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Simulation and optimization of a multi-agent system on physical internet enabled interconnected urban logistics.

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SIMULATION AND OPTIMIZATION OF A MULTI-AGENT SYSTEM ON PHYSICAL INTERNET ENABLED INTERCONNECTED URBAN LOGISTICS

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A Dissertation Approved On

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ABSTRACT

SIMULATION AND OPTIMIZATION OF A MULTI-AGENT SYSTEM ON PHYSICAL INTERNET ENABLED INTERCONNECTED URBAN LOGISTICS

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An urban logistics system is composed of multiple agents, e.g., shippers, carriers, and distribution centers, etc., and multi-modal networks. The structure of Physical Internet (PI) transportation network is different from current logistics practices, and simulation can effectively model a series of PI-approach scenarios. In addition to the baseline model, three more scenarios are enacted based on different characteristics: shared trucks, shared hubs, and shared flows with other less-than-truckload shipments passing through the urban area. Five performance measures, i.e., truck distance per container, mean truck time per container, lead time, CO_2 emissions, and transport mean fill rate, are included in the proposed procedures using real data in an urban logistics case. The results show that PI enables a significant improvement of urban transportation efficiency and sustainability. Specifically, truck time per container reduces 26 percent from that of the Private Direct scenario. A 42 percent reduction of CO_2 emissions is made from the current logistics

practice. The fill rate of truckload is increased by almost 33 percent, whereas the relevant longer distance per container and the lead time has been increased by an acceptable range.

Next, the dissertation applies an auction mechanism in the PI network. Within the auction-based transportation planning approach, a model is developed to match the requests and the transport services in transport marketplaces and maximize the carriers' revenue. In such transportation planning under the protocol of PI, it is a critical system design problem for decision makers to understand how various parameters through interactions affect this multi-agent system. This study provides a comprehensive three-layer structure model, i.e. agent-based simulation, auction mechanism, and optimization via simulation. In term of simulation, a multi-agent model simulates a complex PI transportation network in the context of sharing economy. Then, an auction mechanism structure is developed to demonstrate a transport selection scheme. With regard of an optimization via simulation approach and sensitivity analysis, it has been provided with insights on effects of combination of decision variables (i.e. truck number and truck capacity) and parameters settings, where results can be drawn by using a case study in an urban freight transportation network.

In the end, conclusions and discussions of the studies have been summarized. Additionally, some relevant areas are required for further elaborate research, e.g., operational research on airport gate assignment problems and the simulation modelling of air cargo transportation networks. Due to the complexity of integration with models, I relegate those for future independent research.

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CHAPTER I

INTRODUCTION

1.1 Background

Freight transportation and logistics in-and-out, through-or-within the urban areas serve as the backbone of modern urban economies and social activities. It manages flows of goods in supply chains and needs to meet more various requirements of customer's consumption. Higher customer's demands, naval technologies and systematical innovations bring challenges and opportunities to the efficiency and sustainability on the development of urban logistics.

Nowadays, with the globally economical and informational evolutions, customers are becoming increasingly knowledgeable and sophisticated, demanding and flexible to exploit the emerging electronic commerce (EC). In the EC era, consumers experience the convenience of sharing and receiving with the fast-developing delivery services in urban logistics.

The thriving of EC business is obviously a global trend in every main market. In the United States, the largest Internet shopping market of the world, EC wholesale trade has been increasing annually, and reached $2.12 trillion in 2014 as shown in Figure 1.1. The number of Internet users in the largest developing country China has grown rapidly to 564 million, and the share of Internet users among the total population was 42.1% at the end of 2012 (Taniguchi et al., 2015). In EC wholesales, businesses to consumers (B2C), which represents Internet shopping by services of delivery to consumers, has been more popular than other categories in city logistics. In the European Union (EU), B2C EC market was approximately 94 billion Euros in 2010, which accounted for around 3.5% of the total EU retails (Civic Consulting, 2011). With the growth of EC, it brings huge changes to the urban logistics with a significant influence of their shipping behaviors. Customers value highly the convenience of online shopping in package with delivery services, as well as being able to compare many online stores and buy merchandise at any time of the day without going out to shop, according to the Ministry of Economy, Trade, and Industry in Japan, (METI, 2012). EC activities reduce passenger trips with a shopping purpose to the urban area to some extent, but increase more small parcels over the Internet-accessed market into the cities. An increase of small-lot freight transport worsens road traffic conditions in urban areas. The urban economic, social, and environmental states are affected by the logistics, attributed to urban traffic congestions, space constraints, greenhouse gas emissions, and road safety concerns. In order to provide qualified service, urban logistics should be planned efficiently.

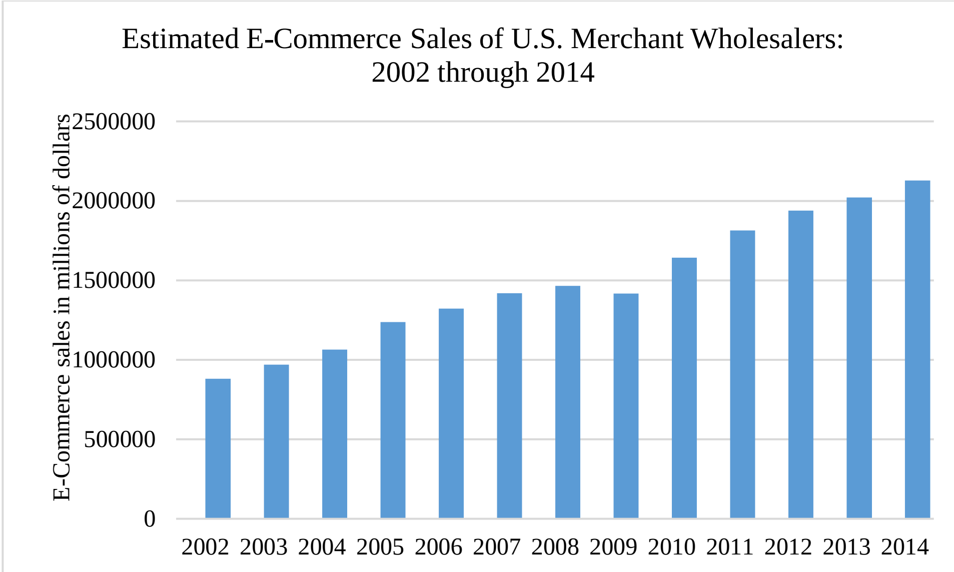


Figure 1.1: E-Commerce sales estimates based on data from the annual wholesale trade survey (2014 E-commerce Multi-sector Data; Source: https://www.census.gov/data/tables/2014/econ/e-stats/2014-e-stats.html)

Such technologies, e.g., the Internet of Things (IoT), autonomous vehicles (AVs), and state-of-the-art storage systems, allow a range of urban logistics solutions to be feasible. The IoT is comprised of sensor networks, actuators, and decision-making tools that can be used for real-time monitoring and optimizing urban freight systems (Taniguchi et al., 2015). Intelligent agents and dynamic decision support systems become practical with software procedures, which are developed to integrate data from a range of technologies, e.g., radio frequency identification (RFID), global position systems (GPS), and remote sensing. Autonomous transport systems, that is capable of sensing its environment and navigating without human input, can facilitate the transformation of existing cities into “smart cities”. Compared to other modes, they can reduce operational and maintenance costs coupled with benefits in the form of traffic congestion reduction, increases of road safety, and low carbon emissions. Gue et al. (2014) proposed a new decentralized grid storage system

(GRIDSTORE) in warehouses, which is capable of conveying in the four cardinal directions, and offers a high storage density and a large throughput. It is because storage locations are conveyable by self-transport that this system is able to deliver items at almost any required rate. Modules communicate only with neighbor modules to which they are connected in the grid. They are also capable of communicating with items contained (via RFID, for example). Those technologies enable numerous potential applications in urban freight transportation such as dynamic road pricing based on congestion levels, weight, and load factors, and route guidance for congestion avoidance.

However, there are tremendous pressures of air pollutions and environment constraints on urban freight logistics. From 2000 to 2010, total anthropogenic greenhouse gas (GHG) emissions have increased by about 10 GtCO_2-eq (Gigatonne of CO_2 equivalent, a common unit of CO_2-equivalent emissions). Accounting for direct emissions only, 11 percent (medium confidence) of the increase came from transport in sectoral CO_2 emissions (IPCC, 2014). Figure 1.2 shows that, in the next 50 years, annual transportation direct emissions are expected to increase by 70 percent, and the total number including indirect emissions are expected to increase by about 100 percent. They need to be reduced by 40 to 70 percent during that timeframe in order to keep the increase below 2 degrees by 2100 (IPCC, 2014) in average global temperature. Reduction in carbon use and CO_2 emissions are key requirements for cities striving towards sustainability. As the average vehicle fill rate is less than 50 percent, the current state-of-the-art freight system is not environmentally sustainable. Although the integration of electronic data interchange (EDI) technology into enterprise systems has enabled vertical collaboration (such as outsourcing logistics or vendor-managed inventories) between supply chain partners for a long time, horizontal collaboration is yet to break through.

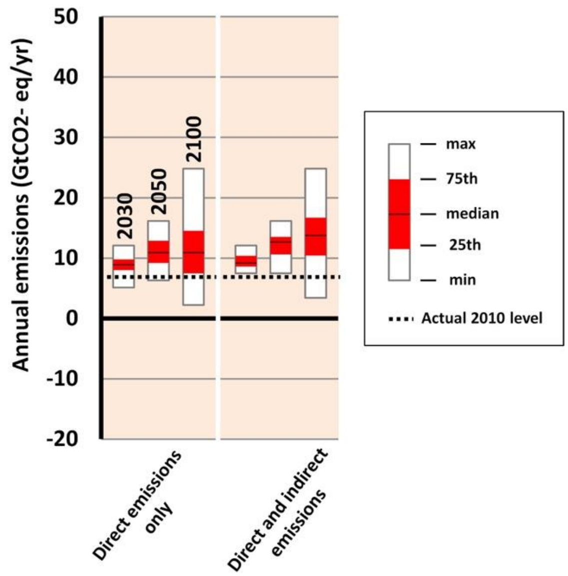


Figure 1.2: Transport-related CO_2 annual GHG emissions in 2030, 2050, 2100 (IPCC, 2014: Climate Change 2014: Synthesis Report; Source: http://www.ipcc.ch/report/ar5/syr/)

Systematically, collaborative shipping is extending from vertical supply chain integration towards horizontal collaboration among companies at the same level of the supply chain. Multiple shippers partner up to bundle freight loads to the same transport in a milk-run manner. Regarding to the issue, the new concept of Physical Internet (PI or π) has been introduced as a solution to enable an efficient and sustainable Logistics Web with the foundations on physical, digital, and operational interconnectivity through encapsulation, interfaces, and protocols (Montreuil et al., 2012). By analogy to digital internet, the "Web" consists of a set of interconnected physical objects on an open and global platform. However, in the urban environment, the systemic performance faces the risks and challenges of maintaining efficiency and sustainability associated with limited resources and dynamic, fast-changing urban goods transportation context. More precisely, the goal is to reduce and control the presence and motorization of freight vehicles operating through and within the city, and to eliminate the wastes due to the lack of resource sharing, as well as to improve the benefit of efficient performance of urban transportation system and environmental footprint (Dablanc, 2007; Benjelloun et al.,2010).

The concept of co-modality has been promoted in some cities, which involves the efficient use of different modes individually and in combination with each other that results in optimal and sustainable utilization of resources (Commission of the European Community, 2006). Traditionally, a transport policy has been considered exclusively for its own domain, that is, road, rail, sea, and air, thus not well co-ordinated. Co-modality requires comprehensive and integrated approaches for transport problems using technological and management innovations. In this regard, co-modality provides a more holistic view of transport policy toward more mobile, sustainable, and livable societies. Although trucks on road networks are a dominant freight transport mode in urban areas, city logistics is similar in concept to co-modality in terms of global optimization of urban freight transport systems.

Connectivity by air is a critical element in urban logistics systems. Air transports operate as pipes for connecting cities in a fastest way, to sustain and speed up logistics sectors adapting to the consumer's demands. The growth of air cargo shortens demanding lead times of goods home delivery. It has improved door-to-door transit times of trans-shipment cargo from a whole week to the next-day delivery since 2000. It provides a speed advantage on EC retailers and urban industries which depend as much on "economies of speed" and in PI urban networks. Hub airports, serving as the "routers" in the PI networks, anchor and sort growing airborne freight flows. They are embedded on co-modality transportations and act as logistics magnets and business catalysts in urban economies to develop the most efficient PI.

1.2 Research Motivation

The potential of horizontal collaboration among supply chains is necessary to tap on in Physical Internet. Here is an example that two less-than-truckload (LTL) shipments A and B from Indianapolis, IN are transported to Nashville, TN and Lexington, KY, respectively. According to the shortest time, their routes are shown in Figure 1.3. Shipment A takes 4 hours and 20 minutes from the origin to the destination, while shipment B takes 3 hours passing by Cincinnati, OH.

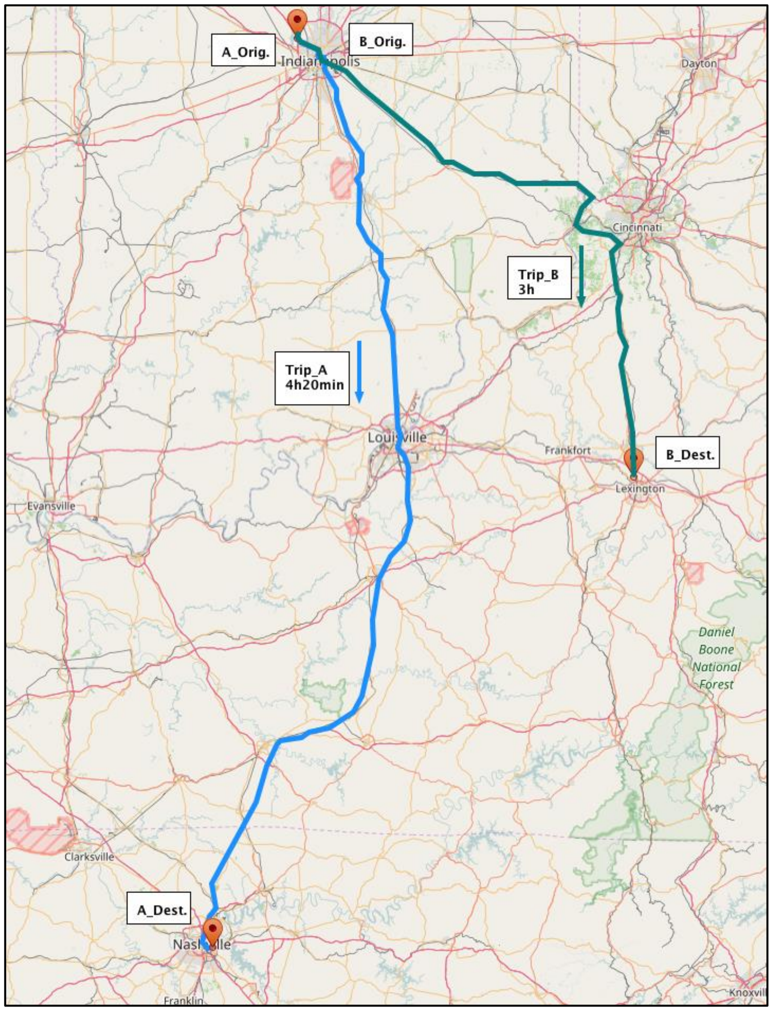


Figure 1.3: Example of two shipments

The minimization of the use of resources is a common motivation in all logistics fields. Particularly, the parcel delivery from a clear majority of merchandise B2C retailers generates a lot volume of less than truckloads (LTL), which is less than the capacity of a truck. In this case, PI can take advantage of consolidation of LTL to increase delivery efficiency. Figure 1.4 allows for an opportunity that shipment A and B can bundle their LTL freight in one truckload from Indianapolis to Louisville, KY. When there is Shipment C from Louisville to Lexington, Shipment B can transship along with Shipment C in a truckload to the destination. The travel time for trip B in the case is 3 hours and 10 minutes.

Bundling of shipments takes one truck off the road and improves the utilization of truckload in trip A with only 10-minute additional travel time of trip B compared to the previous scenario.

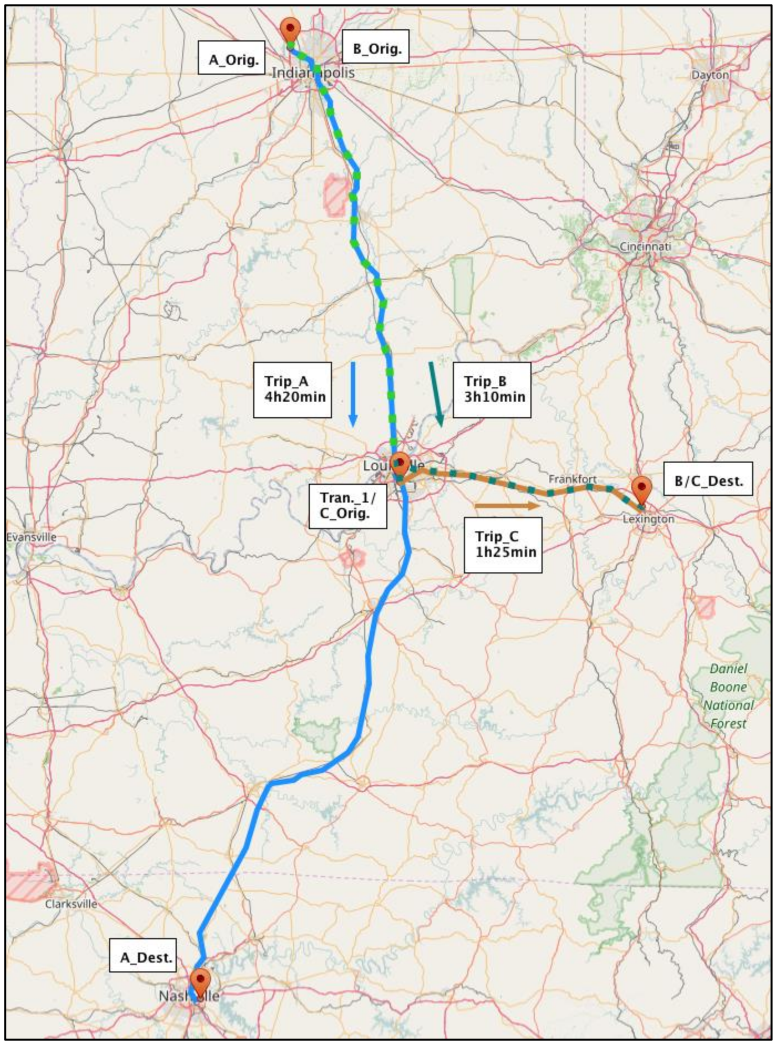


Figure 1.4: Scenario of bundling of shipments

Figure 1.5 depicts a scenario of backhauling of Shipment A. In order to avoid an empty truckload returning from Nashville, a truck can deliver any shipment towards Indianapolis, Cincinnati, and Lexington to the transshipment point in Louisville. In this way, freights in the same direction to Indianapolis can fill in LTL vehicles during back trips.

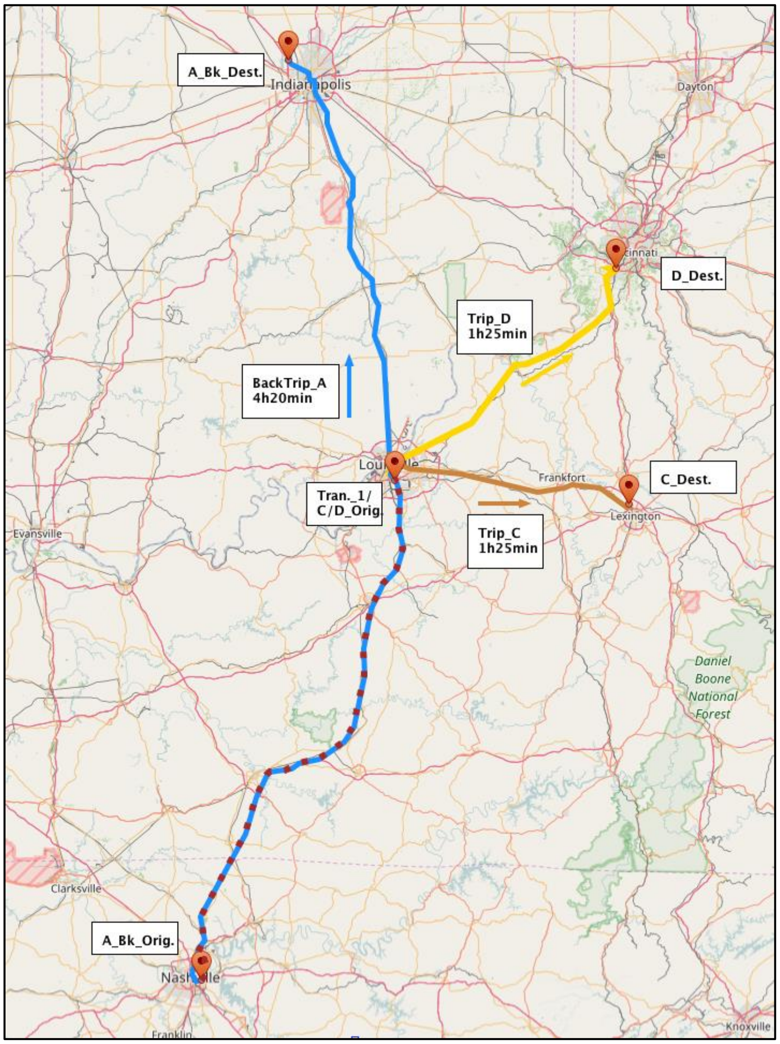


Figure 1.5: Scenario of backhauling of shipments

Figure 1.6 assumes a roundtrip starting from Indianapolis. The Shipment B and Shipment A rides together to Louisville. The freights of Shipment A are unloaded in the truck and bundled with other shipments to complete the trip for Shipment B in Lexington. By the shipment of freights from Lexington through Cincinnati to Indianapolis, it makes a roundtrip as the manner of a milk-run.

