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Revenue Optimization for Less-than-truckload Carriers in the Physical Internet: dynamic pricing and request selection

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ABSTRACT: This paper investigates a less-than-truckload (LTL) request pricing and selection problem taking forecasting and uncertainty of transport requests at the selected destination into consideration. An optimization model coupling Dynamic Programming and Integer Programming is developed to optimize carrier revenue based on historical data of transport flows. The proposed model is studied in the context of the Physical Internet (PI). PI can be considered as a global interconnected logistics system that connects logistics networks via open logistics hubs. In each hub, LTL requests of different volumes and destinations arrive continually and are immediately allocated or reallocated to carriers. Carriers can bid for these requests through participating auctions. Carriers are confronted with numerous heterogeneous requests and must select one or several requests to bid for while at the same time deciding on a bidding price to maximize profit. Moreover, the carrier needs to forecast the number of requests at the destination hub to improve total profit, for example by improving the backhaul fill-rate. In this research, the number of requests is formulated as a distribution function due to uncertainty. Then, the optimization model is used for a multi-leg dynamic pricing and request selection decision. An experimental study based on real data is conducted to demonstrate the feasibility of the model and the impact of transport forecasting uncertainty on carrier revenue.

Keywords: Less-than-truckload Freight; Revenue Management; Task Selection; Dynamic Pricing; Data-driven Decision Making; Physical Internet

1. Introduction

For freight transport carriers, the request selection problem consists in selecting and pricing the most profitable transport requests out of all the requests placed by shippers at the depot of origin. Once carriers are assigned requests, they can then establish transport plans for direct long-haul routes or for multiple pickup and delivery routes. A transport request can be defined simply as a request to transport an object from one location to another. When selecting requests, carriers should forecast upcoming requests at the destination in order to improve total profit. Typical examples include backhaul transport (Zhou et al., 2009, Berling et al., 2016) and request exchange between carriers (Berger et al., 2010, Vanovermeire et

al., 2014, Xu et al., 2016). To help decision-making, carriers forecast the number of requests based on historical data, which is the forecasting problem in this paper.

Request pricing and selection play a vital role in optimizing a carrier's revenue, especially as competition is fierce in the transport market - the top 10 third-party logistics providers (3PLs) in Europe only have a market share of 5% (AECOM 2014). An increasing number of Member States have joined the European cabotage market, which has grown significantly in the market share in recent years. This shows the growing competition in this major, newly emerged market. Over the past few decades, competition in the less-than-truckload (LTL) segment has been increasing while the market has been shrinking. This is due to the fact that the LTL market share has been eroded by the Full-truckload (FTL) market and by the package/courier market (Prokop 2014). Here, the LTL market is operated by LTL trucking companies who handle pallet-size LTL shipments, e.g., *FedEx Freight*, *YRC Freight*, and the package/courier market concerns small-size shipments handled by parcel shipping companies, e.g., *FedEx Express*, *UPS*. According to the definition of the European Commission (2015), the LTL segment transports goods weighing between 30 kg and 2 to 3 tonnes while the courier segment covers shipments weighing less than 31 kg. In the current competitive environment, logistics service providers (LSP) need to concentrate more on revenue management. Revenue optimization has been studied intensively at operational level or transport planning level. For example, Liu et al., (2010) and Li et al., (2015) investigate the request selection problem in the field of FTL collaboration with the objective of minimizing costs or maximizing profit. Figliozzi et al., (2007) propose dynamic vehicle routing pricing to optimize carrier revenue. In Luo et al., (2015), the authors present how to use dynamic forecasting to optimize revenue in intermodal transportation. Innovative logistics organization models such as horizontal collaboration (Cruijssen et al., 2007, Hernández et al., 2011, Özener et al., 2011) and the Physical Internet (Ballot et al., 2014, Sarraj et al., 2014, Pan et al., 2015) have recently been proposed to improve logistics efficiency as well as the revenue of LSPs. However, the application of revenue management in innovative logistics organizations has not been studied adequately. It is, therefore, important to investigate the use of the revenue optimization problem using these new logistics organization models.

This paper introduces and investigates the revenue optimization problem for LTL carriers in the Physical Internet (PI). PI is a global interconnected logistics system that connects logistic networks via open logistic hubs, i.e. PI-hubs where carriers can acquire transport requests or exchange in-hand requests for transport efficiency (Montreuil 2011, Montreuil et al., 2013). In PI-hubs, shippers and carriers can offer transport requests encapsulated in modular and standard PI-containers. The requests are mostly LTL requests with different destinations and volumes (or quantities) that arrive over time (Ballot et al., 2014, Sarraj et al., 2014, Qiao et al., 2016). Carriers propose prices to win requests. The requests are then

optimally allocated to carriers (for the lowest price, for example). The auction mechanism is one of the most efficient solutions for request allocation in PI-hubs (Huang et al., 2013, Xu et al., 2013, Kuyzu et al., 2015). Moreover, the allocation process in PI-hubs is very dynamic due to stochastic demands and offers. As a result, carriers need to propose dynamic prices for different requests to maximize profit. In addition, due to a finite capacity and route restrictions, carriers are unable to bid for all requests and must bid for the requests that will bring them the highest profit.

More precisely, this paper aims to provide a method and models to help LTL carriers make their pricing and request selection decisions in PI-hubs. We aim to help LTL carriers decide which requests to bid for and at what price while simultaneously considering upcoming requests in the next hubs based on historical freight flow data. In general, two decisions should be made by LTL carriers in order to optimize revenue, i.e. pricing and selection of requests to be fulfilled. The pricing problem has already been studied in the literature. For example, Qiao et al., (2016) investigate dynamic pricing decisions for one-leg and single-size LTL requests in a hub with the objective of optimizing the carrier's price and maximizing their global profits in a PI-hub. In this paper, we extend the one-leg situation to multi-legs. In a given PI-hub, a carrier is confronted with many requests of varying quantity and destination. To maximize profits, we assume that the carrier takes into account the predicted situation at the next hub (quantity and destination of requests) when selecting and pricing requests. This extends the pricing problem in Qiao et al., (2016) to the request selection problem. For that, based on a dynamic pricing model, we propose two integer-programming models for two different scenarios to select the request to bid for in order to maximize the carrier's profit. The first one considers a full capacity carrier (without load and destination). The other one considers a partially loaded carrier with a determinate destination. This paper aims to provide decision-making models for carrier request selection decisions in PI-hubs and to investigate the following questions: 1) which factors influence the request selection decision; 2) how forecasting and the uncertainty of the request quantity distribution influence the request selection decision compared to no forecasting.

This paper is organized as follows. Section 2 presents a literature review of the related research in order to identify research gaps and position our contribution. Section 3 describes the request pricing and selection problem in PI, which is formulated in Section 4. Section 5 investigates how the transport factors influence pricing and selection decisions. Then, in Section 6, the proposed model is applied to real-life cases with real data to demonstrate its feasibility. Finally, Section 7 concludes this work and presents some research prospects.

