Recent Advances in Science and Engineering
Web page info: https://rase.yildiz.edu.tr
DOI: 10.14744/rase.2022.0009

Review Article

A request selection and dynamic pricing in physical internet

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ARTICLE INFO

Article history
Received: 20 June 2022
Accepted: 15 August 2022

Key words:
Dynamic pricing, request selection, physical internet, dynamic programming, freight transportation.

ABSTRACT

Recently, many companies are dynamically changing their pricing strategies in order to increase their profits and competitive advantage. Thanks to dynamic pricing strategies, companies that adapt quickly to changing conditions maximize their profits. In this study, a dynamic pricing model is proposed for demand pricing and selection in physical internet centers. Bid prices are given to the demands with the dynamic pricing model created by using the dynamic programming method. The bid price given with the dynamic pricing aims to maximize the carrier's profit. After determining the prices that maximize the profit, demand selection is made in line with the vehicle capacities and integer programming model is used for the request selection model. Sample data was created to test the model. According to the findings, developing a dynamic pricing strategy is critical for logistic providers in the physical internet.

Cite this article as: Gülüm MN, Çetinsaya Özkır V, Yıldırım UM. A request selection and dynamic pricing in physical internet. Recent Adv Sci Eng 2022;2:2:58–63.

INTRODUCTION

The Physical Internet, that is initiated by Montreuil (2011), is a global logistics system based on physical, digital, and operational interconnectivity in logistics [1]. Regardless of the service or production sector, logistics is used in almost all areas of life that every sector needs to use today. Although the physical internet has become more widespread lately, Montreuil (2011) defined the physical internet as a network that generalizes the transport processes such as unloading, loading, routing and storage, functionally standardizing it and expected to operate uninterruptedly and conveniently anywhere in the world [1]. Nella et al. (2021) indicated that the physical Internet is a metaphor for the digital internet that connects to logistics networks and processes [2]. Basically, the physical internet approach is based on global collaboration to improve the vertical and horizontal integration of transportation systems globally with the shared use of warehouses, tools, data and spaces [3].

Due to the fact that the physical internet provides the common use of warehouses, vehicles and data in a global way creates a price problem between the transport companies and their customers. The dynamic pricing method, which is one of the income management techniques draws attention to solve this problem. While the concept of physical internet increases sustainability due to its nature, the use of dynamic pricing for this concept helps to maximize the profitability of the companies. The use of dynamic pricing in internet channels and in many fields has become widespread over time [4]. Today, dynamic pricing is preferred by many companies because there are so many alternative and variable factors. The use of pricing strategies by companies in this way provides benefits in competing with other companies and helps them reach maximum profit by

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serving their customers at more cheaper prices.

Unused carrier capacities are returned to companies as additional costs. In order to use the carrier's capacity effectively and maximize its profits, the carrier's current capacity should be evaluated using an effective pricing method among existing demands. Companies can adjust to changing conditions, demands, and customer expectations by employing dynamic pricing methods. When conditions such as time, density and capacity are considered, determining the price to be given to customers with dynamic pricing provides the opportunity to increase customer satisfaction and market share. In addition, it is aimed to use the existing carrier capacity in the most efficient way with the demands planned to be achieved.

When we look at the studies in the field of dynamic pricing, it is seen that methods such as markov chains [5], auction mechanism [6-8], dynamic programming [6-9], greedy search algorithm [5], branch boundary algorithm [10], artificial neural networks [11] are used.

In this study, we aim to propose a dynamic pricing model that increases capacity utilization by creating promising offers for customers with dynamic pricing and an integer programming model to choose the best demand set under these pricing decisions. Therefore, the main goal of this study is to maximize profit by utilizing capacity effectively via dynamic programming and integer programming models and simplifying the model of Qiao et al. (2020) [7].

LITERATURE REVIEW

In the literature, dynamic pricing studies are mostly carried out in service sectors such as passenger ticket pricing in the transportation sector, product pricing in the retail sector and reservation pricing in the tourism sector. In addition to these studies, there are studies for air, sea, rail, and road transport modes in the field of logistics and transportation. Studies on railways and airlines are mostly in the field of passenger ticket pricing. Studies about demand pricing have been observed in intermodal [5] and multimodal [12] transportation.

Despite the fact that road freight transport plays an important role in logistics, there are very few studies in the literature on demand pricing studies in road freight transport. In this section, dynamic pricing studies in the field of transportation will be discussed. The physical internet is defined as the global logistics system which demands with different quantities and destinations are constantly arriving at open logistics centers and are allocated to carriers [7]. Qiao et al. (2019), in their studies addresses dynamic pricing strategy for less-than-truckload in the physical internet. For this problem, they present a dynamic programming model to optimize the carrier's optimal bid price and expected profit using an auction mechanism. In the study, they focus on a single logistics center with two different strategies which the unique price strategy and the variable price strategy. In view of the scenarios, their results show that the variable price strategy provides better results than the unique price strategy. The study is empirical case study and not tested on a real case application [6].