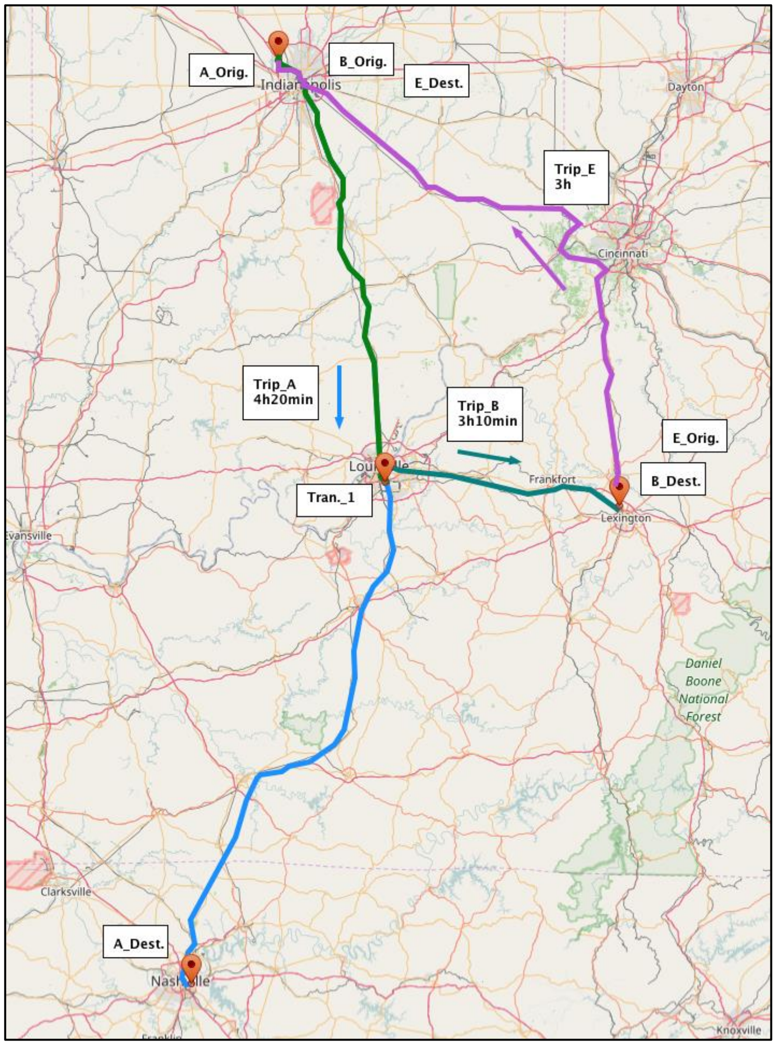


Figure 1.6: Scenario of roundtrips of shipments

Air transport bridges two collaborative shipping networks in a short time delay (see Figure 1.7). For example, the flight between Louisville, KY and Philadelphia, PA takes about 2 hours by air. There are supposed to be many opportunities of collaborative shipping connected by air transports, and it is benefit from fast shipping in longer distances with well-connected systems among cities. Physical Internet can make the whole logistics and transport interconnected in the air and ground.

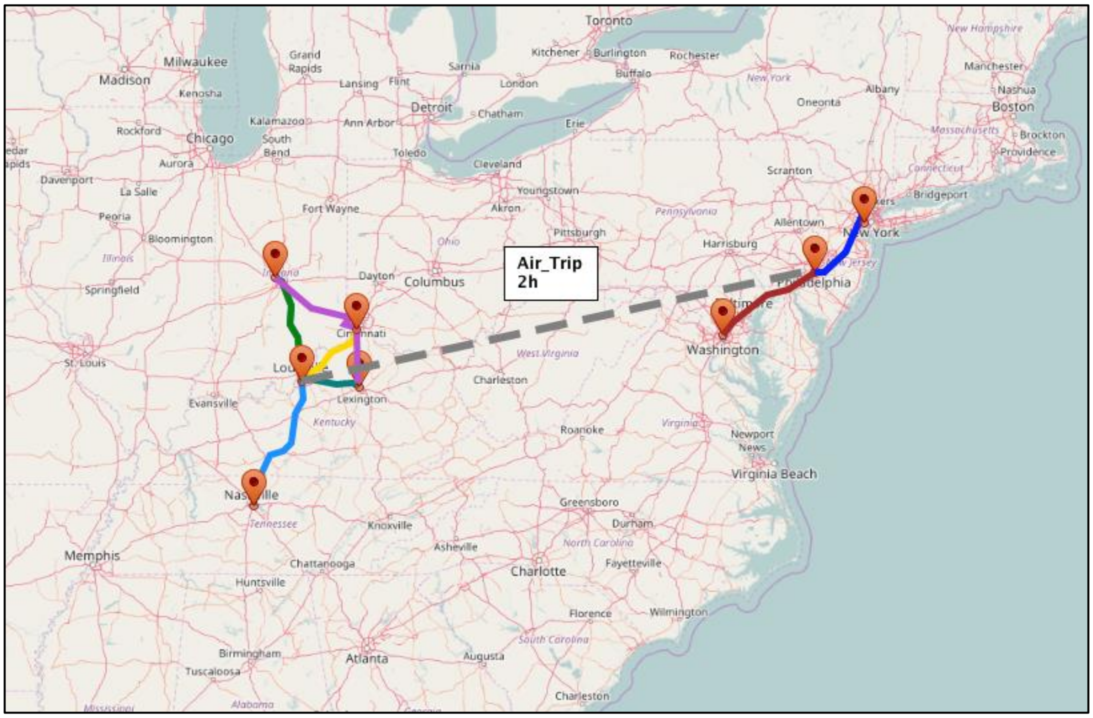


Figure 1.7: Scenario of roundtrips of shipments

Increasing consolidation of goods is essential for improving the sustainability of urban freight systems (OECD, 2003). Decision makers are required to model what-if scenarios, and perform ex-ante evaluation of potential solutions prior to implementation. When focusing on a scope of an urban area of Louisville in Figure 1.8, there are shipments from warehouses to hubs, as well as transports from all directions through gateways. Therefore, potential opportunities of collaborative shipments fit to the PI initiative. For example, more LTL shipments within the scope of an urban area mean better chance to find bundling opportunities. In order to collaborate shipments, goods from warehouses or EC retailers can be shipped to hubs nearby, where truck freights from gateways may stop by for cross-docking to increase truckload filling rates.

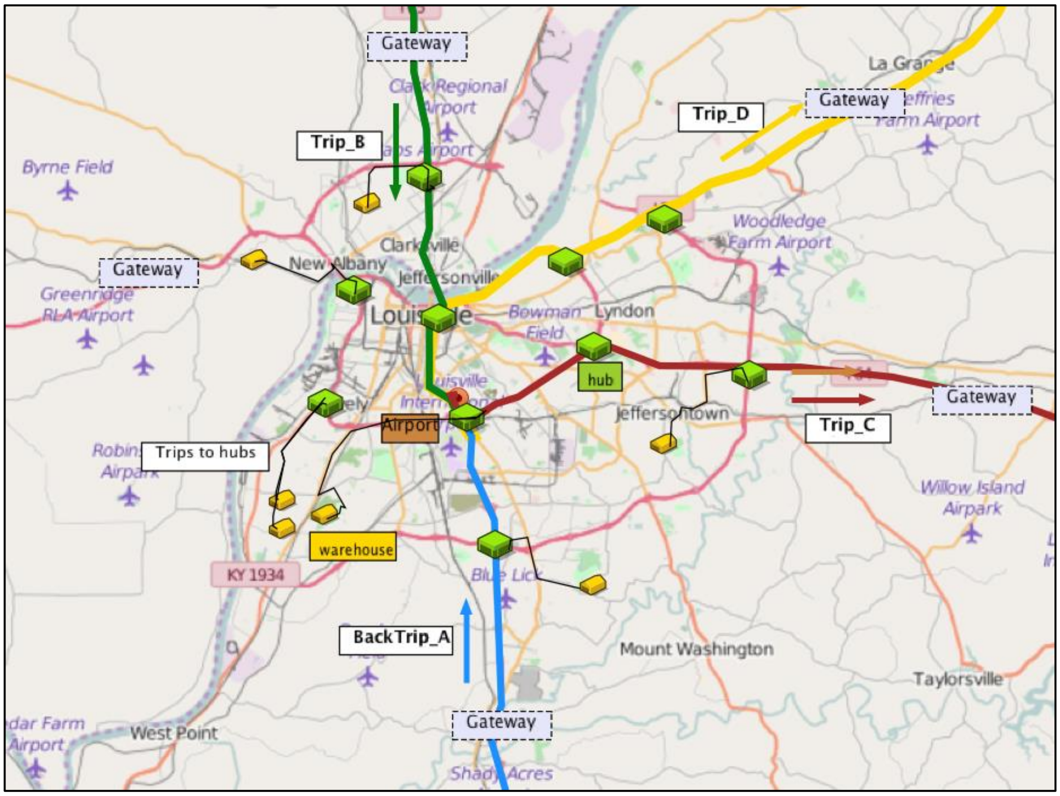


Figure 1.8: Urban and regional trips in networks of hubs and gateway connections

Another what-if scenario is the same day delivery. That is because Internet consumers seem to be more time-sensitive that any longer time delay of home delivery prompts them to leave for other EC websites. The similar scenario in an urban area is illustrated as 24-hour transport service provided by Yamato (Taniguchi et al., 2015), which is the biggest parcel delivery company in Japan. Yamato developed a new transport system (see Figure 1.9) including “gateway terminals” for e-retailers, which are equipped with automatic sorting machines. They allow e-retailers to place their ordered goods on the stock floor of gateway terminals or nearby logistics centers, and sort by destination. Trailers of Yamato pick them up from gateway terminals, and consolidate for out-bound shipping to the destination in the same day.

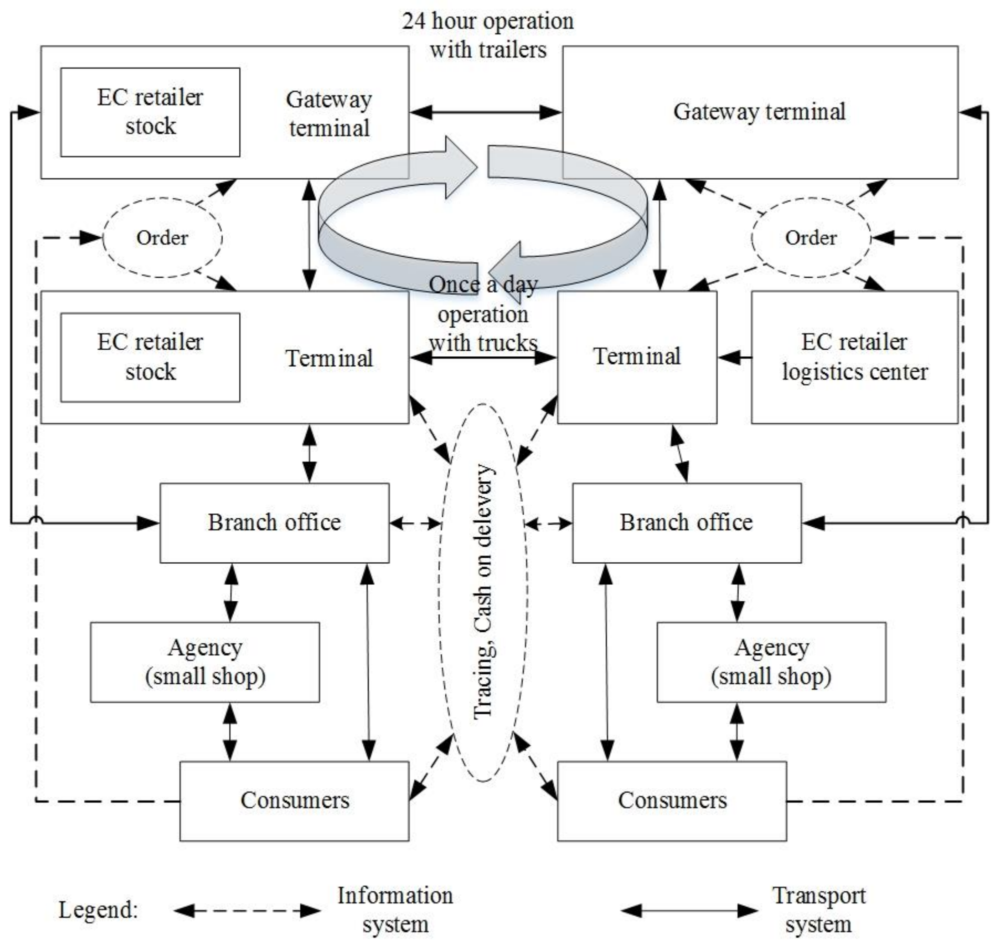


Figure 1.9: A 24-hour urban transport system by a parcel delivery company in Japan

Motivated by these opportunities from collaborations, we investigate the potential of an interconnected logistics network, designed on the principles of PI, in an urban area with e-commerce warehouses. A motivation in this research is to understand benefits gained by incorporating PI into the existing logistics system. For this aim, a multiagent-based simulation model is developed to demonstrate the efficacy of our proposed approach in this framework. Based on simulation approaches, we are mainly focusing on three studies: (1) performance assessment of an urban logistics system in a PI framework; (2) applying auction theory as a bidding-decision-making process of carriers and shippers in the PI scenario; and (3) investigating how hub’s operation efficiency affect the system’s performance, and also conduct operational research in optimization of transit hub layout and operations, e.g., gate assignment problems.

1.3 Organization

This dissertation is organized as follows. In Chapter 2, literatures are reviewed on the contents separately: PI enabled urban logistics, simulations approaches, auction-based transport planning, urban distribution center and airport operations, and air cargo transportation. Chapter 3 develops a multiagent-based simulation model to demonstrate the efficacy of the proposed solution approach in the PI framework. A case study is applied to the simulation model based on an urban transportation network in Louisville, KY. Chapter 4 solves two research problems: (1) an auction-based transportation planning approach for matching requests and transport services in transport marketplaces; (2) a simulation optimization framework to provide insights of system performance effects on a combination of decision variables (i.e. truck number and truck capacity) and parameters settings. Finally, Chapter 5 provides conclusions and discussions on the research, and proposes some relevant research works for future studies.

CHAPTER II

LITERATURE REVIEW

In this chapter, previous related studies have been reviewed on PI and collaborative transportation planning, auction mechanism, urban logistics and air transport, agent-based simulation techniques, and airport gate assignment problems.

2.1 Physical Internet

The Physical Internet has been introduced for freight transportation as a solution to enable an efficient and sustainable Logistics Web with the foundations on physical, digital, and operational interconnectivity through encapsulation, interfaces, and protocols (Montreuil et al., 2012). The terminology of Physical Internet came from an analogy with Digital Internet. Sarraj et al. (2014) addressed a new way to look at the consolidation problem through the Physical Internet approach to build universally interconnect logistic networks with transposition from computer networks. Specifically, the concept proposes exploring an impact of changes from dissociated logistic services networks to an open logistics network based on the universal interconnection of those isolated services networks. PI enables encapsulated goods to be transferred in the open logistics network and routed as "packets" with information in principles of Digital Internet. Main differences should be taken into account as a result of physical constraints relative to the size and weight of goods, and the capacity and speed of transportation means. In general, the foundations of PI framework are built around multi-dimensional collaboration of physical objects in an integrated interconnectivity of mobility web, distribution web, realization web, supply web, and service web (Montreuil, 2011). From the perspectives of physical objects, the PI functions are mobility, distribution, realization, supply and service of physical objects across the world. A mobility web serves the needs for moving physical objects from sources to destinations. A distribution web serves for storing goods within open distribution centers across the world. Through the mobility web and the distribution web, a realization web is expected to realize physical entities, deconstructed form materials to components and modules to products and systems. A supply web supplies entities connected through an open platform across supply chains and networks. A service web is expected to offer accessibility of the services for physical object usage, and PI should be open and global logistics system with efficiency and sustainability of concerns. The PI allows its components in the system to be interconnected, e.g., facilitating the movement and storage of physical entities, and sharing and contracting responsibility among all actors.

Previously, industries have been working on vertical supply chain collaborations for decades. The related topics include vendor managed inventory (VMI), efficient customer response (ECR), and collaborative, planning, forecasting, and replenishment (CPFR), etc. These approaches are designed to tackle the problems at different levels of supply chains for forecast accuracy and inventory management. Based on above foundations, PI is defined to offer a new way to look at the consolidation problem. In PI, the horizontally collaborative shipping happens in partnerships with companies at the same level of supply chains, where multiple shippers (i.e., suppliers, buyers, and third-party logistics) work on concerted actions to look for bundling opportunities in order to reduce transportation costs. Although the horizontal collaboration is still in its infancy, the concept boasts a considerable amount of related literature in transport and logistics. Win-win situations are the expectations among companies through horizontal inter-firm cooperation (Pfohl and Buse, 2000). Hageback and Segersted (2004) studied on joint transportation among the approximately twenty companies in Pajala Municipality in Northern Sweden. This "co-distribution" saved the possible cost of filling incoming and outgoing trucks more than 33 percent. Bartlett and Ghoshal (2004) summarized the benefits that collaborating shipping firms can reap in three ways: (1) concentrating on core business but pooling their resources, (2) sharing and leveraging different strengths and capabilities, and (3) trading complementary resources to achieve mutual gains. Cruijssen et al. (2007) provided an overview of opportunities, i.e., cost and productivity, customer service, and market position, which may trigger potential participators in horizontal cooperation. Leitner et al. (2011) developed a framework for horizontal logistics cooperation to increase efficiency. In a practical application in Romania and Spain, companies cooperated by optimizing the collection and distribution of their good, to gain a 15 percent transportation cost reduction. Shifting their main legs of the distribution to railway made a dramatic improved ecological impact, e.g., reducing 50 percent fuel consumption and 40 percent CO_2 emissions.

In the protocol of PI, containerization of goods is equivalent of encapsulation in digital internet. When a group of goods is ordered for shipment, it is necessary to make decisions on sizing for containers, loading sequences and patterns of package within each container. In PI, goods with the same destination are collected from and to transshipment points in the same shipment time period. To increase utilization of container loads, container modularization should be followed by composition from unitary PI-containers (see Figure 2.1); namely, PI containers may be inter-locked or encapsulated within each other. Later, those PI-containers can be decomposed back into separate and smaller unitary containers for cross-docking at the PI hubs.

In Sarraj et al. (2014), containerization is assumed to encapsulate a set of goods in sizes of 2.4m × 2.4m × {1.2, 2.4, 3.6, 4.8, 6, 12(m)} containers with maximal length of 12-meter on pallet wide in adaptation to the flexibility of transportation modes such as ships, trains and trailer trucks.

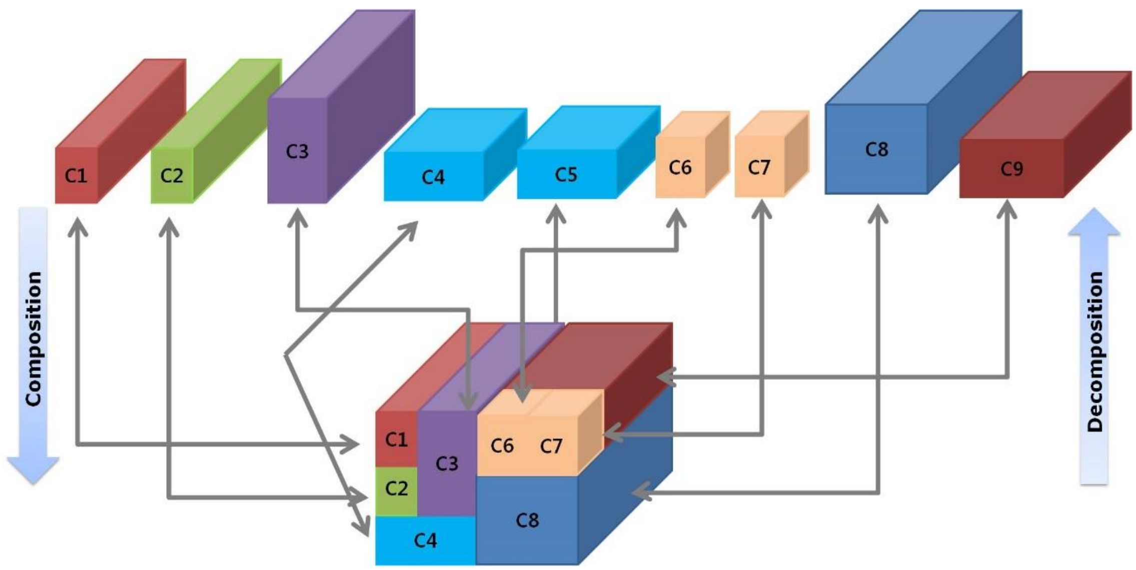


Figure 2.1: Illustrating PI-container modularization for consolidation and deconsolidation (source from Montreuil et al. (2011))

Even more, Sallez et al. (2014) addressed on the activeness of intelligent PI containers. They analogize them with the concept of product activeness. That is, an active product is able to identify its state, compare the state with a desired one, and send the information out whenever certain conditions are met. Applied to the PI context, PI-container is considered as an active product in a usage phase of its life cycle, and able to play an active role in the PI management and operations to take advantage of the opening of the system. In addition, it can be capable of more complex activities such as memorization, communication, negotiation and learning. Informational aspects of PI-containers and relevant project can be used for description of communication capabilities in a PI transportation system.

Some literature is related to demonstration and assessment the potentiality with PI protocols of improving transportation efficiency and sustainability. Sarraj et al. (2014) proposed an agent-based simulation model and tested several simulation experiments based on a series of scenarios according to container sets and route criterions. The transportation protocols of PI are structuring the decisions and operations of handling the PI-containers on the path made through several segments in the logistic networks. The paper regards CO_2 emissions, cost, lead time, delivery travel time as the key environmental, economic and operational performance indicators (KPIs) on the consolidated and interconnected PI. The simulation-based research involves three main agents which are sub-protocols designed in the research, namely, goods containerization, routing, and consolidation on transportation means. For container routing problem, the A* algorithm is used to find at each node the best path to destination satisfying KPIs' optimization objectives. In addition, the consolidation of PI-containers per common destination and loading is also optimized by the First Fit Decreasing (FFD) algorithm.

