Choice-Based Periodic Vehicle Routing and Pricing for Urban Last-Mile Deliveries

Chenghua Yang*[1], Jie Gao[2], and Bilge Atasoy[3]

[1]PhD Student, Department of Maritime and Transport Technology, Delft University of Technology, the Netherlands
[2]Assistant Professor, Department of Transport and Planning, Delft University of Technology, the Netherlands
[3]Associate Professor, Department of Maritime and Transport Technology, Delft University of Technology, the Netherlands

Short summary

In urban periodic deliveries, business customers exhibit heterogeneous preferences over price, visit frequency, timing, and time window length. Ignoring such heterogeneity leads to service designs that misalign with customer needs. We propose the choice-based periodic vehicle routing and pricing problem (CB-PVRP), which incorporates stochastic customer choices into joint optimization of service offering, pricing, and vehicle routing. We formulate CB-PVRP as a two-stage stochastic mixed-integer program. The first stage determines offerings and pricing to maximize expected profit. The second stage, which embeds a bilevel structure, decides daily routing subject to revealed choices. We capture preference heterogeneity using a multinomial logit model with segmentation. We apply sample average approximation to address stochasticity and propose linear best-response sets for the bilevel reformulation. Our tailored logic-based Benders decomposition algorithm outperforms a commercial solver on solution quality and speed. By incorporating customer choice behaviors, the provider achieves higher expected profitability while customers receive improved services.
Keywords: periodic vehicle routing, choice-based optimization, two-stage stochastic programming, bilevel optimization, sample average approximation, logic-based Benders decomposition.

1 Introduction

In urban contract-based logistics, service providers plan periodic deliveries to business customers, such as those in the HoReCa (i.e., hotels, restaurants, and cafes) sector over a given planning horizon (e.g., a week). To fulfill the increasing demand for more flexible and customized services under limited delivery resources, service providers are increasingly seeking to leverage customer preference insights in their design of service offerings and planning of transportation operations.

In practice, services typically differ across various attributes, including price, frequency (i.e., number of visits), timing (i.e., time of day), and time window length (i.e., duration of the promised window). Customers make choices by trading off these attributes and show substantial heterogeneity in their willingness to pay. For example, a customer might be willing to pay a higher price for increased visit frequency or to accept a wider time window in exchange for earlier delivery timing. By leveraging such behavioral trade-offs, a service provider may gain flexibility to design service offerings that benefit both sides: the service provider might use tailored offerings to shape customer choices for more efficient resource utilization, and customers might receive offers that reflect their individual preferences.

Despite the potential benefits, incorporating disaggregated customer choices into the planning of periodic deliveries raises several open challenges. First, customer choices are inherently stochastic: their decision to accept or reject an offering is governed not only by observable attributes but also by privately known factors that are unobservable to the service provider. Second, both revenue and fulfillment cost depend heavily on customer choices. Due to this stochasticity and interdependency, the service provider cannot anticipate with certainty how customers will respond to the offerings

and prices, nor the corresponding revenue and cost.

In the existing literature, while many studies have examined demand management in various urban delivery systems (Yang & Strauss, 2017; Arslan et al., 2025), they mostly focus on the design of time windows and pricing. Research on the context of periodic deliveries and the corresponding joint management of visit frequency, time windows, and pricing remains limited. From the modeling perspective, our research is closely related to two research streams: (i) time window assignment studies in VRP and TSP (Spliet & Gabor, 2015; Spliet et al., 2018; Çelik et al., 2025) that design time window assignments; and (ii) PVRP models (Francis et al., 2006; Archetti et al., 2017, 2018) that endogenize visit frequency decisions. However, these two research streams each address only parts of our problem and do not explicitly represent stochastic customer choice behaviors as we do. To address these challenges, we propose a new problem termed choice-based periodic vehicle routing and pricing (CB-PVRP) and develop a tailored logic-based benders decomposition (LBBD) algorithm to solve the large-scale problem. We summarize our contributions as follows.

