.4%	70.0%	23.2%	20.4%	53.7%	41.0%
<b>7</b>	21.6%	24.9%	50.0%	50.0%	24.2%	21.8%	56.1%	43.9%
<b>8</b>	21.1%	29.6%	39.9%	54.2%	28.8%	19.9%	54.5%	36.5%
<b>9</b>	39.2%	10.3%	71.8%	22.0%	22.6%	24.5%	41.3%	52.4%
<b>10</b>	26.4%	19.4%	54.2%	48.4%	21.8%	22.2%	44.7%	55.3%
<b>Avg</b>	24.2%	19.3%	51.5%	42.7%	25.7%	18.7%	56.1%	40.3%

In low demand and ICC setting of 30 customer instances, carrier *A* transfers 24.2% of its total demand in average and carrier *B* transfers 19.3% of its total demand in average. Which means, on average, approximately 20% of demands are exchanged

by carriers. In average, carrier  $A$  chose to transfer 51.5% of transferable amount where carrier  $B$  chose to transfer 42.7% of total transferable amount.

On high demand setting, a similar behaviour to low demand setting is observed. When the transfer amount is compared through total demand amounts, in average, carrier  $A$  transferred 25.7% of its total demand and carrier  $B$  transferred 18.7% of its total demand. In average, carrier  $A$  chose to transfer 56.1% of transferable amount where carrier  $B$  chose to transfer 40.3% of total transferable amount.

Later, in order to investigate strategic aspects discussed above and to see the effect of problem size, experiments are repeated with 50 customer instances. Results of individual experiments with ICC scenario of 50 customer instances can be found in Table 6.46.

Table 6.46 Individual PB Formulation results for ICC scenario of 50 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
1	100838	51836	49002	85884	44174	41710	118874	60095	58780	102624	50198	52426
2	103434	56241	47193	92657	54120	38538	138557	74733	63824	118839	63005	55833
3	89020	43118	45902	82663	42731	39932	132008	60282	71726	113558	60556	53002
4	97620	49403	48218	88608	45647	42961	123757	61935	61822	103221	58861	44360
5	103322	50243	53080	86911	45951	40961	135243	62410	72833	111538	54013	57525
6	95436	46227	49210	84591	45736	38854	125312	62932	62380	107299	48336	58964
7	99122	48470	50652	90956	39374	51581	130543	63153	67390	112998	58003	54995
8	112711	59168	53544	100368	50299	50070	137451	70227	67224	120297	64610	55687
9	98097	47944	50153	89009	41119	47890	126161	60892	65270	110823	55383	55441
10	109700	53069	56631	101852	50555	51297	140978	68176	72803	122948	63880	59069

Gain amounts achieved through collaboration can be found for PB Formulation results with 50 customers and ICC scenario in Table 6.47.

In low demand environment of ICC scenario setting of 50 customer instances, average gain amount by centralized collaboration schema is 10.4%. Average gain for carrier  $A$  is 8.9% where maximum gain amount is 18.8%. For carrier  $B$  average gain amount is 12% and maximum gain amount is 22.8%. Carrier  $A$  benefited from collaboration in all instances. Similarly, carrier  $B$  benefited from collaboration in 9 out of 10 instances, it only reported a worse outcome for only one instance.

In high demand environment and ICC scenario setting of 50 customer instances, average gain for collaborative schema is 14.1%. Minimum gain amount is 12.2% and maximum gain amount is 17.5%. Overall, it can be identified that saving amounts are higher in high demand environments when compared to low demand

Table 6.47 Gain comparison for ICC scenario of 50 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
<b>1</b>	14.8%	14.8%	14.9%	13.7%	16.5%	10.8%
<b>2</b>	10.4%	3.8%	18.3%	14.2%	15.7%	12.5%
<b>3</b>	7.1%	0.9%	13.0%	14.0%	-0.5%	26.1%
<b>4</b>	9.2%	7.6%	10.9%	16.6%	5.0%	28.2%
<b>5</b>	15.9%	8.5%	22.8%	17.5%	13.5%	21.0%
<b>6</b>	11.4%	1.1%	21.0%	14.4%	23.2%	5.5%
<b>7</b>	8.2%	18.8%	-1.8%	13.4%	8.2%	18.4%
<b>8</b>	11.0%	15.0%	6.5%	12.5%	8.0%	17.2%
<b>9</b>	9.3%	14.2%	4.5%	12.2%	9.0%	15.1%
<b>10</b>	7.2%	4.7%	9.4%	12.8%	6.3%	18.9%
<b>Avg</b>	10.4%	8.9%	12.0%	14.1%	10.5%	17.4%

environments. Carrier *A* reported higher costs for one instance. Average gain of carrier *A* is 10.5% where maximum gain of *A* is 23.2%. On the other hand, carrier *B* benefited from collaboration in all instances with an average gain amount of 17.4% and maximum gain amount of 28.2%.

Transfer amounts in percentages for ICC scenario of 50 customer instances can be found in Table 6.48.

Table 6.48 Transfer percentages for ICC setting of 50 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$
<b>1</b>	9.5%	18.6%	29.2%	55.8%	12.9%	17.0%	39.6%	50.9%
<b>2</b>	12.0%	20.6%	31.7%	51.9%	18.9%	17.2%	49.9%	43.4%
<b>3</b>	9.6%	18.7%	24.7%	48.7%	9.7%	25.2%	24.8%	65.7%
<b>4</b>	16.5%	21.3%	47.5%	55.9%	9.3%	25.3%	26.8%	66.3%
<b>5</b>	13.9%	18.2%	37.5%	56.6%	16.7%	17.0%	45.1%	52.9%
<b>6</b>	13.3%	25.4%	33.6%	67.1%	28.5%	4.8%	72.0%	12.7%
<b>7</b>	28.1%	12.6%	70.8%	33.4%	14.7%	22.6%	37.0%	59.8%
<b>8</b>	17.8%	20.1%	47.8%	48.6%	15.3%	24.0%	40.9%	57.9%
<b>9</b>	19.2%	22.2%	46.7%	57.5%	7.2%	27.1%	17.6%	70.3%
<b>10</b>	18.0%	13.8%	43.4%	36.9%	16.1%	24.1%	38.8%	64.1%
<b>Avg</b>	15.8%	19.2%	41.3%	51.2%	14.9%	20.4%	39.2%	54.4%

In low demand and ICC setting of 50 customer instances, carrier *A* transfers 15.2% of its total demand in average and carrier *B* transfers 19.2% of its total demand in average. When the transfer percentages are compared through total shared amounts, carrier *A* transfers 41.3% of transferable amount and carrier *B* transfers 51.2% of transferable amount. For given instances, PB model may choose to transfer up to

70.8% of transferable amount.

For the high demand setting, carrier A transfers 14.9% of its total demand in average and carrier B transfers 20.4% of its total demand on average. When total possible transfer amounts are compared, it is observed that carrier *A* prefers to transfer 39.2% of shared demand on average. Carrier *B* transferred 54.4% percent of the possible transferable amount.

Last set of experiments for ICC scenario, conducted with 100 customers. Results of individual experiments with original scenario of 100 customer instances can be found in Table 6.49.