Real data from Fast Moving Customer Goods (FMCG) industry in France is used in the simulation experiments. Three families of PI scenarios and several sub-scenarios are set to investigate the potential of interconnected protocols against the current logistic network as reference scenario. The results show a significant fill rate progress (up to 17 percent), more chances to share rail transportation, and 60 percent reduction of CO_2

emissions with PI protocol versus the status quo networks. Meanwhile, it does not negatively affect lead times nor operational costs. Although there are limitations of study without alteration of the current orders within PI protocols and lack of consideration of loading plan problems for containers, the convincing results based on real-world orders from FMCG industry prove PI to be efficient and able to bring benefits compared to current logistic networks.

Beem et al. (2016) provided an example of PI implemented case study of EC businesses in an urban area. A multi-agent system of a PI network was created to simulate independent agents and their actions in specific situations in decentralized control mode. Several scenarios were tested using real data from EC businesses with objectives on minimizing delivery cost and lead time. Conclusions drawn by the research are to understand the model behaviors and the performance of the system of PI in comparison with direct delivery.

With an implementation of the PI approach, the aim is to integrate logistics networks into a universal, interconnected system, and inventories can be divided among shared hubs to serve the market and source substitution. Pan et al. (2015) defined a new research question related to inventory management in a PI network, and provided a view of how PI affects traditional inventory control policies.

2.2 Urban Logistics

The fast-growing transportation enhances the prosperous economy in each industry. For instance, expenditure in the U.S. logistics and transportation industry was $1.48 trillion in total in 2015 (International Trade Administration, 2017), and represented 8 percent of annual gross domestic product (GDP). Logistics and transportation of goods in-and-out, through-or-within the urban areas contribute as the backbone of modern urban economies and social activities. Urban logistics bridges the demand of consumers with the supply of goods from suppliers. For industries, it is also vital to the functions in regional and global supply chains, serving the delivery of goods between distribution centers, warehouses and retail stores as well as in-and-out city gateways such as highways, rail terminals, ports and airports, etc. Meanwhile, the urban economic, social and environmental efficiency and sustainability are also involved in the logistics, which is a complicated procedure, causing impacts on urban traffic congestion, space constraints, greenhouse gas emissions and road safety. Cities around the world have raised the awareness for urban logistics operations, striving to improve logistics performance as well as reducing the negative impacts.

However, in the scale of urban scope, the systemic performance faces the risks and challenges of maintaining efficiency and sustainability associated with limited resources and dynamic, fast-changing urban goods transportation context. More precisely, the goal is to reduce and control the presence and motorization of freight vehicles operating through and within the city, and to eliminate the wastes due to the lack of resource sharing, as well as to improve the benefit of efficient performance of urban transportation system and environmental footprint (Dablanc, 2007; Benjelloun et al., 2010). However, there are few researches bridging this gap of two concepts between urban logistics and PI, not to mention applications and analysis.

As a relatively new terminology, PI has been introduced not long since an interim concept of *Supply Web* (Montreuil et al., 2009; Hakimi et al., 2009) and revised in 2011 (Montreuil, 2011). Even before PI being established, there were some studies on open interconnection logistics innovations in the regional urban level. It is not until 2015 that the first approach to address the concept of the urban logistics focused on the particular PI protocol as *Interconnected City Logistics* (LCL; or *Hyperconnected City Logistics*, HCL) has been termed out (Crainic and Montreuil, 2016). However, there are few applications in practises under the framework. Therefore, the literature review here is extended to the related sectors concerning urban freight transportation, city logistics in open and interconnected logistics strategies. In most cases, urban logistics is not distinguished from city logistics, contrary to what we do in this dissertation, even though technically the city contains urban and suburb areas.

The development of urbanization causes several social, operational, infrastructural and environmental impacts and challenges in urban logistics market (Boloukian and Siegmann, 2016). On one hand, urban logistics can contribute to the functional specialization of cities, the industrial division of production, the prosperity of service activities with a high frequency of deliveries, and large quantities of freight shipments in densely populated areas (Dablanc and Rodrigue, 2009). On the other hand, the urban transport system has city traffic restrictions and an environmental carrying capacity on the basis for sustainable and liveable cities. The capacity cap makes the current urban freight transport system inefficient and unsustainable. Even worse, almost all future population growth is expected to take place in urban area (UN Habitat, 2013). For example, from 2010 to 2020, the number of large cities (a population of 1 to 5 million) is projected to increase from 388 to 506; while the number of megacities (a population of more than 5 million) is growing from 61 to 83 in the United States.

Freight transport in cities takes many forms of operations in urban logistics market. It is identified with the seven following categories: retail, consumer shopping trips, parcels, catering, construction, waste, industrial and terminal haulage (Behrends, 2016). In the market, various actors and stakeholders such as shippers, receivers, carriers and public authorities, are involved in the urban logistics activities (Behrends, 2011). They share the common urban space and interact with each other, while some of them may not have direct business relations. There are more opportunities and options for each stakeholder being connected in urban logistics networks.

According to the nature of freight transportation characteristics, *City Logistics* has been introduced as a new organizational and business model to consider behaviours of stakeholders involved in the urban logistics activities (Taniguchi et al., 2001). Stakeholders will take the advantage of utilizing and providing all transportation resources in the open logistics network as a whole system. Such a model optimizes an advanced integrated system with multiple objectives and resolves the negative impacts (Crainic et al., 2007; Gonzalez-Feliu et al., 2014). From the point of the supply side, it can be summarized as an integrated logistics system, emphasizing the optimized consolidation of loads of various shippers and carriers within the same vehicles and the coordination of the resulting freight transportation activities.

The concept of PI is a horizontal transportation protocol under which it is expected to enable the shift from a private transportation to an open and interconnected logistics web (Montreuil et al., 2012). It applies across a vast urban community of users to encapsulate goods in modular, re-usable and smart containers (PI-container, or π-container) and routes through intermodal transport networks (Meller et al., 2012). One of the core logistics facilities devoted to the urban distribution network are *Horizontal Distribution Centres (HDCs)*, which offer cross-docking, short-term storage and consolidation functionalities deployed for serving the city. Through HDCs of the network, freights loaded in a set of π-containers in vehicles are encapsulated, moved and stored in transit in relay mode to end destinations.

Several studies have evaluated PI with huge potential gains for logistics performance in efficiency and sustainability. France-Canada-Switzerland team provided a clear evidence, using a representative application from the fast moving consumer goods (FMCG) industry in France, that PI could significantly improve the transportation efficiency about almost 17% increase in vehicles' fill rate, 30% decrease in total induced costs, as well as up to 60% reduction of CO_2 emissions (Sarraj et al., 2014). The CELDi research team in the United States predicted that average distance traveled would decrease by 20-30% and the inventory at the retailer could reduce by 33% in a PI logistics network. For the social aspect, the research measured in terms of driver turnover ratios from currently and historically much over 100% in the dedicated networks to less than 10% for private fleet and less than 15% for Less-than-load (LTL) shipping (Ellis et al. 2012).

2.3 Agent-based Simulation in PI

Computer-based simulation has been used for a long time to draw insights and analysis on the logistics and transportation domain. The ability of simulation to explicate complex system behaviours and stochastic interrelationship among components, with benefits of short run times (Chang and Makatsoris, 2001), makes it a powerful tool for performance assessment, hypotheses testing, inferences and decision making.

There are three main simulation modelling approaches widely used as decision support tools in transport logistics: discrete event simulation (DES), system dynamics (SD), and the relatively new agent-based simulation (ABS) (Tako and Robinson, 2012; Davidsson et al, 2005). Each simulation technique has been claimed to be targeted at particular type of problems by nature. DES models represent the systems where state changes occur at discrete points of time, and concentrate on evaluating the expected performance measures of logistics operations under uncertainty at an operational or tactical level; whereas SD modelling is more suited to logistics and inventory planning at a strategic level, and the state changes occur continuously over time (Shah, 2005). Compared with the two traditional approaches, ABS tends to reproduce a system from the standpoint of the individuals (agents) which comprise the system and consider their individual decision-making behaviours and rules. The distinguishing features of ABS are the emphasis on modelling the heterogeneity of the autonomous agents which act independently in the environment and the emergence of self-organization (Macal and North, 2010). The agent perspective allows decision makers to work with models of real, or supposed, agent behaviours, rather than idealized or normative versions, and to see what the logical implications are of agent interactions on a large scale (Macal and North, 2013). By observing effects of those attributes, behaviours, and their interactions, ABS offers the flexibility to understand the behaviours of the system as a whole.

Agent based approaches can be traced for applications in a broad range of areas, such as distributed and heterogeneous systems (Weiss, 1999; Wooldridge, 2002), complex adaptive systems (Kauffman, 1993), artificial life (Langton, 1989), etc. In agent-based logic, large-scale complex interacting nodes, facilities, transport entities or even decision makers as part of the distributed system, work intelligently on parameters of each network node at a local level (Niazi and Hussain, 2009). Transport logistics are distributed and very complex multi-agent systems by nature. Up to now, the agent-based technology has been applied to investigate an enormous range of strategic decision-making problems in the area of transport logistics including transport planning and scheduling, intermodal transportation operations, road traffic control and management, etc. (Davidsson et al, 2005).

For further illustration purposes, two of most related applications on the interconnected transport logistics are presented next. In France, a multi-agent based simulation model was proposed and tested on demonstration and assessment of the potential with PI protocols for improving transportation efficiency and sustainability (Sarraj et al., 2014). The simulation-based research involves three main agents, which are sub-protocols designed in the research, namely goods containerization, routing and consolidation on transportation means. Several simulation experiments based on a series of scenarios are set, according to container sets and route criteria, to investigate the potential of interconnected protocols against the current logistic network as baseline. The convincing results based on real-world orders from FMCG industry prove PI is efficient and able to bring significant benefits compared to current logistic networks. The other similar application is assessing the impacts of a shared-taxi system in Lisbon, Portugal (Martinez et al., 2015). The model, which is identified by a set of rules for space and time matching, addresses the interaction elements between client agents and shared taxi agents, and simulates their connections and how the services are performed.

2.4 Transportation Planning and Auctions

For transportation planning, a heterogeneous vehicle fleet based at multiple stops are required to satisfy a set of transportation requests, which is known as a Vehicle Routing Problem (VRP). Each requested transport starts from a pickup point and heads to a designated delivery point. There are a series of constraints possibly from a particular situation, i.e., time windows, capacity limitations, and other resources restrictions, etc. For an objective, the cost of the total system is commonly used. VRP has a variety of practical applications, including the transport of the disabled and elderly, sealift and airlift of cargo and troops, and pickup and delivery for overnight carriers or urban services (Toth et al., 2002). Those applications have focused on vehicles or fleets of vehicles to find the shortest path from a source to a destination or to generate an optimal tour of a set of pickup and delivery locations. Savelsbergh and Sol (1995) summarized several characteristics and modeling methodologies of general pick and delivery problems in static, dynamic, and demand responsive situations. In public transportations, an alternative system is called "Dial-a-Ride" (Stein, 1978), somewhat similar between a rigid bus system and a flexible taxicab system, and ideally provides large numbers of passengers with personalized service. In Berlin, a dial-a-ride system with a fleet of about 100 mini-buses, called *Telebus* (Borndorfer et al., 1999), serves for handicap transportation requests of pick-ups and drops in the urban area.

Container routing is another key function for PI. It is discussed how to use routing techniques to transport PI-containers from requesting locations to transshipment locations. Given the protocols of Digital Internet (such as TCP/IP, RIP, and OSPF), PI routing problems are made in comparison with those on the digital counterpart.

Sarraj et al. (2014) addressed container routing protocols as follows. (1) Network structure and design of PI is similar to Digital Internet in dynamic traffic patterns. But PI can maintain traffic flows and updates in a routing table at each node, due to freight flow and state changes being much slower than digital information. (2) Routing objectives in PI logistics focus on decreasing neglect environmental impacts and transportation cost in such processes, i.e., traveling, handling, and waiting etc., while minimizing loads and avoiding congestion points are basic considerations in Digital Internet. (3) For algorithms, the authors use the A* algorithm to find at each node the best path to destination satisfying KPIs' optimization objectives.

In PI, the routing is also a collaborative transportation planning task. Transportation carriers in same urban logistics system can exchange their shipping requests with others which could bundle the complementary requests in the transport. The collaboration can optimize their shipping requests among carriers so as to increase the vehicle fill rates and reduce their transportation costs. Krajewska and Kopfer (2006) presented a request reassignment procedure with three phases for LTL carriers based on a modified matrix auction to maximize the total profit of a carrier coalition. Wang and Kopfer (2014) assumed that each request can be fulfilled by any freight forwarder or carrier in the combinatorial auction. They proposed a route-based multi-round iterative combinatorial auction for collaborative transportation planning of LTL freight carriers.

The situation of general VRPs is that the schedule is predetermined. In PI, vehicle routing is scheduled by accepting loads, namely, routes need to be fixated based on the costs and profits of offering transportation services. This is why carriers apply revenue management concepts for consolidated transportation planning problems. Auction mechanism is commonly used for reallocation of transportation requests and management the total revenue of transport carriers. In order to interconnect spots in logistics networks, such as PI-hubs, pricing decisions need to be made on many shipping requests. Carriers can bid for the requests during the finite time interval based on a short-term contract so as to maximize its own profits under the limited capacity.

In a simple auction, agents can place a bid for each item for sale. A central auctioneer makes allocation based on bids. There are a large variety of common auction types (See Table 2.1). When a set of shipping tasks needs to be distributed among carriers, the carriers have complex preferences over the set of requests. Then a combinatorial auction is suitable for the case. Combinatorial auctions are mostly used and simple ways of performing resource allocation in a multi-agent system. It acts as multi-agents are allowed to post bids for a set of items. In PI logistics, agents can submit bids as they expect for sets of transport requests.

Table 2.1: The common auctions and types

Name	Type	Meaning	Example and reference
English auction	First-price open-cry ascending auction	The auctioneer raises the price, and the highest bid gets the item.	Lopomo, G. (1998)
Blind auction	First-price sealed-bid auction	Each bidder writes a bidding price in a sealed envelope, and the auctioneer picks the highest bid.	"Cra to Be Sold in Blind Auction" (2000)
Dutch auction	Open-cry descending price auction	The seller continuously lowers the selling price until a buyer hits a buzzer.	Schill, R. L. (1977)
Vickrey auction	Second-price sealed-bid auction	The highest bid wins the auction, but the agent just needs to pay the second highest bidding price.	Borndörfer Ralf, Mura, A. and Schlechte, T. (2008)

There is such limited literature on dynamic pricing in a specific context of Physical Internet. In freight transport industry, relevant literature has been introduced such as liner shipping and air cargo shipping industries. In liner shipping industry, companies are often cartelized to avoid competing on price, because they claim that pricing competition would lead to destructive competition that undermines the stability of worldwide goods trading (Munari, 2012). In air cargo industry, being a real competitive market, companies usually sell their capacity through the common selling format, saying allotment, by which shippers propose freight with price so airlines only decide to accept or not (Kasilingam, 1997).

In such a decentralized transport network, the most important question is how to dynamically and locally match the requests and offers in each PI-hub meanwhile globally optimize the transport in the network. That is the reason why centralized VRP hardly make the transportation planning in PI container routing auction efficient. Douma et at. (2006) applied revenue management to agent-based transportation planning, and developed a dynamic programming and an approximation calculation approach to price loads in a single-leg problem. Qiao et al. (2016) proposed a less-than-truckload dynamic pricing problem in PI (PI-LTLDP), in which first-price sealed bid auction mechanism was adopted and applied in a single-transport problem. Requests quantity, carrier capacity, and transportation cost are the factors considered in the optimal pricing decision. Pan et al. (2014) presented rules, auction mechanism, as well as bidding and auctioning agents in a simulation framework for auction-based transport services allocation process in PI. However, those approaches have not been validated by PI network structures with real data. Auction theories applied for PI network provides a mechanism in decision making on choices of distinct carriers, and hubs and transit nodes to pick up the orders. In this regard, an auction-based simulation approach is required to further study and provide an accurate performance assessment of the PI logistics system.

2.5 Urban Distribution Centers and Airports

In urban logistics, distribution centers or airports play roles as hubs in PI networks. One of basic functions is the consolidation of freight. It allows trucks from different transport companies to cross-dock their containers and combine their cargo for shipping in a bundle. In this way, the number of trucks is reduced and the load factor is able to highly increase; even more stops per vehicle can be made and routes can be combined.

From a point of view in PI, trucks are required to make multiple stops in hubs, where trucks should approach to docks and get containers loaded, unloaded, and into sorting process. It will take a significant share of a total lead time of a container on the route and the waiting time from trucks in the hubs. Optimal handling operations in distribution centers and the airports are the key to improve the system's performance. In the section, we review the evolution of concepts on urban distribution centers (UDC) and related literatures about operating in UDC and the airport.

Cadotte and Robicheaux (1979) found high concentrations of truck activity in urban area is typically performed by a very large number of small carriers who duplicate each other's paths with partially filled trucks while each truck is in the process of picking up and delivering a large number of very small shipments. This distribution structure results in unnecessarily high levels of congestion, pollution and energy consumption, as well as high distribution costs which are passed on to consumers in higher product costs.

In 1999, the European program COST 321 (COST 3231, 1999) identified several consolidation-oriented measures of UDC, i.e., outsourcing of freight transport, transport coordination and cooperation of retailers, consolidation by means of ‘urban’ containers, road pricing in cities, optimization of distribution systems including transport centers, etc.

Browne et al. (2005) extended the UDC concept with a range of terms including: public distribution depot, central goods sorting point, urban transshipment center, shared-user urban transshipment depot, consolidation center, pick-up drop-off location, and city logistics schemes, and freight platforms.

To evaluate the performance of UDC, Browne presented the impacts quantified in 10 UDS schemes: changes in the number of vehicle trips, travel distance, the number of vehicles used, travel times, volume of goods delivered, vehicle load factors, loading/unloading time and frequencies of delivery, total fuel consumption, vehicle emissions, and operating costs.

Before Tsui and Chang (1990) proposed a microcomputer based bilinear program for recognition of the shipping pattern, and the assignment of the dock doors, all decisions were made manually. The assignment of doors should be adjusted accordingly with the changes of shipping patterns from time to time. The objective is to find an assignment of receiving doors to the origins and shipping doors to the destinations, such that the distance traveled by the forklifts is minimized. The model provided the results which can be applied directly or modified and used as the initial assignment for another iteration under particular circumstances.

Bartholdi and Gue (2000), described a cost model including travel cost and three types of congestion in LTL crossdocking terminals. Their model shows an efficient layout of cross-docks reduces travel distances without creating congestion. Benefits from changing the layout of a terminal are less workers' traveling time, balancing travel distances and congestion, and reducing labor costs without investing in new systems.

Flights with cargo from around airports make the transaction in the cross-docking hubs. From this standpoint, an airport in a PI network serves functionally as an urban distribution center. Especially, in some main hubs such as Louisville International Airport for the UPS Worldport and Memphis International Airport for the Federal Express global hub, there are more than 50 loading (or unloading) docks placed along several terminals and hundreds of air cargo planes operated by each carrier. During the peak hours, hundreds of aircrafts require to be assigned to the limited number of docks whenever unloading or loading containers. In those cases, airport gates are the restricted resources to park aircrafts. The "ungated" aircrafts are parking in the parking lot and tug-and-dollies are used to deliver the containers to the terminals.

In the following, we review literatures about the air cargo airport gate assignment problems. Gate assignment is a complicated problem as it is involved within several processes from containers unloading off incoming flight, then cargo handling and transporting in the facilities, to containers loading onto outgoing flight. It also deals with various interdependent resources including aircrafts, gates, gate facilities and crews (Cheng et al., 2012). Improper assignment may result in cargo delivery delays, inefficient use of gate facilities and costly expenses in airport operations. To avoid the loss and provide better quality of service, carriers can use many analytical and operations research methods to reduce costs and search for optimal assignment solutions (Dorndorf et al., 2007).

Good airport gate assignments can minimize the total travel distances cargos are distributed through the hub terminals, while those, for passenger flight, are the walking distances from one gate to another or entrances/exits (Lim et al., 2005). However, Bartholdi and Gue (2000) found drawbacks on shortest gate-to-gate distances as the measurement in optimization models, when taking into account different types of material handling systems for cargos. In a gate assignment problem of LTL crossdocking terminals, they modeled the objective function as minimizing the cost of moving cargos from door to door in man-hours, including worker travel time and worker waiting time. Besides two deterministic models above, Seker and Noyan (2012) proposed a minimum expected number of flight conflicts model as the stochastic model for robust assignments. Even more different optimization criteria are described by Kumar (2014) in multi-objective airport gate assignment problem. For the over-constrained airport gate assignment problem, Ding et al. (2004) addressed the objectives are minimizing the number of ungated flights and total walking distances or connection times, while Genc et al. (2012) modeled them with maximizationg gate utilization.

Unlike gate assignment in airports for passengers, the problem of cargo airport gate assignment is required to measure the performance of cargo movements based on specific types of material-handling systems. It is also needed to model the cost of delays due to congestion on the dock, for example, excessive labor cost and wait time caused by containers interfering with each other, which is not common for passengers getting struck by traffic jams when transferring among the terminals.

In contrast, the cargo airport gate assignment problem is more similar in spirit to the much-studied problem of freight terminal dock door assignments. For instance, Tsui and Chang (1990) issued the assignment of dock doors to incoming and outgoing trucks of logistics carriers, where trucks come in from vendors and get shipments unloaded and reloaded outgoing trucks, and later they proposed mathematical programming model to solve the assignment problem (Tsui et al., 1992). Bartholdi and Gue (2000) described models of travel cost and three types of congestion, and they use them to assign trailers to fixed dock doors that minimize the labor cost of transferring freight.