- From the modeling perspective, CB-PVRP contributes two novelties. First, it explicitly captures customer-level trade-offs among service price, frequency, timing, and time window length through an MNL model, while accounting for observable preference heterogeneity through customer segmentation. Second, it jointly optimizes service offering, pricing, and vehicle routing under stochastic customer choices in the context of urban periodic deliveries. To the best of our knowledge, CB-PVRP is the first stochastic PVRP in which stochasticity arises from uncertain customer choice behaviors.
- From the methodological perspective, our contribution is two-fold. First, we propose two customer best-response sets as alternatives to KKT conditions for reformulating the bilevel optimization structure. These sets are shown to be computationally more efficient than the KKT-based approach. Second, we develop a tailored LBBD algorithm that solves the reformulated CB-PVRP with provable solution quality guarantees. To the best of our knowledge, our algorithm is the first LBBD application for solving stochastic mixed-integer programs whose subproblems are vehicle routing problems with time windows.
- From the managerial perspective, we perform an extensive numerical study to assess the practical significance of the choice-based planning for periodic delivery services. Our results demonstrate the benefits of CB-PVRP for both service providers and customers in terms of improved profitability and enhanced service levels, respectively.

2 Mathematical Model

The problem is defined on a complete graph $\mathcal{G} = (\mathcal{N}^+, \mathcal{A})$, where $\mathcal{N}^+ = \mathcal{N} \cup \{0\}$ is the set of nodes and $\mathcal{A} = \{(i,j) \in \mathcal{N}^+ \times \mathcal{N}^+ : i \neq j\}$ is the set of arcs. The set $\mathcal{N}$ contains customer nodes, and node 0 represents the depot at which a fleet of homogeneous uncapacitated vehicles $\mathcal{V}$ is available. For arc $(i,j) \in \mathcal{A}$, let t_{ij} denote the travel time and c_{ij} the travel cost.

Deliveries are planned over a preset planning horizon consisting of a set of days $\mathcal{D} = \{1, 2, \ldots, |\mathcal{D}|\}$. A service alternative (s, w) is defined as a combination of a schedule $s \in \mathcal{S}$ and a time window $w \in \mathcal{W}$, where $\mathcal{S}$ and $\mathcal{W}$ denote the global sets of schedules and time windows that the service provider considers. Here, a schedule s represents a subset of days $d \in \mathcal{D}$ on which a customer is visited, with associated frequency $F_s = |s|$. A time window w is defined by its earliest start time e_w and latest end time l_w, with length $L_w = l_w - e_w$. Following the assumption of Amorim et al. (2024), we measure the timing of window w in terms of its earliest start time e_w. We define the binary parameter $\alpha_{sd} \in \{0, 1\}$, which equals 1 if schedule s includes day $d \in \mathcal{D}$, and 0 otherwise.

Each customer $i \in \mathcal{N}$ requires q_i units of goods during the planning horizon. The service provider considers offering each customer i one alternative from a set of feasible candidates $\mathcal{O}_i = \mathcal{S}_i \times \mathcal{W}_i$, where $\mathcal{S}_i \subseteq \mathcal{S}$ and $\mathcal{W}_i \subseteq \mathcal{W}$ denote the set of feasible schedules and the set of feasible time windows of customer i, respectively. When presented to customers, an alternative (s, w) is associated with a price p_{sw} per unit of goods under this service. Customers who are offered the same alternative (s, w) face the same price p_{sw}.

Given the observed customer trade-offs among service attributes and the heterogeneity in preferences, we represent customer choices using a MNL model with segmentation. The market is

partitioned into a set of disjoint customer segments $\mathcal{H} = \{1, \ldots, |\mathcal{H}|\}$, where each customer i belongs to one segment $h(i) \in \mathcal{H}$. Customers in the same segment are assumed to be homogeneous with respect to their systematic utility parameters, while individual stochastic preferences are captured by i.i.d. Gumbel-distributed random error terms.

Under the assumption that customers generally value lower prices, higher visit frequencies, earlier timing, and shorter time window length, the utility that customer i places on an alternative (s, w) per unit of goods is defined as:

$$U_{isw}(p_{sw}, \epsilon_{isw}) = -\beta_{h(i)}^{\text{COST}} p_{sw} + \beta_{h(i)}^{\text{FRQ}} F_s - \beta_{h(i)}^{\text{TIMING}} e_w - \beta_{h(i)}^{\text{TWL}} L_w + \epsilon_{isw},$$

where β_h^{COST} is the segment-h sensitivity to price, β_h^{FRQ} the sensitivity to visit frequency, β_h^{TIMING} the sensitivity to timing, and β_h^{TWL} the sensitivity to the time window length. The error term ϵ_{isw} follows a standard Gumbel distribution. To account for market competition, we include an opt-out alternative for each customer, representing the utility obtained from a competitor or the *status quo*. We presume the service provider is aware of each customer's opt-out alternative and the corresponding price. Specifically, we denote $U_{i,\text{out}}$ as the utility customer i places on the opt-out alternative per unit of goods.