2. Literature Review

Two research problems in the freight transport literature are related to this paper and will be discussed in this section: dynamic pricing for revenue management and request selection.

2.1 Dynamic pricing for revenue management in freight transport

Pricing in revenue management aims to determine various prices for different customers and to maximize revenue over time (Chiang et al., 2006). Firms always use dynamic pricing to respond to market fluctuations and demand uncertainty (Talluri et al., 2006). According to Bitran et al., (2003), in practice, dynamic pricing is particularly useful for industries with high start-up costs, perishable capacity, short selling horizons, and demand that is both stochastic and price sensitive such as the airline industry, retailers, car rental, hotels, and passenger railways.

However, in freight transport, dynamic pricing has not been applied widely, especially in the LTL transport industry. In air cargo transport, for example, under the traditional allotment mechanism cargo carriers just need to decide whether to accept the shipments at a given price (Kasilingam 1997). Amaruchkul et al., (2007) discuss how to choose the right policy to help the carrier decide dynamically whether or not to accept the incoming shipment according to the remaining capacity and waiting time. However, no attention has been paid to dynamic pricing for transport requests. In railway freight transport, Kraft (2002) and Crevier et al., (2012) both investigate how to maximize carrier revenue. A scheduling problem is discussed in the former while a pre-established optimal set of prices is provided in the latter. The price is determined statistically and statically in both these studies. In road freight transport, in both the TL and LTL sectors, there is still very little research regarding dynamic pricing decisions. In TL pricing, opportunity costs, which can describe the loss in expected future revenue due to fulfilling a new request, are studied the most. Figliozzi et al., (2006) consider opportunity costs in the context of a dynamic routing problem modeled in a stochastic simulation framework. Based on this research, Figliozzi et al., (2007) propose a carrier pricing strategy for the dynamic vehicle routing problem. Similarly, the pricing strategy of vehicle agents considering the opportunity cost of inserting a new request in a current task sequence is discussed in Mes et al., (2006). In the LTL transport sector, reference (Douma et al., 2006) discusses how to determine the price of loads dynamically to maximize carrier profit according to the remaining capacity and the time left before departure. In Qiao et al., (2016), the authors also present the dynamic pricing problem for one-leg transport requests with an auction mechanism.

The pricing problem in request selection in PI discussed in this paper is quite different from the studies mentioned above. First, the dynamic and stochastic environment in PI makes pricing more complex than in a traditional transport network. Then, in request selection, carriers are confronted with a variety of

requests of varying number and routes. However, while most of the current research investigates single-leg transport problems, pricing is based on multi-leg requests and very little attention has been paid to the multi-leg LTL request pricing problem in the literature.

2.2 Request selection in freight transport

In the freight transport literature, request selection has been particularly discussed in the area of transport collaboration. For example, how to select which requests that carrier received from customers to be subcontracted to other carriers (see Berger et al., (2010) and Xu et al., (2016)). Two references relevant to the problem investigated in this paper can be found. In Liu et al., (2010), the authors present the task selection and routing problem for TL carriers in collaborative transportation. The objective is to minimize the total cost when a carrier serves the requests. According to their model, the carrier just needs to decide which requests to fulfill and which to outsource to external carriers but does not need to decide on the price of the request. In Li et al., (2015), the authors focus on the request selection and exchange problem between carriers in collaborative transportation. Carriers need to select requests for outsourcing and sourcing with the objective of maximizing their profit. The auction-based exchange of requests with the objective of maximizing overall profit is also introduced. However, we are unable to use either of these methods to solve our problem directly. First, the focus of the studies is not on request pricing, but on solving the fleet management problem with pre-established requests. Second, the environment researched is static and the future situation after request selection is not considered. This is very different from the very dynamic and stochastic environment of PI-hubs.

The traveling salesman problem with profits (TSPP) and the vehicle routing problem (VRP) also investigate request selection in freight transport. As stated in Feillet et al., (2005), TSPP is a generalization of the traveling salesman problem (TSP) and each vertex is associated with a profit. The multi-objective of this problem is to maximize the profit collected while minimizing travel costs. According to the way the objectives are addressed, TSPP can be divided into three categories: profit tour problems, orienteering problems, and prize collecting TSPs. The profit in TSPP is related to a vertex. The TSPP can be extended to the vehicle routing problem (VRP) taking profit into account. In Figliozzi et al., (2007), the TSPP is generalized to the VRP in a dynamic environment. The authors investigate the pricing problem for a TL carrier using an auction mechanism in order to determine a vehicle route that maximizes the carrier's profit. In reference Aras et al., (2011), the authors discuss the VRP for the reverse logistics problem in which vehicles have to pay the customers when they visit them. In the context of the VRP, the pickup and delivery problem (PDP) is also related to request selection, see Berbeglia et al., (2007) who provide a survey of static PDPs and the methods used. Gansterer et al., (2017) investigate the multi-vehicle profitable PDP in which LTL paired pickup and delivery requests are selected with the objective

of maximizing the total profit the carrier can collect from the requests fulfilled. Moreover, each request provides a fixed revenue. Likewise, the dial-a-ride problem is similar to the PDP. Egan et al., (2016) propose a mechanism to optimize the scheduling, routing and passenger pricing of on-demand services, which highlights the key role of provider profit in allocating resources.

Other research proposes considering demand forecasting in request selection. Ichoua et al., (2006) present how to exploit information about future events to improve vehicle fleet management with the objective of minimizing the total cost of fulfilling the possible requests. However, the vehicle dispatching problem is solved rather than the request selection problem. Thomas et al., (2004) propose a similar fleet management problem while considering the revenue to fulfill the request. Figliozzi et al., (2007) forecast possible transport requests associated with an incoming probability for each. Some dynamic pricing research also addresses how to forecast future customer demands to improve pricing decisions. For example, Lin (2006) develops a real-time learning method to improve forecasting of future customer numbers over a time horizon, and thus to adjust the pricing decision dynamically in real time. Some other research assumes that customers/demands arrive according to a discrete or continuous probability distribution (Gallego et al., 1994, Chatwin 2000). The main objective of these studies is to determine how to make dynamic pricing decisions based on the forecasting result. Differently, in this paper, we are interested in selecting requests according to the forecasting result of future demands at the destination. Moreover, we also discuss how the uncertainty of the forecasts can influence the request selection decision.