Qiao et al. (2020) examine the dynamic pricing strategy and optimization problem that the demands at the center are distributed through an auction system. They define the carriers in two different ways as full-capacity carrier without a route and loaded carrier with a certain route. Two scenarios are generated for each carrier type. The proposed model has been tested on a real case application. In order to optimize the carrier's profit, dynamic programming for demand pricing and integer programming model for demand selection problem, which takes into account demand forecasting were created. In addition, they examine multi-center demand under stochastic conditions [7].

Qiao et al. (2019) consider the highest demand forecast and extended their study by enabling carriers to participate more than one auction at multiple periods [8].

Douma et al. (2006) address the problem of carrying less than a truck load in their study. In this study, the loads are allocated to the vehicles by giving the first price with a closed tender. Since it is difficult to model the loads affecting the basic capacity in the study, the additional loads combined with the current load of the carrier going on a certain route are taken as a basis. In the pricing model, dynamic programming method was used in order to compete in a constantly changing environment [13].

Van Riessen et al. (2020) examined the cargo fare class mix problem, which aims to find the most suitable fare class mix according to customer demands for an intermodal transport network including road and rail. They aimed to balance revenue maximization and capacity utilization by optimally combining the two delivery service levels. Greedy search algorithm and Markov chains are used in the model to solve the problem. In an intermodal network consisting of multiple corridors, numerical results are obtained by comparing the optimum values of each corridor with the values generated by rerouting. According to the findings, the proposed method is proved to be more efficient [5].

Liu and Yang (2015) present stochastic integer programming method for slot allocation for multimodal transport including sea and rail. For the next stage of the model, the pricing problem for each period is handled and the stochastic nonlinear programming model is formulated. Robust optimization models with chance constrained programming are used to transform stochastic models to deterministic models [12].

Neila et al. (2021), in their studies, examine the studies in the field of physical internet since there is a need for development in issues such as capacity utilization, increasing efficiency and planning of sustainable transportation networks. 59 studies in the literature were examined and the points open to improvement were mentioned. When it comes to the dynamic pricing issue on the physical internet, it is said to be a useful directive for carriers in real life. Because the physical internet is a new subject, a lack of data impedes the progress of the studies [2].

Plasch et al. (2020) investigate why it is necessary to enter the physical internet environment in their studies. They examine the cooperation and success factors in the physical internet environment that contributes to sustainable logistics. The physical internet studies are classified according to their subjects. There are three studies in the field of dynamic pricing on the physical internet [14].

Lafkihi et al. (2019) examine a literature review in the field of freight transportation in their work. A total of 78 articles were reviewed. New perspectives and gaps have identified for researchers. In the study, they emphasize that there is little interest in auction-based multimodal transport, more focus is placed on unimodal transport [15].

Van Heeswijk (2022) presented a multi-factor reinforcement learning algorithm to represent the strategic bidding behavior of carriers in freight transport. He has modeled an agent-based environment where he generates bid and sell prices at the individual container level that he actively learns bidding strategies using policy gradient methods [16].

Uğurlu et al. (2012) focus on the dynamic pricing problem for each unsold seat in maritime transportation in their studies. They focus on estimating the demand under different prices by conducting a passenger survey. They examine the price change situation in the current journey on consumer behavior with conjoint analysis. Probabilistic dynamic programming method is used to find the optimal prices [9].

Mozafari et al. (2015) dynamically change their prices in order to maximize the utility of each carrier in freight transport. At the same time, fleet planning is made according to the number of vehicles in different locations. Prices have changed according to the vehicle supply to be made. They solved the problem by modeling with discrete-time Nash equilibrium and branch-bound algorithm [10].

Coşgun et al. (2014) discuss the dynamic pricing problem in maritime public transportation in their studies. They examine the problem with fuzzy logic based on weather conditions, day of the week and time of the week. In this way, they made dynamic ticket pricing by adding criteria and using a dynamic programming model with fuzzy probability [17].

Friesz et al. (2008) present a game-theoretic dynamic pricing model in an urban freight environment with sellers, buyers and shippers. According to the results, when the price applied to the buyer decreases in the two time periods, the amount of demand increases [18].

Ding et al. (2020) discuss the dynamic container handling pricing problem at the terminal in their study. They construct an analytical model by using back propagation neural network algorithm and time/activity based costing method. Thus, a dynamic price is determined for the transportation demand, taking into account factors such as the final fee per container, the transportation time according to the customer class. When the results are compared, the presented method gives more accurate results than the traditional pricing method [11].

