Less-than-truckload Dynamic Pricing Model in Physical Internet

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Abstract

This paper investigates a decision-making problem consisting of less-than-truckload dynamic pricing (LTLDP) under Physical Internet (PI). PI can be seen as the interconnection of logistics networks via open PI-hubs, which can be considered as spot freight markets where LTL requests of different volume/destination continuously arrive over time for a short-stay. Carriers can bid for the requests by using short-term contract. This paper proposes a dynamic pricing model to optimise carrier's bid price to maximise his expected profits. Three influencing factors are investigated: requests quantity, carrier's capacity and cost. The results provide useful guidelines to carriers on pricing decisions in PI-hub.

1. Introduction

In freight transport industry, carrier's pricing decision covers how to set prices for transport requests in order to maximise his profits under limited capacity [1, 2]. Under dynamic environment where transport requests of different volume and/or destination are arriving over time, carriers may adjust their pricing policies in a timely fashion, by taking into account the real-time state and real-time arriving requests (fill-rate, constraints of capacity or departure time etc.) to maximise their expected profits. The problem is known as dynamic pricing decision problem [2, 3]. Examples include air cargo industry in which cargo tariff can be adjusted according to flight's real-time fill-rate prior to scheduled departure time. Another well-known example is ticket pricing strategies in the airline industry [2].

This paper introduces and investigates a decision-making problem consisting of less-than-truckload dynamic pricing (LTLDP) in a specific context - the Physical Internet (PI), called PI-LTLDP hereinafter. PI can be referred to as the interconnection of logistics networks via open logistics hubs, i.e., PI-hubs where carriers can win transport requests or exchange in-hand requests for the sake of economies of scope and scale [4-6]. Either shipper (e.g., retailer or manufacturer) or carrier can offer transport requests in PI-hubs. Accordingly, a PI-hub can be thought of as a spot freight market, where less-than-truckload (LTL) transport requests of different volume and/or different destination continuously arrive over time for a short stay. Then, carriers can propose price to win the spot requests by using short-term contract and, thus, requests will be optimally allocated to carriers according to the proposed prices. Auction mechanism is one of the solutions for such requests allocation problem [7]. However, there is very limited research investigating LTL dynamic (bid) pricing problem in such context.

The PI-LTLDP problem is very different to liner shipping or air cargo shipping industries that could be concerned with dynamic pricing problem. On the one hand, for a given truck in PI-hub, its departure time even its destination is not scheduled but according to its fill-rate, constraint on delivery time and the route of bidding request, whereas liner shipping or air cargo services are generally scheduled for departure time and destination. On the other hand, each industry has different pricing mechanism. In liner shipping industry shipping, 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 [8]. In air cargo industry, being a real competitive market, companies usually sell their capacity through the common selling format - allotment, by which shippers propose freight with price so airlines only decide to accept or not [9]. The selling process may begin few months prior to departure time, where negotiations between shipper and carrier may happen. Obviously, the allotment mechanism is not applicable in PI-hub, due to the short stay of request and the many requests-to-many carriers allocation problem.

The PI-LTLDP problem is also new to the traditional pricing problems in road freight transport, to either TL or LTL. In truckload (TL) industry carriers may consider some factors to adjust price (or bid) for a request, for example asymmetric requests in a truck's round-trip [10], daily scheduling [11], real-time request learning and forecasting [3], considering competitors' behaviour [12], or synergies between lanes of long-term contracts and spot contracts

[7] etc. However, fill-rate (or request size) is not an issue when adjusting pricing in a timely fashion. In LTL industry, to the best of our knowledge, research focusing on LTL pricing problem itself is very limited, except some focusing on bid price in auction [13]. The main reason is that, *as per* current practice, in general LTL carriers sell their capacity with a fixed cost like €/palette or €/kg. Dynamic pricing was not a main issue considered. Also, auction mechanism is not widely used and only few examples can be found, e.g., *Leanlogistics* and *Transplace* etc. By the concept of PI, it is predictable that the traditional pricing models and mechanisms will be fundamentally challenged, because PI will interconnect the fragmented freight markets and intensify the competition between freight carriers. As a result, novel dynamic pricing models are necessary for LTL carriers PI.