Overall, the LTL request pricing and selection problem in PI with consideration of request forecasting based on historical data is a new research problem and has been addressed very little in the literature. First, in a stochastic and dynamic environment such as PI, request numbers and routes vary from hub to hub. Different requests can bring the carrier different profits. Therefore, carriers should pay more attention to how to select requests due to limited capacity, which is a new research problem in traditional transport networks. Second, the carrier's route will depend on the requests selected in PI. However, this is quite different from the classical VRP as it focuses on how to minimize transport costs based on known demands (sometimes with known price), while the request selection problem in PI aims to maximize revenue based on a dynamic pricing decision. Third, in PI, requests are allocated very frequently, which means information regarding requests in the next hub changes frequently. Carriers thus need to forecast upcoming requests at the next destination when making the request selection decision. The aim of this paper is to contribute to the literature on PI and request selection by investigating this new research problem.

3. Problem Description

3.1 Request selection problem definition

The Physical Internet consists of a number of interconnected PI-hubs for freight flow transit. In each hub, shippers can submit transport requests for which carriers can provide transport services. A transport request can be defined as r_{ij}^v , where v is the volume, i is the origin, and j is the destination. We assume that the quantity of requests is huge at the hub and that they will be allocated to carriers via an auction mechanism. This means carriers have to participate in a sequence of auctions to win the requests, taking into account their constraints of capacity (capacity-finite) and time to departure (time-finite). We define the requests with the same route (i,j) as one type of request R_{ij} . In a PI-hub, there will be many different types of requests with different quantities. The transportation cost and the carrier's expected profit associated with each type could be very different. In this context, we could assume that the carrier will adopt a dynamic pricing strategy to maximize the profit.

This paper focuses on how a carrier should select the request type to bid for and decide on the bidding price to maximize the profit. To simplify the problem, it is assumed that request type bundling is not considered, which means a carrier just chooses one type of request to bid for and bids for requests one by one. When selecting the request type R_{ij} , the carrier needs to consider and forecast upcoming requests at destination j in order to improve total revenue. The result will be the request types that the carrier should bid for and also a route consisting of several PI-hubs that will give the carrier the most profit. This is the request selection problem considering forecasting based on dynamic pricing in PI.

In general, there are two kinds of carriers: full-capacity carrier with no determinate destination and loaded carrier with a determinate destination. They are discussed in two scenarios, respectively.

Scenario 1: Full-capacity carrier with no determinate destination

Full-capacity carrier means that the carrier has no request in hand and thus has no determinate destination. The latter will depend on the requests the carrier wins.

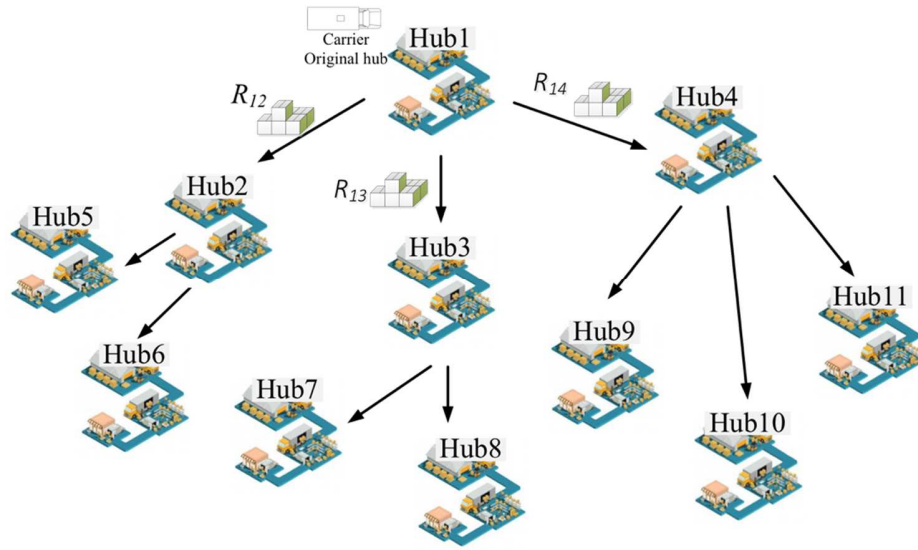


Figure 1. Illustration of Scenario 1

Taking the simple transport network in Figure 1 as an example, let $G = (H, A)$ represent the network, where $i \in H$ is the hub and $(i, j) \in A$ is the route between two hubs. A full-capacity carrier arrives at a PI-hub where there are several types of requests R_{ij} (R_{12} , R_{13} , R_{14}) with different quantities N_{ij} . The carrier must choose one type of request to bid for and at the same time decide on a bidding price to maximize the expected profit. When making the decision, the carrier should consider upcoming requests at the hub the requests currently selected will take them to. Without loss of generality, we just consider the hub one-step ahead, i.e. the hub that the carrier will go to next and not the hub the carrier might go to after the next hub. Thus here, the carrier just needs to consider the requests in hub2, hub3, and hub4. For example, if the carrier selects requests R_{12} , he should consider if the requests in hub2 can provide a greater profit. As a result, the carrier will choose a route that provides the greatest expected profit, e.g. $\text{hub1} \rightarrow \text{hub2} \rightarrow \text{hub6}$.

Scenario2: Loaded carrier with determinate destination

Contrary to a full-capacity carrier, a loaded carrier has already acquired some requests and thus has a determinate destination to go to deliver the requests in hand. If these requests cannot fill the carrier's whole capacity, the carrier could travel to other hubs to collect some requests on the way to the destination hub, with the objective of maximizing the fill rate and profit.

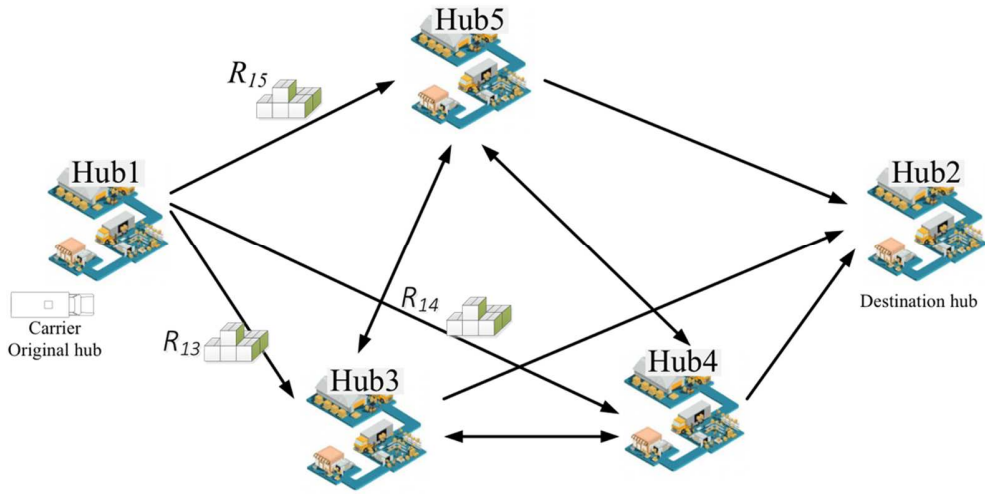


Figure 2. Illustration of Scenario 2

Some intermediary hubs, e.g. hub3, hub4, and hub5 in Figure 2, are located along the carrier's route to the destination hub (hub2). The quantity of requests from one hub to another is different and in addition, N_{ij} and N_{ji} are different. The carrier needs to decide which hubs to travel through and which type of requests to bid for in each hub. Finally, the carrier chooses the most profitable route consisting of several intermediary hubs and the order, e.g. hub1 → hub3 → hub4 → hub2 or hub1 → hub4 → hub3 → hub2.