We formulate CB-PVRP as a two-stage stochastic mixed-integer programming model. In the first stage, the service provider determines the offering and pricing of service alternatives with the objective of maximizing expected total profit. Define the binary variable $\delta_{isw} = 1$ if alternative (s, w) is offered to customer i. Further define the continuous variable $p_{sw} \in [0, p_{sw}^{\text{UB}}]$ as the price of delivering one unit of goods under service alternative (s, w), where p_{sw}^{UB} is a known upper bound. The CB-PVRP is then formulated as follows:

$$\pi^* = \max_{\boldsymbol{\delta}, \boldsymbol{p}} \mathbb{E}_{\boldsymbol{\epsilon}} \big[Q(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\epsilon}) \big] \tag{1a}$$

$$\text{s.t.} \quad p_{s'w} \leq p_{sw}, \quad \forall w \in \mathcal{W}, s, s' \in \mathcal{S} : F_{s'} \leq F_s, \tag{1b}$$

$$p_{sw} \leq p_{sw'}, \quad \forall s \in \mathcal{S}, w, w' \in \mathcal{W} : w' \subseteq w, \tag{1c}$$

$$\sum_{(s,w) \in \mathcal{O}_i} \delta_{isw} = 1, \quad \forall i \in \mathcal{N}, \tag{1d}$$

$$\delta_{isw} \in \{0, 1\}, \quad \forall i \in \mathcal{N}, (s, w) \in \mathcal{O}_i, \tag{1e}$$

$$p_{sw} \in [0, p_{sw}^{\text{UB}}], \quad \forall s \in \mathcal{S}, w \in \mathcal{W}. \tag{1f}$$

Equation (1a) defines the objective of maximizing expected total profit π^* during the planning horizon. $Q(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\epsilon})$ is the objective of the second-stage model that maximizes the realized profit when the first-stage decisions $\boldsymbol{\delta}$ and $\boldsymbol{p}$ are fixed, and the MNL random error terms $\boldsymbol{\epsilon}$ are revealed. Constraints (1b) state that when two alternatives share the same time window, the one with the higher frequency must be priced the same as or above the other. Constraints (1c) impose that for two alternatives with the same schedule, if the time window of one alternative is contained within the other (i.e., it has a narrower time window), this alternative must have the same or higher price. Constraints (1d) ensure that each customer is made an offer. Constraints (1e) and (1f) specify the domain of the first-stage variables.

In the second stage, under fixed assignment and pricing decisions, each customer faces a choice between the offered alternative and opting out. We presume customers maximize their random utilities. Customer choices are constrained by the service provider's assignments. We define the binary choice variable $\zeta_{isw} = 1$ if customer i chooses alternative (s, w). After customers make decisions, the service provider designs the daily routing to serve the customers who accept the offers. We define the binary variable $y_{ivd} = 1$ if customer i is visited by vehicle v on day d, and $x_{ijvd} = 1$ if arc (i, j) is traversed by vehicle v on day d. Let T be the latest time by which all vehicles must return to the depot. We define the continuous variable $a_{ivd} \in [0, T]$ as the arrival time of vehicle v at customer i on day d. The objective of the second-stage model is to maximize the realized profit $Q(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\epsilon})$ under fixed first-stage decisions and revealed random errors. The second-stage model is defined as:

$$Q\big(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\epsilon}\big) = \max_{\boldsymbol{\zeta}, \boldsymbol{y}, \boldsymbol{x}, \boldsymbol{a}} \sum_{i \in \mathcal{N}} \sum_{(s,w) \in \mathcal{O}_i} q_i p_{sw} \zeta_{isw} - \sum_{(i,j) \in \mathcal{A}} \sum_{v \in \mathcal{V}} \sum_{d \in \mathcal{D}} c_{ij} x_{ijvd} \tag{2a}$$