This paper aims to study the PI-LTLDP problem so to make several contributions to the relevant literature. First, we characterise the PI-LTLDP problem and illustrate the differences to the other pricing problems in freight transport in the literature. Second, we propose a dynamic programming approach-based pricing model to the problem, whose aims is to optimise carrier's price and maximise his global profits in PI-hub. Third, through an experimental study, we investigate the impacts of some influencing factors in PI-hubs, such as the number of requests, capacity of carrier and carrier's actual cost. As the first step of the research, the paper provides a decision-making tool as well as useful and significant guidelines to LTL carriers for making pricing decisions. The paper also points out some perspectives for the next research.

This paper is organised as follows. After this introduction section, Section 2 gives a brief literature review on the concept of PI and on related pricing problems and models in freight transport, in order to identify the research gap. Section 3 descripts the PI-LTLDP problem. Then, the problem is formulated in Section 4. An experimental study is also conducted in this section. Finally, Section 5 concludes the contributions of this work and points out some research perspectives.

2. Literature Review

2.1. Road freight transport in Physical Internet

As defined in [14], Physical Internet (PI) is a global interconnection logistic system that connects logistic networks together. Its main objective is to make the freight transport more efficient and sustainable [4, 15]. The PI creates a collaborative transport network by developing standardised containers, common protocols and tools, shared transport and technological assets [16].

The discussion here focuses on the road freight transport in PI. Goods are firstly encapsulated in standard and modular container, named PI-container, which could be in different sizes [17]. Then, these containers will be transported to the destination by one or several carriers from hub to hub. The hubs in PI are open and shared by shippers or carriers, called PI-hubs [18]. In each PI-hub, there are plenty of containers to be transported, which could be in different size and/or destination. On the other hand, there are also numerous carriers, who have different capacity and different route. They can propose price to win the requests of their interest by using short-term contract. Auction mechanism is one of the solutions to match carrier and requests in PI-hubs. Carriers can get some of those containers through participating several auctions. It can be assumed that carrier will have the interest to determine an optimal price to the auction in order to maximise his profit. The pricing characteristics of road freight transport in PI can be concluded for carriers and for requests:

For carriers:

- Sequential: the current decision will affect the state of the next auction in current or next hub, because the capacity and waiting time of the carrier is finite.
- Capacity-finite: although carrier may have more than one vehicle, his capacity would be finite.
- Time-finite: in PI-hub carriers can wait for requests to improve fill-rate. But the waiting time should be finite because a truck has to leave due to some reasons, such as the truck is full; one of the loaded requests is becoming urgent; or scheduled departure time is due etc.

For requests:

- LTL: most of the transport requests in PI-hub are LTL requests, and encapsulated in PI-containers that are standard and modular.

- Stochastic: requests arriving at PI-hub may have some stochastic features such as arrival or departure time, size, destination, and planned lane (routing) etc.
- Bundle: requests arriving at PI-hub may be in large quantity and in form of bundles. It means carrier could bid for several requests in a single auction.

As a result, using open and shared hubs, PI will interconnect the fragmented freight services markets. Each PI-hub is actually a many-requests-to-many-carriers LTL spot market. This will intensify the competition between freight carriers and encourage them to improve their pricing policies.

2.2. Dynamic Pricing in Different Transport Industry

Since there is very limited research investigating dynamic pricing in LTL transport in the literature, the literature review here is extended to other sectors concerning dynamic pricing problem, such as air cargo, liner shipping, railway freight and FTL transport.

As we mentioned before, under allotment mechanism [9], air-cargo carriers just need to decide to whether to accept the shipment with a price given by shippers. Reference [19] studied this problem by considering a single-leg flight, whose goal is maximising the expected profits by finding an accept or reject policy faced with requests with proposed price. The author presented a Markov decision process to solve this problem. He used value function to represent the maximum expected revenue that can be obtained from time period t until the time of departure, which is computed recursively. Similarly, reference [20] also solved the similar problem by dynamic programming using different approximating algorithm. But these two literatures are mainly focus on overbooking and capacity management, not dynamic pricing.

