Day-to-day delivery demand management: Evaluation based on routing efficiency and customer satisfaction

Ryota Okazaki*[1], Yuki Oyama[2], Naoto Imura[3], and Katsuhiro Nishinari[4]

[1]Master Student, Department of Civil Engineering, Shibaura Institute of Technology, Japan
[2]Associate Professor, Department of Civil Engineering, Shibaura Institute of Technology, Japan
[3]Project Professor, Research Center for Advanced Science and Technology, University of Tokyo, Japan
[4]Professor, Research Center for Advanced Science and Technology, University of Tokyo, Japan

Short summary

As demand for online shopping and home delivery increases rapidly, courier companies often offer services focusing on customer satisfaction. This places strong constraints on the planning of delivery routes for courier vehicles, making delivery routes inefficient. The objective of this study is to present a framework to evaluate demand management policies in terms of the balance between customer satisfaction and delivery efficiency. To this end, we first estimate a delivery option choice model using the stated choice data of e-commerce users. Then, based on day-to-day delivery demand simulated by the estimated model, we optimize a multi-period vehicle routing problem and evaluate the delivery efficiency. We implement two policies: a surcharge for morning delivery and an expansion of the time slot range. The results show that the former significantly reduces customer satisfaction, while the latter achieves higher customer satisfaction and delivery efficiency.

Keywords: E-commerce, demand management, discrete choice modeling, multi-period vehicle routing problem, last-mile delivery, operations research applications

1 Introduction

The COVID-19 pandemic has boosted demand for home delivery. Online-shopping customers are placing greater emphasis on speed of delivery, delivery fees, and their own time constraints, resulting in heavy use of express delivery services and demand concentration at certain times of the day. This also imposes severe constraints on delivery route planning, resulting in inefficient deliveries. While delivery demand management (e.g. pricing or slotting) could potentially improve delivery efficiency, changes in service levels could also lead to lower customer satisfaction and fewer orders (Rao et al., 2011; Marium & Arsalan, 2017). Practical demand management requires analyzing customer preferences for delivery options and identifying policies that improve delivery efficiency while retaining customer satisfaction.

E-marketplaces like Amazon often offer their customers several delivery options with different flexibility for delivery, including regular delivery, scheduled delivery where customers can specify the delivery date and time slot, and express delivery such as next-day or same-day delivery. Scheduled delivery may produce the demand concentration on a specific day or time, and express delivery imposes a hard time constraint, while regular delivery gives flexibility to delivery. As such, the delivery option choice behavior of customers highly impacts day-to-day delivery efficiency. Therefore, to analyze the effect of this option choice behavior, delivery efficiency has to be evaluated over multiple days with multiple time slots.

Regarding delivery demand management, the management of delivery time slots has been recently studied, as reviewed by Waßmuth et al. (2023). Agatz et al. (2011) and Köhler et al. (2020) indicated that longer time slots can reduce delivery costs by relaxing time window constraints. However, they did not analyze customers' preferences or model their option choices, and thus could not analyze the policy impact on customer behavior or satisfaction. Most of the studies on delivery time slot management have focused on scheduled delivery services for e-grocers, which require prompt and accurate in-person delivery, and the effect of delivery option choice behavior

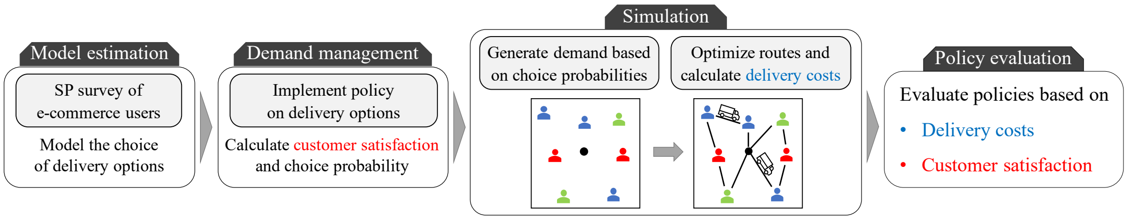

Figure 1: Flamework of this study

on delivery efficiency has yet to be analyzed.

Delivery costs are generally calculated by optimizing delivery routes by solving a Vehicle Routing Problem (VRP). The planning period of a typical VRP is a single day, and delivery options such as next-day delivery or regular delivery cannot be considered in the problem. For this reason, it is necessary to apply a multi-period vehicle routing problem (Multi-period VRP) that extends the planning period to multiple days, e.g., Archetti et al. (2015). Most of the studies related to multi-period VRP focus on formulation and runtime, and there are no studies on analyzing delivery efficiency based on customer choice behavior.

The objective of this study is to evaluate and identify policies that achieve the balance between delivery routing efficiency and customer satisfaction. To this end, we first analyze customer choice behavior of delivery options among next-day, regular, and scheduled delivery, by estimating a discrete choice model using the stated choice data. Then, we formulate and optimize a multi-period VRP with due dates and time windows, given the delivery demand simulated by the estimated choice model, and evaluate the routing costs. Finally, based on routing efficiency and customer satisfaction, different scenarios of policies are evaluated. The framework of the study is summarized in Figure 1.

The contribution of the study lies in the following three items.

1. Behavioral analysis of different delivery options

   To date, most analyses of delivery option choice have focused on specific delivery options, such as scheduled delivery. In contrast, this study analyzes customer choice among delivery options widely offered by Amazon and other e-marketplaces, including next-day, scheduled, and regular delivery.

2. Evaluating policies based on customer Satisfaction

   Most previous studies that attempted to improve delivery efficiency did not take customer satisfaction into account. In this study, to consider more realistic demand management, customer satisfaction was calculated and evaluated as an indicator for policy considering the balance with routing efficiency.