$$\text{s.t.} \quad \boldsymbol{\zeta}_i \in \underset{\boldsymbol{\zeta}_i}{\operatorname{argmax}} \left\{ \sum_{(s,w)\in\mathcal{O}_i} (U_{isw} - U_{i,\text{out}}) q_i \zeta_{isw} : \zeta_{isw} \leq \delta_{isw}, \forall (s,w) \in \mathcal{O}_i, \zeta_{isw} \in \{0,1\} \right\}, \forall i \in \mathcal{N}, \tag{2b}$$

$$\sum_{v\in\mathcal{V}} y_{ivd} = \sum_{s\in\mathcal{S}_i} \sum_{w\in\mathcal{W}_i} \alpha_{sd} \zeta_{isw}, \quad \forall i \in \mathcal{N}, d \in \mathcal{D}, \tag{2c}$$

$$e_w \sum_{s\in\mathcal{S}_i} \alpha_{sd} \zeta_{isw} \leq a_{ivd}, \forall i \in \mathcal{N}, w \in \mathcal{W}_i, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2d}$$

$$a_{ivd} \leq (l_w - T) \sum_{s\in\mathcal{S}_i} \alpha_{sd} \zeta_{isw} + T, \forall i \in \mathcal{N}, w \in \mathcal{W}_i, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2e}$$

$$\sum_{j\in\mathcal{N}^+:j\neq i} x_{ijvd} = y_{ivd}, \quad \forall i \in \mathcal{N}, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2f}$$

$$\sum_{j\in\mathcal{N}^+:j\neq i} x_{jivd} = y_{ivd}, \quad \forall i \in \mathcal{N}, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2g}$$

$$a_{ivd} + t_{ij} - (T + t_{ij})(1 - x_{ijvd}) \leq a_{jvd}, \forall i \in \mathcal{N}^+, j \in \mathcal{N}, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2h}$$

$$a_{ivd} + t_{i0} \leq T + t_{i0}(1 - x_{i0vd}), \forall i \in \mathcal{N}, v \in \mathcal{V}, d \in \mathcal{D}, \tag{2i}$$

$$\boldsymbol{y} \in \{0,1\}^{|\mathcal{N}||\mathcal{V}||\mathcal{D}|}, \tag{2j}$$

$$\boldsymbol{x} \in \{0,1\}^{|\mathcal{A}||\mathcal{V}||\mathcal{D}|}, \tag{2k}$$

$$\boldsymbol{a} \in \mathbb{R}_+^{|\mathcal{N}^+||\mathcal{V}||\mathcal{D}|}. \tag{2l}$$

Equation (2a) is the objective function of the second-stage model. Constraints (2b) define independent customer choices, where each customer chooses between the offered alternative and the opt-out to maximize the obtained utility. Constraints (2c) state that customer i should be visited on day d if the selected schedule contains the day. Constraints (2d) and (2e) further ensure that customer i is visited within the agreed time window. Constraints (2f) and (2g) link $\boldsymbol{x}$ and $\boldsymbol{y}$ to ensure node flow conservation. Constraints (2h) make sure the feasibility of arc travel times, which serves as subtour elimination. Constraints (2i) ensure that vehicles return to the depot before the end of the day. Constraints (2j)-(2l) specify the domain of the second-stage variables.

3 Solution Approach

Sample average approximation

Solving CB-PVRP (1) requires evaluating an expectation with respect to a collection of random error terms. To address this, we adopt the SAA approach to approximate the expected total profit in the first-stage objective function (1a). The SAA method is a Monte Carlo sampling-based approach in which we generate a sample of $|\mathcal{R}|$ scenarios $\Omega_{|\mathcal{R}|} = \{\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \ldots, \boldsymbol{\epsilon}_{|\mathcal{R}|}\}$. A scenario $r \in \mathcal{R}$ is represented by a vector $\boldsymbol{\epsilon}_r$ of random error terms independently drawn from the standard Gumbel distribution. After extending the second-stage variables to the scenario-based form, the resulting deterministic equivalent maximizes the average realized profit across scenarios.