2.6 Air Cargo Transportation

The first all-cargo airline was introduced after World War II, but only two carriers, Slick Airways and Flying Tigers, continued their business due to bankruptcies and accidents in early 1950s. Air cargo remained a very small percentage of air traffic in the following 30 years. As the trend shown in Figure 3, the air cargo industry has stepped in the high growth era, and the freight business has changed tremendously since late 1970s and early 1980s. FedEx founder, Fred Smith, believed freight traffic should be separated from passengers' due to the route pattern differences, and he started his freight business in 1973. Its competitor, United Parcel Service (UPS) started operating its own airline in 1988, and began to build its largest sorting facility called "Worldport" in Louisville, Kentucky by 2002. It processes an average of 1.6 million packages a day using 155 miles of conveyors. Nowadays, more than two-thirds of the U.S. air cargo market is controlled by the two largest cargo airlines.

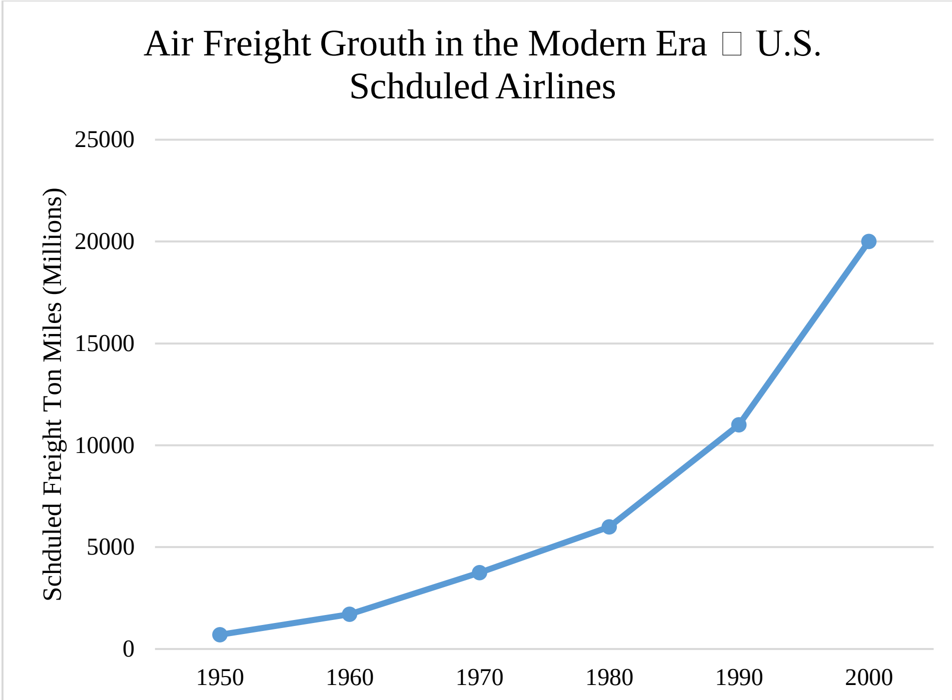


Figure 2.2: Air Freight Revenue Ton-Miles by Carrier Type, 1950-2000

(Source: DOT Form 41)

In today's freight industry, air cargo has been playing a significant role. Compared with ships, trains, and trucks used to ship bulk freight and heavy packages, aircrafts are used for relatively lightweight, rapid shipments. According to the Organizations for Economic Cooperation and Development (OECD), the value of air cargo accounts for more than 33% of the world trade in merchandise, while its weight is only 2% of all the cargo moved world-wide (Cosmas and Martini, 2007). In U.S., it maintains more than 60,000 million ton-miles worth of air cargo revenue from 2003 to 2016, except for a 13% decrease in growth during 2008 due to the global financial crisis (see Figure 3).

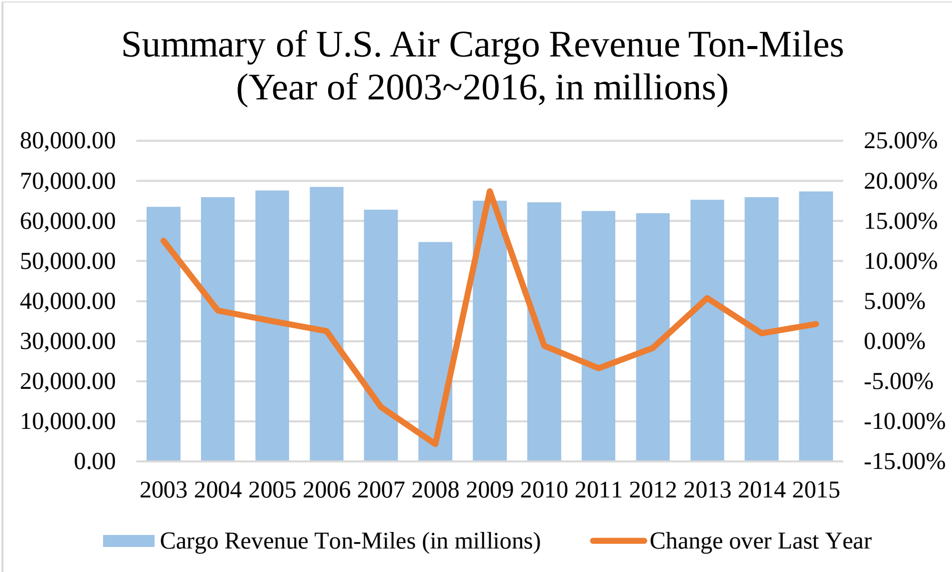


Figure 2.3: Air Cargo Summary Data

(Source: Bureau of Transportation Statistics T100 Segment data source:

https://www.transtats.bts.gov/freight.asp?pn=0&display=data1)

The global trend of EC has been creating several challenges and opportunities for the air cargo industry with multinational company integration and cooperation amongst air cargo agents in the supply chain, including warehousing and distributing agents. Leung et al. (2000) presented an information infrastructure enabling air cargo related EC business to develop and engage in logistics integration. The framework provides a virtual market for shippers and buyers and other logistics agents to locate each other and negotiate terms of service. A freight forwarder conducts an online virtual integration. Required cargo space may be obtained from Cathay Pacific through E-auction Facility provider such as warehouse operators, terminal operators and airlines may also trade their cargo space and services on the marketspace.

For operations, air cargo carriers run the system in a bimodal structure, i.e., ground and airways, in order to offer door-to-door package delivery service. It is usually optimized with efficiency in a hub-and-spoke network, which is within a single company or by cooperation with others in a limited scope. This is because, within each separated carrier, cargo from hundreds of airports would be challenging to distribute cost-efficiently from each origin to the destination directly, namely point-to-point airline network. The airline distribution network with a hub-and-spoke structure is able to take advantage of economies of scale in shipping and sorting in the hubs. Shipping companies such as FedEx and UPS own many different types of cargo planes including Boeing 747. When configured as a freighter, the Boeing 747-400 can hold about 736 m^3 of cargo, which are equivalent to about five semi-trailers.

However, it brings a problem of taking longer lead time due to a large portion in waiting for batching cargo in a full aircraft-load. Besides, it is hardly able to balance the inbound and outbound of air cargo hubs, which results in wastes of aircrafts space in the back-shipping trip flight.

Aside from dedicated cargo flights, collaborative opportunities can be found with passenger freight flights. Just about every passenger flight is carrying some freight along with the passengers and their baggage. The U.S. Postal Service alone leases space on 15,000 of the approximately 25,000 scheduled passenger flights each day (Nice, 2017). When a package is shipped along the flight, it is usually consolidated with other packages and freight, and packed into special containers that fit in the storage area under the passenger compartment. For instance, a Boeing 747-400, one of the largest passenger planes, can hold 416 passengers along with 150 m^3 of cargo. That's about as much cargo as can fit in two semi-trailers.

In an urban logistics scope, collaborative shipping for ground freight delivery is relevant with air cargo transport in airports. Our motivation is to build an interconnected airways and ground integrated systems in the PI platform. This mode is necessary and urgent for efficient and sustainable economies.

CHAPTER III

SIMULATION MODEL AND TRANSPORTATION IN PI

3.1 Urban logistics system and air cargo transport network

An urban city area sets a geographical boundary as shown in Figure 3.1. Highway gateways, railway stations, water ports, and cargo airports serve as part of the system in multi-dimensions. Within the boundary, the system contains facilities including warehouses and gateways, hubs, as well as various types of transportations, e.g., trucks, trailers, aircrafts. Warehouses represent EC companies which are located in the urban area. Gateways generate freights from outside of the city. There are two types of containers in the model: containers with EC freights and other containers from out of city through gateways. Hubs are typically placed close to intersections of major highways and warehouse-dense areas, facilitating consolidation of shipments. Once those freights situate in the urban logistics system, they are either distributed to gateways or transshipped to other transportation nodes, e.g., railway stations, water ports, or cargo airports for outbound shipment.

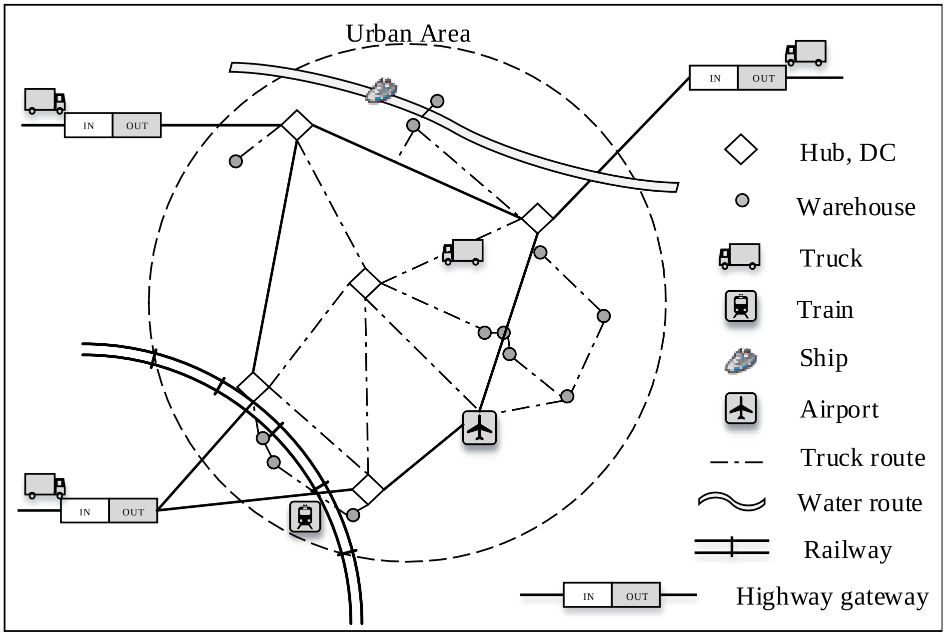


Figure 3.1: An urban logistics network system

Freight flows are included in two processes of shipping in urban area, i.e., direct distribution and shipping through the PI network. For the direct distribution, containers find a path directly to their destination; whereas, through the PI network, the process needs to use hubs for transitions as shown in Figure 3.2.

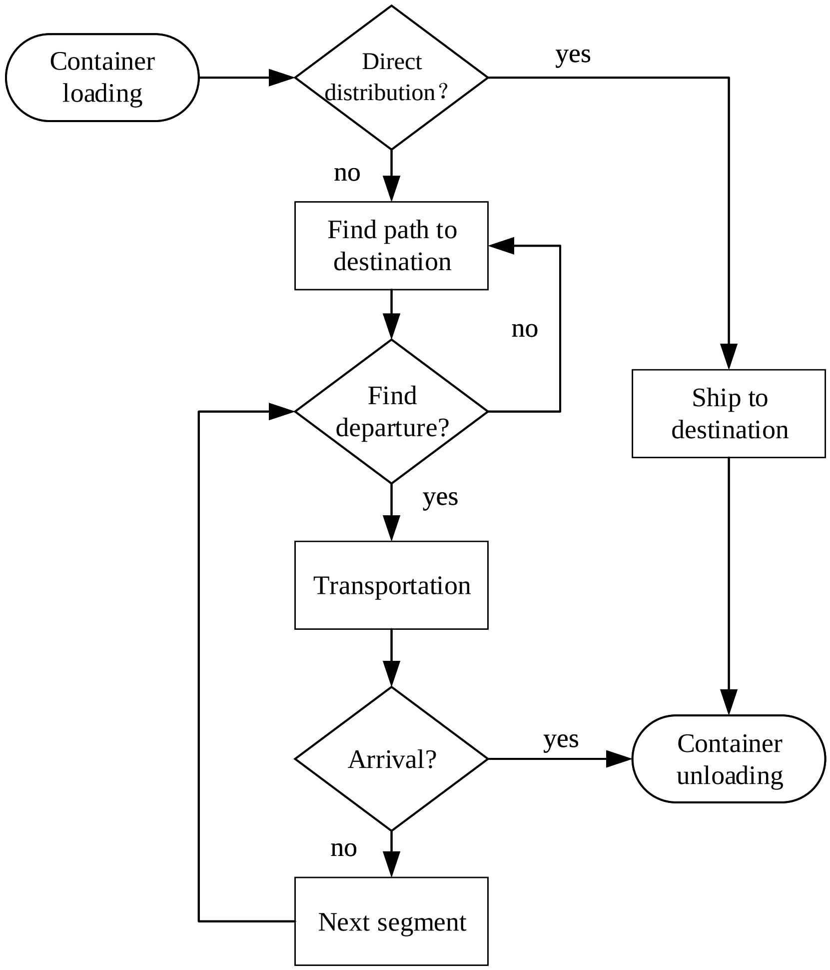
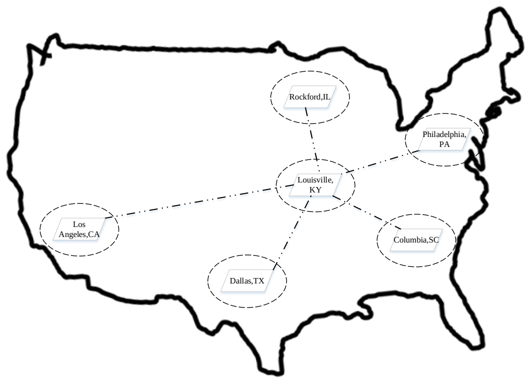
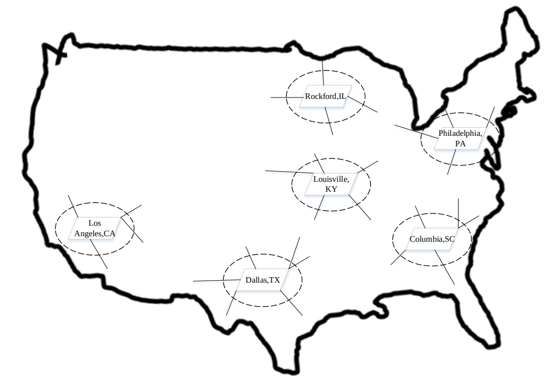


Figure 3.2: Freight container flow logic

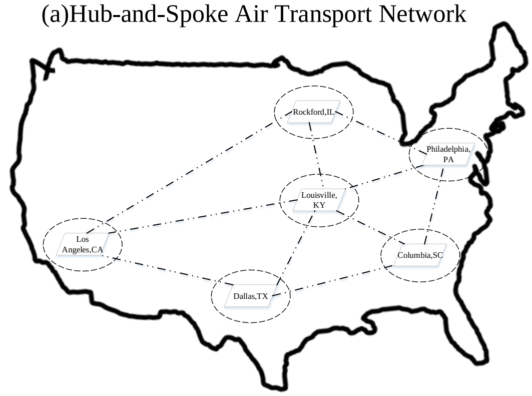
The current air cargo transportation network is described as a hub-and-spoke structure shown in Figure 3.3 (a). In the urban logistics, ground transport network similar to Figure 3.3 (b) is collecting freight for the outbound transportation. In synchronization with passenger flights, air cargo collaborative transport (see Figure 3.3 (c)) can be realized to connect to every “spoke” urban city under the PI platform. Figure 3.3 (d) shows the air cargo transport links up the ground shipping networks with a integrated air-and-ground PI network.



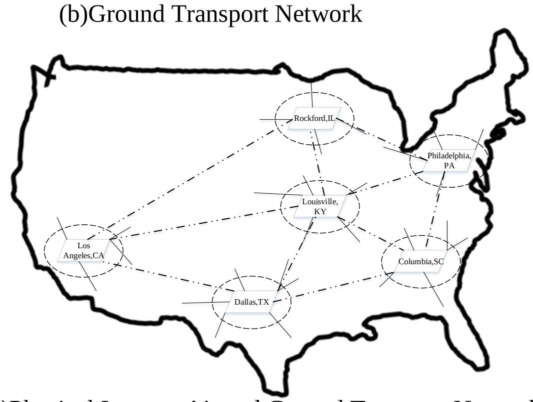
(a)Hub-and-Spoke Air Transport Network



(b)Ground Transport Network



(c)Physical Internet Air Transport Network



(d)Physical Internet Air and Ground Transport Network

Figure 3.3: Air transport patterns

3.2 Simulation model design

An agent-based simulation model is developed to represent an interconnected urban logistics and air transport system. The model is built in the AnyLogic simulation software, which supports three main simulations methods, i.e., discrete event, system dynamics, and agent-based simulations. That makes AnyLogic as the right tool that is suitable for models mixed with multi-methods. The model in this study is built on an agent-based structure, within which each agent is on a discrete event basis.

The global structure of the multi-agent system is shown in Figure 3.4. The agent system structure models a real-time urban transportation network. There are four main agent classes: freight generator agent, transport protocol agent, transport agent and transshipment facilities agent. Freight is created in the freight generator agent, such as a warehouse, and gateways from interstate highways. In this model, the containerization of freight is not the primary focus of research. Therefore, a load of one container is modeled as a unit size of freight. Freights are shipped by a transportation mode with a communication via the transport protocol agent. Meanwhile, hubs and airports are required components as a transshipment facility for collaborative routing and consolidation in the network.

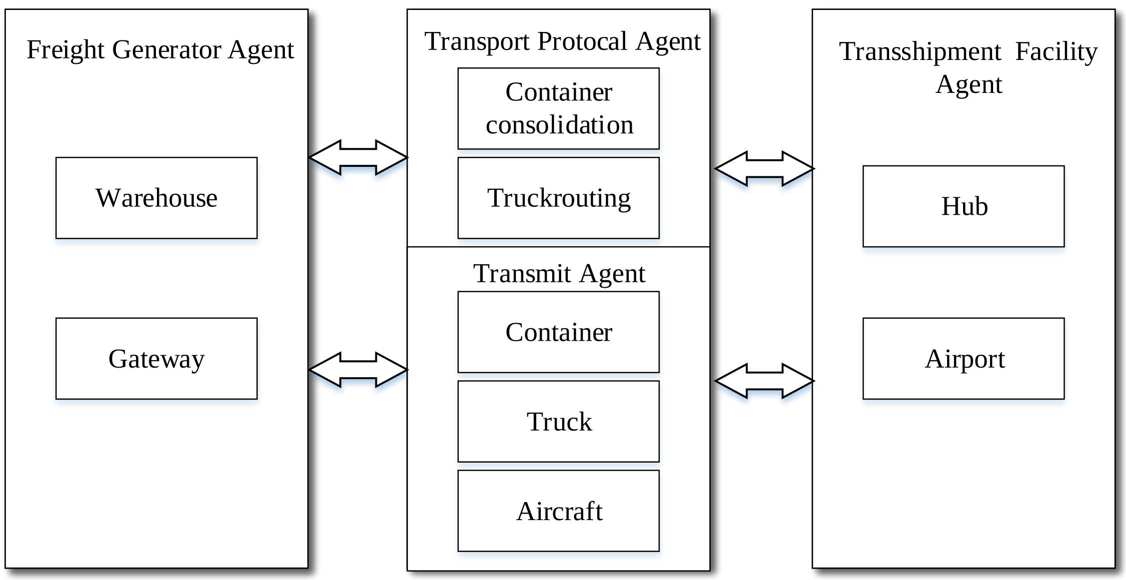


Figure 3.4: A general structure of the multi-agent system in the proposed model

The model consists of two main elements: agent entities living in the GIS environment representing various buildings, containers, trucks and aircrafts in the logistics system; and the protocols for communications, which can only carry information, representing the order and the ride triggering the shipping from request to handling.

First of all, the superclass BUILDING is built as a genetic type of all kinds of buildings, e.g., warehouse, gateways, hub, and airport, etc., from which the subclass buildings can inherit the general functionalities. The functionalities of BUILDING include:

- let containers wait for pick up by an assigned truck;
- dock a truck in a loading bay;
- load a truck with assigned containers;
- unload a truck and receive unloaded containers;
- undock a truck from a loading bay and let it leave the property.

3.2.1 Freight generator agent

The Warehouse and Gateways are subclasses of BUILDING as the generators of freights in the model. The locations of instances of class Warehouse are selected according to real estate properties. When a warehouse instance is placed in the model's GIS environment, a location index is given an attribute in the model instead of any specific names. On the other hand, gateways are located in the suburb around an urban area from each direction of interstate highways. Besides locations, the main difference between the two is the freight destination where it is generated. Freights are generated per units of containers. A container is assigned an origin and a destination according to properties of the freights. Warehouse generates EC containers whose destinations are gateways and airport. Gateways generate containers for passing through the urban city to another gateway. The structure of a generator agent is shown in Figure 3.5.

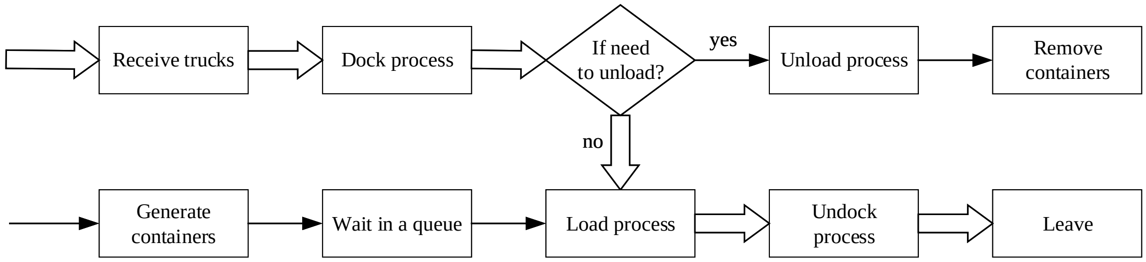


Figure 3.5: The structure of a generator agent

3.2.2 Transshipment facilities agent

Transshipment facility agents inherit functionalities from the superclass BUILDING to have the abilities to handle arrived trucks and associated containers. But they mainly serve as the stop station, where containers can be transshipped into other trucks or aircraft. The structure of a Hub agent is depicted in Figure 3.6.