As we discussed above, in the liner shipping industry competition on price is not actually practiced in order to avoid destructive competition. It is the peculiarities of the sector [8]. But the pricing problem in maritime passenger transport is similar to the pricing problem in LTL freight transport, as well as some pricing models. In [21] and [22], authors discussed the dynamic pricing problem faced by the maritime transport service provider, who are selling seats to consumers. By using probabilistic dynamic programming, they found the optimal prices under different conditions, for example, weather or time.

The railway freight transport is also similar to LTL freight transport because of the finite capacity. Reference [23] used a bid-price approach to solve a capacity-constrained railway scheduling problem. The author presented a train segment pricing model to maximise the revenue, in which prices are pre-established. Reference [24] studied the revenue management for carriers in rail freight transport. Author proposed a mathematical method including pricing decision. With the determinate request, this method can give the optimal price set and the equipment flow set that make the profit maximum.

There are also some researches investigating pricing problem in the intermodal transport. Reference [25] discussed the dynamic pricing problem with uncertain conditions in the container sea-rail intermodal transport. Except for the slot allocation in contract market, the author considers the dynamic pricing problem in free market. The optimal price was decided according to the forecast of the future requests, using an equation to indicate the relation between the request and the price. In [26], a cost-plus-pricing strategy is presented for intermodal freight transport service with determinate requests. This strategy aimed to minimize the total delivery cost, which includes storage cost, transfer cost and subcontracting cost. Then the price can be decided by adding targeted profit margins to the minimizing cost.

It can be found that pricing strategies in the transport industries mentioned above are not relying on auction mechanism. Auction is more studied in road transport industry in the literature. However, only few relevant papers focusing on pricing decision can be found in TL transport sector, and even fewer in LTL sector. The consideration of opportunity costs is one the most studied issue in TL pricing. Here opportunity costs are used to describe the influence of current decision (bidding price) to the future state. For example, the opportunity costs can describe the loss in future expected revenue due to serving a new request. Reference [27] presented a method to calculate the opportunity cost in sequential TL requests auctions. The author considered the opportunity costs in the context of dynamic routing problem, which are modelled in a stochastic simulation framework. Based on this research, reference [28] studied the carrier pricing strategy for dynamic vehicle routing problem. Similarly, reference [29] discussed the pricing strategy of vehicle agents when making the decision that whether to insert a new request in current task sequence with considering the opportunity cost. Besides, opportunity costs also could be used in scheduling decisions [11]. In the literature of LTL pricing, reference [13] is the only working paper most related to our study. In this paper, the author presented how the carrier should decide the price of loads dynamically to maximise carrier's profit. He considered a one-leg problem, i.e., request from point i to j. A vehicle travels from i to *j* and waits at most *t* time units. In every time unit, a vehicle bids for one load if there is a load arriving. This method decides the price according to the remaining capacity and the left time before departure.

Overall, the novelty of PI-LTLDP problem to the relevant literature can be justified from several aspects. First, pricing decisions in PI are mostly concerned with LTL shipping, where carriers are constrained by both capacity and time. It is more complex than TL shipping. Second, in PI-hub, pricing decisions occur under auction mechanism. Although auction mechanism has been already studied in freight transport industry, there is very little research focusing on pricing problem in LTL industry, and even less from ocean, rail and air transport. Third, most of the research studied one-leg transport problem. However, pricing in PI-hub should take into account routing of either request or carrier at network level. Due to the above novelties of pricing problem in PI, we are unable to find a similar study or model that could be applied in our research. Therefore, a novel dynamic pricing model is needed.

3. THE PI-LTLDP PROBLEM

The network of Physical Internet consists of plenty of interconnected hubs, for example as indexed from A to D in figure.1. In each hub, there are shippers (or carriers) that offer transport requests encapsulated in containers, e.g., $r_1 \dots r_n$ in PI-hub A. Carriers *1…m*, providers of transport services, participate in a sequence of auctions to win these requests, by taking into account their constraint of capacity (capacity-finite) and, eventually, time to depart (time-finite). We assume that auction mechanism is employed here to allocate the *n* requests to the *m* carriers. In such setting, the problem studied in this paper is how carrier should decide his biding price for requests to maximise his expected profit according to the present situation, such as request quantity and size, remaining capacity and left time before departure. It is the so-called PI-LTLDP problem in this paper.