3.2 Factors influencing request selection

In this context, we investigate which factors have significant influence on the request selection decision. To this end, three factors are identified and evaluated independently in an experimental study.

Request quantity: the number of different types of request determines the maximum number of auction periods that the carrier can participate in. According to Qiao et al., (2016), the number of requests for one route will influence the carrier's expected profit, and therefore the request selected. In this paper, we will investigate if this conclusion is still tenable in a network.

Route distance: the distance will decide the transport cost for carriers, which is closely related to the average price of the requests along this route. Thus, whether the route distance can influence the request selection decision by influencing the price of requests should be investigated.

Forecasting uncertainty: according to the description above, the carrier needs to forecast the number of upcoming requests at the next hubs based on the historical data. The forecasting result is the request quantity distribution during one auction period. The forecasting uncertainty here is the request quantity distribution at a given time, which means the dispersion of the historical request quantity, also known as the distribution variance. In real transportation hubs, there are a huge number of requests and the

distribution uncertainty of the number of different types of requests is variable. Two types of requests with the same average quantity might have totally different uncertainties, e.g. the average quantity is 100 for both but one ranges from 90 to 110 and the other from 60 to 130. By considering this factor, we discuss whether and in which situation the forecasting uncertainty can influence the request selection decision.

4. Model Formulation

4.1 Notions and Methodology

The following notions and methodology (see Figure 3) are used to describe and model the problem.

r : the index of requests remaining in the auction period. We assume that a vehicle can bid n times at most if there are n requests during the auction period, so $r = n, n-1, \dots, 1$.

S : the capacity of a vehicle, which is assumed to be 20 *units* in the experimental study. We also assume the requests in this paper have a uniform size of one *unit*.

(i,j) : the route of one type of request.

Dis_{ij} : the distance from hub i to hub j .

C_u : unit cost, i.e. the cost to deliver a uniform-size request in unit distance, here $C_u = 1 \text{ €/unit-km}$.

C_{ij} : the cost of fulfilling a request for route (i,j) , i.e. $C_{ij} = C_u * Dis_{ij}$.

N_{ij} : request quantity (number) from hub i to hub j .

(s_r, n, c) : the vehicle status, defined according to the remaining capacity s_r when bidding for r requests, the total quantity of requests n to bid for and the travel cost c .

$p(y)$: the probability of winning with a given bid price y at an auction. Based on Qiao et al., (2016), we have $p(y) = e^{-\left(\frac{y}{\lambda}\right)^k}$. We assume that the average price $\lambda = 1.1 * c$, which comes from actual market operations, and $k=5$.

$V_r(s_r, n, c)$: the expected maximum profit for one type of request with the status (s_r, n, c) .

$V_{ij}(S)$: the maximum expected carrier profit with the request for route (i,j) .

$VF_{ij}(S)$: the maximum expected carrier profit with the request for route (i,j) and forecasting quantity.

A : the set of request routes, $(i,j) \in A$. (O,D) represents the original hub and the destination hub.

Y : the set of bid prices, i.e. range of prices to be tested in the model.

Variable:

y : bid price given by the carrier for a request during each auction period. The optimal bid price determined by the model is noted as y^* and $y^* \in Y$. Moreover, $y \geq 0$.

x_{ij} : the binary variable, set to one if carrier selects request from hub i to hub j , and $i \neq j$.

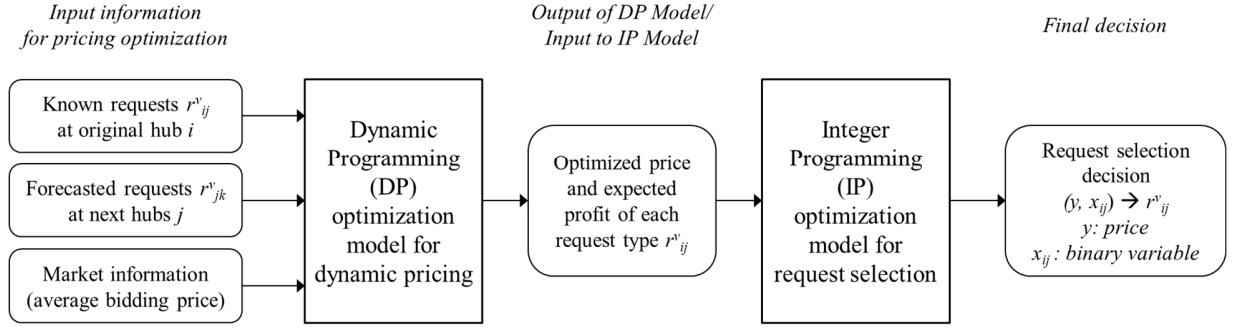


Figure 3. Modeling Methodology

4.2 Dynamic pricing model

We extend the one-leg pricing model in Qiao et al., (2016) to multi-legs. The main difference is that the different travel costs associated with the route are considered in the model. The multi-leg dynamic pricing model is presented below.

$$V_r(s_r, n, c) = \max_{x \in X} [p(y) * [y - c + V_{r+1}(s_r - 1, n, c)] + (1 - p(y)) * V_{r+1}(s_r, n, c)], r = 1, \dots, n \quad (1.1)$$

$$V_r(s_r, n, c) = 0, \text{ if } s_r \leq 0 \text{ OR } r > n \quad (1.2)$$

$$V_{ij}(S) = V_1(S, N_{ij}, c_{ij}) \quad (1.3)$$

Function (1.1) is a recursive function to calculate the carrier's maximum expected profit when bidding for r requests using price x with a remaining capacity of s_r and travel cost c . When the carrier wins a request, its capacity is minus 1, otherwise, the actual capacity does not change. Function (1.2) is the boundary condition representing the expected profit, which is 0 when the capacity is sold out or there are no more requests to bid for. Finally, function (1.3) is used to calculate the maximum expected profit V_{ij} obtained with the request for route (i, j) .

4.3 Request selection model not considering forecasting

First, we design the models without considering forecasting. We assume that the number of requests in the next hubs is already known and will not change.