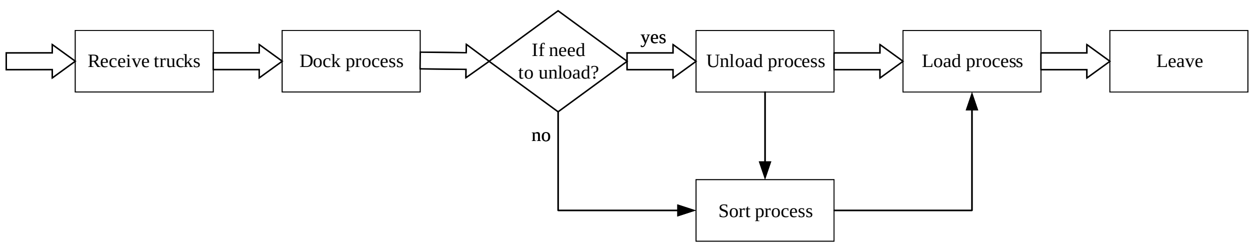


Figure 3.6: The structure of a hub agent

A hub, an instance of the class Hub, is able to:

- sort arrived containers;
- store containers for the next ride.

Within an urban city, an airport is regarded as a road-air hub, as shown in Figure 3.7 below. The airport, an instance of the class Airport, is able to:

- receive containers prepared for air transportation;

- sort containers based on air shipping destinations;
- load trucks with arrived containers from air side.

In addition, an airport serves as a gateway to:

- let aircrafts arrive and depart;
- dock an aircraft in a terminal gate;
- load an aircraft with assigned containers;
- unload an aircraft and receive unloaded containers.

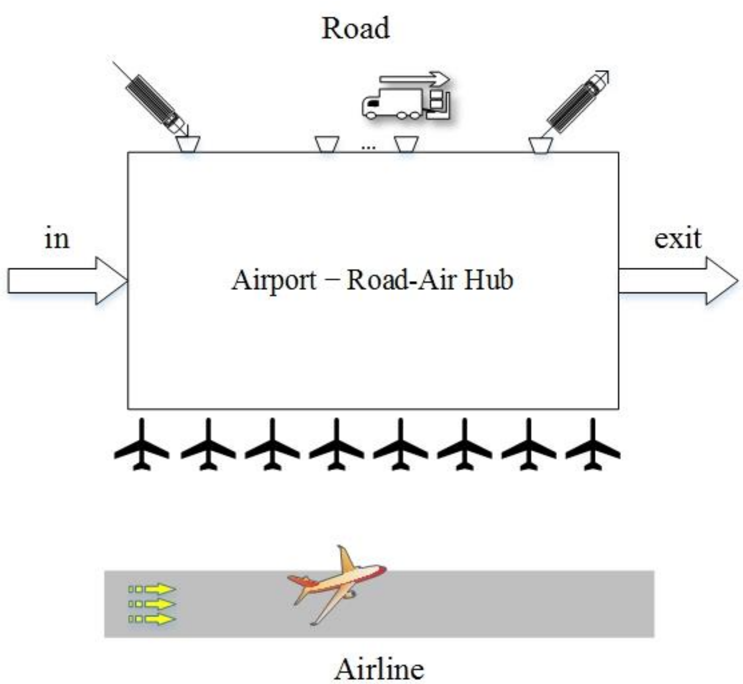


Figure 3.7: A road-air hub airport agent

3.2.3 Container agent

A container is created in a Freight Generator agent and assigned its destination. It is designed to select the shortest route and pass through a network of hubs. A container can send a request for the first leg of its trip to all trucks and selects the closest or earliest available one based on the selection rules. Once a truck picks up a container, it moves to a next stop. If this stop is the container's destination, its trip comes to an end, and the container is removed at the arrival location. When the container arrives at an intermediate hub, it seeks the earliest available truck again after being sorted. This procedure repeats until the container reaches its destination.

There are two types of containers in the model: containers with e-commerce goods and other containers. Containers with e-commerce shipments are created at warehouses and travel to the airport or gateways. The other type of containers in the model originate from one gateway and exit to another gateway. Figure 3.8 depicts the logic of state flows of a container:

1) *receivingInstructions*: The container gets assigned a destination and proceeds to generate its route;

2) *lookingForTruck*: The container sends a request for transportation to all trucks and selects the preferred truck according to its truck selection method;

3) *waitingForTruck*: Once the preferred truck has been assigned, the container waits for pick up;

4) *inTruck*: When the truck is ready for loading, the container enters the truck;

5) *inHubSort*: If a container arrives at the hub, it is sorted for its next ride.

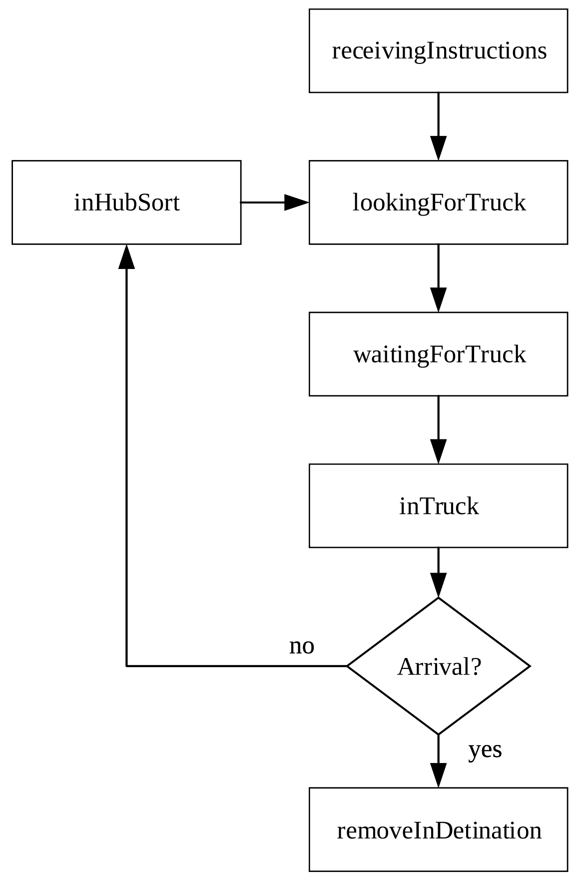


Figure 3.8: State flows of a container instance

3.2.4 Truck agent

A truck transports and responds to the requests from containers. Trucks carry out the transportation requests of containers, and take the shortest route on the existing road network. Trucks hold a schedule of rides and are only allowed to add a container to a scheduled ride if additional capacity is available or append a new ride at the end of its current schedule. This route is considered to be also the fastest in time since we assume that all roads are homogeneous and the truck speed is constant.

All instances of the Truck agent are generated at the beginning of a simulation run, and can be in one of such states as: waiting for a ride or a container, loading containers, undocking from a loading bay, moving to a destination, docking in a loading bay, and unloading containers. After completion of one ride, the truck proceeds to next ride on the list or wait for a next one to be scheduled. The logic flow of a truck agent is illustrated in Figure 3.9 and include the following states:

1) *waitingForRide*: A truck is sitting idle in a loading bay and its schedule is empty;

2) *loading*: Containers are being loaded into a truck;

3) *waitingForCont*: A truck is partially loaded and waits for more containers while still in a loading bay;

4） *undocking*: After loading, a truck starts undocking from a loading bay and leaves a building;

5） *moving*: A truck moves towards its destination;

6） *docking*: At destination a truck enters the property and docks in a loading bay;

7） *unloading*: After docking, a truck unloads containers.

When a truck finishes unloading, it stays in a waiting state if there is no additional schedule. Otherwise, it directly proceeds to the loading state.

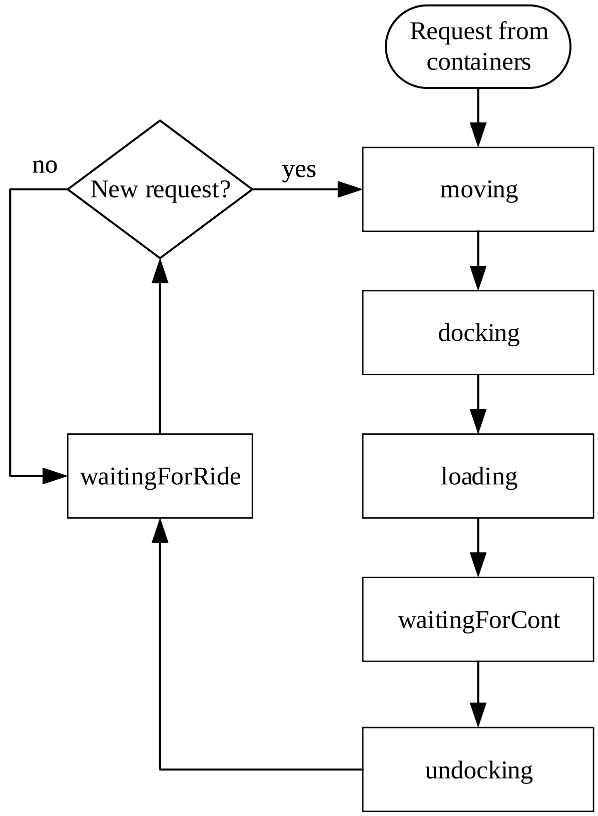


Figure 3.9: Flow logic of a truck instance

3.2.5 Communication protocols

The Dijkstra's shortest path algorithmic procedure of finding a shortest path works effectively using the distances between hubs as the weights between the nodes. This allows a container to travel multiple hubs when consolidating shipments. Table 3.1 is the Pseudo code of Dijkstra's Shortest Path Algorithm. Figure 3.10 shows an example of a network with multiple hubs.

Table 3.1: Pseudo code of Dijkstra's Shortest Path Algorithm

distance[s] $\leftarrow$ 0
for all v $\in$ V–{s}
do distance[v] $\leftarrow\infty$
S$\leftarrow$Ø

```
Q←V
while Q ≠ Ø
do u ← min distance (Q, distance) S←S ∪ {u}
     for all v ∈ neighbours[u]
          do if distance[v] > distance[u] + w(u, v)
                  then d[v] ←d[u] + w(u, v)
return distance
```

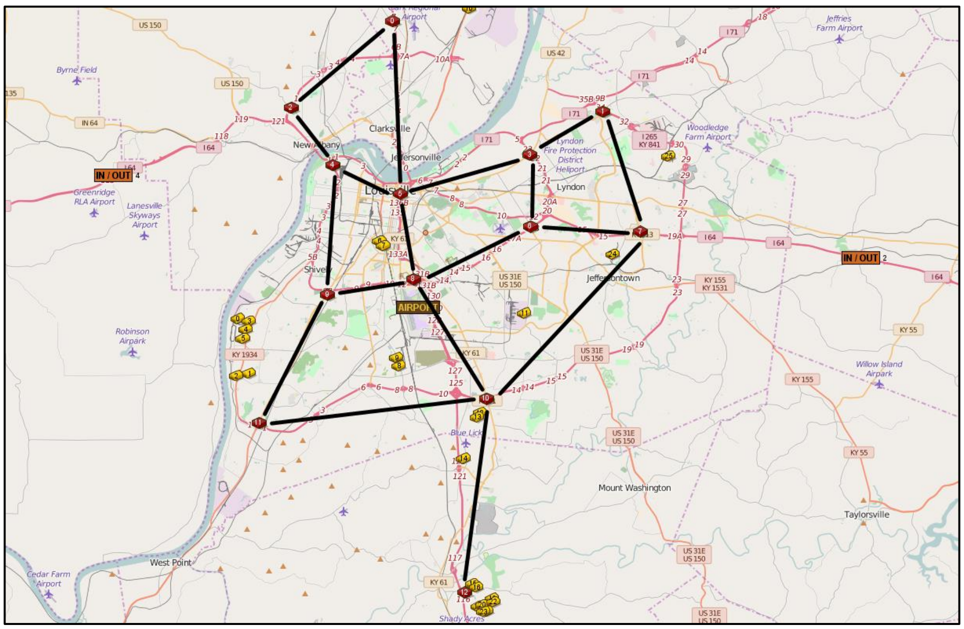


Figure 3.10: A network based on the model's hubs

3.3 Scenarios and Experiments

3.3.1 Transportation Scenarios

There are three key differences between the current logistics practice and the Physical Internet. In order to couple performance with design aspects, the traditional system is stepwise enriched with a functionality. The three steps result in four transportation scenarios. These scenarios allow for better understanding main contributors to a difference in performance.

Four transportation scenarios are modelled and listed in Table 3.2. Each scenario has one major advancement over its predecessor. The first scenario simulates the current logistics networks: trucks are owned by warehouses and only direct origin destination rides are made. The second and third scenario are intermediate scenarios that respectively implement a shared fleet of trucks and the usage of hubs. The fourth scenario simulates the Physical Internet: trucks are shared, hubs are involved, and shipments are consolidated.

Table 3.2: The transportation scenarios and their features

Transportation scenario	Share trucks	Use hubs	Extra flows
Private Direct (Current Logistics Network)			
Shared Direct	√		
Shared Hub	√	√	
Shared Hub with Flow (Physical Internet)	√	√	√

3.3.2 Performance Measures

In this section, we define five performance measures for a logistics system.

(1) Mean truck distance per container (Td)

Td indicates the average truck distance traveled per container. Truck distance is the sum of the distance covered by all trucks in favor of the delivery of containers. The truck distance includes empty rides made in order to pick up e-commerce containers. Rides that were made in favor of other containers are not included. Rides with both e-commerce and other containers are accounted for pro rata.

$$\text{Td} = \frac{\sum truck\ distance\ traveled\ in\ the\ system}{\sum number\ of\ containers\ in\ the\ system} \tag{3.1}$$

(2) Mean truck time per container (Tt)

Tt is the average truck time spent per container. The truck time spent is the sum of the time spent by all trucks in favor of the delivery of containers. This includes the time for driving and handling, e.g., (un)docking and (un)loading time. It also includes waiting in case a truck has to wait for more containers to arrive.

$$\text{Tt} = \frac{\sum truck\ travelling\ time\ in\ the\ system}{\sum number\ of\ containers\ in\ the\ system} \tag{3.2}$$

(3) Mean lead time per container (Lt)

Lt is the average lead time of a container. It measures the length of time from the moment a container is created at a warehouse until it is delivered at the destination.

$$\text{Lt} = \frac{\sum (loading\ time + docking\ time + track\ travelling\ time)}{\sum number\ of\ containers\ in\ the\ system} \tag{3.3}$$

(4) CO2 Emissions (Ce)

Ce is the total CO_2 Emissions from trucks with EC containers in the system per scenario per day. According to the emission factor per truck in the paper by Sarraj et al. (2014), the assumption is the $(772 + 13 \times x)$ kg CO_2 per kilometer, where x is the truck weight (tons).

$$\text{Ce} = \sum truck\ emission\ factor \times truck\ weight \times truck\ distance \tag{3.4}$$

(5) Mean transportation means fill rate (Fr)

Fr is the truck's filling rate in the system. It measures the average truck utilization. For the current truck utilization, trucks are only counted when their trip is completed.

$$\text{Fr} = \frac{\sum truck\ distance\ traveled\ in\ the\ system}{\sum number\ of\ containers\ in\ the\ system} \tag{3.5}$$

3.3.3 Experiments

Experiments are designed to run four scenarios by varying the number of trucks available. A range of the number of trucks is considered since performance outcomes are different depending on a fleet size. Based on initial test runs for assessment of feasibility, both high and low limits on the number of trucks are determined. For this experiment, however, the range of values between the minimum and maximum are evaluated with a fixed increment of the number of trucks as in Table 3.3. In addition, Table 3.4 provides model parameters and values required for simulation runs.

Table 3.3: A range of the number of trucks by four transportation scenarios

Transportation scenario	Min	Increment	Max
Private Direct	26	26	78
Shared Direct	12	2	42
Shared Hub	24	2	54
Shared Hub with Flow	80	5	155

Table 3.4: Simulation model and run parameters

Parameters	Values
Arrival rate at warehouses	2 containers / hour
Arrival rate at gateways	18 containers / hour
Sorting time	15 minutes
Docking time	5 minutes
Loading time	5 minutes per cycle

Truck speed	50 kilometers / hour
Truck capacity	5 containers
Number of hubs	13
Warm-up period	4 days

3.4 Results and Analysis

3.4.1 Truck distance per container

The average truck distance per container is shown in Figure 3.11. The Private Direct scenario indicates the lowest truck distance. In this scenario, the routes are shortest, and trucks bound for the airport are full while returning trucks are empty. In the Shared Direct scenario, the routes are the same, yet there is no restriction that trucks must be full. Consequently, this implies a decrease in truck utilization and an increase in truck distance per container. For the scenarios other than Private Direct, an increasing number of trucks are needed to reach optimality.

When hubs are included in the model, average container route distances get longer than otherwise. Nevertheless, hubs are the essential elements of PI. The challenge is to gain more benefits from increased truck utilization and offset the disadvantage of covering longer routes. In the Shared Hub scenario, this accounts for 38% increase in truck distance per container compared to Private Direct. When additional flows are introduced, it decreases to 18% in the Shared Hub with Flow (PI) scenario. However, the amount of extra flows is limited and thus many rides remain empty.

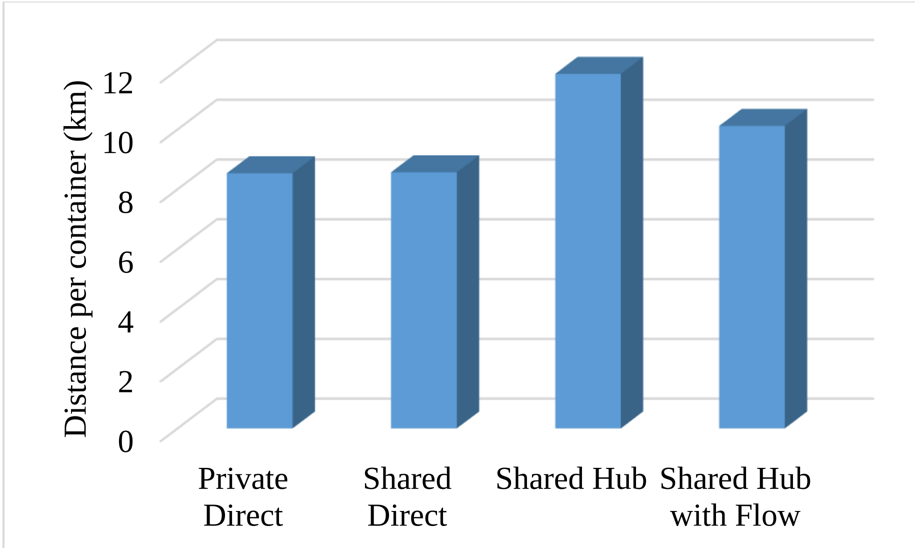


Figure 3.11: Comparison of scenario performance on average distance per container

3.4.2 Truck time per container

Figure 3.12 shows the average truck time per container. Notably, Private Direct scenario does not yield the least truck time per container, despite having the shortest route and full truckloads. The warehouse only needs about half the throughput of a truck, while truck time starts when the first container is loaded in the truck. From that point on, the truck is no longer available for other tasks. On the other hand, the Shared Direct scenario has the shorter truck time. This is because trucks are almost full for rides to the airport and empty on return rides.

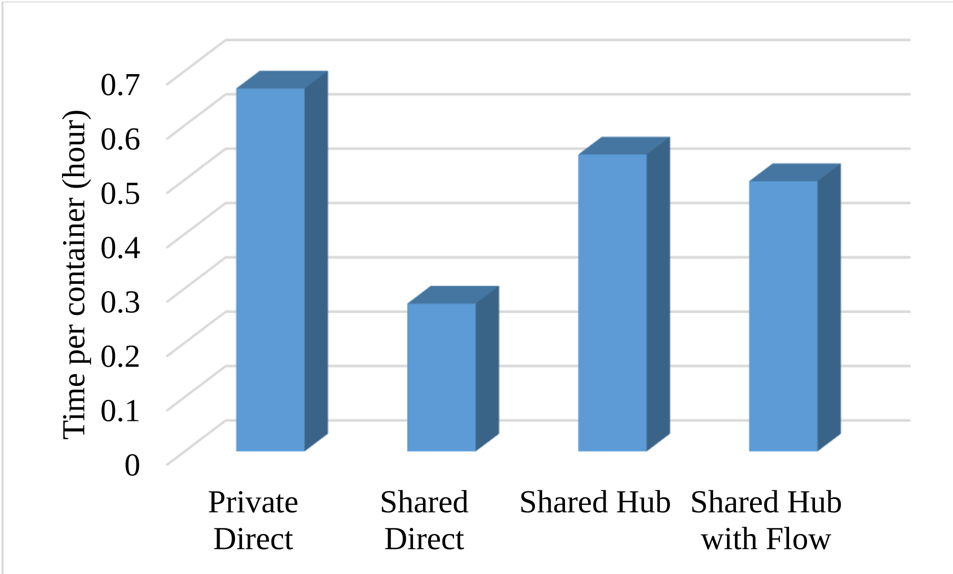


Figure 3.12: Comparison of scenario performance on average time per container

3.4.3 Lead time

Including hubs significantly increases the time per container. Not only longer routes, the extra stops also add more truck times. With short distances of rides, the proportion of combined times for docking, unloading, loading, and undocking becomes quite large. Short handling times are thus of major importance for a network of hubs. Allowing extra flows into the system reduces the truck time per container due to less empty rides on return trips. In fact, when minimizing costs, Shared Hub with Flow performs slightly better than Private Direct where trucks spend a lot of time in loading bays. Figure 3.13 demonstrates that the average lead time of a container benefits from more available trucks in a shared system. Compared to Private Direct, Shared Direct is the only scenario to obtain shorter lead times. This is due to lifting the requirement of a full truckload.

