A Dynamic Pricing Model for Time Slot Management in Attended Home Delivery Logistics

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Abstract

In this paper, we propose a dynamic pricing model, with the objective of maximizing the total expected revenue of a provider of attended home deliveries, while also improving the matches between customers' preferred delivery time and price and carriers' desirable time slots and charge fees. The models are formulated to determine the optimal posted price and the minimum acceptable bid price for each time slot, which is determined by an insertion-based vehicle routing problem with time windows (VRPTW). The study starts from a typical dynamic pricing model with three kinds of customers' behaviors (i.e. price-taker, bidders, and leave-without-pay) and then considers heterogeneous characteristics of peak and off-peak time slots. Through a series of case studies, the model has shown its ability to determine a price movement which is efficient in response to changed conditions.

Keywords: Dynamic Pricing; Vehicle Routing Problem; Attended Home Delivery Logistics

Résumé

Cet article présente un modèle de tarification dynamique visant à maximiser les recettes totales d'un fournisseur de prestations de livraisons à domicile, tout en conciliant au mieux les attentes des clients en termes d'horaires et de prix, et celles des livreurs en termes de créneaux horaires et de coûts. Les modèles sont élaborés de façon à déterminer le prix optimal affiché et le prix minimum acceptable de vente de chaque créneau horaire, défini comme solution d'un problème du voyageur de commerce dans une fenêtre de temps (VRPTW). L'étude part d'un modèle classique de tarification dynamique à trois types de comportements de clients (privilégiant le prix, enchérisseurs et ceux qui partent sans payer), puis prend en compte les caractéristiques hétérogènes des créneaux des heures de pointe et des heures creuses. Par une série d'études de cas le modèle a prouvé sa capacité à déterminer un prix par livraison adapté à diverses conditions.

Mots-clé: tarification dynamique ; problème du voyageur de commerce ; logistique de la livraison à domicile.

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1. Introduction

Over the past decade, online shopping has grown in popularity with customers and grocers alike. Offering customers the choice of delivery time slots is an emerging business strategy in attended home delivery service since it has potential to provide higher service level and reduce the risk of delivery failure. In Figure 1, a recent survey in Taiwan indicates that 48.2% of respondents prefer to select their preferred delivery time slots.

This issue is a significant concern especially for attended home delivery, which needs consignees to be present to confirm the receipt of the products (e.g. perishable goods, jewelry, furniture, high technology products, holiday gifts, etc.). Since there are lots of uncertainties with the shipment arrival date and time, a significant fraction of first-time delivery may fail due to consignees' absence, temporarily leave, or other conditions. Carriers have to schedule re-delivery with higher operating costs and lower customer satisfaction. In order to improve the efficiency and reliability of conventional attend home delivery service, offering customer a choice of narrow and desirable shipping time slots has become an innovative approach, which can effectively reduce the risk of failure delivery.

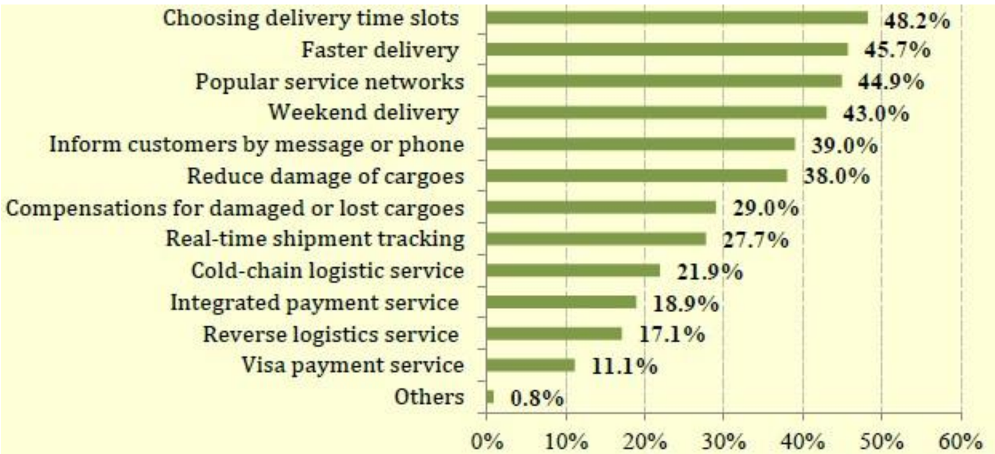

Fig. 1. A Survey of the Best Delivery Service in Taiwan (Source：InsightXplorer Ltd., 2011)

Although offering delivery service can provide customers more conveniences (e.g. higher service quality, shorter waiting times, more efficient operations, more customer choices, etc.), maintaining the efficiency and profitability of this service has been recognized as one of the great challenges faced by both shippers (i.e. sellers and cargo owners) and carriers. Only few logistics service providers in Taiwan currently allow customers to select their preferred time slots. However, the lengths of service time slots are still somewhat too wide to significantly reduce the expected waiting time.