Scenario 1: Full-capacity carrier with no determinate destination

Based on the dynamic pricing model above, an integer programming (IP) model to select requests for the carrier is given as (2.1) - (2.4). This model is constructed according to the idea of maximum expected profit.

Objective :

$$Max \sum_{(i,j) \in A} V_{ij}(S) * x_{ij} \quad (2.1)$$

Constraints:

$$x_{ij} - \sum_{(j,k) \in A} x_{jk} \geq 0, (i,j) \in A \quad (2.2)$$

$$\sum_{(i,j) \in A} x_{ij} \leq 1, i \in N \quad (2.3)$$

$$x_{ij} \in \{0,1\}, (i,j) \in A \quad (2.4)$$

The objective function (2.1) maximizes the carrier's total expected profit after selecting one type of request to bid for. Constraint (2.2) ensures that information relating to upcoming requests in the next hub will only be considered if the request going to this hub is selected. Constraint (2.3) ensures only one type of request can be selected in one hub.

Scenario 2: Loaded carrier with determinate destination

Similar to scenario 1, an integer programming (IP) model to select requests for the loaded carrier is formulated below.

Objective:

$$Max \sum_{(i,j) \in A} V_{ij}(S) * x_{ij} - (\sum_{(i,j) \in A} Dis_{ij} * x_{ij} - Dis_{OD}) * N_{OD} * C_u \quad (2.5)$$

Constraints:

$$\sum_{(i,j) \in A} x_{ij} - \sum_{(j,k) \in A} x_{jk} = 0, j \in N^- \quad (2.6)$$

$$\sum_{(i,j) \in A} x_{ij} \leq 1, i \in N^- \quad (2.7)$$

$$\sum_{(O,j) \in A} x_{Oj} = 1 \quad (2.8)$$

$$\sum_{(i,D) \in A} x_{iD} = 1 \quad (2.9)$$

$$x_{ij} + x_{ji} \leq 1, i \in N^-, j \in N^- \quad (2.10)$$

$$x_{ij} \in \{0,1\}, (i,j) \in A \quad (2.11)$$

Function (2.5) maximizes the carrier's expected profit after selecting the intermediary hubs to go through. The first term represents the total expected profit gained from passing through the intermediary hubs. The second term calculates the detour cost for loaded requests in hand where N_{OD} is the number of loaded requests. Constraint (2.6) imposes a balance in each hub, i.e. if the carrier travels to a hub it must leave from this hub, except for the hubs of origin and destination. Constraint (2.7) ensures only one type of request can be selected in one hub. Constraints (2.8) and (2.9) ensure that for the hubs of origin and destination, only one type of request goes out and in. Finally, constraint (2.10) prevents the carrier from going back and forth between two hubs.

4.4 Request selection model considering forecasting

In reality, the carrier is not able to accurately know how many requests there will be when he arrives at the following hubs after a period of travel. The carrier can only use the historical data to estimate the possible number of requests, which is normally given as a probability distribution.

Following some similar studies (Kuyumcu et al., 2000, Helve 2015, Hassani et al., 2017), in this research, we also use Normal Distribution to model the request quantity distribution in the next hubs. We assume the distribution of the quantity N_{ij} of requests R_{ij} is Normal $N(\mu_{ij}, \sigma_{ij}^2)$ with the following density function:

$$f_{ij}(x) = \frac{1}{\sqrt{2\pi}\sigma_{ij}} e^{-\frac{(x-\mu_{ij})^2}{2\sigma_{ij}^2}}$$

So the probability that no more than k requests arrive will be:

$$P_{ij}(N_{ij} \leq k) = \int_{-\infty}^k f_{ij}(x) dx = \frac{1}{\sqrt{2\pi}\sigma_{ij}} \int_{-\infty}^k e^{-\frac{(x-\mu_{ij})^2}{2\sigma_{ij}^2}} dx$$

Equation (1.3) to calculate the expected profit from request R_{ij} will be transformed to:

$$VF_{ij}(S) = \int_0^N V_1(S, k, c_{ij}) f_{ij}(k) dk \quad (1.4)$$

where N is a large number and k is the possible number of requests. But this integration formula has a dynamic programming function inside, which makes the equation very complex to solve. To simplify the calculation and without loss of generality, we approximate the continuous probability with a discrete probability, that is, we calculate the probability that k requests arrive as follows:

$$P_{ij}(N_{ij} = k) = P_{ij}(k) = P_{ij}(N_{ij} \leq k + 0.5) - P_{ij}(N_{ij} \leq k - 0.5)$$

Then equation (1.4) can be transformed to:

$$VF_{ij}(S) = \sum_0^N P_{ij}(k)V_1(S, k, c_{ij}) \quad (1.5)$$

As the number of requests in the current hub is already known, when calculating the total expected profit, the carrier just needs to consider the predicted number of requests in the following hubs. So, the objective functions (2.1) and (2.5) become:

$$Max \sum_{(i,j) \in A_O} V_{ij}(S) * x_{ij} + \sum_{(i,j) \in A_{O-}} VF_{ij}(S) * x_{ij} \quad (2.12)$$

$$Max \sum_{(i,j) \in A_O} V_{ij}(S) * x_{ij} + \sum_{(i,j) \in A_{O-}} VF_{ij}(S) * x_{ij} - (\sum_{(i,j) \in A} Dis_{ij} * x_{ij} - Dis_{OD}) * N_{OD} * C_u \quad (2.13)$$

Where A_O represents the routes departing from the original hub and A_{O-} represents the other routes in the network. All the constraints (2.2) - (2.4) and (2.6) - (2.11) stay the same because the predicted number of requests just changes the way in which the expected profit of each type of request is calculated.

5. Investigation of Influencing Factors

Based on the proposed model, this section qualitatively investigates the influence of the three factors discussed in 3.2. Here, we are interested in studying the influence of these factors on the profit rather than the pricing decision for the requests.

5.1 Request quantity and route distance

Without loss of generality, the experimental design is based on the simplified networks shown in Figure 1. As discussed in 3.2, the number of requests and the route distance are two factors that might influence the request selection decision. We evaluate the influence of the factors separately. The quantity for each request type is randomized over four levels (5-50, 51-100, 101-150, 151-200) and each distance is randomized over three levels (20-100km, 200-300km, 400-500km). Two groups of experiments are conducted. The input data and results are presented in Table 1 and Table 2.

- The first group using the input data in Table 1, which gives the same distance but different quantities of each type of request over four levels, is used to study how the number of requests influences request selection. We find that the route that maximizes the carrier's expected profit always has the highest total number of requests. However, the route with the lowest total number of requests minimizes the profit. This result shows that the carrier should select the route with the most requests if the travel distance is the same. Nevertheless, the difference between the maximal and the minimal expected profit decreases as the request quantity increases.