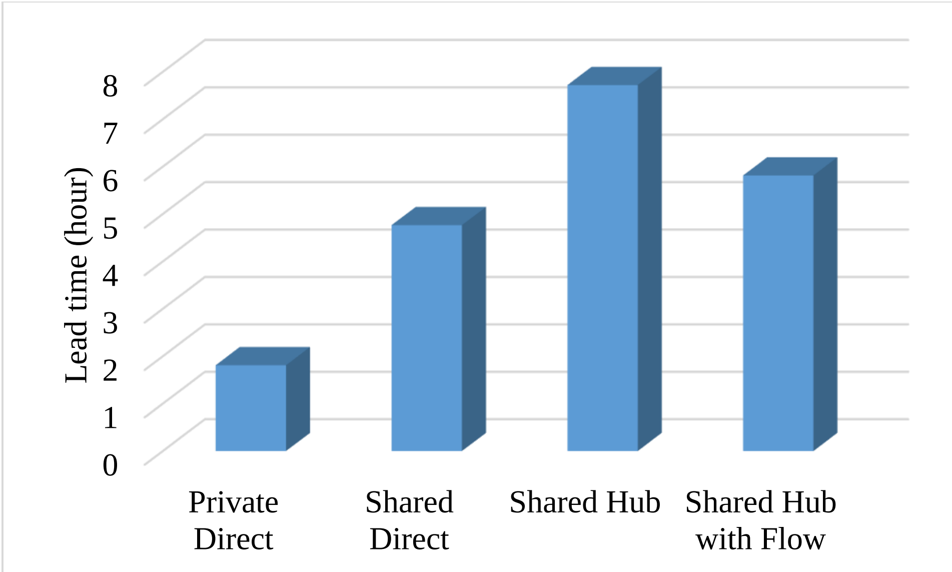


Figure 3.13: Comparison of scenario performance on average lead time

3.4.4 CO_2 Emissions

Results of the greenhouse gas emission show that a collaboration in shipments in the PI scenario allows a substantial reduction of CO_2 emissions about 42 percent from the current logistics practice. Compared with Shared Hub, the results in Figure 3.14 depict that the collaborative polling approach makes a significant environmental contribution in reduction of the green gas emission with an increase in truck utilization.

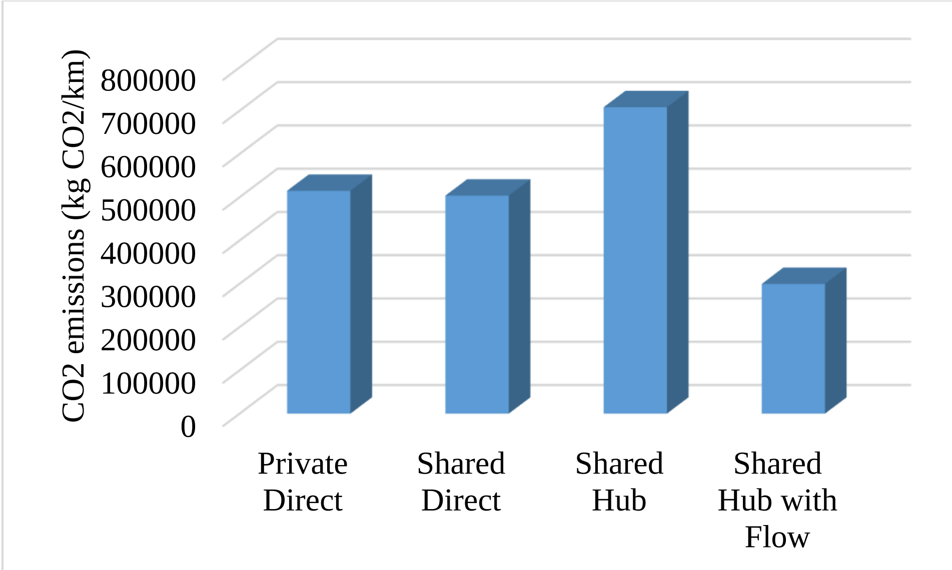


Figure 3.14: Comparison of scenario performance on truck CO_2 emissions

3.4.5 Transportation means fill rate

The fill rate results depicted in Figure 3.15 show that there is a significant gain in truck utilization from a shift towards the PI, with about 33 percent improvement up to 81 percent of truck fill rate from the current logistics practice.

Although full truckload shipments are processed from warehouses to the airport in current logistics practice and empty truckloads in backhauling, Private Direct scenario is 61 percent of filling rate rather than half of truckloads overall. This is due to the full truckloads accounted for during docking time in the airport.

Truck fill rates of Shared Direct and Shared Hub scenarios are less than that of the current scenario. This is because trucks in both scenarios are enabled to travel with less-than-truckload. Shared Hub achieves a little higher truck fill rate with the collaboration of shipment in hubs.

The PI scenario produces a 60 percent of increase on truck utilization from the baseline case of Shared Hub. This is because more use of spaces of less-than-truckloads in the system. Containers from the gateways increase the chances to collaboration with EC containers in shipments from hubs.

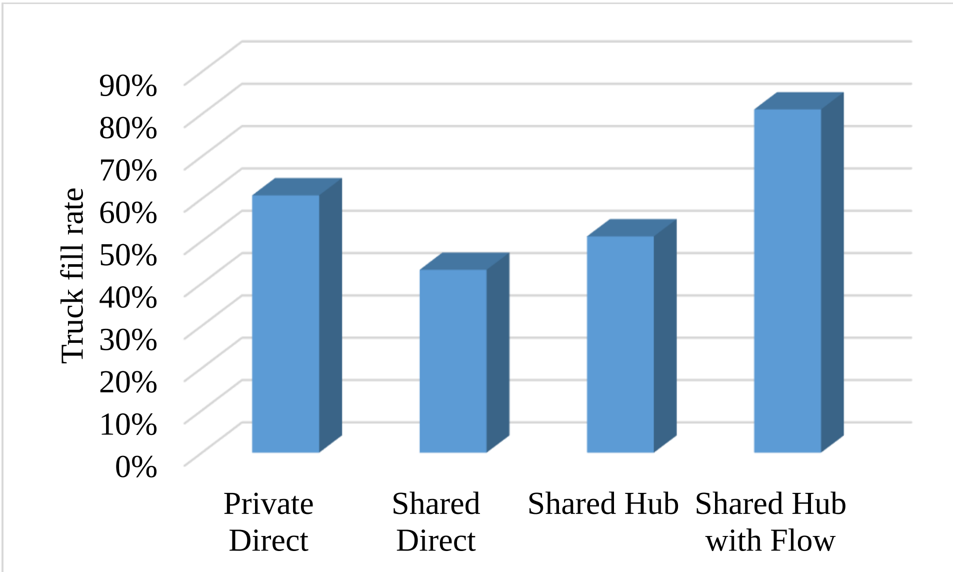


Figure 3.15: Comparison of scenario performance on truck fill rate

3.5 Summary

In this section, we have demonstrated that the PI concept enables significant improvement of urban transportation efficiency and sustainability. Based on the simulation experiments, four scenarios are tested. The PI scenario has achieved much more gains than other scenarios, as we summarize as follows. Truck time per container reduces 26 percent from that of the Private Direct scenario. A 42 percent of CO_2 emissions is cut from the current logistics practice. The fill rate of transportation means is increased by almost 33 percent, whereas the relevant longer distance per container and the lead time has been increased by an acceptable range. Therefore, it can be concluded with an acceptable trade-off in shipping time, the PI can make the urban logistics efficient and sustainable.

CHAPTER IV

AUCTION-BASED SIMULATION AND OPRIMIZATION ON PI TRANSPORTATION PLANNING

4.1 Introduction

Transportation planning intends to improve a series of operations and joint decision-making processes on transport resources in a transportation network. In the platform of PI, key elements, e.g., containers, transit centres, and trucks, are interconnected within a collaborative freight logistics system. In detail, containers are designed as modular and multifunctional load units, effectively working as a key enabler of implementing PI scenarios (Landschützer, Ehrentraut, & Jodin, 2015; Meller, Lin, & Ellis, 2012). Transit centres (Oktaei, 2015) provide functionalities of freight consolidation and cross-docking instead of a direct peer-to-peer delivery from source to destination. Coalition trucks planning extends to reallocation of requests among the carriers in case of freight consolidation to maximise profits (Douma, Schuur, & Heijden, 2006), rather than only to minimise individual carrier costs associated with vehicle routings.

Several large-scale studies have shown more evidence of PI on huge potential gains in efficiency and sustainability. Hakimi, Montreuil, Sarraj, Ballot, & Pan (2012) studied a fast-moving consumer goods (FMCG) industry in France, and found that PI significantly improved the transportation efficiency by as much as 17% increase in vehicle fill rate, 30% decrease in cost, and up to 60% reduction of CO_2 emissions. Meller et al. (2012) estimated that average distance travelled would decrease by 20-30% and the inventory at the retailer could reduce by 33% in a PI logistics network. Furthermore, performance assessments on reducing the inventory costs (Venkatadri, Krishna, & Ülkü, 2016) have been proposed to understand the impact of consolidation in Physical Internet logistics networks.

PI transportation planning (PITP) aims to find a suitable allocation of resources by exchanging transport requests from carriers. Therefore, PITP is an agent-based transportation planning, which takes an advantage of decentralised and dynamic characteristics. It maximizes carrier's joint profits while meeting delivery requests under a framework of collaborative fulfilments. In other words, it is to achieve benefits by a coalition of (LTL) carriers than individually. To maintain a maximization of carrier revenue and cost minimization of shippers, we propose a bidding-decision-making process of carriers and shippers. We use an auction-based mechanism to allocate the requests of transport services in transport marketplaces. The auctioneers are the shippers, and the bidders are the carriers. In this chapter, we maintain the hypothesis that a container is a shipper, and a truck is equivalent to a carrier. The structure pertaining to auction mechanism is shown in Figure 4.1. Shippers send out transport requests, and then carriers bid on them in an auction setting. The auction mechanism in our study considers travel cost factors and (re)assigns a container to a truck at hubs during request exchanges between bidders and auctioneers under a given time-window restriction. The auction process takes into account remaining capacities of a truck, i.e., the truckload utilisation, when determining a winner of most cost savings.

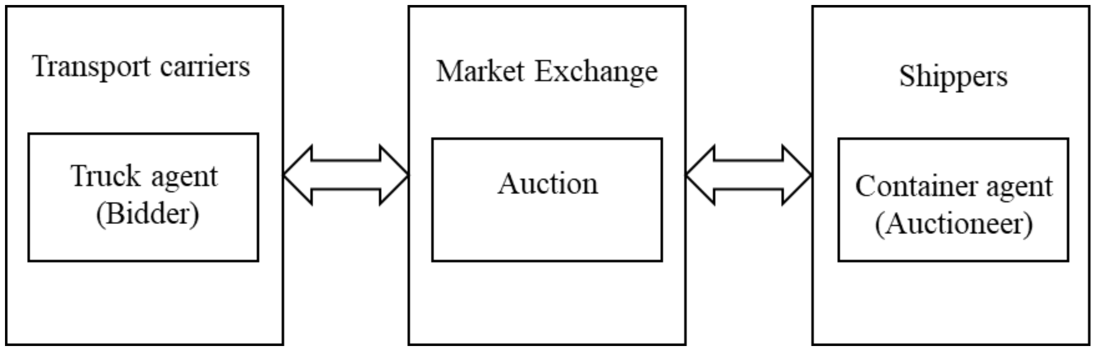


Figure 4.1: Joint relationships between carriers and shippers by auction mechanism in a PI transportation system

4.2 Auction mechanism in PITP

Auctions serve as a platform to request shipments and fulfil less-than-truckloads from a set of independent freight carriers. In general, auction theories provide a mechanism that can be applied for decision making on choices of distinct carriers, and hubs and transit nodes to pick up the orders. Nevertheless, this approach has not been used and validated by PI network structures with real data. To this end, we demonstrate the efficacy of using auction-based simulation approaches to PI logistics and provide accurate performance assessments of the system.

In a PI transportation system, shippers benefit from selecting their carriers and the allocation of shipping service to a carrier becomes important. The communication between shippers and carriers follows auction-based principles by matching transport requests and services. When a container needs transportation, it sends a request to available trucks and selects one based on the auction criteria. To achieve revenue maximization of carriers and cost minimization of shippers, we propose a bidding process of allocating shippers to carriers, who are acting as bidders and auctioneers, respectively, and the simulation model calls an optimization subroutine as a truck-selection method in each bidding process. In this framework, the logistics information of each carrier (e.g., cost rate, revenue expectation, and capacity) is also considered, and subsequently these factors are used as parameters in the next optimization level. Before describing the auction model, we first define the notations as follows.

Notations:

T Set of total trucks in the auction market, indexed by t.

R Set of total requests in the auction market, indexed by r.

R_t Set of requests that can be served by a truck $t \in T$, $R_t \subseteq R$.

d_r Truck distance of a request, $r \in R$.

n_r Number of containers of a request, $r \in R$

f_t Truckload fill rate before submitting a bid, $t \in T$.

c_f^t Fixed/processing cost, $t \in T$.

c_v^t Distance-volume based variable cost, $t \in T$.

TC_r^t Transportation cost of truck t, $t \in T$.

P_r^t Bidding price by the carrier for a request r, $r \in R$.

PA_r^t Payment for a given request r, $r \in R$.

In the simulation model, we design an auction protocol to include bidders and auctioneers which are represented as trucks (carriers) and containers (shippers), respectively. A carrier makes a bid for each feasible request with a bidding price based on transport cost and expected profits. A shipper essentially takes the role of an auctioneer and facilitates allocation of containers and determination of route selections while satisfying carrier capacity. Figure 4.2 shows a procedure of the auction scheme.

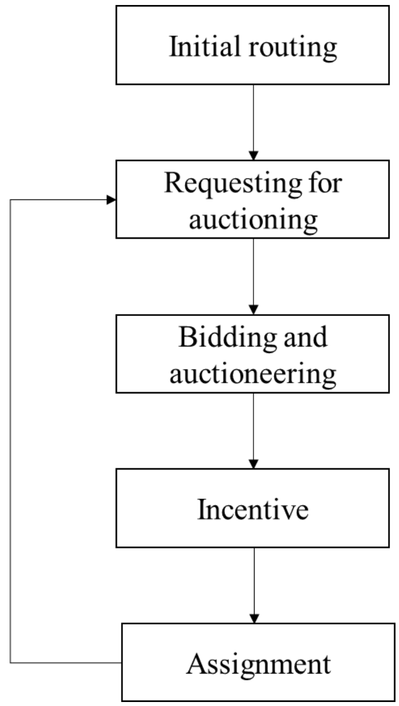


Figure 4.2: A procedure of auction process

Initial routing provides the shortest route of a container at the point of time when it is first generated in the network. Basically, we distinguish the content of a route with a ride. A ride is used for trucks that transport containers from one stop to another, whereas a route refers to the path of a container with a sequence of stops that include an origin and a destination. The Dijkstra's shortest path algorithm is used to generate the initial node sequences between departure and arrival hubs along the path.

In requesting, shippers make transport requests that comprise a selection pool in the auction for carriers. Requests are compatible and grouped along the portion of the route in common.

Once requests are generated, next step populates bidding prices for each request by auctioneers. The transportation cost of truck t for request r, TC_r^t, is defined in Equation (4.1).

$$TC_r^t = c_f^t + c_v^t(1 - f_t)d_r n_r,\ \forall\, r \in R_t, \forall\, t \in T \tag{4.1}$$

where the transportation cost consists of fixed cost and variable cost associated with the current truckload utilisation, travel distance, and number of containers for the request. Based on the cost function and an expected profit factor, a bidding price by the carrier for a request *r*, P_r^t, is set by Equation (4.2).

$$P_r^t = TC_r^t(1 + m^t) \tag{4.2}$$

where *m* is a margin rate of bidding price by carrier *t*.

For the incentive, shippers determine the payment to carriers. We define that the payment for a given request *r* as PA_r^t as in Equation (4.3).

$$PA_r^t = \begin{cases} P_r^t - c_f^t, & if\ a\ container\ stays\ the\ same\ truck; \\ P_r^t, & otherwise \end{cases} \tag{4.3}$$

where the processing cost c_f^t incurs at a hub. If a truck wins the bid for the same shipment consecutively, it incentivises a continuity of shipments by waiving the associated processing cost.

Winner determination program (WDP) selects the winning bid (Lehmann, Müller, & Sandholm, 2006). In case where no winner is found in the auction process, the container waits for a given time limit, then go back to the *Requesting*. A WDP problem is formulated as follows:

$$\text{Minimise}\ \sum_{t \in T} \sum_{r \in R} PA_r^t\, x_r^t \tag{4.4}$$

subject to

$$\sum_{t \in T} x_r^t = 1, \forall\, r \in R \tag{4.5}$$

$$\sum_{r \in R} x_r^t \leq 1, \forall\, t \in T \tag{4.6}$$

$$x_r^t \in \{0,1\}, \forall\, t \in T, \forall\, r \in R \tag{4.7}$$

where the objective function (4.4) minimises a total cost for allocating all requests. Constraint (4.5) ensures each request is assigned to exactly one truck, while Constraint (4.6) guarantees each carrier will win at most one request. x_r^t is a binary decision variable with its value of one if request *r* is allocated to carrier *t*, and zero otherwise in Constraint (4.7).

4.3 Simulation optimization

The WDP is solved using a Java package of IBM ILOG CPLEX as an optimisation routine called by the simulation model. In the search process of finding an improved objective function value, an optimization solver is called using heuristic algorithms including artificial neural networks, tabu search, and scatter search. Feasible request constraints are taken into account in the simulation process module including time window constraint, truckload capacity, and travel speed. While a winner to each request is optimally determined during the simulation run, system-wide performance metrics are measured by a simulation optimisation approach. To determine better input variables for transportation planning in a stochastic system, a simulation optimization approach is employed in this study. By simulating various multiple scenarios where input decisions change and random samplings are required, the model identifies the best case based on performance measures by comparing objective values. Moreover, optimization problems are formulated and solved as single or multi-objective models according to key performance metrics related to time and cost.

4.3.1 Objectives

A cost-associated objective is most common in freight transportation planning which is a focus in this study. Additionally, time- and environment-related objectives are also considered. This section defines and explains three individual objectives (Objectives 1-3) as performance measures of interest, based on which each optimization problem is solved.

(1) Objective 1

To maximize the economic output of the system, the objective is to minimize average truck distance per container delivered as in Equation (4.8).

$$\underset{D}{Min}\left\{\frac{\text{total truck distance}}{\text{total number of containers shipped}}\right\} = \frac{\sum_{t\in T} b_t}{\sum_{t\in T} n_t^c} \tag{4.8}$$

where D is the decision space of variables in the system, e.g., truck capacity and truck numbers. b_t is the travel distance of truck t, and n_t^c is the number of containers shipped by truck t.

(2) Objective 2

The time-based objective is to minimise average truck lead time per container, i.e., total truck lead time divided by the number of containers shipped.

$$\underset{D}{Min}\left\{\frac{\text{total truck lead time}}{\text{total number of containers shipped}}\right\} = \frac{\sum_{t\in T} l_t}{\sum_{t\in T} n_t^c} \tag{4.9}$$

where l_t is the lead time of truck t.

(3) Objective 3

The objective of environmental sustainability is formulated as the number of containers shipped divided by the total amount of truck space.

$$\underset{D}{Max}\left\{\frac{\text{total truckload}}{\text{total amount of truck space}}\right\} = \frac{\sum_{t\in T} n_t^c}{\sum_{t\in T} n_t cap_t} \tag{4.10}$$

Where n_t is the number of trucks, and cap_t is the capacity of truck t in number of containers.

4.3.2 Parameters and variables

Multiple inputs of logistics system components have variable effects on the model outcomes with regards to efficiency and sustainability. This includes parameters such as cost settings, arrival rates of containers, and time-window constraints, as well as decision variables (e.g., truck capacity) that can take a limited range of values. To find a set of decision variable values resulting in optimality, our study takes an optimization via simulation approach using OptQuest, which guides the search path for optimal solutions to the simulation model.

Decision variables take a range of discrete values to investigate their varying effects on the model objectives in Table 2.

Table 4.1: Decision variables and ranges

Decision variable	Range
Truck capacity	5-10
Truck numbers	25-50

Parameters related to a container agent include arrival rates at gateways and warehouses. Parameters related to trucks include the number of trucks, truck capacity, truck speed, and a maximum wait time threshold which controls estimated time of arrival. Parameters associated with hubs include docking time, loading time, and sorting time. Table 3 shows a list of parameters along with their corresponding values. It is assumed that indicative values of cost parameters are based on the estimation of shares of all containers in the PI system. Variable cost consists of fuel cost and externality costs, while fixed/setup cost involves only sorting and (un)loading costs.

Table 4.2: Parameters and initial values

Parameter	Value
Truck speed	50 km/h
Maximum wait time	2 hours
Dock time	5 minutes
Load time	5 minutes
Sort time	15 minutes
Arrival rate in warehouses	1.8 containers/hour
Arrival rate in gateways	18 containers/hour
Variable cost rate	$1/km-container
Fixed /setup cost	$3/container
Profit margin	15%
Number of warehouses	26
Number of gateways	5
Number of hubs	13
Number of airport	1

4.3.3 Computational experiments

For simulation runs, we determine the number of replications required to limit a relative error β using the following approximation of Equation (4.11) from Law (2013).

$$n_r(\beta) = min\left\{i \geq n_r: \delta = \frac{t_{i-1,1-\alpha/2}\sqrt{S^2(n_0)/i}}{|\bar{X}(n_0)|} \leq \beta'\right\} \tag{4.11}$$

where i is the number of replications to decide subject to β and $\beta' = \beta/(1+\beta)$ is the adjusted relative error threshold. With β = 0.05 (or $\beta' \approx$ 0.048) and a confidence interval of 95%, ten replications (i = 10) sufficed to contain the value of δ no more than β'. Table 4.3 provides the relevant statistics. In addition, a batch means method is used to find a warm-up period required to reach steady states. The mean value of warm-up period over ten replications was two days, and we estimate performance metrics after determining the length of the warm-up period, the length of a batch, and the number of batches.

Table 4.3: Sample means and variances with ten replications.