Attended home delivery service poses significant logistic challenges due to demand unpredictability, strict delivery time window, and low margin profit. Time slots affected by peak demand or rush hour traffic may hamper these deliveries. A dynamic pricing mechanism is designed to maximize total service providers' revenue, while at the same time offer more flexibility for customers to select their preferable time slots.

Several previous studies investigated different home delivery service strategies. Lin and Mahmassani (2002) compared both unattended and attended delivery policies for many online grocers with different settings of delivery time window widths. They claimed that providing the high level of service and convenience (in the form of specific and tight delivery time slots) desired by online customers often results in higher delivery costs, which directly affect the profitability of the operation. Boyer et al. (2003) examined the operational challenges involved in offering some value-added services to consumers, such as delivering groceries a specified delivery window (typically ranging from 1 to 3 hours). Findings of the above study show that: the tighter service time window may attract more consumers, but the logistic difficulties are also severely increased.

Kawakatsu and Sandoh (2005) proposed a stochastic model to determine an optimal appointed home delivery date based on the trade-off between attracting more demand and maintaining satisfactory success rate of delivery. Campbell and Savelsbergh (2005) developed methodologies for making order rejection/acceptance decisions to maximize expected profit. The key idea is to exploit information about potential future orders to evaluate whether it is better to accept a customer's order or to reserve capacity for potential future orders. The idea is sound; nevertheless, discriminating customers based on specific rules and rejecting some customer's requests will reduce customer satisfaction and lead to the loss of potential future demand. Additionally, the uncertainties of predicting the 'potential future orders' may increase the failure probabilities of the models. They also resolved this issue and examine the use of incentives to influence consumer behavior to reduce delivery costs (Campbell and Savelsbergh, 2006). Kursad et al. (2009) developed a Markov decision-based model to balance utilization of delivery capacity and the most convenient time for customer's delivery. The model dynamically adjusts delivery prices as customers arrive with their capacity requirements.

Reinartz (2002) developed the dynamic adjustment of prices to consumers depending on the value of a good or service. Different prices are charged to end consumers based on their discriminatory variables (i.e. similar to concepts of willingness-to-pay). Su (2007) considered a monopolist who sells a finite inventory over a finite time horizon to maximize revenue through dynamic pricing. A continuous-time game between the seller and the customers with heterogeneity in both valuation and patience are developed.

While the types of pricing policies and methods used in the exchange of goods and services greatly vary, they fall into two broad categories: *posted-price mechanisms*, and *price-discovery mechanisms* (Boyer et al., 2003). Under the posted-price mechanism, goods are sold at take it-or-leave-it prices determined by sellers; most of above studies are attributed in this category. In a price-discovery mechanism, prices are determined via bidding processes such as auctions. The 'bid-price control' mechanism has been widely used in airline revenue management fields (Talluri and van Ryzin, 1998; Bertsimas and De Boer, 2005; Adelman, 2007), but rarely applied in the logistic market.

Etzion et al. (2006) developed a model of the key trade-offs sellers face in such a dual-channel setting (i.e. sell identical products online using auctions and posted prices at the same time) built around the optimal choice of three design parameters: the posted price, the auction lot size, and the auction duration, as shown in Figure 2. The idea is interesting but customers may still want to pay the posted price for the low valuation products rather than bid them directly. In addition, the term 'valuation' may vary much among different customers.

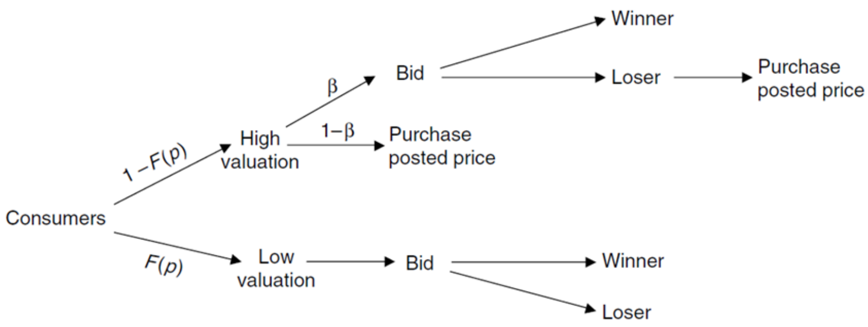

Fig. 2. An Illustration of Dual Channel Settings (Etzion et al., 2006)