In view of all these studies, it is seen that the dynamic programming model is useful for making dynamic pricing in the field of road freight transportation. Therefore, the dynamic programming model was established in our study.

METHODOLOGY

In this study, dynamic programming method was used for the dynamic pricing of the bids and integer programming method was used for demand selection. The problem definition and corresponding mathematical model is provided in this section, the mathematical model, and its explanations will be discussed.

Problem Definition

Physical Internet hubs are logistic networks that contain demands. Carriers give price offers to receive these demands. In order to maximize their profits, they must offer the best price. Carriers give n number of bid prices y_n with probability $p(y_n)$ considering unit transportation cost c, vehicle capacity W, number of demand requests r. Let $V_{ij}(W)$ be the maximum expected profit of the carrier. Carrier has different vehicle types with different capacities. When the carriers make a request selection, the demands are assigned to the vehicle suitable for their type. In Figure 1, the requests located inside the PI hub are shown. For the sake of understanding, the departures of two demand points to other centers are shown with arrows.

In this study, while giving the bid price that will maximize the profit, it is also decided which demand to choose. In this way, carriers will be able to use their capacities effectively thanks to the demands they receive. There are one-way crossings between the requests in the center. In the

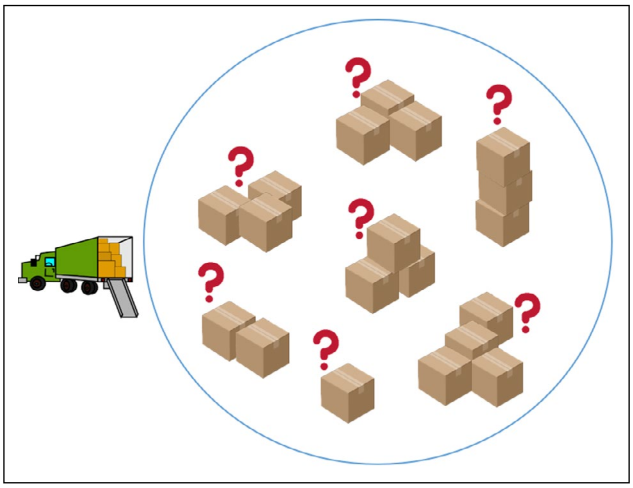

Figure 1. Request in PI hub.

initial state, the vehicles serve at full capacity. In this way, since the destination is not certain, there will be no route restriction when choosing a request. Parameter and variable descriptions of the model are given in Tables 1 and 2.

Dynamic Pricing Model

The dynamic programming model is given as in the following Equations (1)-(3).

$$V_r(W,n,c) = \boldsymbol{max}_{x\epsilon X}\left[p(y)\left[y-c+V_{r+1}(W-w_{n-1},n-1,c)\right]+\left(1-p(y)\right)V_{r+1}(W,n-1,c)\right] \quad \forall r\in N \tag{1}$$

$$V_r(W,n,c)=0 \quad \textbf{if } W\le 0 \ \textbf{ or } r>n \tag{2}$$

$$V_r(W,n,c)=V_r(W) \tag{3}$$

Equation (1) is the recursive function aiming to maximize the expected carrier profit. He gives the bid price given here in a way that maximizes profit. It proceeds based on the profit of the previous situation. Equation (2) states that if the vehicle capacity is zero, that is, it runs out or there is no demand to bid, the profit is zero. Equation (3) is the function specifying the maximum expected profit.

Request Selection Model

The request selection model is given as in the following equations (4)-(7):

Table 1. Parameters and variables for dynamic pricing model

Notation	Descriptions
N	Number of requests n=1,2,3,…,N.
r	Requests remaining in the auction period r=N,N-1,…,1.
W_v	Remaining capacity of vehicle
w_n	The number of items in request n
c	Unit transportation cost ($/unit)
(W, n, c)	Vehicle status. When bidding for requests, the capacity is defined in terms of W. The total number of requests to be bid is n and the cost is c.
$V_r(W, n, c)$	The expected maximum profit for the type of demand in (W, n, c)
y	Bid price
$p(y)$	The probability of winning the request at a given bid price y.

Table 2. Parameters and variables for request selection model

Notation	Descriptions
r	Requests n=1,2,3,…,N.
W	Remaining capacity of vehicle
w_n	The number of items in request n
$V_r(W)$	The maximum profit for remaining capacity for demand in (W, n, c)
x_r	1, if the request r is selected, 0 otherwise

$$Max \sum_{(i,j)\in A} V_r(W)\,x_r \tag{4}$$

$$\sum_r x_r \le 1 \tag{5}$$

$$\sum_r x_r w_r \le W \tag{6}$$

$$x_r \in \{0,1\} \tag{7}$$

The objective function (4) aims to maximize the maximum expected profit from the selected demands. Constraint (5) ensures that only one request is selected for each stage. Constraint (6) is the constraint required so that the selected demands do not exceed the total capacity. Constraint (7) indicates that it is a binary variable.