Table 6.49 Individual PB Formulation results for ICC scenario of 100 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
1	148042	70690	77352	128694	56056	72638	198320	94339	103982	171710	77686	94024
2	145072	68416	76656	129742	57798	71945	190706	90288	100418	163346	79945	83401
3	145428	74912	70517	127583	63829	63755	191213	103207	88006	162491	81949	80542
4	145760	72830	72930	128180	69858	58322	191715	93040	98675	162973	80907	82066
5	148116	71702	76415	136663	70309	66353	204090	100317	103773	182783	95253	87531
6	143813	69715	74098	129174	55453	73721	186545	89488	97057	165413	79464	85949
7	148928	71957	76972	132599	68772	63827	179781	86361	93420	158518	75119	83399
8	151678	73904	77774	138466	67378	71088	207525	100603	106922	185498	100967	84531
9	148456	72846	75610	138107	70187	67920	185733	92038	93695	159548	79042	80505
10	155737	81753	73985	139141	75873	63268	205438	105278	100160	175915	94526	81389

For the 100 customer instances, gains are compared in Table 6.50.

Table 6.50 Gain comparison for ICC scenario of 100 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
1	13.1%	20.7%	6.1%	13.4%	17.7%	9.6%
2	10.6%	15.5%	6.1%	14.3%	11.5%	16.9%
3	12.3%	14.8%	9.6%	15.0%	20.6%	8.5%
4	12.1%	4.1%	20.0%	15.0%	13.0%	16.8%
5	7.7%	1.9%	13.2%	10.4%	5.0%	15.7%
6	10.2%	20.5%	0.5%	11.3%	11.2%	11.4%
7	11.0%	4.4%	17.1%	11.8%	13.0%	10.7%
8	8.7%	8.8%	8.6%	10.6%	-0.4%	20.9%
9	7.0%	3.6%	10.2%	14.1%	14.1%	14.1%
10	10.7%	7.2%	14.5%	14.4%	10.2%	18.7%
Avg	10.3%	10.2%	10.6%	13.0%	11.6%	14.3%

In low demand setup of ICC setting of 100 customer instances, average gain amount for centralized is 10.3%. For carrier  $A$  average gain is 10.2% and for carrier  $B$  average gain amount is 10.6%. None of the carriers suffer from collaboration. In high demand setup, average gains are higher for centralized system and both carriers. Average saving through collaboration in joint system is 13% where average gain for carrier  $A$  is 11.6% and average gain for carrier  $B$  is 14.3%.

Transfer amount information for 100 customer and ICC setting can be found in Table 6.51.

Table 6.51 Transfer percentages for ICC setting of 100 customer instances of PB formulation experiments

Ins	Low Demand					High Demand			
	% $TD_A$	% $TD_B$	% $TP_A$	% $TP_B$	% $TD_A$	% $TD_B$	% $TP_A$	% $TP_B$	
1	27.1%	12.0%	69.8%	30.2%	17.5%	20.0%	45.2%	50.3%	
2	23.1%	18.0%	57.7%	44.6%	17.8%	23.8%	44.4%	58.9%	
3	21.8%	15.9%	55.8%	39.0%	23.8%	15.0%	61.0%	36.9%	
4	15.1%	26.5%	36.1%	63.5%	18.2%	21.8%	43.4%	52.2%	
5	16.8%	24.1%	39.2%	61.3%	16.8%	23.4%	39.2%	59.4%	
6	29.4%	15.1%	68.7%	35.6%	20.2%	23.4%	47.0%	55.1%	
7	15.3%	26.5%	39.6%	69.5%	18.3%	18.3%	47.3%	48.0%	
8	19.3%	20.0%	49.1%	52.2%	10.1%	26.6%	25.8%	69.7%	
9	16.1%	21.7%	42.9%	56.4%	17.9%	19.0%	47.6%	49.5%	
10	12.0%	21.4%	38.6%	61.8%	11.8%	21.2%	37.9%	61.1%	
Avg	19.6%	20.1%	49.7%	51.4%	17.2%	21.3%	43.9%	54.1%	

In low demand and ICC setting of 100 customer instances, carrier  $A$  and carrier  $B$  transfers 19.6% and 20.1% of their total demands in average, respectively. Carrier  $A$  transfers 49.7% of total possible transferable amount in average. Carrier  $B$  transfers 51.4% of its possible transferable amount in average. In short, carriers preferred to transfer approximately half of their shared demand with other carriers. In high demand environment, carrier  $A$  and carrier  $B$  transfers 17.2% and 21.3% of their total demands on average, respectively. Moreover, carrier  $A$  and carrier  $B$  transfers 43.9% and 54.1% of their total possible transferable demand in average, respectively.

Last set of experiments for PB formulation are conducted under NCD setting in which carriers do not have a chance to setup facilities in same location, in order to see the effect of common depot declaration on saving and transfer amounts. First, individual experiments of NCD scenario is conducted with 30 customer instances. Results can be found in Table 6.52.

Gain amounts achieved through collaboration can be found for PB Formulation

Table 6.52 Individual PB Formulation results for NCD scenario of 30 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>
<b>1</b>	64144	30955	33189	62373	30610	31762	90329	43764	46565	86322	44535	41787
<b>2</b>	72674	34678	37996	68354	31458	36897	102565	45504	57061	89328	41463	47866
<b>3</b>	70390	37605	32786	69004	36390	32614	94154	49138	45017	85718	47741	37977
<b>4</b>	57988	30122	27866	56480	28615	27866	80325	42479	37846	76847	39792	37055
<b>5</b>	65891	34768	31123	62815	33996	28818	91543	50978	40565	81508	47715	33794
<b>6</b>	68806	36851	31955	63365	35077	28287	91172	47993	43179	83165	43643	39522
<b>7</b>	68239	35120	33119	66503	32122	34381	89316	44992	44324	82852	41615	41237
<b>8</b>	63647	33056	30591	63489	32684	30805	87075	46628	40447	81581	39435	42146
<b>9</b>	71054	37170	33884	67429	34404	33024	94107	47745	46362	85209	45088	40121
<b>10</b>	69119	37504	31616	66736	35860	30876	89077	44556	44521	82206	42062	40143

results with 30 customers and NCD scenario in Table 6.53.

Table 6.53 Gain comparison for NCD scenario of 30 customer instances

Ins	Low Demand				High Demand			
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>		
<b>1</b>	2.8%	1.1%	4.3%	4.4%	-1.8%	10.3%		
<b>2</b>	5.9%	9.3%	2.9%	12.9%	8.9%	16.1%		
<b>3</b>	2.0%	3.2%	0.5%	9.0%	2.8%	15.6%		
<b>4</b>	2.6%	5.0%	0.0%	4.3%	6.3%	2.1%		
<b>5</b>	4.7%	2.2%	7.4%	11.0%	6.4%	16.7%		
<b>6</b>	7.9%	4.8%	11.5%	8.8%	9.1%	8.5%		
<b>7</b>	2.5%	8.5%	-3.8%	7.2%	7.5%	7.0%		
<b>8</b>	0.2%	1.1%	-0.7%	6.3%	15.4%	-4.2%		
<b>9</b>	5.1%	7.4%	2.5%	9.5%	5.6%	13.5%		
<b>10</b>	3.4%	4.4%	2.3%	7.7%	5.6%	9.8%		
<b>Avg</b>	3.7%	4.7%	2.7%	8.1%	6.6%	9.5%		

In low demand environment of NCD scenario setting of 30 customer instances, average gain amount by centralized collaboration schema is 3.7%. For carriers *A* and *B* average gain amounts are 4.7% and 2.7%, respectively. Carrier *A* benefited from collaboration in all instances. Carrier *B* reported worse OFVs in two instances. Moreover, carrier *B* reported a 0% gain for instance 4, which means that carrier *B* was impartial for collaboration or non-collaboration. In high demand environment, average gain for collaborative schema is 8.1% which is higher than the low demand setting. For carriers *A* and *B* average gain amounts are 6.6% and 9.6%, respectively. Next transfer amounts are investigated for NCD setting and 30 customer instances. Results can be found in Table 6.54.