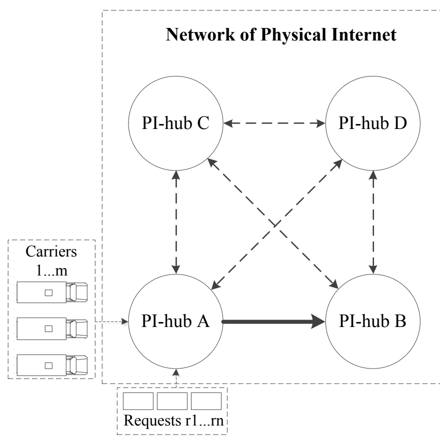


Fig1 A simple network of PI with n request and m carriers at Hub A

At the first step of the research, and to simplify the problem, this paper focuses on a single hub in the network and considers a capacity-finite one-leg and one-period PI-LTLDP problem. One-leg transport means a carrier (vehicle) considers only the requests from hub A to hub B, for example in Fig 1, without considering the complete route of requests and carrier himself. In hub A, a vehicle can wait at most *t* time units. Each time unit is considered as an auction period, for example each hour, in which the carrier bid for all the requests accumulated during this time unite. Carriers will bid for the requests one by one (without considering bundle or combination auction). In other words, a carrier can define an optimal price for each period of auction, and then a vector of biding price $\{x_i\}$ with $i=1 \dots t$. In this paper, we focus on the bid pricing problem in one time unit. Because at this stage we aim to investigate capacity-finite PI-LTLDP rather than time-finite, in other words, dynamic pricing decision based on real-time fill-rate (or unsold capacity) for a carrier.

It is also important to analyse what factors that could significantly influence the optimal pricing decision. To this end, the following three factors are identified and independently studied in the experimental study later.

Requests quantity: since requests quantity accumulated in each auction period could be different, carrier could be faced with some extreme scenarios, from very few to many requests to bid for example, where the optimal pricing decision should be different. By considering this factor, we can study, in a given hub, how does the quantity of requests impact on a carrier's pricing decision and expected profit under fixed capacity – a truck for example.

Carrier capacity: if a carrier can assign more than one truck to a hub, he may thus adjust the total capacity and price policy according to the estimated number of requests in the hub. By investigating this factor, we aim to answer the following question: in a given hub, if the quantify of requests can be estimated, what is the optimal decision on allocating capacity and bidding price for a carrier.

Carrier's actual transport cost: in real-word situation the actual transport cost, e.g., €/ton-km, is private information that is different for each carrier. So the following question could be of interest to carriers: if their cost is changed, either increased or decreased, what are the impacts on the pricing decision, and most importantly on the expected profit.

4. MODEL

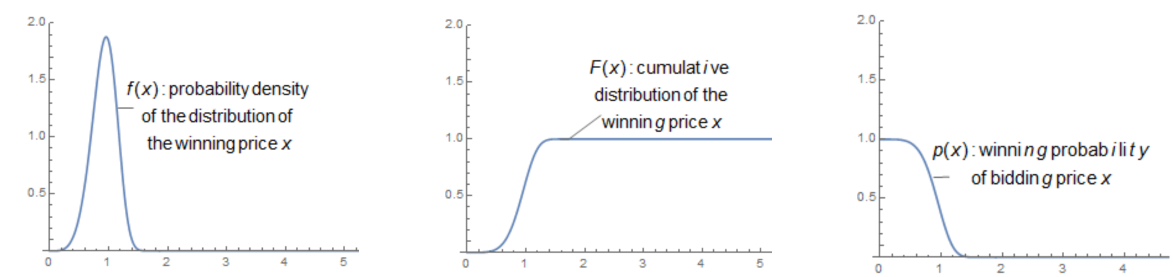
4.1. ASSUMPTIONS

As said this paper studies a capacity-finite one-leg and one-period PI-LTLDP problem. We propose some assumptions shown below:

1. Auction Mechanism: (1) we adopt first-price sealed-bid auction mechanism as discussed in [7]; (2) a carrier will bid for all requests one by one in a single auction period, without considering request bundle; (3) each auction is independent of the other auctions or other carriers; (4) a carrier bids the same price for each request, i.e., single optimal price strategy.