APPLICATION

The purpose of this section is to apply the model on the case with the data. Thanks to the application, the results of the established model will be seen. Assuming that the demand is known without estimating it, we proceeded through the example of full-capacity carriers.

Experiments in the study were carried out on ASUS Intel Core i5 with 8 GB RAM in Python 3.10 under Windows 8. Python codes are written via PyCharm. The dynamic programming part of the problem was first run and its output was used for demand selection. The integer programming model is written using the pulp library.

Quantity and cost data regarding the demands are given in Table 3. Variable units are units for quantity demanded and dollars for cost. The set of quotes tested is given as [0.90, 0.80, 0.70]. The probability of winning the demand with each offered price is given as [0.55, 0.72, 0.84], respectively. Vehicle capacity is 7 units.

Request 7 was selected based on the model and the inputs in Table 3. For each demand and remaining capacity pair, the bid price is 0.90 $ when the request is 7 and the remaining vehicle capacity is 7. The maximum expected profit resulted in $2,169. A request for 2 units was selected. In the next step, request selection will be made for the case where the vehicle capacity is 5.

According to the results, the fact that request 7 does not have the highest amount of request and the lowest cost does not mean that it will reduce the carrier's profit. The

Table 3. Input Data

Request	Quantity of Request	Cost
Request 1	2	0.5
Request 2	1	0.14
Request 3	2	0.05
Request 4	1	0.45
Request 5	3	0.11
Request 6	1	0.27
Request 7	2	0.3

problem is evaluated for the given criteria and the profit from the next stages. In this way, it is possible to maximize carrier profit. In such problems, not only the profit of the first stage, but also the profit that will come as a result of the evaluation of all demands gains importance. The main purpose is to decide on the demand selection and the optimum bid price that maximizes the total profit among all the demands.

Except for the weight value, other data values are kept constant in our input data. The change in the weight of the demand on the profit is examined. It is observed that the maximum expected profit of the carrier decreases as the demand weight increases. When the weight values given in Table 4. are used, the carrier profit gives the value 1.068 $. When analyzed in this way, the increase in demand request reduces the variety of demand for vehicle capacity, leading to a decrease in profits.

It has been examined how the profit is affected when the cost values given in Table 5. increase and other inputs remain constant. With the increase in costs, the expected maximum profit value decreases by 1.39$. A certain increase in costs for all requests causes a decrease in the maximum expected profit value. Therefore, it is expected that the costs will always be at lower values.

The situation where the bid price set is changed and other data are kept constant has been examined. The bid price set from [0.90, 0.80, 0.70] has been changed to [0.95, 0.90, 0.92]. When the bid price values to be given are increased, the expected maximum profit value becomes 2.65 $. Compared to the first case, the expected maximum profit value increases. By changing the values, the third bid price is given to the request. When the situation is examined, the increase in the bid price and the high probability of winning with that price is a variable that increases the profit. The first bid price is higher at 0.95 $. However, since the probability of winning the demand is also a factor, the bid price value alone does not make sense.

Table 4. Input Data for Weight

Request	Quantity of Request	Cost
Request 1	4	0.5
Request 2	5	0.14
Request 3	3	0.05
Request 4	4	0.45
Request 5	4	0.11
Request 6	5	0.27
Request 7	3	0.3

Table 5. Input Data for Cost

Request	Quantity of Request	Cost
Request 1	2	0.62
Request 2	1	0.51
Request 3	2	0.25
Request 4	1	0.56
Request 5	3	0.31
Request 6	1	0.46
Request 7	2	0.68

CONCLUSION

Today, there are some processes that are important for every sector. Regardless of the service or production sector, the transportation process is at the forefront of these processes. Examples such as the transportation of raw materials for production, the shipment of the produced product to the customer can be given. There are many modes of transportation, especially road, for these shipments. Road transport companies enter the physical internet centers where all requests are made. In these centers, bid prices are given to receive the demand. In this way, they maximize their profits by giving different prices to each request.

In this study, dynamic pricing and request selection model is presented for carriers to maximize their profits. Dynamic programming method is used for dynamic pricing model. Request selection model is solved by integer programming method. When the results are examined, it is important to evaluate the bid price and the probability of winning together with the price. Increasing the values in the bid price set increased the maximum expected profit. Increasing the cost values for each request shows that the maximum expected profit value decreases.

We plan to develop our work by integrating a dynamic pricing model into a production-inventory-distribution problem with three stakeholders: the manufacturer, the PI hubs and the customer. For future research, the study can be developed by combining the dynamic pricing problem with fleet planning, pricing according to customer segments, and routing problems to be made between all hubs.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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