Kuo and Huang (2012) formulated a dynamic pricing model to address a retailer selling products from two different generations (e.g. a dealer sold used and new cars), both with limited inventory over a predetermined selling horizon. The model proposed by Kuo and Huang is sound; however, there are still some drawbacks which can be improved by our approach. First, the switch between two products is restricted. Customers can only consider one type of product each time. Second, the shopping mechanism in Kuo and Huang's algorithm seems somewhat insufficient. Customers can negotiate one type of product only if they were not willing to pay the posted price of another product. In our approach, we allow customers to consider multiple products simultaneously with an integrated dual-channel setting based on Etzion et al.'s method. Moreover, we assume the decision makers (i.e. logistic service providers) as a unified company (e.g. Walmart) or an alliance (e.g.

Giant and Peapod) among shippers and carriers based on carriage contracts. Another major assumption views demand as exogenous and independent across time.

2. Overview of VRPTW into the Time Slot Allocation Problem

Attended home delivery poses significant logistic challenges due to demand unpredictability, strict delivery time window, and low margin profit. Time slots affected by peak demand or rush hour traffic may hamper these deliveries. A dynamic pricing mechanism is designed to maximize the logistic company's revenue, while at the same time offer more flexibility for customers to select their preferable time slots and/or prices.

Before running the dynamic pricing models, several works for the preparedness phase should be implemented, such as: (1) define the studied area; (2) identify the types and lengths of service time slots; (3) estimate the maximum service capacity of each time slot based on given fleet and crew sizes; (4) collect the historical data to estimate the reference prices for corresponding time slots; and (5) determine the available and biddable time slots for price-taker and bidders, respectively. The first four steps can be defined by service providers directly, and the fifth work is determined by the following approach.

2.1. An Improved Sequential Insertion-based VRPTW Algorithm

VRPTW is a NP-hard problem, therefore it would be quite time-consuming to re-optimize every time when new customer arrives. Assume that demand information in the real-time stage is unpredictable and randomly generated within the studied area. In order to serve the various demand requests at different geographic locations within the specific service time windows, an improved sequential insertion heuristic algorithm is developed on the basis of previous related works (Braysy and Gendreau, 2005).

First, a route is initialized with a 'seed' customer and the remaining un-routed customers are added into this route until it is full, with respect to the scheduling horizon and capacity constraint. The above pre-optimized routes provide the required 'seed' in this study. Second, if un-routed customers remain, the initializations and insertion procedures are then repeated until all customers are served. It should be noted that the original algorithm proposed by Braysy and Gendreau is focused on finding 'the nearest insertion', which may not be suitable for a customer's multiple time slot requests. Thus, we change the insertion logic from finding the "nearest" insertion to searching all feasible ones. Several inputs are required for this model, such as: customers' locations, their desired time slots, freight weight, and residual workload of delivery vehicles.

2.2. Testing the Sequential Insertion Algorithm for Solomon's Instance

The overall model consists of two parts, namely the pre-planned routing stage and the dynamic pricing stage. A VRPTW problem is first solved by Lingo software and the results are connected as an assembly into Visual C++ environments with the proposed insertion algorithms.

The basic demand information is based on the Solomon's VRPTW instances. The original 56 instances designed by Prof. Marius M. Solomon (1983) contain 100 customers with Depot (customer ID = 0), demand locations, cargo units, required vehicle arrival and departure time windows, and service time. A customer's demand data improved from the Solomon's R103 instance including 101 nodes, 25 available trucks, and the capacity of each truck is 200 boxes (i.e. single-wall corrugated with contents up to 95 lbs) has been tested. There are totally 13 service routes optimized in the first stage, as shown in Table 1.