Single-level reformulation

The SAA formulation embeds, for each customer and each scenario, an independent customer best-response problem through the scenario-extended version of constraints (2b). This creates a bilevel structure where the service provider determines first-stage offering and pricing, while customers subsequently respond by accepting or rejecting offered alternatives under their realized random utilities. To reformulate this bilevel structure, we develop two linear customer best-response sets as alternatives to the KKT-based approach.

The first is a utility-based customer best-response set (U-CBRS), which exploits the logic that a customer accepts an alternative if and only if its revealed utility is greater than or equal to that of the opt-out option. Thus, U-CBRS relies on comparing utilities of the offered alternative and the opt-out.

The second is a price-based customer best-response set (P-CBRS), which further simplifies U-CBRS by observing that opt-out utilities are revealed upon sampling and the utility of an alternative for a customer under a scenario depends solely on its price. We pre-calculate a threshold price $\tilde{p}_{risw}$ such that customer i accepts alternative (s, w) under scenario r if and only if $p_{sw} \leq \tilde{p}_{risw}$. Thus, P-CBRS reduces to comparing the offer price with the threshold price. We denote the single-level reformulations using KKT conditions, U-CBRS, and P-CBRS as $\mathrm{M_{KKT}}$, $\mathrm{M_{UCBRS}}$, and $\mathrm{M_{PCBRS}}$, respectively.

Logic-based Benders Decomposition (LBBD)

The single-level SAA reformulation remains a large-scale mixed-integer program with two computational challenges: (1) the first-stage problem admits exponentially many feasible solutions, and (2) the second-stage problem involves a vehicle routing problem for each scenario and day. Given the specific structure of our problem, we instead employ an LBBD-based method and design a tailored algorithm, which exploits the separability between first-stage decisions and scenario-dependent routing subproblems.

We decompose $\mathrm{M_{PCBRS}}$ into an MP and a set of SPs. The MP determines the first-stage offerings $\boldsymbol{\delta}$, prices $\boldsymbol{p}$, and the second-stage customer choice variables $\boldsymbol{\zeta}$. Note that we include $\boldsymbol{\zeta}$ to allow the MP to decide on offering and pricing with consideration of customer reactions, while SPs evaluate the routing costs due to these decisions. The MP also includes a variable η_{rd} representing the approximated routing cost on day d under scenario r. Initially, η_{rd} underestimates the true routing cost as the MP lacks detailed information regarding the cost to serve specific choices. The SPs compute the actual routing costs, which are then communicated to the MP via cutting planes.

We develop three versions of LBBD algorithms based on how we use the optimality cuts and valid inequalities. The first version, which we refer to as LBBD-1, adapts the cuts proposed in Fachini & Armentano (2020). The second version, which we refer to as LBBD-2, uses strengthened optimality cuts where we exploit the structural similarities between SPs to approximate unsolved SPs more efficiently. The third version, which we refer to as LBBD-3, adds valid inequality using the optimal objective value of the SP time window relaxation.

4 Results and discussion

We generate 60 new benchmark instances by adapting the openly available PVRPTW dataset, retaining customer locations and demands. The instances comprise two homogeneous uncapacitated vehicles, $|\mathcal{N}| \in \{6, 8, 12, 16, 20\}$ customers, and a 4-day planning horizon. All customers share the same feasible schedule set $\{\{1\}, \{2\}, \{3\}, \{4\}, \{1, 3\}, \{2, 4\}, \{1, 2, 3, 4\}\}$ and are randomly assigned to price-sensitive, frequency-sensitive, or time-sensitive segments. Each segment's utility coefficients are defined by the maximum utility difference $\Delta V \in \{0.1, 2, 6\}$ and segment-specific willingness-to-pay values for frequency, timing, and time window length. For each tuple $(\Delta V, |\mathcal{N}|)$, we generate 4 replications with different random assignments of available half-days, opt-out schedules, and segments, yielding $3 \times 5 \times 4 = 60$ instances. The SAA framework employs systematic sampling with $|\mathcal{R}| = 300$ scenarios per instance. All instances are solved with a time limit of 4 hours.