- The second group based on the data in Table 2 is used to evaluate the influence of the travel distance on request selection. The results show that the longest route maximizes the carrier's expected profit, which can be explained by our assumption that the travel cost is the distance multiplied by a fixed unit cost and the average market price is 1.1*the travel cost, and so the expected profit will increase as the distance increases. If the number of different requests is the same, the carrier should select the one with the longest distance.

The results also show that the number of requests and the travel distance influence the decision simultaneously. An optimization model is, therefore, essential to help carriers select the most profitable ones out of the numerous heterogeneous requests.

Table 1. Same distance, different number over four levels

Random Quantity Range	Input Data (distance is 50 km for all routes)										Output Results			
	Request Quantity										Solution for Maximal Expected Profit		Solution for Minimal Expected Profit	
	R ₁₂	R ₁₃	R ₁₄	R ₂₅	R ₂₆	R ₃₇	R ₃₈	R ₄₉	R ₄₋₁₀	R ₄₋₁₁	route	profit	route	profit
(5-50)	40	13	27	50	39	30	36	8	48	5	1-2-5	195	1-4-11	69
(51-100)	91	98	63	83	76	82	100	85	83	58	1-3-8	386	1-4-11	261
(101-150)	124	137	138	124	106	124	146	148	102	111	1-4-9	475	1-2-6	422
(151-200)	172	189	171	167	195	192	190	156	158	179	1-3-7	538	1-4-9	505

Table 2. Same number, different distance over three levels

Random Distance Range (km)	Input Data (request quantity is 100 for all hubs)										Output Results			
	Route Distance										Solution for Maximal Expected Profit		Solution for Minimal Expected Profit	
	D ₁₂	D ₁₃	D ₁₄	D ₂₅	D ₂₆	D ₃₇	D ₃₈	D ₄₉	D ₄₋₁₀	D ₄₋₁₁	route	profit	route	profit
(20-100)	83	79	67	93	21	36	39	92	91	20	1-2-5	686	1-4-11	341
(200-300)	220	292	246	203	291	249	289	271	202	294	1-3-8	2262	1-2-5	1647
(400-500)	438	422	479	427	444	476	444	439	498	453	1-4-10	3803	1-2-5	3370

5.2 Forecasting uncertainty

Now we investigate the influence of forecasting uncertainty on the request selection decision. Forecasting uncertainty is defined as the dispersion of the request quantity historical data, which can also be represented by the request quantity distribution variance. When the average number of requests μ is determinate, we calculate the variance as follows: (1) as Figure 4 shows, we assume 98% of the quantity are distributed in the range $[\mu*(1-x), \mu*(1+x)]$, where $0 < x < 1$; (2) based on the symmetrical features of

Normal Distribution, we obtain the variance σ^2 by solving the equation $P(\mu * (1 + x)) = 0.99$, where P is the cumulative distribution function.

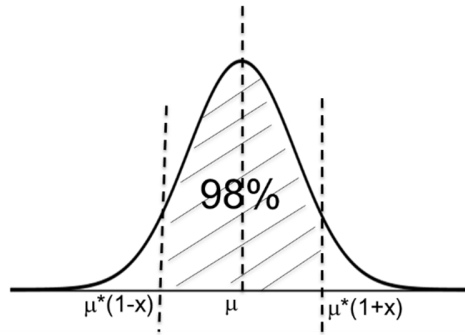


Figure 4. Request quantity distribution function

Without loss of generality, we can take just one type of request, e.g. R_{25} in Figure 1, to qualitatively study how forecasting uncertainty influences the expected profit based on equation (1.5). In this experiment, we consider 9 degrees of dispersion, that is x changes from 0.1 to 0.9 in increments of 0.1. In addition, we conduct the test at different average levels of request quantity and route distance. The average number of requests increases from 10 to 200 in increments of 10 while the route distance varies from 10 to 400 in increments of 10. We thus can obtain 7200 sets of input data of which the output is the expected profit. Some of the results are shown in Figure 5 and Figure 6.

As shown in Figure 5 and Figure 6, we can observe that when the average number of requests and the route distance stay the same, the smaller the uncertainty and the higher the expected profit. This can be concluded by the negative linear correlation ($R^2 > 0.9$ in most cases). However, the influence of the uncertainty on the expected profit varies according to the levels of request quantities and route distances.

(1) Same route distance: as the average number of requests increases, the expected profit increases very fast, but the rate of increase begins to decrease and drops dramatically once a specific number of requests is reached. We can see from the bottom half of Figure 5 that the negative linear correlation becomes more significant along with the increase in request quantity. This means the uncertainty does not significantly influence the expected profit and a greater number of requests always gives a higher profit and should be selected, no matter how the uncertainty changes. However, as the average number of requests increases, the uncertainty has a more significant influence on the profit and can influence request selection. For example, 190 requests with an uncertainty of 0.3 produce a greater profit than 200 requests with an uncertainty of 0.9, so the carrier should select the request with the quantity of 190. This result can help the carrier to decide whether to consider the forecasting uncertainty when making decisions.

(2) Same number of requests: with the increase in route distance, the expected profit increases linearly based on the assumption in 4.1 regarding the relation between average price and transport cost. The conclusion being the same as above, the uncertainty influences the expected profit significantly and can influence request selection when the distance is long (see Figure 6).

According to the experimental results in 5.1 and 5.2, all three factors (request quantity, route distance, forecasting uncertainty) work together to influence request selection. It is therefore complicated to select requests with different quantities, travel distances and uncertainties. This is why our models are useful for solving the request selection problem.