2. As it is one leg transport problem (from A to B), the complete route of requests or carrier is not considered.

3. Winning probability to a given price. If historical data of wining price (the lowest price) to each request were somehow available (the historical data of all historical auctions for example), it would be possible to construct a distribution function of winning prices, then deduce the wining probability of a given price. But due to lacking of data, we assume the wining prices are distributed according to Weibull distribution. Because, based on our knowledge and confirmed by [13], this distribution well corresponds to current carriers' pricing strategies. Reference [13] also infers that this distribution can be used to present the independent auction mechanism in the paper. Further, according to the conclusion of the reference, we may assume that λ is 1 and k is 5, as illustrated Fig 2.a. By that, the distribution function of winning prices and the wining probability function of a given price can be determined, respectively, b and c in Fig 2.



a. probability density of the distribution of the winning price x

b. cumulative distribution of the winning price x

c. winning probability of bidding price x

Fig2 Winning probability submitted to Weibull Distribution

4. For all carriers their valuation of cost for a given request is different an independent, i.e., private value auction [30]. In this, when a carrier determines or adjusts his pricing strategy, the other carriers-competitors- are not immediately following and their pricing strategy is not changed. It also means the Weibull distribution function proposed in assumption 3 is always valid. Strategic interactions on pricing between carriers can be studied via the question of "learning", which is not the scope of this paper.

5. The capacity of vehicle is defined as D unites. As a carrier may have n≥1 vehicles, his total capacity is n*D.

6. All requests are encapsulated in PI-containers of unique and standard size, i.e., homogeneous size of 1 unit.

7. The cost to serve a request is fixed for a carrier.

4.2. Notions and Model

Parameters:

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

p(x): the winning probability to a given bid price x in an auction. Based on assumption 3, we have $p(x) = e^{-(\frac{x}{\lambda})^k}, with\ \lambda = 1, k = 5$

D: capacity of a vehicle.

c: the cost to serve a request.

d_r: the vehicle state, defined with the remaining capacity units when bidding for r request.

$V_r(d_r)$: the expected maximum profit at state d_r.

V_r: the maximum expected profit in an auction period.

X: the bid prices set, i.e., rang of prices to be tested in the model, and X= [0, 2] here.

Variable:

x: bid price given to the request at each auction by carrier. Especially, the optimal bid price determined by the model is noted as x* and x*∈X.

Dynamic Programming Model:

As the PI-LTLDP problem concerns sequential auction, i.e. the decision in present state will affect the future state, we propose the following dynamic programming (DP) model to solve this problem:

$$V_r(d_r) = \max_{x \in X}[p(x) \cdot [x - c + V_{r+1}(d_r - 1)] + (1 - p(x)) \cdot V_{r+1}(d_r)],\ r = 1,2, \dots n-1, n \quad (1)$$

And considering the boundary condition (2):

$$V_r(d_r) = 0, if\ d_r \leq 0\ OR\ r \geq n + 1 \quad (2)$$

Then the optimal bidding price x* for all requests can be found through (3),

$$x^* = arg \max_{x \in X}[p(x) \cdot [x - c + V_{r+1}(d_r - 1)] + (1 - p(x)) \cdot V_{r+1}(d_r)],\ r = 1,2, \dots n-1, n \quad (3)$$

The maximum expected profit will be:

$$V_r = \max[V_r(d_r)],\ r = 1,2, \dots n \quad (4)$$

Function (1) is a recursive function. It calculates the maximum expected profit of carrier when he is bidding for r request using price x with remaining capacity of dr. When carrier wins a request, its capacity will minus 1, otherwise the capacity does not change. The boundary condition (2) presents that the expected profit will be 0 when the capacity is sold out or there are no requests to bid. Function (3) and (4) presents the optimal pricing decision x^* and the resulted maximum expected profit V_r.