Table 1 Detailed Service Sequences of the Optimized Routes

Routes	Delivery Sequences
Route 1	D – 60 – 45 – 83 – 5 – 99 – 6 – D
Route 2	D – 71 – 65 – 78 – 34 – 35 – 81 – 77 – 28 – D
Route 3	D – 2 – 22 – 75 – 56 – 4 – 25 – 54 – D
Route 4	D –7 – 19 – 11 – 8 – 46 – 47 – 48 – 82 – 18 –89 – D
Route 5	D – 27 – 69 – 30 – 9 – 66 – 20 – 51 – 1 – D
Route 6	D – 94 – 95 – 96 – 97 – 87 – 13 – D
Route 7	D – 42 – 43 – 15 – 57 – 41 – 74 – 72 – 73 –21 – 58 – D
Route 8	D – 52 – 62 – 88 – 84 – 17 – 93 – 59 – D
Route 9	D – 26 – 39 – 23 – 67 – 55 – 24 – 29 –3 – D
Route 10	D – 92 – 98 – 14 – 44 – 38 – 86 – 16 –61 – 85 – 91 – 100 – 37 – D
Route 11	D – 36 – 64 – 49 – 63 – 90 – 32 – 70 – D
Route 12	D – 50 – 33 – 76 – 79 – 10 – 31 – D
Route 13	D – 40 – 53 – 12 – 68 – 80 – D

When a new customer comes, our program tries to insert him into the candidate routes. A feasible insertion indicates all previous customers are still served with the original time slot. If there were more than one available time slot for this customer, the dynamic pricing model in the section 3 can help service providers determine the optimal posted price and the minimum acceptable bid price for each time slot.
Based on the optimized results in Table 1, a new customer (ID = 101) is randomly generated at location (20, 10) in the Solomon's instance, carries 12 boxes of cargos and requires 10 minutes service time. There are two possible insertion routes listed below: Route 7 and Route 10. Table 2a states the optimized vehicle arrival and departure times of Route 7 solved by the above VRPTW model.

Table 2(a) Optimized VRPTW Results of Route 7 (Before Insertion)

ID	Demand (boxes)	Arrival (mins)	Departure (mins)	Time Slot (mins)	ID	Demand (boxes)	Arrival (mins)	Departure (mins)	Time Slot (mins)
0	0	0	0	--	74	8	117.501	127.501	60-120
42	5	25.495	35.495	0-60	72	25	130.663	140.663	120-180
43	7	44.55	54.55	0-60	73	9	143.825	153.825	120-180
15	8	61.83	71.83	60-120	21	11	156.987	166.987	120-180
57	7	79.11	89.11	60-120	58	18	177.804	187.804	180-240
41	31	100.29	110.29	60-120	0	0	196.589	--	--

After the insertion, the estimated new arrival and departure times are listed in Table 2b. The insertion is defined as infeasible because there are four violations occurred (i.e. customers' ID: 43, 41, 74, and 21.)

Table 2(b) Optimized VRPTW Results of Route 7 (After Insertion)

ID	Demand (boxes)	Arrival (mins)	Departure (mins)	Time Slot (mins)
0	0	0	0	--
42	5	25.495	35.495	0-60
101	**12**	**49.967**	**59.967**	**0-60**
43	7	67.643	77.643	**60-120**
15	8	84.923	94.923	60-120
57	7	102.203	112.203	60-120
41	31	123.383	133.383	**120-180**
74	8	140.594	150.594	**120-180**
72	25	153.756	163.756	120-180
73	9	167.368	177.368	120-180
21	11	180.98	190.98	**180-240**
58	18	201.797	211.797	180-240
0	0	220.852	--	--

Table 3a states the original vehicle arrival and departure times of Route 10. After the insertion, the estimated new arrival and departure times are listed in the Table 3b. The insertion is defined as feasible because there is no violation occurred.

Table 3(a) Optimized VRPTW Results of Route 10 (Before Insertion)

ID	Demand (boxes)	Arrival (mins)	Departure (mins)	Time Slot (mins)
0	0	0	0	--
92	3	18.385	28.385	0-60
98	10	31.547	41.547	0-60
14	20	53.252	63.252	0-60
44	18	68.909	78.909	60-120
38	16	89.726	99.726	60-120
86	35	112.764	122.764	60-120
16	19	129.089	139.089	120-180
61	13	143.561	153.561	120-180
85	21	158.033	168.033	120-180
91	1	171.195	181.195	120-180
100	17	184.357	194.357	180-240
37	8	197.185	207.185	180-240
0	0	228.398	--	--

Table 3(b) Optimized VRPTW Results of Route 10 (After Insertion)

ID	Demand (boxes)	Arrival (mins)	Departure (mins)	Time Slot (mins)
0	0	0	0	--
92	3	18.385	28.385	0-60
98	10	31.547	41.547	0-60
14	20	53.252	63.252	0-60
44	18	68.909	78.909	60-120
38	16	89.726	99.726	60-120
86	35	112.764	122.764	60-120
16	19	129.089	139.089	120-180
61	13	143.561	153.561	120-180
85	21	158.033	168.033	120-180
91	1	171.195	181.195	120-180
100	17	184.357	194.357	180-240
101	**12**	**212.603**	**222.603**	**180-240**
37	8	232.603	242.603	180-240
0	0	263.816	--	--