In low demand setting, carrier *A* transfers 11.4% of its total demand in average and carrier *B* transfers 12.2% of its total demand in average. When total possible

Table 6.54 Transfer percentages for NCD setting of 30 customer instances of PB formulation experiments

Ins	Low Demand					High Demand			
	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>	%TD <sub>A</sub>	%TD <sub>B</sub>	%TP <sub>A</sub>	%TP <sub>B</sub>	
1	8.1%	12.9%	29.1%	57.0%	10.4%	15.5%	31.1%	55.9%	
2	9.5%	13.3%	39.8%	50.2%	8.4%	19.8%	33.7%	71.1%	
3	11.0%	21.1%	43.9%	75.6%	4.3%	24.8%	15.4%	84.6%	
4	13.2%	0.0%	46.9%	0.0%	12.9%	7.1%	58.2%	41.8%	
5	9.9%	10.6%	35.0%	39.0%	15.6%	14.2%	56.2%	43.8%	
6	12.2%	15.4%	48.0%	53.2%	10.6%	15.2%	39.5%	60.5%	
7	11.2%	12.3%	44.1%	42.6%	12.6%	13.3%	47.1%	52.9%	
8	12.7%	14.3%	37.9%	44.5%	14.5%	6.6%	58.5%	24.6%	
9	11.3%	12.2%	38.0%	50.0%	10.5%	13.1%	43.2%	56.8%	
10	14.8%	10.1%	56.7%	47.3%	9.1%	18.8%	35.1%	64.9%	
Avg	11.4%	12.2%	41.9%	45.9%	10.9%	14.8%	41.8%	55.7%	

transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 41.9% of shared demand in average. Carrier  $B$  transferred 45.9% percent of the possible transferable amount in average.

For the high demand setting, carrier  $A$  transfers 10.9% of its total demand in average and carrier  $B$  transfers 14.8% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 41.5% of shared demand in average. Carrier  $B$  transferred 55.7% percent of the possible transferable amount. In some cases, PB formulation can transfer up to 71.1% of the transferable amount of a carrier. However, it may also choose to only transfer 15.4% of the transferable amount is transferred to other carrier.

In order to investigate strategic aspects discussed above and to see the effect of problem size, experiments are repeated with 50 customer instances. Results of individual experiments with NCD scenario of 50 customer instances can be found in Table 6.55.

Table 6.55 Individual PB Formulation results for NCD scenario of 50 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>	Obj	Obj <sub>A</sub>	Obj <sub>B</sub>
1	98108	51103	47005	87908	43486	44422	127383	68869	58514	115718	58034	57685
2	96776	52645	44131	92528	45972	46557	134949	72823	62126	116431	54685	61746
3	87745	40949	46796	82109	41232	40877	125823	59783	66040	115473	55665	59808
4	94543	48953	45591	88358	46828	41530	124192	64327	59865	114511	61551	52960
5	99148	47848	51300	93751	45423	48328	133502	64852	68650	124417	53764	70653
6	91933	44378	47555	85270	44321	40949	117556	57716	59841	110843	57115	53729
7	92244	43109	49135	90827	43085	47742	122323	55541	66782	114360	51852	62509
8	111217	58671	52546	102740	52825	49914	134755	69539	65216	124894	72843	52052
9	98252	49279	48973	89349	40514	48835	130183	64601	65582	117288	59698	57590
10	105640	55298	50342	103108	53742	49366	134333	66933	67400	126785	67859	58926

Gain amount in which individual and collaborative scenarios of NCD setting of 50 customer instances can be found in Table 6.56.

Table 6.56 Gain comparison for NCD scenario of 50 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
<b>1</b>	10.4%	14.9%	5.5%	9.2%	15.7%	1.4%
<b>2</b>	4.4%	12.7%	-5.5%	13.7%	24.9%	0.6%
<b>3</b>	6.4%	-0.7%	12.6%	8.2%	6.9%	9.4%
<b>4</b>	6.5%	4.3%	8.9%	7.8%	4.3%	11.5%
<b>5</b>	5.4%	5.1%	5.8%	6.8%	17.1%	-2.9%
<b>6</b>	7.2%	0.1%	13.9%	5.7%	1.0%	10.2%
<b>7</b>	1.5%	0.1%	2.8%	6.5%	6.6%	6.4%
<b>8</b>	7.6%	10.0%	5.0%	7.3%	-4.8%	20.2%
<b>9</b>	9.1%	17.8%	0.3%	9.9%	7.6%	12.2%
<b>10</b>	2.4%	2.8%	1.9%	5.6%	-1.4%	12.6%
<b>Avg</b>	6.1%	6.7%	5.1%	8.1%	7.8%	8.2%

For the low demand and NCD setting of 50 customer instances, average gain amount for centralized system is 6.1%. Carrier *A* and *B* gains from the collaboration by 6.7% and 5.1%, respectively. Both carriers suffer from collaboration in only one instance. Maximum gain amount for carrier *A* is 17.8% and for carrier *B* 13.9%. For the high demand setting, average gain amount is 8.1%. Average gain for carrier *A* is 7.8% and 8.2% for carrier *B*. Gain amounts deviate between -4.8% and 24.9% for independent carriers depending on instance.

Transfer amounts in percentages for NCD scenario of 50 customer instances can be found in Table 6.57.

Table 6.57 Transfer percentages for NCD setting of 50 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	<i>%TD<sub>A</sub></i>	<i>%TD<sub>B</sub></i>	<i>%TP<sub>A</sub></i>	<i>%TP<sub>B</sub></i>	<i>%TD<sub>A</sub></i>	<i>%TD<sub>B</sub></i>	<i>%TP<sub>A</sub></i>	<i>%TP<sub>B</sub></i>
<b>1</b>	14.1%	8.7%	72.2%	36.2%	11.1%	4.3%	56.7%	17.9%
<b>2</b>	13.9%	6.9%	57.2%	28.2%	18.9%	3.2%	77.5%	13.0%
<b>3</b>	10.8%	13.1%	44.4%	55.6%	4.6%	16.2%	19.0%	68.8%
<b>4</b>	3.0%	4.7%	19.3%	26.2%	2.4%	11.9%	15.9%	66.7%
<b>5</b>	9.8%	11.4%	41.3%	56.8%	20.0%	1.5%	84.7%	7.4%
<b>6</b>	4.9%	10.8%	27.6%	63.9%	4.2%	8.1%	23.5%	48.2%
<b>7</b>	1.2%	8.2%	6.8%	48.8%	7.0%	10.2%	39.3%	60.7%
<b>8</b>	7.6%	10.6%	30.1%	36.9%	1.3%	22.2%	5.2%	77.5%
<b>9</b>	17.0%	5.4%	77.1%	22.9%	7.3%	15.9%	32.9%	67.1%
<b>10</b>	12.2%	11.5%	59.1%	54.7%	3.0%	11.3%	14.4%	53.5%
<b>Avg</b>	9.4%	9.1%	43.5%	43.0%	8.0%	10.5%	36.9%	48.1%

In low demand setting, carrier *A* transfers 9.4% of its total demand in average

and carrier  $B$  transfers 9.1% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier  $A$  prefers to transfer 43.5% of shared demand in average. Carrier  $B$  transferred 43% percent of the possible transferable amount in average.