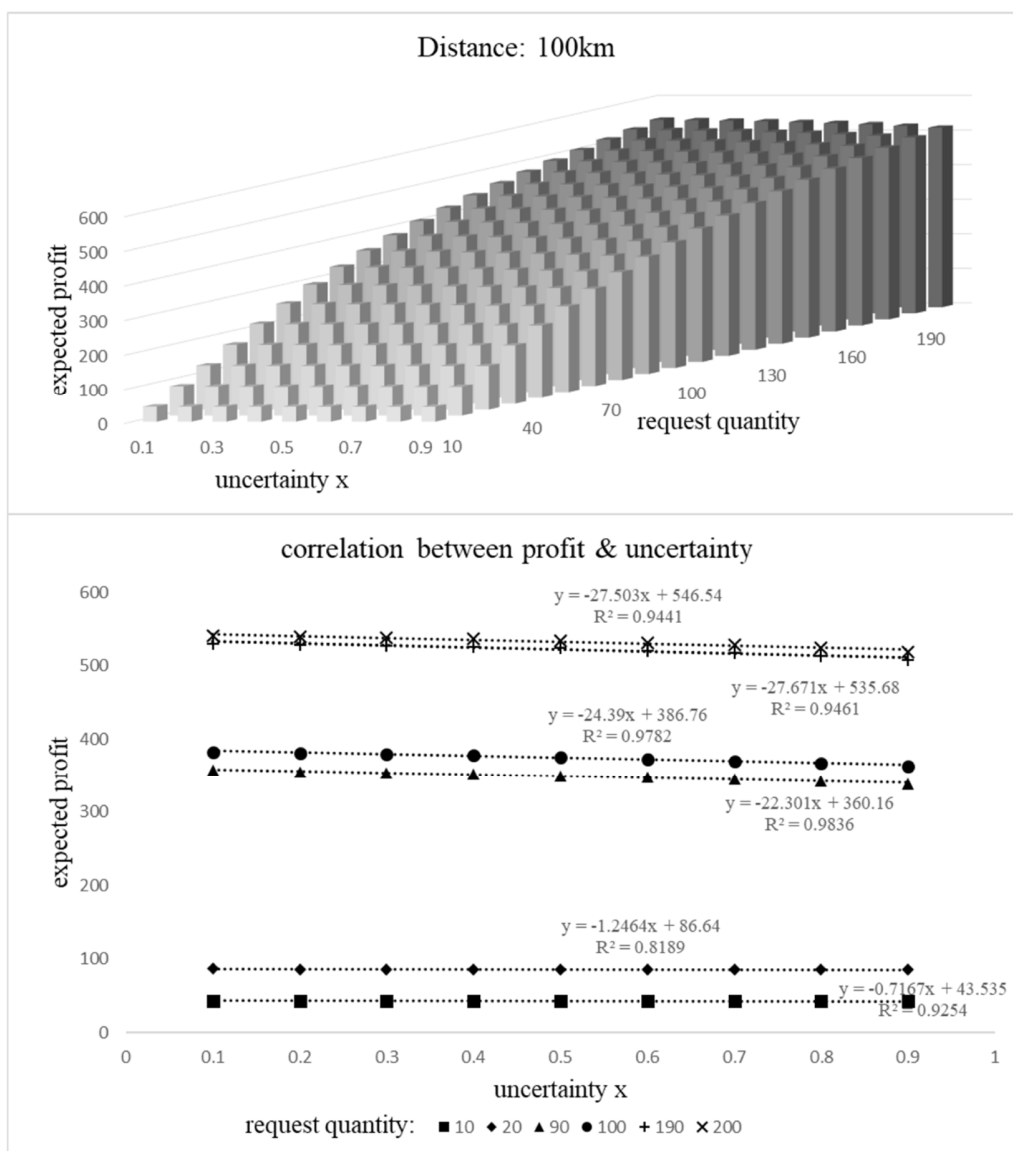


Figure 5. Expected profit over a distance of 100 km

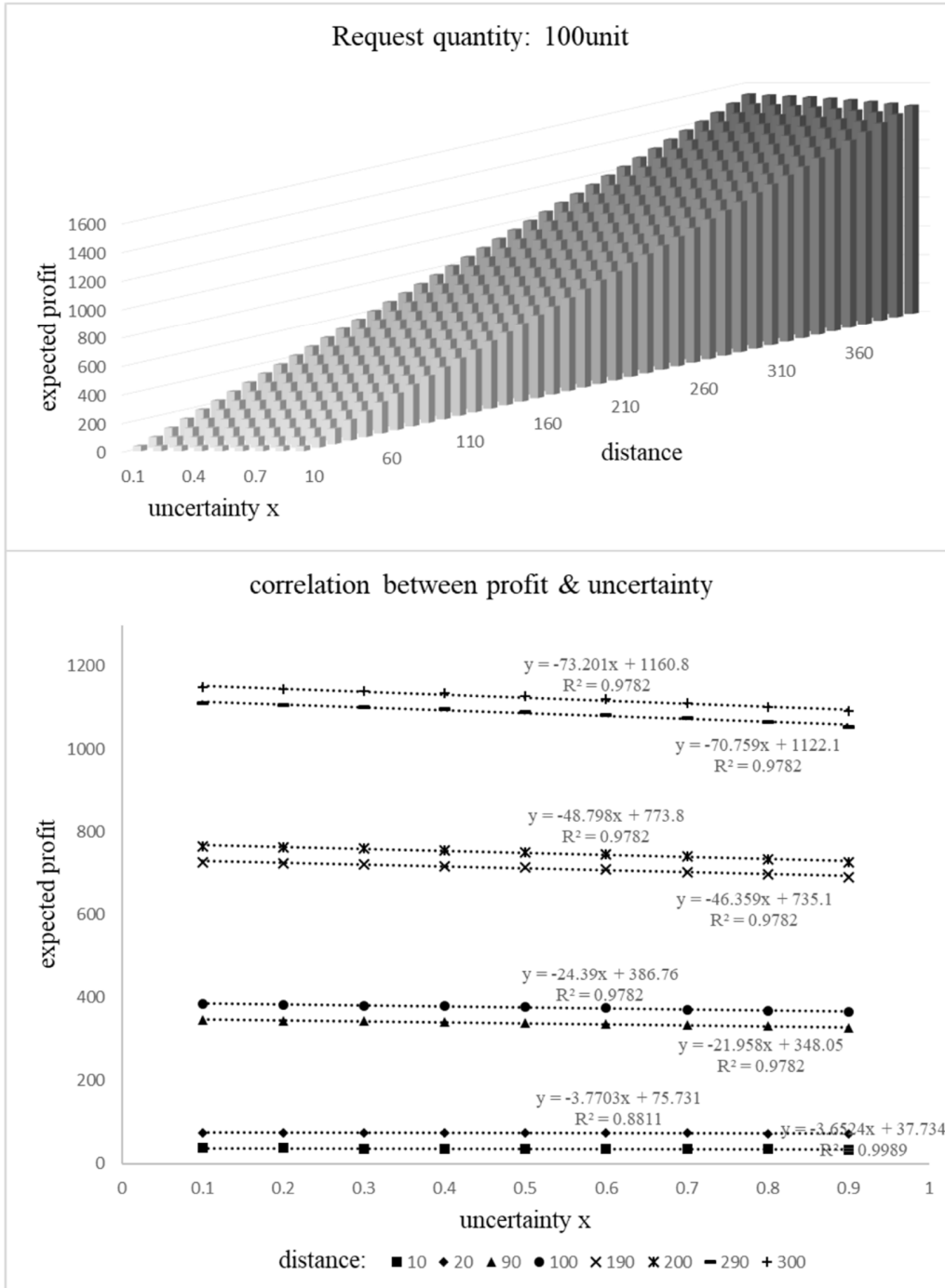


Figure 6. Expected profit for a request quantity of 100 units

6. Application to a real-life case

This part aims to apply the model developed to real-life cases with real data to demonstrate its feasibility. The two scenarios are studied here (full-capacity carrier vs. loaded carrier). The input data is from the historical data of a logistics company we work with. Based on the data, we first extract two sub-networks shown in Figure 1 and Figure 2 from the company's entire transport network. Second, we extract the data we need, which are the daily request quantity and travel distance for each route. In addition, we analyze and conduct some statistical analyses on the data to obtain the extra information we need for forecasting, which is the distribution uncertainty of request quantity. The uncertainty (the value of x assumed in 5.2) is determined using real data because we can obtain the request quantity distribution variance from the historical data. Finally, the original data extracted and the statistical results are taken as the input data for the two scenarios in Table 3 and Table 4.