3. Model Development of Dynamic Pricing

The dynamic pricing model is developed for maximizing the total expected revenue of a provider of attended home deliveries, while improving the matches between customers' preferred delivery time and price and carriers' desirable time slots and charge fees. In practice, the conventional delivery service providers tend to charge the fixed shipping fee which may be not significantly varied with the available delivery capacity for each time slot i (θ_i), the remaining time before scheduling delivery trucks (t), and average customers' arrival rate *(λ)*.

Some research questions are answered in this section: (1) How to incorporate the dynamic pricing mechanism into the attended home delivery logistics systems? (2) Instead of arbitrarily making incentive decisions (e.g.

Peapod Online Grocery Shopping and Delivery in USA), how to quantify and optimize the posted charge fees and the minimum acceptable bid price for each available and biddable time slot, respectively?

Three dynamic pricing models are introduced. The model 1 assumes single type of time slot without considering bidding behavior; the model 2 incorporates customers' bidding behaviors; the model 3 assumes multiple types of time slots (e.g. peak and off-peak demand periods).

3.1. Model 1: Single Type of Time Slot without Bidding Behavior

Two kinds of customers' behaviors (i.e. price-taker, and leave-without-pay) are considered in this stage. If customers decide to request a time slot with the listed shipping fee, this request can be immediately accepted. But if they are not satisfied with the offered prices, they will leave without any action. The basic model is expressed as follows:

$$\begin{aligned} \pi_P(\theta,t) &= \max_P V_P(\theta,t) \text{ for } \theta>0,\ t=1,\dots,T \\ &= \max_P \{\lambda\times\overline{F}(P)\times\left[P+\pi_P(\theta-1,t-1)\right]+\left[1-\lambda\times\overline{F}(P)\right]\pi_P(\theta,t-1)\} \end{aligned} \tag{1}$$

The objective function (Equation 1) is formulated as the maximization of total expected revenue *(* π_p*)* resulting from price-takers' behavior. The remaining time before scheduled delivery trucks t is between T and T_0. θ represents the available delivery capacity for each time slot; λ is the probability of customers entering the system; $\overline{F}(P)$ denotes the cumulative probability for customers who decide to request a time slot with the listed shipping fee; $F(P)$ denotes the cumulative probability for customers who leave without any action.

3.2. Model 2: Single Type of Time Slot with Bidding Behavior

In model 2, we assume that customers are allowed to negotiate the listed shipping fee, if they are not satisfied with the offered prices but still interested in the specific time slot. Customers who are willing to place their bids may have flexible attendance time and/or be more sensitive with the delivery price while those price-takers do not actively try to find the best deal due to fixed schedule, lack of patience, insensitivity to the delivery cost, etc. The model is formulated as follows, where β = the percentage of customers who are willing to bid; $\overline{F}(c)$ = the cumulative probability for customers whose reservation price is between the posted shipping fee and the minimum acceptable bid price; F(c) = the cumulative probability for customers whose reservation price is even lower than the minimum acceptable bid price.

$$\begin{aligned} &\pi_P(\theta,t) = \max_P V_P(\theta,t) \text{ for } \theta>0,\ t=1,\dots,T \\ &V_P(\theta,t) = \lambda\times(1-\beta)\times\overline{F}(P)\times\left[P+\pi_P(\theta-1,t-1)\right] \\ &+\lambda\times\beta\times\left\{\int_P^R\left[\alpha P+(1-\alpha)c\right]f(x)dx+\int_c^P\left[\alpha P+(1-\alpha)c\right]f(x)dx+\overline{F}(c)\times\pi_P(\theta-1,t-1)\right\} \\ &+\left[1\text{-}\lambda\times(1\text{-}\beta)\times\overline{F}(P)-\lambda\times\beta\times\overline{F}(c)\right]\pi_P(\theta,t-1) \end{aligned} \tag{2}$$

$$c = f(\theta,t) = \pi_P(\theta,t-1)-\pi_P(\theta-1,t-1) \tag{3}$$

$$\pi_P(\theta,t=0)=0 \text{ for } \theta\ge 0, \text{ and } \pi_P(\theta=0,t)=0 \text{ for } t=1,\dots,T \tag{4}$$

Equation 2 shows the five possible outcomes at each time t: (a) customer is a price-taker; (b) customer can accept the listed price but still want to place a bid; (c) customer is a bidder whose reservation price is between the posted shipping fee and the minimum acceptable bid price; (d) customer is a bidder whose reservation price is lower than the minimum acceptable bid price; and (e) leave without any action.