Performance measures	$\bar{X}$	S^2	δ
Average truck distance per container	13.7km	0.520	0.038
Average lead time of a container	3.5hour	0.039	0.040

The model is implemented using a real urban transport network that include the outbound and transhipment flows of 26 e-commerce warehouses in Louisville, Kentucky in the US. For model verification, the output performance measures are compared on *truck distance per container* and *average lead time per container* with counterpart scenarios of *Shared Hub with Flow* (SHF) in the study by Zheng, Beem, & Bae (2019) as indicated in Table 4.4. The SHF scenario with a selection method of "closest truck first" achieves the minimum average truck distance per container, while the other SHF scenario with an "earliest truck first" selection method attains the minimum average lead time per container. The performance of this model falls in between these two SHF scenarios. It is noted that the CFTP values in both metrics are relatively close (within 3% difference) to those resulting from the SHF scenario with a closeness selection method. This is due in part to bidding price being set up by considering truck travel distance cost rather than travel time.

Table 4.4: Performance measures comparison between the two scenarios in Zheng et. al.(2019)

Scenario	Selection method	Average truck distance per container(km)	Gap percent relative to CFTP	Average lead time of a container(hour)	Gap percent relative to CFTP

SHF	Closest truck first	13.4	-2.2%	3.6	2.9%
	Earliest truck first	14.2	3.6%	3.2	-8.6%
CFTP	Auction mechanism	13.7	-	3.5	-

Next, Section 4.4 demonstrates the fidelity of our model from each performance measure standpoint via sensitivity analysis, and Section 4.5 presents experiments in search for Pareto frontiers with multi-objectives in Table 4.5.

4.4 Results and analysis

(1) The solution to Objective 1 is *D*(truck capacity, truck numbers)=[9, 27] and the objective value is 1,264.73.

Sensitivity analyse is conducted to assess the effects individual parameters have on Objectives 1, hereinafter on Objective 2 and 3. The experiments are set up by changing one parameter at a time while keeping the others remain as same values. We use forward differencing to compute the amount of changes in the objective function value when increasing one percent of each selected parameter.

Figure 4.3 illustrates the result of a one-way sensitivity analysis of cost-related Objective 1. Most of parameters have substantial impacts on the objective function value. Profit margin plays an inhibiting role in the minimisation process with a 0.95% increase of objective function value, so do variable cost and fixed cost by 0.65% and 0.46% respectively. Bidding price rises due to the increase of cost factors and profit margin, which leads to less collaborating shipments but more individual direct shipments, thus increasing the overall travel distance. In contrast, the other parameters enhance the collaboration and contribute to reducing the objective value, particularly maximum wait time (-1.43%), arrival rate in warehouses (-1.39%), and arrival rate in gateways (-0.67%). As a result, average truck distance per container decreases. Longer maximum wait time and higher truck speed allow carriers to have sufficient time to allocate shipments in the auction. Arrival rates increase the number of containers, and subsequently the number of requests in the bidding process. The reason that arrival rates in warehouses have a more significant impact (-1.39%) than arrival rates in gateways is accelerating truckload fill rates during pickups in warehouses.

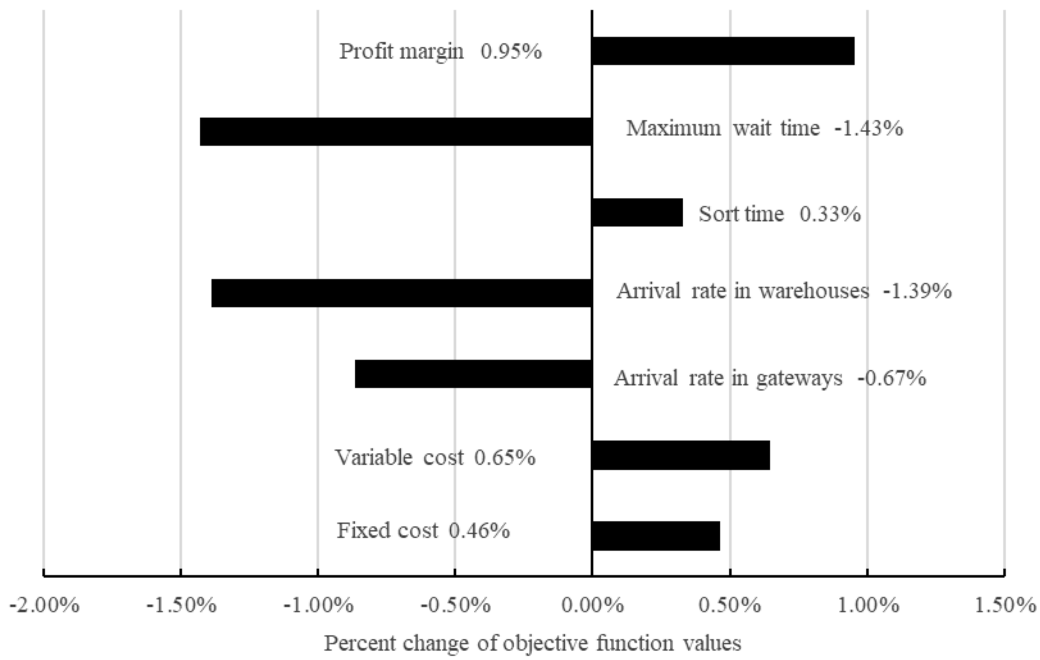


Figure 4.3: Effects of increasing parameters by one percent on the Objective 1 value of average truck distance per container

(2) The solution to Objective 2 of the average truck lead time per container is *D*(truck capacity, truck numbers)=[10, 50] and the optimal objective value is 0.81 hour.

Figure 4.4 shows the result of sensitivity analysis for each of parameters and their effects on Objective 2. Arrival rates in warehouses and gateways affect the number of containers in the system for a given time period, resulting in decreases of 0.42% and 0.33% on average lead time per container, respectively. However, time-related factors greatly affect the objective value. For example, a one-percent increase of maximum wait time extends the average lead time per container by 1.32%, while the same additional amount sorting times spent in hubs inflates it by as much as 1.04%. Cost-related factors including profit margin, variable cost, and fixed cost have a little or very limited impact on Objective 2.

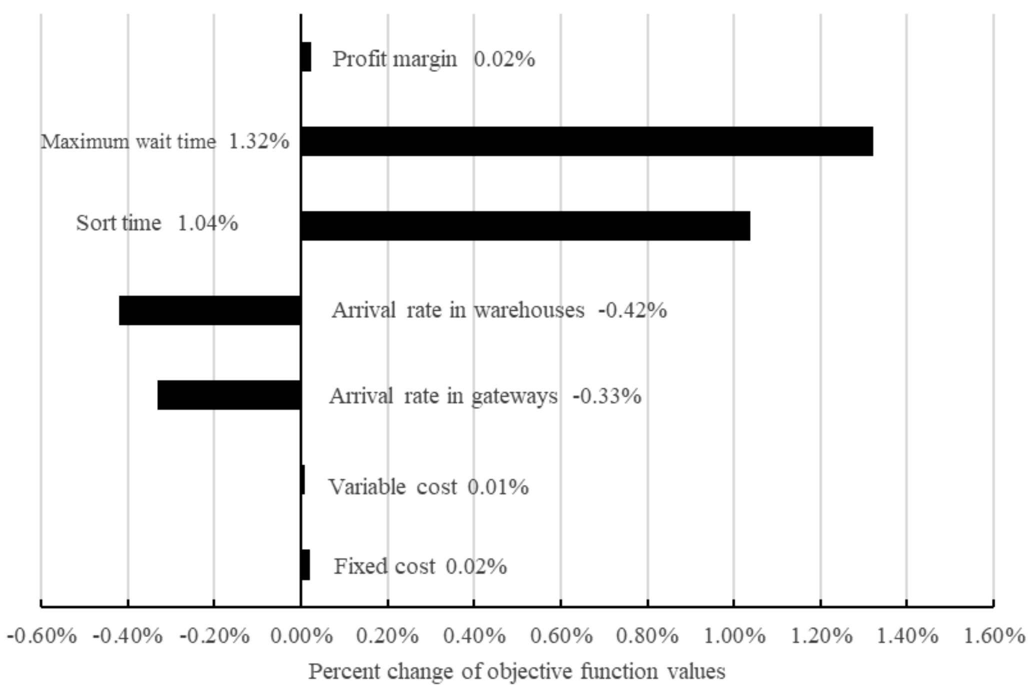


Figure 4.4: Effects of increasing parameters by one percent on the Objective 2 value of average truck lead time per container

(3) The solution to Objective 3 of average truckload utilisation is *D*(truck capacity, truck numbers)=[8, 32] and the optimal objective value is 0.77.

Figure 4.5 shows sensitivity analysis for each of parameters and their effects on the objective. The maximum waiting time allowed in the hub plays an important role on inducing a collaboration of shipments and an increase of the truckload utilisation by 1.73%. Higher arrival rates of containers from warehouses and gateways are more likely to fill the vacant truck space during pickups and backhauls. On the other hand, increasing profit margin, variable and fixed cost has negative effects on Objective 3, resulting in decreases of truckload utilisation by 0.85%, 1.20%, and 0.91%, respectively. This is because these factors reduce opportunities of collaborating shipments.

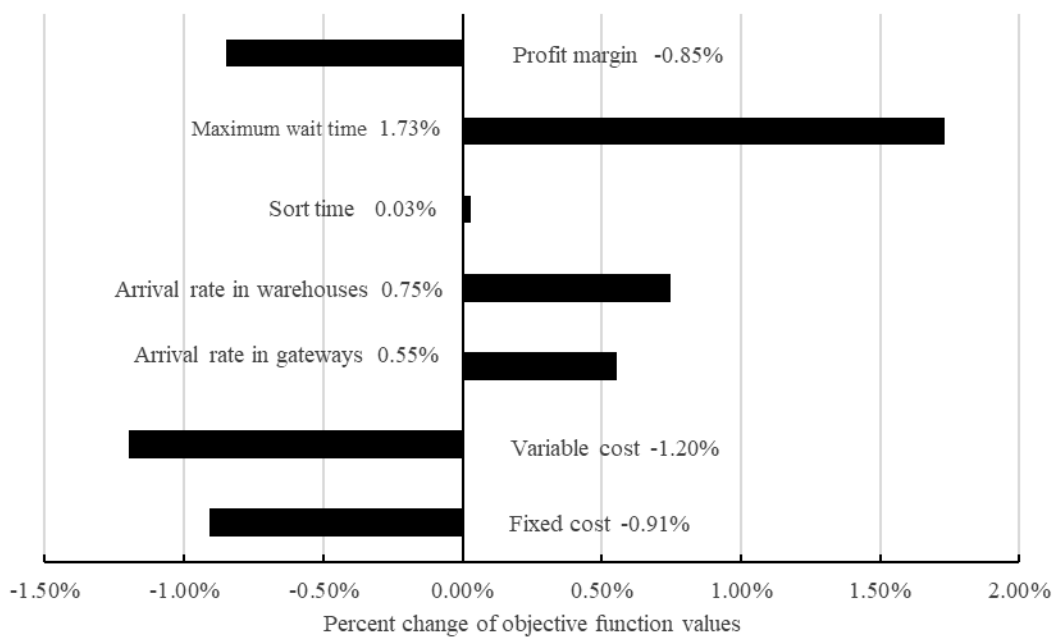


Figure 4.5: Effects of increasing parameters by one percent on the Objective 3 value of average truckload utilisation

4.5 Multi-objective optimization

Four multi-objectives of the optimization problem have been investigated by considering two or three objectives concurrently. Objectives 4-6 in Table 4.5 are bi-objectives integrating any two of Objective 1-3, whereas Objective 7 combines and linearly weights all three single objectives. For multi-objective optimisation, a weighted sum approach (Stadler, 1984) is initially used to find the pareto front in the trade-space. Weighting factors $\omega, \lambda, \theta, \varphi \in [0,1]$ control the weight given to each of the two (or φ_1, φ_2 for three) parts of the objective function.

Table 4.5: Formulations of bi/multi-objectives

Objective	Formulation
4	$\underset{D}{Min}\{\sum \omega * \text{travel cost} + (1-\omega) * (\text{lead time})\}$
5	$\underset{D}{Min}\{\sum \lambda * \text{travel cost} - (1-\lambda) * (\text{truckload utilization})\}$
6	$\underset{D}{Min}\{\sum \theta * \text{lead time} - (1-\theta) * (\text{truckload utilization})\}$
7	$\underset{D}{Min}\{\sum \varphi_1 * \text{travel cost} + \varphi_2 * \text{lead time} - (1-\varphi_1-\varphi_2) *$ $(\text{truckload utilization})\}$

Multi-objective optimization takes an overall consideration of those factors in the design space on multiple criteria. In this study, a weighted sum approach (Stadler W., 1984) is initially used to find the Pareto front in the trade-space. Three bi-objective optimization experiments are conducted based on the three single Objectives 1-3. The weighting factors ω, λ, θ in Table 3 are varied from 0 to 1, using a step interval of 0.05 in the experiments. Figure 4.6–4.8 draw a summary of all Pareto frontiers of the bi-objective optimization scenarios, which show the trade-offs between objectives.

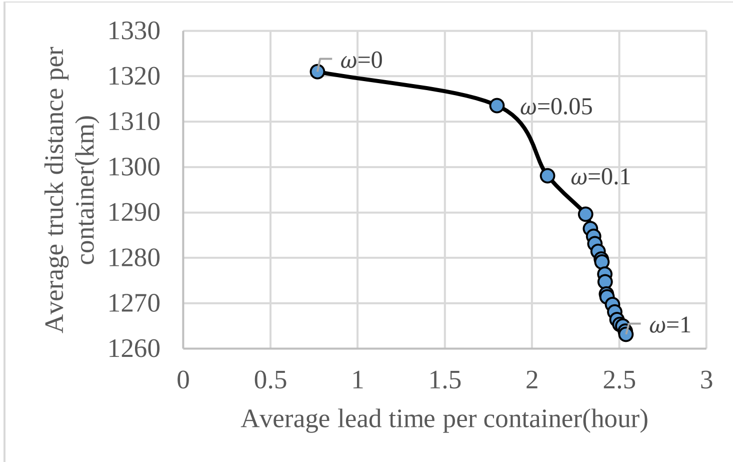


Figure 4.6: Objective 4 pareto front in trade-space between average truck distance per container and average lead time per container

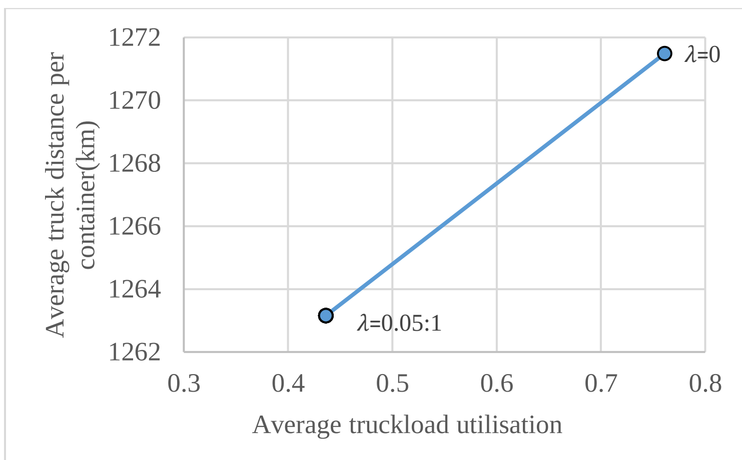


Figure 4.7: Objective 5 pareto front in trade-space between average truck distance per container and average truckload utilization

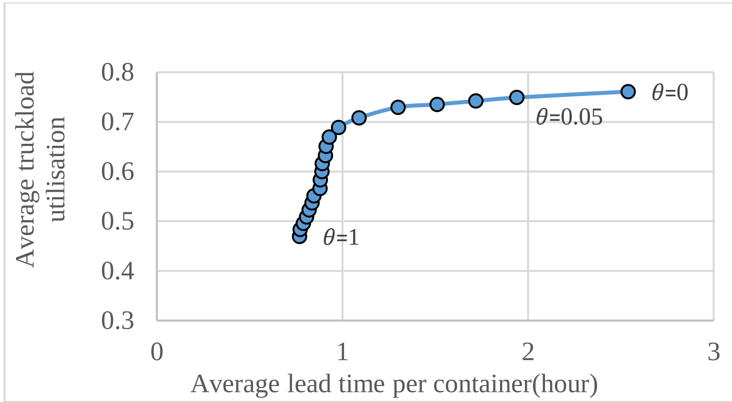


Figure 4.8: Objective 6 pareto front in trade-space between average truckload utilization and average lead time per container

As $\omega, \lambda,$ and θ increases from 0 to 1, Figure 4.6 indicates the relationship between two competing Objectives 1 and 2 while there is a higher concentration of observations above two hours of average lead time per container. On the other hand, Figures 4.7 and 4.8 show that higher truckload utilisation accommodates an increase of truck distance or lead time per container, implicating the complementary relationships between each pair. There are still some unpopulated sections along the Pareto front in all three cases. As $\omega, \lambda,$ and θ approach to one the points are slowly converging to lower ends; particularly in Figure 4.7 19 coincident points are on the left end. In order to achieve more suitably scaled relationships between various objective criteria, another approach is employed to transform multi-objective optimisation into a single objective format. Specifically, while keeping still one single objective, it is regarded that the remaining measure(s) as constraints subject to a range of values which are obtained through objective values resulting from the weighted sum approach.

Figure 4.9 illustrates the relevant results on an objective of average truck distance per container through varying values of average lead time per container in the constraint.

In the scenario, longer average lead time allows carriers to consolidate shipments, therefore, it turns out to achieve the less average truck distance per container in the system. Figure 4.10 shows the higher utilization of truckload benefits in shortening average truck distance per container until an extreme lowest of average distance with 0.7 truckload utilization per container. The solution is: *D*(Truck capacity, Truck numbers)=[9, 44]. However, after the point, the more truckload utilization in the constraint causes a little more truck distance. With a truckload utilization of 0.78, there are a less truck number of 35 and a smaller capacity of 8 in the scenario's decision variables. It can be seen from Figure 4.11 that a higher utilization needs a trade-off against a longer average lead time per container. In Figure 4.12, the objective value of average truck distance per container decreases from front left to right behind, as constraints of average lead time and truckload utilization. Whereas, it should be noted that the optimization is infeasible when the average lead time per container is less than 0.9 hour and average truckload utilization is greater than 0.66.

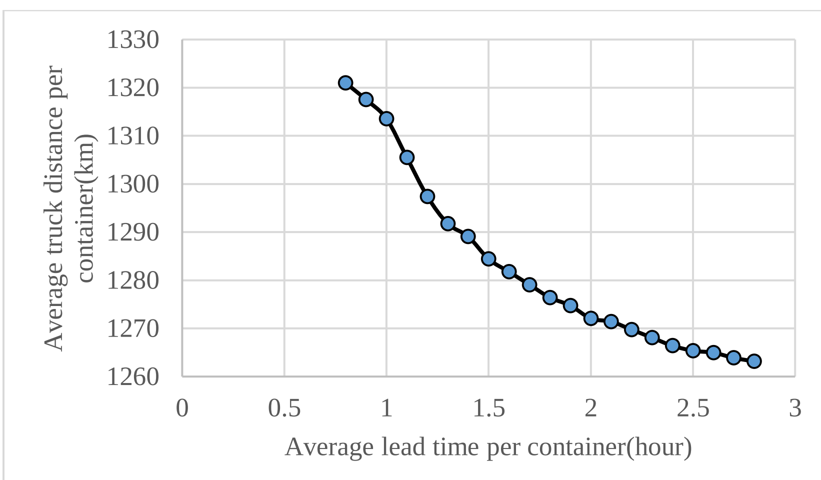


Figure 4.9: Average truck distance per container under various values of average lead time per container

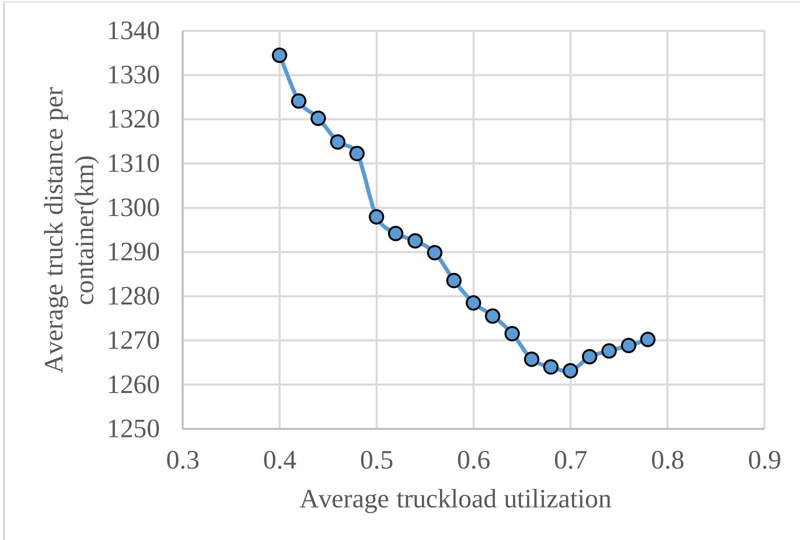


Figure 4.10: Average truck distance per container under average truckload utilization per container

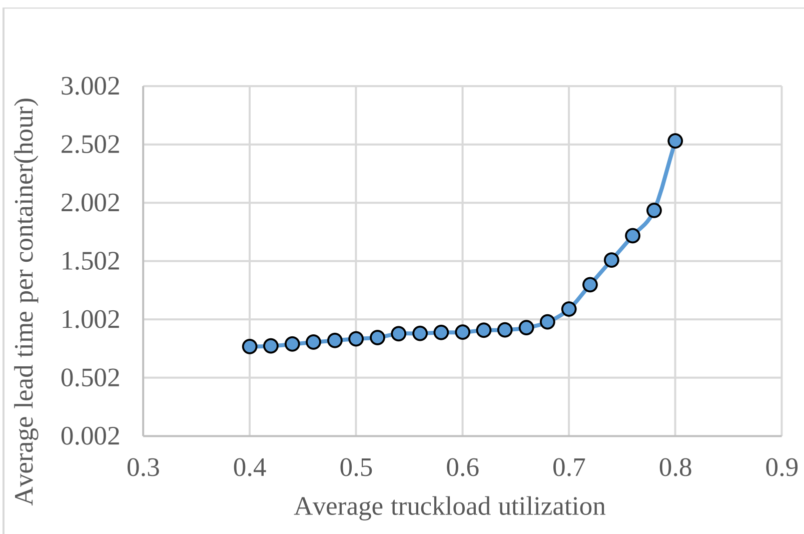


Figure 4.11: Average lead time per container under various values of average truckload utilization per container

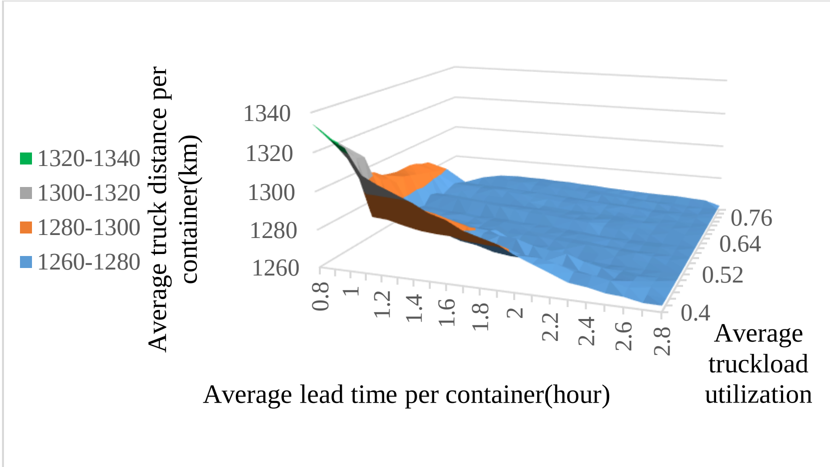


Figure 4.12: Average truck distance per container under various values of average lead time per container and average truckload utilization

4.6 Summary

This section addresses a problem to allocate transport requests to services in PI network. An auction mechanism is designed as the communication protocol between shippers and carriers, where the bidding price is determined as a function of travelling cost and truckload fill rate. An agent-based simulation model is built in an urban area to represent a collaborative freight transportation system. The model adopts an auction mechanism designed for allocating requests more efficiently to consolidate transports. Based on the simulation model, I have (1) developed the simulation based on a logistics system enabled by PI to demonstrate the benefit of horizontal cooperation among service providers and solve the problem on a real urban freight transportation network in a simulation optimization framework; (2) embedded the auction mechanism on the simulation model as an optimization subroutine to match delivery requests and service vehicles in a transport exchange.