On high demand setting, when the transfer amount is compared through total demand amounts, in average, carrier  $A$  transferred 8% of its total demand and carrier  $B$  transferred 10.5% of its total demand. In average, carrier  $A$  chose to transfer 36.9% of transferable amount where carrier  $B$  chose to transfer 48.1% of total transferable amount.

Last experiments are conducted with 100 customer instances. Results of individual runs of NCD scenario can be found in Table 6.58.

Table 6.58 Individual PB Formulation results for NCD scenario of 100 customer instances

Ins	Low Demand						High Demand					
	Individual			Collaboration			Individual			Collaboration		
	$Obj$	$Obj_A$	$Obj_B$	$Obj$	$Obj_A$	$Obj_B$	$Obj$	$Obj_A$	$Obj_B$	$Obj$	$Obj_A$	$Obj_B$
1	141730	65537	76194	136420	62995	73425	197742	92353	105389	182381	84717	97663
2	139075	66240	72835	133221	62212	71008	183439	85872	97567	171402	76676	94726
3	144115	71444	72671	134427	68625	65802	191746	98309	93437	178360	90850	87510
4	140281	68358	71923	134611	66603	68008	183993	88281	95712	171617	86116	85501
5	147374	73295	74079	140476	70739	69737	196348	99911	96437	184627	89863	94764
6	138240	65170	73071	133781	63293	70489	181345	90101	91245	172335	78350	93985
7	146086	72181	73905	138358	67052	71305	181354	89804	91550	169075	82562	86512
8	147093	72534	74560	140567	64549	76019	205265	105431	99834	193339	93195	100144
9	146372	70927	75445	141770	69315	72455	177792	87156	90636	167551	80449	87102
10	148446	71113	77333	143327	67682	75645	193820	91883	101937	182750	85297	97453

Gains that are achieved through collaboration for NCD setting of 100 customer instances can be identified in Table 6.59.

Table 6.59 Gain comparison for NCD scenario of 100 customer instances

Ins	Low Demand			High Demand		
	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>	<i>Gain</i>	<i>Gain<sub>A</sub></i>	<i>Gain<sub>B</sub></i>
<b>1</b>	3.7%	3.9%	3.6%	7.8%	8.3%	7.3%
<b>2</b>	4.2%	6.1%	2.5%	6.6%	10.7%	2.9%
<b>3</b>	6.7%	3.9%	9.5%	7.0%	7.6%	6.3%
<b>4</b>	4.0%	2.6%	5.4%	6.7%	2.5%	10.7%
<b>5</b>	4.7%	3.5%	5.9%	6.0%	10.1%	1.7%
<b>6</b>	3.2%	2.9%	3.5%	5.0%	13.0%	-3.0%
<b>7</b>	5.3%	7.1%	3.5%	6.8%	8.1%	5.5%
<b>8</b>	4.4%	11.0%	-2.0%	5.8%	11.6%	-0.3%
<b>9</b>	3.1%	2.3%	4.0%	5.8%	7.7%	3.9%
<b>10</b>	3.4%	4.8%	2.2%	5.7%	7.2%	4.4%
<b>Avg</b>	4.3%	4.8%	3.8%	6.3%	8.7%	3.9%

In low demand and NCD setting of 100 customer instances, average gain amount for centralized system is 4.3% where gains deviate between 3.1% and 6.7%. For carriers *A* and *B*, average gain percentages are 4.8 and 3.8, respectively. Only one instance of carrier *B* reported a loss. In high demand setting, for collaborative system, average gain amount is 6.3%. Carrier *A* and *B* have an average gain of 8.7% and 3.9%, respectively. Maximum gain amount in collaborative system is 7.8%. Again, in high demand setting, gain average is higher than the low demand environment.

Transfer amounts in percentages for NCD scenario of 100 customer instances can be found in Table 6.60.

Table 6.60 Transfer percentages for NCD setting of 100 customer instances of PB formulation experiments

Ins	Low Demand				High Demand			
	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$	$\%TD_A$	$\%TD_B$	$\%TP_A$	$\%TP_B$
<b>1</b>	8.3%	6.4%	46.7%	38.9%	8.0%	8.3%	44.6%	49.9%
<b>2</b>	12.0%	10.7%	58.6%	48.6%	13.2%	7.1%	64.6%	32.1%
<b>3</b>	5.9%	9.1%	32.8%	53.1%	10.9%	5.4%	60.9%	31.6%
<b>4</b>	9.7%	9.0%	46.4%	41.7%	4.7%	13.0%	22.8%	60.0%
<b>5</b>	8.5%	7.5%	43.7%	40.0%	13.5%	7.1%	69.7%	37.7%
<b>6</b>	8.8%	9.3%	43.8%	46.5%	8.9%	4.8%	44.1%	24.1%
<b>7</b>	7.3%	7.1%	39.7%	37.5%	7.0%	7.3%	38.0%	38.6%
<b>8</b>	12.9%	4.8%	69.1%	24.7%	12.3%	4.9%	66.3%	25.0%
<b>9</b>	9.4%	6.0%	46.3%	31.2%	10.1%	8.6%	49.6%	44.7%
<b>10</b>	12.4%	7.9%	54.3%	37.8%	11.4%	11.4%	50.0%	54.2%
<b>Avg</b>	9.5%	7.8%	48.1%	40.0%	10.0%	7.8%	51.0%	39.8%

In low demand setting, carrier *A* transfers 9.5% of its total demand in average and carrier *B* transfers 7.8% of its total demand in average. When total possible transfer amounts are compared, it is observed that carrier *A* prefers to transfer 48.1% of

shared demand in average. Carrier  $B$  transferred 40% of the possible transferable amount in average.

On high demand setting, when the transfer amount is compared through total demand amounts, in average, carrier  $A$  transferred 10% of its total demand and carrier  $B$  transferred 7.8% of its total demand. In average, carrier  $A$  chose to transfer 51% of transferable amount where carrier  $B$  chose to transfer 39.8% of total transferable amount. It is observed that, in some instances carriers chose to transfer up to 69.7% of transferable amount.