The opportunity cost function (also implies the minimum acceptable bidding price) is specified in Equation 3. Finally, the boundary conditions are stated in Equation 4.

3.3. Model 3: Multiple Types of Time Slots with Bidding Behavior

The above models are initially designed with the number of customers assigned to one specific time slot; however, the models might be somewhat arguable due to lack of considering the characteristics of various demand in different time slots. Here we assume that two types of time slot settings are introduced in this model. θ_i is the available delivery capacity for each time slot i, where i = 1 and i = 2 representing the peak and off-peak demand periods, respectively. Customers may prefer the time slot 1 rather than the slot 2, and the posted shipping fee of the time slot 1 is higher at the beginning.

Similarly, for those customers entering to the system, seven outcomes will be considered, as expressed in Equation 5. All other equations are as in model 2.

$$
\begin{aligned}
&\pi_P(P_1,P_2,\theta_1,\theta_2,t)=\max_{P_1,P_2} V_P(P_1,P_2,\theta_1,\theta_2,t) \text{ for } \theta_1,\theta_2>0,\ t=1,\dots,T\\
&V_P(P_1,P_2,\theta_1,\theta_2,t)\\
&=\lambda(1-\beta_1)\overline{F}(P_1)\left[P_1+\pi_P(\theta_1-1,\theta_2,t-1)\right]\\
&+\lambda(1-\beta_1)F(P_1)(1-\beta_2)\overline{F}(P_2)\left[P_2+\pi_P(\theta_1,\theta_2\text{-}1,t-1)\right]\\
&+\lambda(1\text{-}\beta_1)F(P_1)\beta_2\left\{\int_{P_2}^{R}\left[\alpha P_2+(1-\alpha)c_2\right]f(x)dx+\int_{c_2}^{P_2}\left[\alpha P_2+(1-\alpha)c_2\right]f(x)dx+\overline{F}(c_2)\times\pi_P(\theta_1,\theta_2\text{-}1,t-1)\right\}\\
&+\lambda\beta_1\left\{\int_{P_1}^{R}\left[\alpha P_1+(1-\alpha)c_1\right]f(x)dx+\int_{c_1}^{P_1}\left[\alpha P_1+(1-\alpha)c_1\right]f(x)dx+\overline{F}(c_1)\pi_P(\theta_1-1,\theta_2,t-1)\right\}\\
&+\lambda\beta_1F(c_1)(1-\beta_3)\overline{F}(P_2)\left[P_2+\pi_P(\theta_1,\theta_2-1,t-1)\right]\\
&+\lambda\beta_1F(c_1)\beta_3\left\{\int_{P_2}^{R}\left[\alpha P_2+(1-\alpha)c_2\right]f(x)dx+\int_{c_2}^{P_2}\left[\alpha P_2+(1-\alpha)c_2\right]f(x)dx+\overline{F}(c_2)\pi_P(\theta_1,\theta_2-1,t-1)\right\}\\
&+\Big\{1-\lambda\Big[(1-\beta_1)\Big[\overline{F}(P_1)+(1-\beta_2)F(P_1)\overline{F}(P_2)+\beta_2F(P_1)\overline{F}(c_2)\Big]\\
&-\beta_1\Big[\overline{F}(c_1)+(1-\beta_3)F(c_1)\overline{F}(P_2)+\beta_3F(c_1)\overline{F}(c_2)\Big]\Big]\Big\}\pi_P(\theta_1,\theta_2,t-1)
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
c_1&=g(\theta_1,\theta_2,t)=\pi_P(\theta_1,\theta_2,t-1)-\pi_P(\theta_1-1,\theta_2,t-1)\\
c_2&=h(\theta_1,\theta_2,t)=\pi_P(\theta_1,\theta_2,t-1)-\pi_P(\theta_1,\theta_2\text{-}1,t-1)
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
&\pi_P(\theta_1,\theta_2,t=0)=0 \text{ for } \theta_1,\theta_2\geq 0\\
&\pi_P(\theta_1=0,\theta_2=0,t)=0 \text{ for } t=1,\dots,T
\end{aligned}
\tag{7}
$$

4. Application of Models and Computational Results

Through this work we seek to optimize the shipping fee based on several dynamic pricing oriented factors: the available capacity for each time slot i (θ_i), the remaining time before scheduling and dispatching trucks (t), and average arrival rate *(λ)*. It should be noted that this study we first develop a general model, but those formulations could be further revised for certain specific products, such as perishable cargos in cold-chain logistics with nonlinear time value settings. Some applications arise when the service time slots have significantly different demand. Additionally, this study provides flexibility for behaviorally-realistic decision rules among customers and attended home delivery logistics service providers.