Computational performance

Figure 1 compares the number of instances solved to optimality (out of 60 instances) and the average optimality gap across all 60 instances for each method. The results of $\mathrm{M_{KKT}}$ are excluded from the figure as it solves zero instances to optimality and yields an unreasonably high average gap of 1,023%. As reported in the figure, $\mathrm{M_{UCBRS}}$ and $\mathrm{M_{PCBRS}}$ solve 1 and 2 instances to optimality with average gaps of 90% and 58%, respectively. The LBBD algorithms further improve upon $\mathrm{M_{PCBRS}}$. LBBD-1, LBBD-2, and LBBD-3 solve 9, 12, and 12 instances to optimality with average gaps of 29%, 26%, and 22%, respectively. LBBD-2 and LBBD-3 more than double the number of solved instances compared to $\mathrm{M_{PCBRS}}$ (12 versus 2). LBBD-3 reduces the average gap from 58% of $\mathrm{M_{PCBRS}}$ to 22%. These results demonstrate that: (1) the proposed linear customer best-response sets outperform the KKT-based approach for single-level reformulation in terms of computational efficiency, (2) the decomposition-based methods outperform the direct Gurobi implementations in

terms of both solution quality and speed.

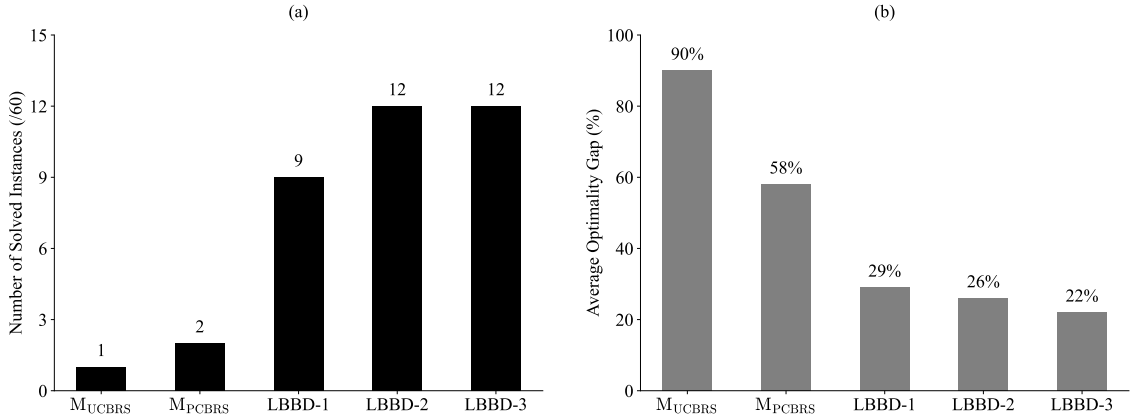


Figure 1: Number of Instances Solved and Average Optimality Gap.
Note: (a) Number (out of 60) of instances solved to optimality. (b) Average optimality gap across the 60 instances.

Value of Stochastic Solution

To evaluate the value of our stochastic optimization approach and the expected value of perfect information regarding choice stochasticity, we consider three solutions that differ in how the generated scenarios are used. The first is the stochastic solution (SS) obtained by solving CB-PVRP using LBBD-3. The second is the deterministic solution (DS) obtained by using a single representative scenario, which is the average across the 300 scenarios. The third is the wait-and-see solution (WSS) obtained by solving a deterministic problem for each scenario under perfect information. The difference SS-DS quantifies the benefits of incorporating stochastic customer choices compared with the deterministic approach that optimizes using a single representative scenario. The difference WSS-SS measures the residual uncertainty cost due to the fact that first-stage offering and pricing must be made before choice uncertainty is resolved. For this analysis, we use LBBD-3 as an MIP-based heuristic with a 1-hour time limit. The results are reported in Table 1.

As can be seen from the table, the value of the stochastic solution is substantial, with the relative value of SS, defined as $\frac{\text{SS}-\text{DS}}{\text{DS}}$, ranging from 2.46% to 111.11%. This demonstrates that the stochastic optimization approach substantially improves first-stage assignments and pricing compared with the deterministic approach. Specifically, the relative value of SS decreases as ΔV increases, reflecting that customer choices become increasingly dominated by systematic utilities and thus more deterministic. The expected value of perfect information is also large, with the relative value $\frac{\text{WSS}-\text{SS}}{\text{WSS}}$ ranging from 40.99% to 67.46%, suggesting that first-stage decisions are highly sensitive to choice uncertainty. Finally, the ratios $\frac{\text{SS}-\text{DS}}{\text{WSS}-\text{DS}}$, ranging from 1.15% to 39.16%, show that SS bridges the gap between the baseline DS and the ideal WSS obtained under perfect information.