Table 6.61 Summary of gain averages

	Low Demand			High Demand		
	30	50	100	30	50	100
<b><math>O</math></b>	6.7%	5.9%	5.7%	8.0%	7.0%	7.0%
<b><math>ICC</math></b>	12.1%	10.4%	10.3%	15.5%	14.1%	13.0%
<b><math>NCD</math></b>	3.7%	6.1%	4.3%	8.1%	8.1%	6.3%

Overall, when the Table 6.61 examined, it can be concluded that collaborative schema yield gains. Minimum average gain amount is 3.7% in NCD and low demand setting of 30 customer instances. On the other hand, collaboration resulted with 15.5% gains in average for ICC and high demand setting of 30 customer instances. Under all scenario types of all problem sizes, collaboration reported higher savings in high demand environments. Moreover, ICC scenario is always reported a higher gain percentage in average for all experiments.

## 7. CONCLUSION

We study a two echelon strategic network design problem in which more than two firms (or carriers) simultaneously make decisions to collaborate in their distribution activities under a centralized schema. While there is no collaboration opportunity at the upper echelon transportation, firms can collaborate at the lower echelon and a firm can deliver the demand of a common customer for both itself and the other carrier(s). Three different mixed-integer linear programming models are proposed. Two of these models provide exact solutions to the problem whereas third model relies on a restricted solution space. The objective is to minimize the total cost arising from opening and operating regional depots, constructing transfer lines between depots and establishing both inbound and outbound routes.

Proposed MILP models differ in terms of modelling the decisions on outbound transportation, i.e., routing operations. In the VB model, outbound transportation decision modelling is derived from the traditional CVRP formulations and routing decisions are controlled over vehicles. In the LB model, outbound routing decisions are represented through load amounts carried on arcs. Both VB and LB formulations yield an exact solution to the problem. In the PB model, routes are selected from heuristically pre-generated route pool which does not necessarily include all theoretically possible routes.

To solve the proposed models various methods are used. A cut generation approach is utilized to control exponentially many sub-tour elimination constraints in the VB formulation. Several valid inequalities are proposed for all three formulations. In the PB model, a route pool is generated through well known five different heuristics to create diversity among routes in an iterative approach to mimic collaborative behaviour. In order to test effects of solution techniques and valid inequalities, models are tested under different collaboration scenarios and demand density for different problem sizes.

From a methodological point of view, results showed that the VB formulation has a high space and time complexity. Proposed cut generation method solves the space

complexity problem and decreases solution times. Despite the decreased time complexity, the LB formulation still outperforms the VB formulation. The LB formulation is strengthened with valid inequalities; two of the proposed valid inequalities for the LB formulation successfully decrease the optimality gaps within limited solution time. Even though the LB formulation was able to solve instances, solution times were still high and some gaps are reported. The PB formulation was able to solve all instances of all problem sizes to optimality. Deviations of the PB formulation solutions from the best bounds of LB formulation solutions vary between 3.9% and 19.4%. In some cases, the PB formulation yield better solutions than LB formulation within given time limits, when best solutions are compared.

From a managerial point of view, proposed collaborative scheme definitely reduces total distribution and facility costs. Depending on different parameters such as the number of candidate depot locations, common customers, problem size and customer distribution, the cost saving differ. When different scenarios are compared to identify the effect above parameters on collaboration, ICC setting yield more savings than the original setting on average. Hence, the savings due to collaboration increase as the number of common customers in the system increases. Higher demand density leads to higher gains on average when compared to low density. We emphasize that the proposed models aim to minimize total cost of a centralized system. In only few instances, individual carriers report worse outcomes in exchange of better integrated system outcomes.

In the future studies, this problem can be considered in a multi-period setting. Alternative exact solution methods can be implemented in order to solve larger instances to optimality. For the PB formulation, the route pool generation can be extended with other heuristic algorithms or meta-heuristic algorithms to create high quality routes in order to reduce deviation from the true optimal solutions. Moreover, other scenario types can be created such as clustered customers or high density customer regions to investigate the effect of geographical distribution of customers. Another challenging extension may be the increasing number of echelons in which parties can collaborate. The potential gains and collaboration behaviour can be tested with more than two carriers to study the effect of number of carriers in the system.

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## APPENDIX A

### Individual Load-Based Formulation

$$\text{minimize} \quad \sum_{d \in D} \sum_{(i,j) \in A^d} c_{ij} x_{ij}^d + \sum_{d \in D} B_d y_d + \sum_{d \in D} \sum_{p \in P} \Delta_{pd} \delta_{pd}$$

subject to

$$(A.1) \quad \sum_{d \in D} z_{id} = 1 \quad \forall i \in N$$

$$(A.2) \quad \sum_{\substack{j \in N \cup \{d\} \\ i \neq j}} x_{j,i}^d - \sum_{\substack{j \in N \cup \{d\} \\ i \neq j}} x_{i,j}^d = 0 \quad \forall d \in D, i \in N$$

$$(A.3) \quad \sum_{\substack{j \in N \cup \{d\} \\ i \neq j}} x_{i,j}^d \geq z_{id} \quad \forall i \in N, d \in D$$

$$(A.4) \quad \sum_{j \in N} l_{d,j}^{dh} = d_h z_{hd} \quad \forall d \in D, h \in N$$

$$(A.5) \quad \sum_{\substack{j \in N \cup \{d\} \\ i \neq j}} l_{i,j}^{dh} - \sum_{\substack{j \in N \cup \{d\} \\ i \neq j}} l_{j,i}^{dh} = \begin{cases} -d_i z_{id} & \text{if } i = h \\ 0 & \text{if } i \neq h \end{cases} \quad \forall d \in D, i, h \in N$$

$$(A.6) \quad \sum_{h \in N} l_{i,j}^{dh} \leq Q x_{i,j}^d \quad \forall d \in D, (i,j) \in A^d$$

$$(A.7) \quad M * y_d \geq \sum_{i \in N} z_{id} \quad \forall d \in D$$

$$(A.8) \quad M * \delta_{pd} \geq u_{pd} \quad \forall p \in P, d \in D$$

$$(A.9) \quad u_{pd} = \sum_{i \in N} d_i z_{id} \quad \forall d \in D, p \in P$$

$$(A.10) \quad x_{ij}^d \in \{0,1\} \quad \forall d \in D, (i,j) \in A^d$$

$$(A.11) \quad z_{id} \in \{0,1\} \quad \forall i \in N, d \in D$$

$$(A.12) \quad l_{ij}^{dh} \in \mathbb{R}_+ \quad \forall d \in D, (i,j) \in A^d, h \in N$$

$$(A.13) \quad y_d \in \{0,1\} \quad \forall d \in D$$

$$(A.14) \quad \delta_{pd} \in \{0,1\} \quad \forall p \in P, d \in D$$

$$(A.15) \quad u_{pd} \in \mathbb{R}_+ \quad \forall p \in P, d \in D$$

### Load-Based Formulation Results of 50 Customer Instances

Table A.1 LB results for original and low demand setting of 50 customer instances