Single time slot without any bidding behavior (Model 1) is first analysed (Fig. 3) when $\lambda = 0.8$, $\theta = 3$, and T = 5. $\bar{F}(x)$ is assumed as the Weibull distribution with shape parameter 2 and scale parameter 80. The expected revenue at time t (π_t) is derived from the one in prior time period t – 1 (π_{t-1}). According to the optimized results (i.e. in terms of posted shipping fee / total system expected revenue), it is easily observed that service providers can charge higher posted shipping fee at the early stage to reach higher total expected revenue.

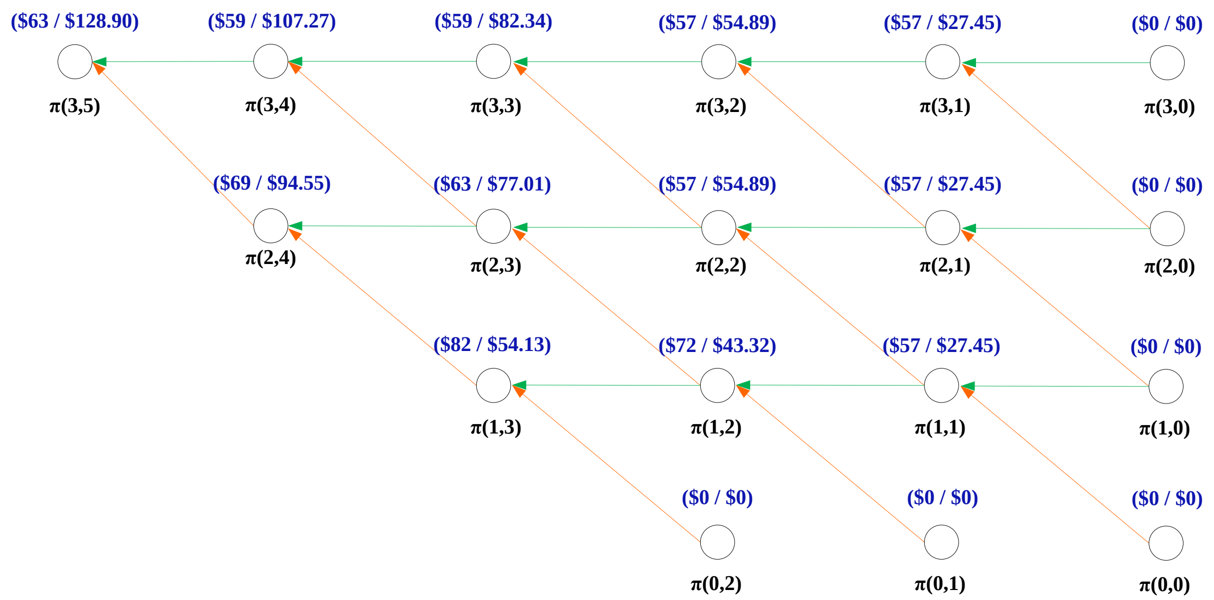

Fig. 3 Overall Results in Model 1 ($\lambda = 0.8$, $\theta = 3$, and T = 5)

The optimized results in Model 2 are illustrated in Fig. 4. The percentage of customers willing to bid could be surveyed and estimated. The survey results of existing customers (i.e. without experiencing the time slot selection and bidding service before) may be somewhat biased, but the service provider could keep collect the real-time data and re-estimate this percentage after providing the time slot choice service. Here we assume that half of customers are willingness to bid (i.e. $\beta = 1\text{-}\beta = 0.5$). All other settings are as in Model 1. Since customers are allowed to negotiate the shipping fee with delivery service providers, the expected revenue resulting from the bidding behaviors are derived from the average between the original posted fee and the minimum acceptable bid price (i.e. $\alpha = 0.5$).