Impact of Behavioral Assumptions

We also seek to understand how the provider's assumptions regarding preference heterogeneity impact the performance of CB-PVRP. In this analysis, we presume that the underlying customer population is heterogeneous and compare four policies that differ in the behavioral assumptions: (i) Hetero, which correctly captures the heterogeneity; (ii) Price, which assumes all customers are price-sensitive; (iii) Frequency, which assumes all customers are frequency-sensitive; and (iv) Time, which assumes all customers are time-sensitive. We use instances with $\Delta V = 6$ for this analysis, as customers are highly sensitive to service attributes in this setting. We report the expected revenue, cost, and profit under each policy, alongside the relative profit difference (Diff.) with respect to the Hetero policy. The detailed results are presented in Table 2. As expected, the Hetero policy yields the highest expected profit on all tested instances, with relative improvements ranging from 1.00% to 52.35% over the homogeneity-based policies. The results emphasize the importance of correctly capturing preference heterogeneity for the profitability when applying CB-PVRP.

Table 1: Value of Stochastic Solution and Value of Perfect Information.

$\lvert\mathcal{N}\rvert$	ΔV	SS	DS	WSS	$\frac{\text{SS-DS}}{\text{DS}}$	$\frac{\text{WSS-SS}}{\text{WSS}}$	$\frac{\text{SS-DS}}{\text{WSS-DS}}$
6	0.1	965.62	457.41	1755.23	111.11%	44.99%	39.16%
	2	781.57	468.42	1721.20	66.85%	54.59%	25.00%
	6	529.26	516.54	1626.49	2.46%	67.46%	1.15%
8	0.1	1630.22	1161.56	2865.84	40.35%	43.12%	27.50%
	2	1499.80	1216.90	2854.74	23.25%	47.46%	17.27%
	6	1458.16	1375.35	2813.00	6.02%	48.16%	5.76%
12	0.1	2472.43	1736.23	4342.99	42.40%	43.07%	28.24%
	2	2118.32	1921.51	4303.55	10.24%	50.78%	8.26%
	6	2491.04	2267.86	4221.70	9.84%	40.99%	11.42%
16	0.1	2858.18	1785.49	5038.83	60.08%	43.28%	32.97%
	2	2337.96	1934.74	4976.57	20.84%	53.02%	13.26%
	6	2706.15	2340.14	4844.67	15.64%	44.14%	14.61%
20	0.1	3134.88	1878.94	5562.62	66.84%	43.64%	34.09%
	2	2606.40	2144.57	5499.12	21.53%	52.60%	13.77%
	6	3097.48	2766.99	5380.48	11.94%	42.43%	12.65%

Table 2: Impact of Behavioral Assumption.

$\lvert\mathcal{N}\rvert$	Behavioral Assumption	Exp. Revenue	Exp. Cost	Exp. Profit	Diff.
6	Hetero	847.72	318.46	529.26	
	Price	767.59	272.20	495.39	6.40%
	Frequency	1302.40	1050.22	252.18	52.35%
	Time	638.51	159.87	478.64	9.56%
8	Hetero	2156.84	790.78	1366.06	
	Price	2086.54	911.05	1175.49	13.95%
	Frequency	2445.20	1214.30	1230.90	9.89%
	Time	1582.53	247.04	1335.49	2.24%
12	Hetero	3695.50	1204.46	2491.04	
	Price	3352.30	1375.70	1976.60	20.65%
	Frequency	3903.96	1437.93	2466.03	1.00%
	Time	2738.16	734.67	2003.49	19.57%
16	Hetero	4069.76	1363.61	2706.15	
	Price	3592.96	1407.72	2185.24	19.25%
	Frequency	4168.24	1507.95	2660.29	1.69%
	Time	3278.27	1135.97	2142.30	20.84%
20	Hetero	4673.69	1576.21	3097.48	
	Price	3476.95	1614.51	1862.44	39.87%
	Frequency	4743.28	1760.36	2982.92	3.70%
	Time	3154.63	1187.16	1967.47	36.48%

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