<b>Ins.</b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b><i>Gap</i></b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b><i>I1</i></b>	2	2	2	1	88184	43681	44503	11.4%	57262	17069	147	13706
<b><i>I2</i></b>	1	1	1	1	82885	40724	42160	10.6%	66884	9142	495	6364
<b><i>I3</i></b>	1	1	1	1	81902	41326	40576	13.7%	68410	9142	269	4081
<b><i>I4</i></b>	2	1	1	2	85243	46276	38968	11.3%	64079	11965	592	8607
<b><i>I5</i></b>	2	1	1	2	84943	46791	38153	10.6%	66288	11894	370	6392
<b><i>I6</i></b>	1	1	1	1	80984	37730	43254	10.2%	70297	8590	181	1916
<b><i>I7</i></b>	1	1	1	1	85120	43158	41962	11.4%	74443	8032	223	2422
<b><i>I8</i></b>	2	2	2	2	98903	48413	50490	12.5%	66231	15937	542	16193
<b><i>I9</i></b>	2	2	1	2	87599	47299	40300	14.4%	59222	15292	104	12981
<b><i>I10</i></b>	2	2	2	1	99984	48377	51606	12.5%	70284	17296	573	11831

Table A.2 LB results for original and high demand setting of 50 customer instances

<b>Ins.</b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b><i>Gap</i></b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b><i>I1</i></b>	3	2	2	2	110932	55205	55727	9.5%	70267	22175	560	17930
<b><i>I2</i></b>	2	2	2	1	115871	59294	56577	9.2%	81104	19656	687	14424
<b><i>I3</i></b>	2	2	2	2	114703	55808	58894	12.0%	84515	18822	536	10830
<b><i>I4</i></b>	2	3	1	2	113653	58611	55042	10.9%	75897	20618	531	16607
<b><i>I5</i></b>	3	3	2	2	120797	55977	64820	11.5%	77812	24735	640	17610
<b><i>I6</i></b>	3	3	2	3	114799	57141	57658	10.0%	72813	21911	278	19797
<b><i>I7</i></b>	2	2	2	2	116067	48423	67644	10.8%	86285	17008	603	12171
<b><i>I8</i></b>	3	3	3	2	130314	65564	64750	9.0%	78841	24953	663	25857
<b><i>I9</i></b>	3	2	2	3	111563	59156	52407	10.4%	75186	18939	323	17115
<b><i>I10</i></b>	3	3	3	2	134369	63328	71040	11.8%	84999	25249	607	23514

Table A.3 LB results for ICC and low demand setting of 50 customer instances

<b>Ins.</b>	<b><i>F<sub>A</sub></i></b>	<b><i>F<sub>B</sub></i></b>	<b><i>T<sub>A</sub></i></b>	<b><i>T<sub>B</sub></i></b>	<b><i>Obj</i></b>	<b><i>Obj<sub>A</sub></i></b>	<b><i>Obj<sub>B</sub></i></b>	<b><i>Gap</i></b>	<b><i>RC</i></b>	<b><i>FC</i></b>	<b><i>TC</i></b>	<b><i>IC</i></b>
<b><i>I1</i></b>	2	2	2	2	83263	41867	41396	11.2%	52860	16216	703	13485
<b><i>I2</i></b>	1	1	1	1	84433	41961	42471	11.5%	67339	10235	495	6364
<b><i>I3</i></b>	1	2	2	1	82198	35679	46519	18.2%	64278	12164	222	5534
<b><i>I4</i></b>	2	1	1	2	81117	49619	31497	11.0%	59086	12832	592	8607
<b><i>I5</i></b>	2	1	1	2	83847	45578	38269	10.2%	64714	12372	370	6392
<b><i>I6</i></b>	1	1	1	1	79798	38442	41355	11.0%	68859	8842	181	1916
<b><i>I7</i></b>	1	1	1	1	82583	39797	42785	10.8%	70972	8966	223	2422
<b><i>I8</i></b>	3	1	1	3	93621	54920	38701	11.8%	63875	14393	766	14587
<b><i>I9</i></b>	1	1	1	1	83780	39010	44770	13.4%	67720	8790	650	6620
<b><i>I10</i></b>	2	1	1	2	98063	43747	54315	15.0%	73757	14836	646	8824

Table A.4 LB results for ICC and high demand setting of 50 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b><i>I1</i></b>	3	2	2	3	103423	53195	50227	8.9%	64683	20202	739	17799
<b><i>I2</i></b>	3	2	2	3	113615	62804	50811	10.7%	71466	21427	929	19794
<b><i>I3</i></b>	2	2	2	2	109297	57032	52265	12.2%	80498	17668	532	10600
<b><i>I4</i></b>	2	2	2	2	109488	60968	48521	11.8%	79361	16999	701	12427
<b><i>I5</i></b>	3	2	2	3	114577	52765	61812	9.9%	75571	19514	1016	18477
<b><i>I6</i></b>	2	3	3	2	114308	50232	64077	12.6%	77635	20700	588	15386
<b><i>I7</i></b>	3	3	2	3	120707	57080	63627	13.9%	70266	28570	750	21121
<b><i>I8</i></b>	3	3	3	3	126826	64419	62407	12.7%	78250	24822	917	22837
<b><i>I9</i></b>	3	2	2	3	105980	50572	55407	9.7%	66916	19479	662	18923
<b><i>I10</i></b>	3	2	2	3	126826	65516	61310	11.5%	82696	22071	1052	21007

Table A.5 LB results for NCD and low demand setting of 50 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b><i>I1</i></b>	2	2	2	2	87427	45364	42063	11.1%	56084	17461	364	13518
<b><i>I2</i></b>	2	1	1	1	87903	45916	41987	10.4%	64789	11801	387	10926
<b><i>I3</i></b>	1	1	1	1	77400	39223	38176	12.8%	64896	8154	269	4081
<b><i>I4</i></b>	2	1	1	2	84967	47538	37429	11.4%	64909	12686	481	6891
<b><i>I5</i></b>	1	1	1	1	88593	43364	45229	9.6%	76604	9307	201	2481
<b><i>I6</i></b>	1	1	1	1	81844	44080	37764	9.5%	70708	9039	181	1916
<b><i>I7</i></b>	1	1	1	1	86221	41223	44998	12.0%	74270	9307	223	2422
<b><i>I8</i></b>	2	2	2	2	100115	54480	45634	13.1%	67175	18373	392	14175
<b><i>I9</i></b>	1	1	1	1	85280	40300	44980	12.2%	69591	8830	543	6316
<b><i>I10</i></b>	2	1	1	2	96735	49987	46748	11.5%	75160	11174	569	9832

Table A.6 LB results for NCD and high demand setting of 50 customer instances

<i>Ins.</i>	<i>F<sub>A</sub></i>	<i>F<sub>B</sub></i>	<i>T<sub>A</sub></i>	<i>T<sub>B</sub></i>	<i>Obj</i>	<i>Obj<sub>A</sub></i>	<i>Obj<sub>B</sub></i>	<i>Gap</i>	<i>RC</i>	<i>FC</i>	<i>TC</i>	<i>IC</i>
<b><i>I1</i></b>	3	2	2	2	111195	61098	50097	8.9%	70763	21636	773	18023
<b><i>I2</i></b>	2	3	3	1	113047	53338	59709	9.3%	72597	20319	831	19300
<b><i>I3</i></b>	2	2	1	2	109629	59971	49658	10.6%	81236	16217	243	11933
<b><i>I4</i></b>	2	3	2	2	117987	61623	56364	12.4%	80664	19888	479	16956
<b><i>I5</i></b>	2	3	3	2	131831	59639	72192	12.2%	90509	23261	545	17516
<b><i>I6</i></b>	3	3	2	2	115120	56138	58982	9.7%	71608	22928	565	20019
<b><i>I7</i></b>	2	2	2	2	119526	57679	61846	12.5%	89761	15878	682	13204
<b><i>I8</i></b>	3	3	2	3	129326	72178	57148	11.0%	76910	25997	564	25856
<b><i>I9</i></b>	2	3	3	1	115069	53155	61914	11.9%	76101	20515	675	17778
<b><i>I10</i></b>	3	2	2	2	132982	68391	64591	12.3%	90346	20603	872	21161