All the experiments in this paper were run on Mathematica 10.4 under Windows 10 on a DELL Inspiron 15 (5000) with 16 GB of RAM. We used the function *Maximize* in Mathematica to solve the problems, which can solve any linear (integer) programming problem thanks to the solvers developed by Mathematica¹. In our cases, the average CPU times were around 1 minute and 16 minutes for the two scenarios, respectively.

Scenario 1: Full-capacity carrier with no determinate destination

Based on the network in Figure 1, the distance, average request quantity and distribution uncertainty for each route are given in Table 3. The measurement units are *km* for distance and *unit* for request quantity. At the hub of origin (hub1), the request quantity for the routes to other hubs is already known, so there is no uncertainty for these requests.

Table 3. Input Data for scenario 1: Full-capacity carrier with no determinate destination

Route	Distance	Average Request Quantity	Uncertainty (variance)	Route	Distance	Average Request Quantity	Uncertainty (variance)
1-2	165	13	—	3-7	163	14	14.0
1-3	150	32	—	3-8	176	26	11.0
1-4	104	30	—	4-9	83	33	0.6
2-5	97	23	9.7	4-10	126	31	5.8
2-6	346	32	5.7	4-11	54	25	10.0

Based on the input data in Table 3 and the model proposed, the computation results show that carriers should select requests 1-2 in hub1, and the optimized route is 1-2-6. Accordingly, the maximum expected profit is 576 and the optimal bidding price for requests 1-2 is 193. The optimal bidding price for requests

¹ <https://reference.wolfram.com/language/tutorial/MinimizationAndMaximization.html>

2-6 is not given here since the request quantity is forecasted via a distribution function (same for Scenario 2). The carrier should determine the optimal bidding price once they arrive at hub 2.

According to the results, although there are not many requests on route 1-2, there are many requests on route 2-6 with a high price that can give a higher profit. Therefore, the carrier should select requests 1-2 and go to hub2.

Scenario 2: Loaded carrier with determinate destination

In this scenario, as shown in Figure 2, hub3, hub4 and hub5 are interconnected. However, in the current market there are not three interconnected hubs, so the data on routes 3-4, 3-5, 4-3, 4-5 and 5-3 are assumed based on the flow in the network. Three tests with [10, 4, 1] loaded requests N_{OD} are proposed to evaluate if the loaded request quantity could influence the request selection decision in this scenario.

Table 4. Input Data for scenario 2: Loaded carrier with determinate destination

Route	Distance	Average Request Quantity	Uncertainty (variance)	Route	Distance	Average Request Quantity	Uncertainty (variance)
1-3	104	30	—	4-2	193	15	10.6
1-4	150	32	—	4-3	125	31	4.2
1-5	165	13	—	4-5	267	13	6.2
3-2	36	32	1.8	5-2	98	31	4.6
3-4	125	25	9.6	5-3	100	27	11.0
3-5	100	18	6.0	5-4	267	25	10.9

According to the input data in Table 4 and the model proposed, three optimal decisions are given based on the three tests:

- (1) 10 loaded requests: optimal route 1-2 without extra profit. This means the carrier should go directly to its destination without selecting requests in hub1 because the detour cost for the loaded requests is higher than any profit he can obtain from the intermediary hubs.
- (2) 4 loaded requests: optimal route 1-3-2 with an extra profit of 72. The bidding price for requests 1-3 is 122. The loaded request quantity could influence the request selection decision by affecting the detour cost.
- (3) 1 loaded request: optimal route 1-4-3-2 with an extra profit of 228. The bidding price for requests 1-4 is 176. This extreme example shows that the carrier could go to several intermediary hubs if the extra profit can cover the detour cost.

7. Conclusion

This paper introduces and investigates the LTL request pricing and selection problem considering request forecasting in PI with the aim of optimizing LTL carrier revenue. First, we propose a revenue optimization model based on a dynamic pricing model and IP optimization models to help the carrier select the optimal LTL requests. Second, we qualitatively evaluate the influence of the transport factors on pricing and selection decisions. Third, we consider forecasting in the request selection model and investigate the impact of forecasting uncertainty on revenue optimization. The feasibility of the proposed model is demonstrated through real-life cases with real data. Two scenarios considering full-capacity carriers and partially loaded carriers are proposed and discussed.

This paper contributes to the development of a revenue optimization model for LTL carriers in PI based on dynamic pricing and request selection. First, the paper develops the dynamic pricing model for multi-leg requests, which can be used as a decision-making tool for selecting requests. The pricing model can maximize the revenue gained from each type of request. This model has extended the research on dynamic pricing in LTL transport as well as in PI. Next, this paper introduces and investigates the request selection problem in a stochastic environment such as PI, which has been studied very little up to now. The request selection model is used to help the carrier select the most profitable requests to maximize total revenue. Finally, how forecasting and forecasting uncertainty influence request selection is also a new problem in PI. By investigating this problem, we can illustrate the sensitivity of request selection decisions to forecasting uncertainty. Overall, the dynamic pricing and request selection models provide carriers with guidelines and decision-making tools to optimize revenue.

This paper also contributes to the development and application of appropriate data-driven methods for analyzing variations under uncertain scenarios of transportation market, with the goal of data-driven dynamic pricing and revenue optimization decision making for carriers. This paper firstly aims to develop an LTL request pricing and selection method and model for carriers in PI, which is a highly dynamic future logistics system that relies on data-driven real-time optimization. However, the model proposed can also be used in today's freight market, as it has been becoming more and more dynamic and agile. Examples include city pickup and delivery transportation services, and crowdsourcing deliveries. The current pricing strategy used to optimize carrier revenue, which is normally based on a predefined price catalog (static pricing), is increasingly inadequate in such a highly dynamic environment. It is foreseeable that carriers will tend to employ a dynamic pricing strategy to maximize their revenue. Therefore, the proposed model may help carriers change their pricing strategy from static to dynamic.

This work has some limitations that can be improved. First, the optimization models could be extended to bundles of requests for different routes. In our future research, we aim to propose the request pricing and selection problem taking request bundles into consideration. The problem could also be extended to

request pricing and selection in the vehicle routing problem. Second, the reaction of other players (carriers) to the pricing and task distribution results should also be discussed further. It would be helpful to investigate how the proposed model will influence the decisions of others and therefore the market.

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