4.3. Experimental Study

A numerical experiment is designed to evaluate the performance of the developed model, with studying the impact of three factors - requests quantity, capacity, cost - to the profit and price separately. The value of each factor is independently varied in a given range by a given step, as presented in Table 1. In all cases, the value of variable x is increased from 0 to 2 by step of 0.1, i.e., x=0, 0.1, 0.2….2. The results of expected profit and optimal bidding price are presented in curves shown in Fig 3.

Table 1: Input data

Investigating Factors	**Request quantity**	**Carrier capacity**	**Carrier cost**
F1-request quantity	5≤ r ≤1000, Step=5	D=20	c=0.5
F2-carrier capacity	r=200	1≤ D ≤241, Step=3	c=0.5
F3-carrier cost	r=200	D=20	0.1≤ c ≤1.5, Step=0.05

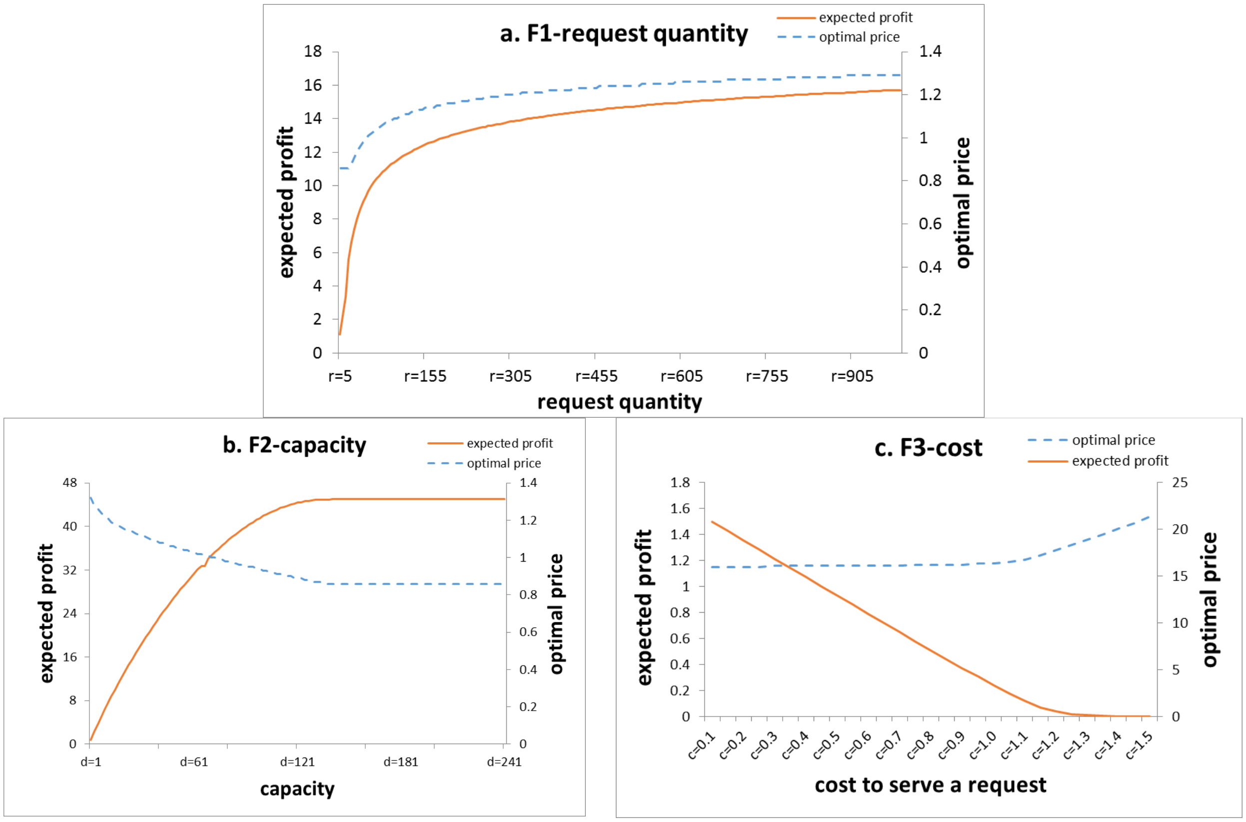


Fig3 Experiment results (a, b and c for investigating factor F1, F2 and F3, respectively)