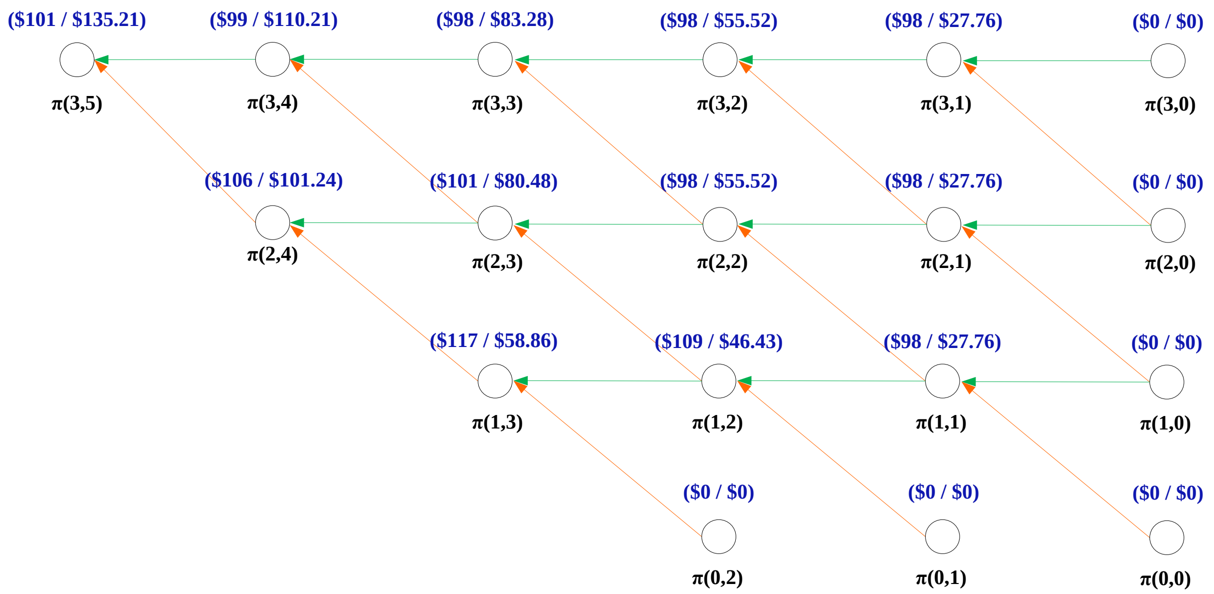

Fig. 4 Overall Results in Model 2 ($\lambda = 0.8$, $\theta = 3$, and T = 5)

While comparing the optimized results in both models, a similar trend is also observed. For those customers whose reservation price is lower than the posted shipping fee in Model 2 may still have a chance to bargain the price of their desired time slots rather than just leave without any action in Model 1, these additional bids yield improvements of the total expected revenue. Fig.5 demonstrates the introduction of bidding has potential to achieve higher system revenue (i.e. up to 8.74%), if the customers willing to bid are successfully attracted.

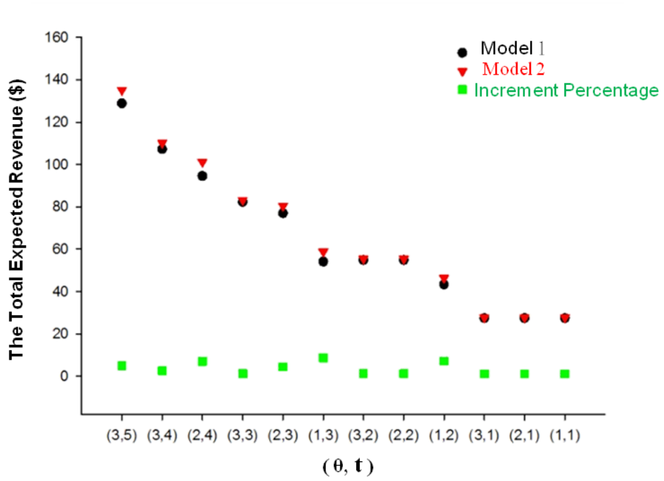

Fig. 5. Comparisons of the Total Expected Revenue in Models 1 and 2

5. Conclusions

Our main purpose is to explore the feasibility of introducing dynamic pricing concept and bidding behavior into the attended home delivery service, starting from the assumption that a proportion of customers would be attracted to the time slots open for selecting and/or bidding. In the preparation stage, an insertion-based algorithm is applied to check the availability of candidate time slots. A quantitative method is developed for optimizing the corresponding posted shipping fee and the minimum acceptable bid price at each time slot during the dynamic pricing operation phase.

Although these assumptions and tested case studies could be extended with greater complexity and realism, such analysis provides a basis for future refined auction models, which will involve the interrelation between customers' choice behaviors and different bid-price control strategies for transferring certain peak delivery requests to the off-peak time slots so as to obtain more profits.

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