CHAPTER V

CONCLUSIONS

5.1 Discussion

In summary, the agent-based simulation model demonstrates the feasibility of an incremental functionality implementation in transition from traditional logistics to PI. The costs are associated with two components: the time that trucks require to transport containers and the distance they travel. The benefits are assessed in terms of the average lead time of a container and the average variation of lead time.

While PD achieved the least truck distance per container, the scenarios predicated on sharing platforms outperforms PD on three out of four key performance indicators. Particularly, the PI represented by SHF performed best on average variation of lead time, three times less than traditional logistics. The model holds more promising results with PI. Reducing empty rides and improving truck fill rates help lowering unit cost per load-distance, making the system more efficient. Comparing the SHF scenario and the SH scenario amplifies the significance cost savings. It is obvious that allowing extra flows decreases the empty and partially filled distance driven, while still 42% of the distance per container is driven empty in the SHF scenario.

On the other hand, a design of an auction mechanism provides a communication protocol between shippers and carriers, where the bidding price is determined as a function of travelling cost and truckload fill rate. The auction mechanism is embedded on the simulation model as an optimization subroutine to match delivery requests and service vehicles in a transport exchange. Furthermore, for freight transport planning, PI has a potential to allocate resources in efficient and environmentally sustainable ways in a shared, open, and collaborative network. To measure the effects of parameter settings in the system, a set of sensitivity analyses is conducted on three single objectives, i.e., average truck distance per container, average truck lead time per container, and average truckload utilization. Moreover, four multi-objectives for optimization have been proposed and explored by combining them together. There are trade-offs in optimal solutions of the decision variables including truck number and truck capacity with regards to the objectives of average truck distance per container and average truckload utilisation. The corresponding results indicate that more trucks and larger capacities contribute to shorter average truck lead time per container. Parameters of maximum wait time and arrival rates have positive impacts on enhancing the collaboration as supported by the results of the sensitive analysis conducted for Objectives 1-3. On the contrary, cost factors including profit margin, variable cost, and fixed cost adversely affect minimising objective values. In multi-objective cases, relationships under multiple criteria assessment in collaborating shipments are inferred in Chapter 4. Longer average lead time allows carriers to achieve the less average truck distance per container. Increasing utilisation of truckload gives the added benefit of shortening average truck distance per container. Nevertheless, there is a trade-off between truckload utilisation and lead time per container.

5.2 Limitations

There are some limitations of these works. First, for the SHF scenario, only a third of the truck time is required per container, whereas the required truck distance per container is

41% higher. Nevertheless, it is noted that the insights drawn from this study is limited due to not practically evaluating every possible parameter value. Another limitation of this study is that we consider only a small amount of flows of freights in the urban area of Louisville in Kentucky; for instance, the outbound flow of 26 warehouses and transshipment flows through the area. Plus, only a handful of hubs are considered and selected in our study, consequently narrowing a scope of consolidating transports in the simulation model. As a result, the system has only a few options for shipment consolidation and flows are unbalanced. In the model, warehouses have only outbound flows and no inbound flows, and the simulated through-traffic utilizes only a subset of hubs in the network. A larger scale problem case warrants further studies in future works.

Next, the formulation of WDP in the auction mechanism considers just cost factors and truck fill rate. In the future research, the model needs to involve other criteria in the stage of truck selection. While logistics as an industry can be disrupted, its stakeholders have an essential role in paving the way for the sharing economy, for example, by streamlining the pickup and delivery of shareable assets as well as reducing transport costs, and thereby growing the overall demand for logistics services. Looking ahead, observing the abundance of idle resources, sharing instead of owning will become a new norm and logistics can be a main driver of this advancement.

Lastly, PI is a context on a platform of a globally interconnected-and-collaborative transportation network. The air-side network is a key to PI for links with urban logistics networks which are most study-focus in the dissertation. Therefore, future research works on air cargo transportation network and airport operations need to be added, which are addressed in detail in Section 5.3.

5.3 Future Research on Gate Assignment Optimization of Urban Distribution Centers and Cargo Airport

5.3.1 Hubs and airport operations in the PI

Handling freight in a hub or airport is time consuming and costly due to a large amount of unloading, sorting, and transferring operations from inbound to outbound trucks. Various docking time in the hub is tested by four scenarios (i.e., 5 minutes, 10 minutes, 15 minutes, and 20 minutes). Differences of lead time between the PI scenario and the current logistics practice are obvious as shown in Figure 5.1. In other words, a less docking time makes a more effective PI system than that of the current practice. An inexpensive way to remove works from the operations is to assign trucks in destinations to the proper doors of the terminal to take advantage of patterns of freight flow. It addresses issues when trucks come in from venders and get their shipments unloaded and reloaded at the shipping/receiving dock of a shipping company. The assignment of dock doors to the incoming and outgoing trucks determines the efficiency of dock operations. The optimal docking operation is an critical piece of components in a model of PI. Therefore, the gate assignment problem needs to be defined and modelled to find an optimization operation of a shorter the total time in a hub or an airport.

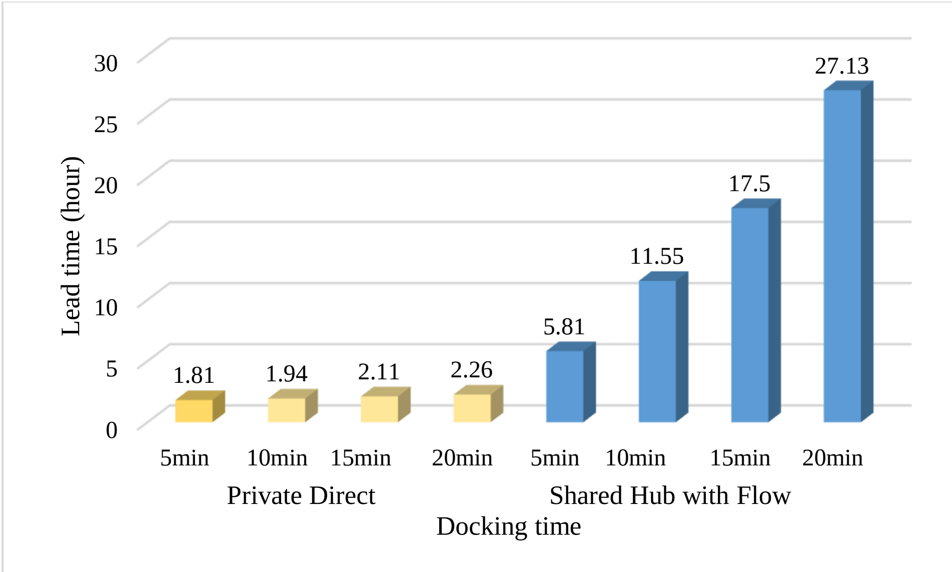


Figure 5.1: Comparison of lead time performance of two scenarios on various docking times

5.3.2 Road-air transportation simulation model

The research demonstrates that PI can be systematically effective in urban logistics. However, due to limitations of the system scale and complexity, the simulation model is supposed to be modified by extending to a multi-urban-system scale and a multi-modal-system complexity. A road-air transportation model is proposed to design and expect to gain more research results in following future works.

A baseline scenario models a current hub-and-spoke air cargo transportation system. In the model, there are one hub and five spokes (See Figure 5.2). Within distances about 300 km from each spoke, there are many warehouses around the major cities, which require to make the freights shipped to nationally wide. Trailers are used as means to transport between those warehouse and spokes. A spoke airport will take cargo with a dedicated cargo flight to the airport hub, which acts as a transshipment point to each spoke.

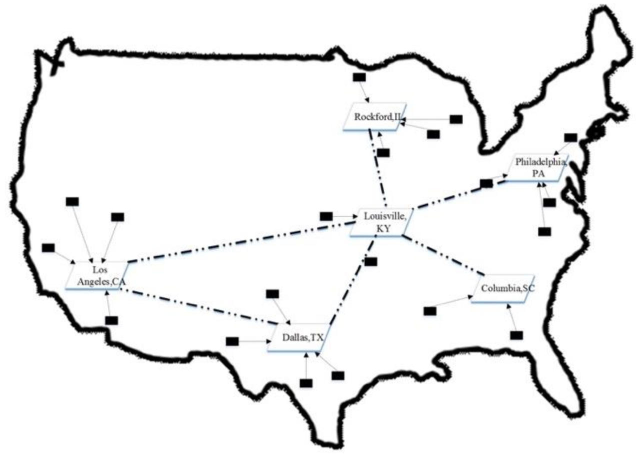


Figure 5.2: The baseline model (hub-and-spoke air cargo transportation system)

A shared-air-cargo-flow scenario is a design of bundling air cargo flow in all available aircrafts including passenger flights and dedicated cargo flights. City airports with passenger dominated flights can be used as transportation carriers to make up the direct shipments by air, which is depicted in Figure 5.3 for this scenario.

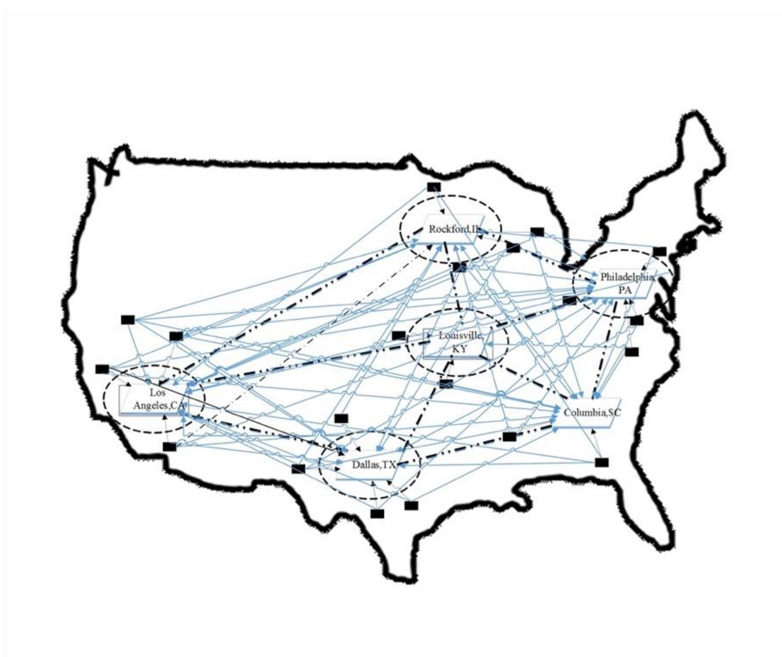


Figure 5.3: A model of the shared-air-cargo-flow scenario

There are some critical agent entities developed in the model, e.g., the aircraft agent, airport agent. Figure 5.4 describes a state flow of an aircraft. An aircraft agent is created in the airport agent and assigned its destination. Figure 5.5 depicts process flows in an airport hub.

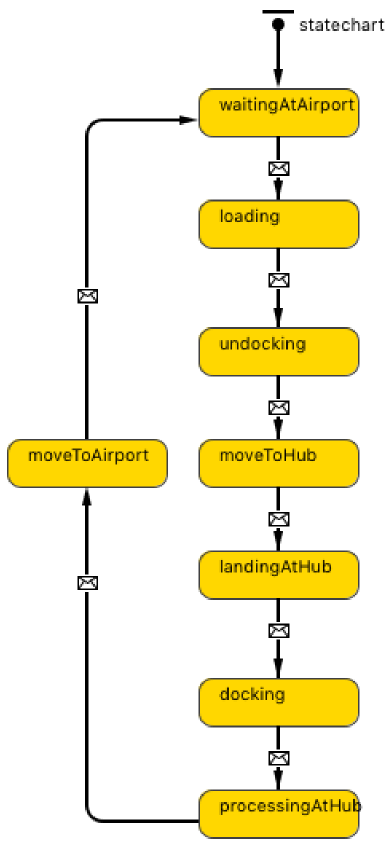


Figure 5.4: State flow simulation of an aircraft instance

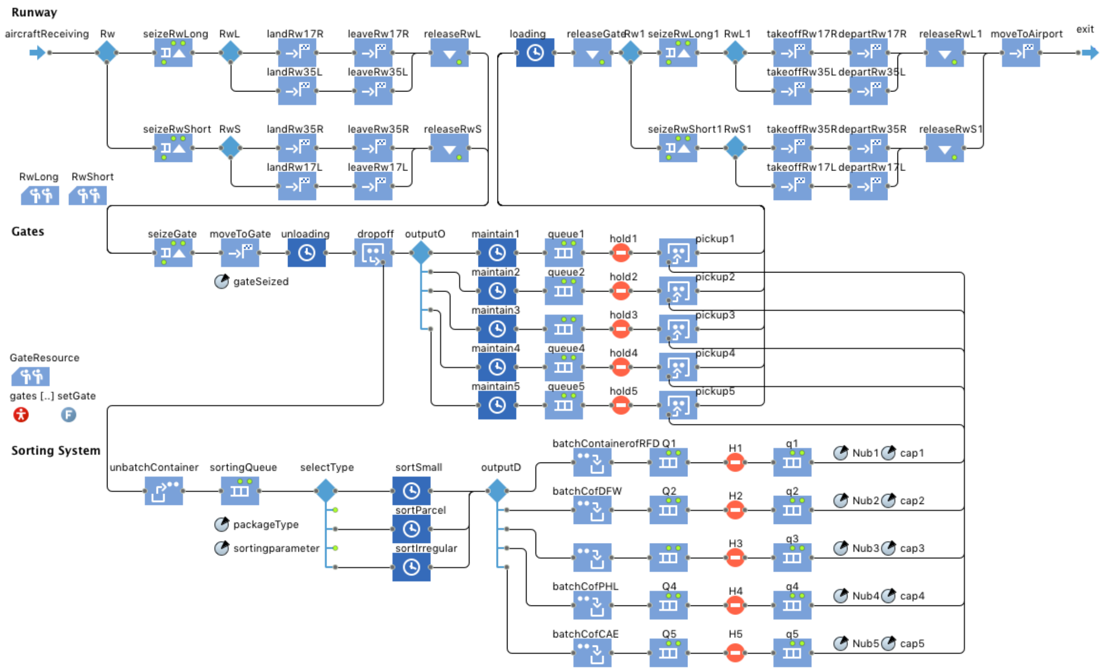


Figure 5.5: An example of process flow simulation of an airport hub instance

5.3.3 Airport gate assignment problem

Last but not least, a gate assignment problem in airports is proposed for a suggestion of future research. Air cargo flows of airport terminal operations are mainly three processes: (un)loading of containers off the aircraft, (un)batching and transporting parcels through terminals, and batching parcels into containers then loading into the determined aircraft. A large cargo airport usually has multiple terminals and likely more than 50 gates. Figure 5.6 illustrates a typical layout of air cargo terminal wing. Within each terminal, there are more than 200 unloading and loading positions. Freights between these positions are carried by an automated conveyor system, whereas the leg from an aircraft gate to a position is handled by labor. In a study, it should be proposed to model the travelling time of freight as well as congestion time due to interference.

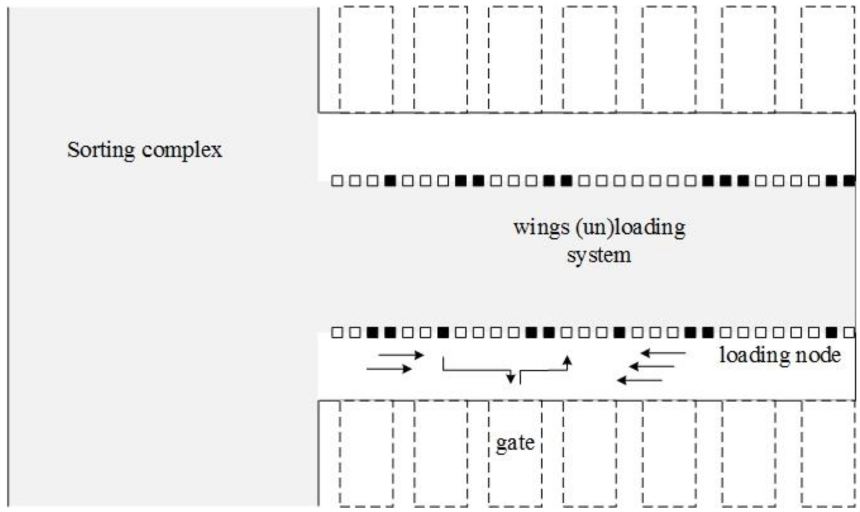


Figure 5.6: A typical layout of air cargo terminal wing

Additionally, an over-constrained cargo airport gate assignment problem is described in a congested airport hub. The problem is required to measure cargo movements based on multi-types of a material-handling system. Ungated aircrafts are parked in a parking lot. The cargo is taken by tugs and dollies to a designated unloading gate. Therefore, a model for the over-constrained cargo airport GAP requires to provide with objectives to minimize the unassigned gates and a total distance between gates.

Several notations of the parameters are shown below:

n: total number of flights;

m: total number of gates at the airport;

a_i: arrival time of flight i;

b_i: departure time of flight i;

d_{kl}: distance for packages from gate k to gate l;

f_{ij} : number of packages transferring from flight i to flight j.

Let y_{ik} =1, if flight i is assigned to gate k; otherwise, 0. Let f_{ijh} represent the amount of freight flowing between fight i and destination fight j using material handling system h. Let c_{ijh} be the time cost in sorting and delivering freight. The cost c_{ijh} depends on the locations of fight i and j, the travel path, and the speed of material handling system h. If s_h is the average speed of moving freight using material handling system h, then the time cost is $c_{ijh} = \frac{d_{kl}}{s_h}$, where the fight i and j are assigned to gate k and l; and d_{kl} stands for the distance between gate k and gate l. Therefore, the total time cost of moving freight in the airport is $\sum_{i,j,h} c_{ijh} f_{ijh}$.

One phenomenon is the congestion due to interference among containers in terminals. As modeled as a single-server queue in the steady-state congestion of each door, the expected queue length of congestion in door j is $L_j = \frac{t\lambda_j\Lambda_j}{\mu(\mu-\lambda_j)}$.

Minimize $\sum_{i=1}^{n} y_{i,m+1}$ (5.1)

and minimize $\sum_{i,j}\sum_{k,l} c_{ijh} f_{ijh} y_{ik} y_{jl} + \sum_j \frac{t\lambda_j\Lambda_j}{\mu(\mu-\lambda_j)}$ (5.2)

subject to,

$$\sum_k y_{ik} = 1 \tag{5.3}$$

$$y_{ik} y_{jk} (b_j - a_i)(b_i - a_j) \leq 0 \tag{5.4}$$

$$y_{ik}, y_{jl} \in \{0,1\} \tag{5.5}$$

The objective function (5.1) minimizes the amount of aircrafts assigned apart from terminals, so as to fulfill the unassigned gates as many as possible. The additional objective function (5.2) minimizes the total time cost of freight in the airport facilities. Constraint set (5.3) guarantees that the aircraft is assigned to the gate or to the parking lot as the ungated. Constraint set (5.4) guarantees that flights cannot overlap if the are assigned the same gate.

Constraint (5.5) is set to say node in the wing should be decided to be unloading or loading node.

In the modelling, two more dummy gates are required, 0 and m+1, where 0 represents the entrance or exit of airport, and m+1 used as lower index stands for directing to the parking lot mainly used in over constrained cases, or large aircrafts like Boeing 747 which need to occupy two gates for placing. Hence, for examples, f_{k0} will represent the number of leaving packages through ground transportation from flight k, and d_{0l} will represent the distance between the airport entrance and gate l. Other similar notations include $y_{i;m+1}$, f_{0l}, and d_{k0}.

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