4.4. DISCUSSION

According to the numerical experiment results, the expected profit and the optimal bidding price under different conditions can be calculated using our model. Furthermore, some conclusions about the impact of different factors on optimal pricing decision can be given:

1. Requests quantity: for a given carrier, his expected profit V_r and the optimal bidding price x^* all increase along with the increase of requests quantity r. But the increase rate is decreasing, and dramatically dropped after r=125. This conclusion is helpful to carriers with fixed capacity in PI, eg D=20. If they were able to know (or estimate) request quantity in each PI-hub, they would be able to select the PI-hubs with the highest profit increase rate.

2. Carrier capacity: the capacity D of a carrier has different impact on the profit and the price, i.e. when the capacity increase under a turning point, the profit is increasing and the price is decreasing. But exceeding this point, both the profit and price will stay the same. We also repeated the experimentation with different request quantity, i.e., r=20, 100, 200, 300, and 400. The conclusion is maintained in all scenarios. And, the turning point is always close to the quantity of request, i.e., the value r. This can be explained by the fact that, if $r<D$, the dynamic program will stop when all requests are auctioned see Function (2). This discovery can help carriers decide allocate how many vehicles facing different numbers of requests estimated. For example, when there 200 requests, the turning point appears at d=137. So a carrier just need to allocate 137 units of capacity to the focal PI-hub during this auction period, so that his profit and price will be, respectively, 45 and 0.86.

3. Transport cost: it is not hard to find that the optimal bidding price x^* increases conjointly with transport cost c, meanwhile the profit V_r decrease. The conclusion is maintained when we repeated the experimentation with different request quantity (i.e., r=20, 100, 200, 300, and 400). The results can help carriers to analyse the sensibility of the variation of their actual cost on the expected profits and pricing strategy. For example, if a carrier in a given hub would adopt some new technologies to reduce its transport cost, he may adjust his pricing strategy and estimate the increase of expected profit by using the model, so as to assess the probability.

5. Conclusion

This research introduces and analyse the dynamic pricing problem of less-than-truckload in the network of Physical Internet, the PI-LTLDP problem. At the first step, this paper focuses on a single hub in the network and considers a capacity-finite one-leg and one-period PI-LTLDP problem. A dynamic programming model to calculate the optimal bidding price and expected profit is derived. Then, based on this model, the impact of three influencing factors - requests quantity, carrier capacity and transport cost - on the optimal result is estimated. The model can be served as a decision making model for LTL carriers in PI, to determine their optimal pricing decision and then optimise their profit.

In summary, this paper has made some significant contributions to the research of pricing in freight transport, as well as to the research of Physical Internet. First, the paper firstly introduced and defined the PI-LTLDP problem, which is different and more complex to the traditional pricing problem in freight transport industries. Thus, a new problem to the literature has been identified and investigated. Second, this paper contributed also to the research of pricing policies in LTL transport industry, to which the literature is currently very limited. Finally, this paper presents the first research on pricing problem in Physical Internet. The decision making tool proposed, as well as the conclusion from the experimental study will give some useful guidelines for the next of the research.

As the first stage, this paper investigated only one of the scenarios in the PI-LTLDP problem. Some limits and research perspectives should be discussed here. One of the main limits is that no real-world data of auction was available for the research. That is why the assumption about the distribution of wining price has been made. This assumption should be further validated once real-data were available.

In the next work, this research can be extended in line with three characteristics of Physical Internet – auctioning time, route of request and carrier, and request size. Auctioning time means the pricing problem considering multiple auction periods, where the price may also be adjusted by time, and not just capacity as in this paper. Moreover, the one leg problem can also be extended to the whole network of Physical Internet, with considering the route of requests and carriers and the synergies in transport. Dimensional pricing is also another research question to be followed, where requests could have homogeneous size, from small to big as TL for example. The pricing decision taking into account all such characteristics of PI will be much more complex.

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