## Instance Data

Column explanations as follows;  $N$  indicates the number of customers in the instance where  $N_A$ ,  $N_B$  and  $N_C$  depict number of customers for carrier  $A$ , carrier  $B$  and number of common customers, respectively.  $d_A$  and  $d_B$  indicate the demand of carriers  $A$  and  $B$ , respectively.  $d_A^S$  and  $d_B^S$  depict the shared amount of demand for carriers  $A$  and  $B$ .  $d^T$  is the total demand.

Table A.7 Original scenario data for 30 customer instances

Ins	N	Low Demand						High Demand					
		$N_A$	$N_B$	$N_C$	$d_A$	$d_A^C$	$d_B$	$d_B^C$	$d_T$	$d_A$	$d_A^C$	$d_B$	$d_B^C$
1	30	19	19	8	3148	880	3895	880	7043	6297	1760	7790	1760
2	30	19	19	8	3845	914	3458	914	7303	7690	1827	6917	1827
3	30	19	19	8	3860	965	3460	965	7320	7720	1930	6920	1930
4	30	19	19	8	2615	734	3889	734	6504	5230	1467	7778	1467
5	30	19	19	8	3544	1007	3711	1007	7255	7089	2015	7421	2015
6	30	19	19	8	3740	950	3281	950	7020	7480	1900	6561	1900
7	30	19	19	8	3740	950	3281	950	7020	7480	1900	6561	1900
8	30	19	19	8	3000	1004	3132	1004	6132	6000	2008	6264	2008
9	30	19	19	8	3104	921	3764	921	6868	6208	1843	7529	1843
10	30	19	19	8	3139	817	3834	817	6974	6279	1635	7669	1635

Table A.8 Original scenario data for 50 customer instances

Ins	N	Low Demand						High Demand					
		$N_A$	$N_B$	$N_C$	$d_A$	$d_A^C$	$d_B$	$d_B^C$	$d_T$	$d_A$	$d_A^C$	$d_B$	$d_B^C$
1	50	30	30	10	5527	732	5465	732	10992	11054	1465	10930	1465
2	50	30	30	10	6271	1303	6011	1303	12283	12543	2605	12023	2605
3	50	30	30	10	5759	1231	5559	1231	11318	11517	2462	11118	2462
4	50	30	30	10	6002	1276	6243	1276	12245	12004	2551	12486	2551
5	50	30	30	10	5894	1243	6336	1243	12230	11789	2485	12671	2485
6	50	30	30	10	5550	1105	6192	1105	11742	11101	2211	12384	2211
7	50	30	30	10	5550	1105	6192	1105	11742	11101	2211	12384	2211
8	50	30	30	10	6500	1080	6046	1080	12547	13000	2161	12093	2161
9	50	30	30	10	5342	1206	5737	1206	11078	10683	2413	11473	2413
10	50	30	30	10	5894	1280	5978	1280	11872	11789	2559	11955	2559

Table A.9 Original scenario data for 100 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_C$	$d_A$	$d_A^C$	$d_B$	$d_B^C$	$d_T$	$d_A$	$d_A^C$	$d_B$	$d_B^C$	
1	100	60	60	20	11821	2357	11166	2357	22987	23642	4713	22331	4713	45973
2	100	60	60	20	11664	2425	11947	2425	23611	23328	4851	23895	4851	47223
3	100	60	60	20	11143	2234	10647	2234	21791	22287	4468	21295	4468	43581
4	100	60	60	20	11215	2475	10711	2475	21926	22429	4949	21422	4949	43852
5	100	60	60	20	10953	2426	11688	2426	22642	21906	4852	23377	4852	45283
6	100	60	60	20	11775	2705	11415	2705	23191	23550	5410	22831	5410	46381
7	100	60	60	20	11835	2587	11987	2587	23822	23670	5174	23974	5174	47644
8	100	60	60	20	11611	2516	11980	2516	23591	23222	5032	23959	5032	47182
9	100	60	60	20	11970	2292	11297	2292	23267	23940	4583	22594	4583	46534
10	100	60	60	20	12220	2047	11476	2047	23696	24440	4093	22953	4093	47393

Table A.10 ICC scenario data for 30 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	30	22	22	14	3292	1540	3751	1540	7043	6584	3079	7502	3079	14087
2	30	22	22	14	3779	1818	3524	1818	7303	7558	3636	7049	3636	14606
3	30	22	22	14	3687	1470	3633	1470	7320	7373	2941	7267	2941	14640
4	30	22	22	14	2796	1308	3708	1308	6504	5591	2617	7417	2617	13008
5	30	22	22	14	3617	1541	3639	1541	7255	7233	3082	7277	3082	14510
6	30	22	22	14	3758	1623	3263	1623	7020	7515	3246	6525	3246	14041
7	30	22	22	14	3758	1623	3263	1623	7020	7515	3246	6525	3246	14041
8	30	22	22	14	3114	1647	3018	1647	6132	6227	3294	6036	3294	12263
9	30	22	22	14	3170	1730	3698	1730	6868	6341	3461	7396	3461	13737
10	30	22	22	14	3150	1535	3823	1535	6974	6301	3071	7646	3071	13947

Table A.11 ICC scenario data for 50 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	50	34	34	18	5559	1811	5434	1811	10992	11117	3623	10867	3623	21985
2	50	34	34	18	6283	2380	6000	2380	12283	12566	4760	11999	4760	24566
3	50	34	34	18	5619	2184	5698	2184	11318	11238	4369	11397	4369	22635
4	50	34	34	18	6419	2225	5826	2225	12245	12837	4450	11653	4450	24490
5	50	34	34	18	5685	2108	6545	2108	12230	11370	4216	13090	4216	24460
6	50	34	34	18	5735	2274	6007	2274	11742	11470	4548	12015	4548	23485
7	50	34	34	18	5735	2274	6007	2274	11742	11470	4548	12015	4548	23485
8	50	34	34	18	6601	2461	5946	2461	12547	13201	4921	11892	4921	25093
9	50	34	34	18	5367	2204	5711	2204	11078	10735	4407	11422	4407	22157
10	50	34	34	18	5649	2337	6223	2337	11872	11298	4674	12446	4674	23744

Table A.12 ICC scenario data for 100 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	100	70	70	40	11639	4515	11348	4515	22987	23277	9031	22696	9031	45973
2	100	70	70	40	11857	4745	11754	4745	23611	23714	9490	23508	9490	47223
3	100	70	70	40	11124	4339	10667	4339	21791	22247	8678	21334	8678	43581
4	100	70	70	40	10942	4587	10984	4587	21926	21885	9174	21967	9174	43852
5	100	70	70	40	10842	4645	11800	4645	22642	21683	9290	23600	9290	45283
6	100	70	70	40	11544	4949	11647	4949	23191	23087	9899	23294	9899	46381
7	100	70	70	40	11803	4575	12019	4575	23822	23606	9150	24037	9150	47644
8	100	70	70	40	11638	4570	11953	4570	23591	23276	9141	23905	9141	47182
9	100	70	70	40	11762	4419	11505	4419	23267	23524	8838	23010	8838	46534
10	100	70	70	40	12468	3890	11229	3890	23696	24936	7780	22457	7780	47393

Table A.13 NCD scenario data for 30 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	30	19	19	8	3148	880	3895	880	7043	6393	2138	7694	2138	14087
2	30	19	19	8	3845	914	3458	914	7303	7708	1924	6898	1924	14606
3	30	19	19	8	3860	965	3460	965	7320	7479	2097	7160	2097	14640
4	30	19	19	8	2615	734	3889	734	6504	5649	1253	7359	1253	13008
5	30	19	19	8	3544	1007	3711	1007	7255	7825	2172	6685	2172	14510
6	30	19	19	8	3740	950	3281	950	7020	6780	1820	7261	1820	14041
7	30	19	19	8	3740	950	3281	950	7020	6780	1820	7261	1820	14041
8	30	19	19	8	3000	1004	3132	1004	6132	6352	1580	5912	1580	12263
9	30	19	19	8	3104	921	3764	921	6868	6683	1622	7054	1622	13737
10	30	19	19	8	3139	817	3834	817	6974	7362	1908	6585	1908	13947

Table A.14 NCD scenario data for 50 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	50	30	30	10	6056	1185	4937	1185	10992	12111	2369	9873	2369	21985
2	50	30	30	10	6145	1497	6138	1497	12283	12290	2993	12276	2993	24566
3	50	30	30	10	5567	1350	5750	1350	11318	11135	2700	11500	2700	22635
4	50	30	30	10	6579	1011	5666	1011	12245	13159	2023	11331	2023	24490
5	50	30	30	10	5603	1325	6627	1325	12230	11206	2650	13254	2650	24460
6	50	30	30	10	5724	1015	6019	1015	11742	11447	2030	12037	2030	23484
7	50	30	30	10	5724	1015	6019	1015	11742	11447	2030	12037	2030	23484
8	50	30	30	10	6686	1677	5860	1677	12547	13372	3354	11721	3354	25093
9	50	30	30	10	5734	1267	5344	1267	11078	11469	2534	10688	2534	22157
10	50	30	30	10	5998	1238	5875	1238	11872	11995	2475	11749	2475	23744

Table A.15 NCD scenario data for 100 customer instances

Ins	N	Low Demand						High Demand						
		$N_A$	$N_B$	$N_S$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	$d_T$	$d_A$	$d_A^S$	$d_B$	$d_B^S$	
1	100	60	60	20	11052	1974	11934	1974	22987	22104	3949	23869	3949	45973
2	100	60	60	20	12285	2507	11326	2507	23611	24571	5014	22652	5014	47223
3	100	60	60	20	10640	1914	11151	1914	21791	21280	3829	22302	3829	43581
4	100	60	60	20	11175	2328	10751	2328	21926	22351	4656	21501	4656	43852
5	100	60	60	20	11128	2160	11514	2160	22642	22256	4319	23027	4319	45283
6	100	60	60	20	11563	2327	11627	2327	23191	23126	4655	23255	4655	46381
7	100	60	60	20	12080	2217	11742	2217	23822	24160	4433	23484	4433	47644
8	100	60	60	20	12084	2249	11507	2249	23591	24168	4499	23014	4499	47182
9	100	60	60	20	11296	2294	11971	2294	23267	22592	4588	23942	4588	46534
10	100	60	60	20	11359	2593	12337	2593	23696	22719	5185	24674	5185	47393

### Transfer Information for Collaborative Scenario Experiments

Columns  $TA_A$  and  $TA_B$  indicate the transfer amounts of carrier  $A$  and  $B$ , respectively.

Table A.16 Transfer amounts for 30 customer instances

Ins	Low Demand						High Demand					
	O		ICC		NCD		O		ICC		NCD	
	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$
1	434	446	562	735	225	268	1027	486	2144	449	478	572
2	409	323	1439	236	262	225	587	1240	532	3104	554	505
3	567	508	894	445	267	252	717	1004	2222	719	462	461
4	396	270	431	670	179	240	619	848	1689	927	396	513
5	650	204	842	618	276	234	1300	715	2662	420	569	490
6	524	341	575	1135	226	233	1150	579	1742	1331	469	528
7	389	320	811	812	229	241	635	1001	1821	1424	476	539
8	690	313	658	893	226	202	295	1076	1796	1203	440	416
9	541	569	1242	380	225	229	212	1041	1431	1814	481	510
10	393	292	833	743	235	231	1051	766	1374	1697	469	436

Table A.17 Transfer amounts for 100 customer instances

Ins	Low Demand						High Demand					
	O		ICC		NCD		O		ICC		NCD	
	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$
1	314	278	529	1010	620	456	681	784	1433	1844	1334	922
2	931	0	755	1236	639	561	1352	1254	2374	2067	1349	1188
3	454	659	540	1065	588	523	1147	1544	1085	2869	1272	1137
4	857	378	1058	1243	671	506	557	1687	1193	2950	1244	918
5	441	884	790	1194	584	605	1356	1129	1901	2230	1055	1099
6	551	555	764	1526	584	533	1730	480	3273	576	1034	1004
7	96	855	1609	759	584	529	1682	528	1682	2720	1047	1015
8	597	483	1176	1195	706	555	324	1837	2013	2849	1345	977
9	238	131	1028	1267	602	487	543	1870	774	3100	1263	1040
10	583	503	1015	861	620	529	692	742	1814	2997	1150	948

Table A.18 Transfer amounts for 50 customer instances

Ins	Low Demand						High Demand					
	O		ICC		NCD		O		ICC		NCD	
	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$	$TA_A$	$TA_B$
1	793	1502	3150	1366	2023	2194	3086	875	4079	4546	4438	4798
2	1215	1161	2737	2116	2312	2125	2470	1838	4213	5592	4473	4055
3	1439	855	2420	1694	1971	2075	2541	1383	5296	3202	4238	4434
4	1229	713	1655	2913	2106	2021	2056	2735	3978	4793	4043	3911
5	1061	1270	1822	2849	2062	2136	2418	1882	3639	5522	4461	4695
6	1492	1062	3400	1762	2151	2190	1827	2488	4657	5455	4180	4207
7	1091	1097	1811	3179	2254	2199	2558	2954	4327	4388	3694	3529
8	946	1455	2245	2386	2262	2139	1283	3295	2359	6368	4949	4761
9	1167	1026	1894	2491	2108	2239	2399	1771	4204	4379	3428	3566
10	1044	811	1501	2403	2149	2325	2430	1413	2946	4756	4109	4666