3. Optimize day-to-day delivery routes based on customer choice of delivery options

   There is no study that reflects customer choice behavior in the optimization of delivery plans by solving a multi-period VRP. The novelty of this study is that it optimizes day-to-day delivery plans using multi-period VRP to analyze the effect of delivery option choices on delivery efficiency.

2 Methodology

Stated choice data

We analyzed customer delivery option choice behavior based on responses from a stated preference (SP) survey conducted from April 30 to May 14, 2021. The respondents were among "Kuroneko Members," members of Yamato Holdings Co., Ltd. which has the largest share of parcel delivery in Japan. The survey was conducted on the assumption that respondents would purchase the same products again that they purchased online the previous time. Respondents were asked to select a delivery option among (1) next-day delivery, (2) scheduled delivery (2 to 8 days after order), and (3) regular delivery (date and time can not be specified). Respondents who selected scheduled delivery were additionally asked to select delivery date and time. Each respondent makes one

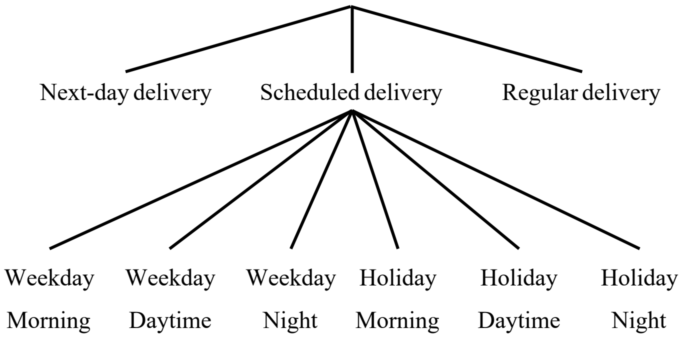

Figure 2: Nest Structure of Choice Model

choice for each of the five different choice scenarios. For each scenario, three attributes were varied: delivery fee, delivery time (the number of days required for delivery), and range of a time slot. For details on the survey design and data, see Oyama et al. (2022). The survey was completed by 4,872 respondents (response rate 4.87%), and given that five scenarios were presented to each respondent, the original sample size is 24360. Data cleaning was then performed based on the experience of online shopping, choice of dominated alternatives, resulting in the final sample size of 18,928.

Delivery option choice model

We then develop a delivery option choice model. In addition to next-day and regular deliveries, we assume six alternatives for scheduled delivery, which are a combination of delivery day (weekday and holiday) and time slot (morning, daytime, and nighttime). With these eight alternatives in total, we apply the Nested Logit (NL) Model with a nest of scheduled delivery based on the assumption that the utilities of the six options are correlated (Figure 2).

The utility V_{ni} of option i for individual n is defined as

$$V_{ni} = \mathrm{ASC}_i + \beta_{\mathrm{day}} \cdot \mathrm{day}_i + \beta_{\mathrm{fee}} \cdot \mathrm{fee}_i + \beta_{\mathrm{slot\_range}} \cdot \mathrm{slot\_range}_i \cdot \delta_{\mathrm{i,\ scheduled}} \tag{1}$$

where ASC_i is the alternative specific constant for i, $\mathrm{day}_i$is the number of days required to be delivered when choosing i, fee_i is the delivery fee in JPY, and $\mathrm{slot\_range}_i$ is the time slot range in hours, which implies how long the individual has to be at home to receive the item. The dummy variable $\delta_{i,\mathrm{scheduled}}$ is 1 if i is an option for scheduled delivery and 0 otherwise, implying that $\mathrm{slot\_range}_i$ only matters for scheduled delivery.

Multi-period VRP

The delivery cost is evaluated on a day-to-day basis, by simultaneously optimizing the delivery routes for multiple days based on a multi-period VRP. Let n be the number of customers, c_{ij} be the travel cost between points i, j (distance between two points), T be the planning horizon. Then, let u_i be the amount of cargo loaded when the vehicle leaves point i, t_i be the arrival time at point i, m be the capacity of the vehicle k, K be the actual number of vehicles in service, and the capacity of all vehicles is Q. For customer i, the holding cost of the package is h_i, the day the package arrives at the depot is o_i, the quantity demanded is q_i, the specified delivery time is e_i to l_i, and the specified delivery day is s_i to d_i ($s_i = d_i$ for next day delivery and scheduled delivery).

The decision variable of the problem is:

$$x_{ijk}^t = \begin{cases} 1 & \text{if vehicle } k \text{ travels from point } i \text{ to } j \text{ on day } t, \\ 0 & \text{otherwise,} \end{cases}$$

and the optimal route is found by solving the following problem:

$$\min_x z(x) \equiv \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{t=1}^{T} c_{ij} x_{ijk}^t + \sum_{i=1}^{n} \sum_{t_1=o_i}^{H} h_i (1 - \sum_{t_2=o_i}^{t_1} \sum_{j=0}^{n} \sum_{k=1}^{K} x_{ijk}^{t_2}), \tag{2}$$

subject to

$$\sum_{k=1}^{K} \sum_{j=0}^{n} \sum_{t=s_i}^{d_i} x_{ijk}^t = 1 \qquad (i = 1, 2, \cdots, n) \tag{3}$$

Table 1: Delivery option choice

Delivery option (N=18928)	Next-day delivery	44.8%
	Scheduled delivery	38.3%
	Regular delivery	16.8%
Delivery time (N=7253)	Morning	45.9%
	Daytime	28.8%
	Night	25.3%
Delivery Date (N=7253)	Weekday	18.5%
	Holiday	81.5%

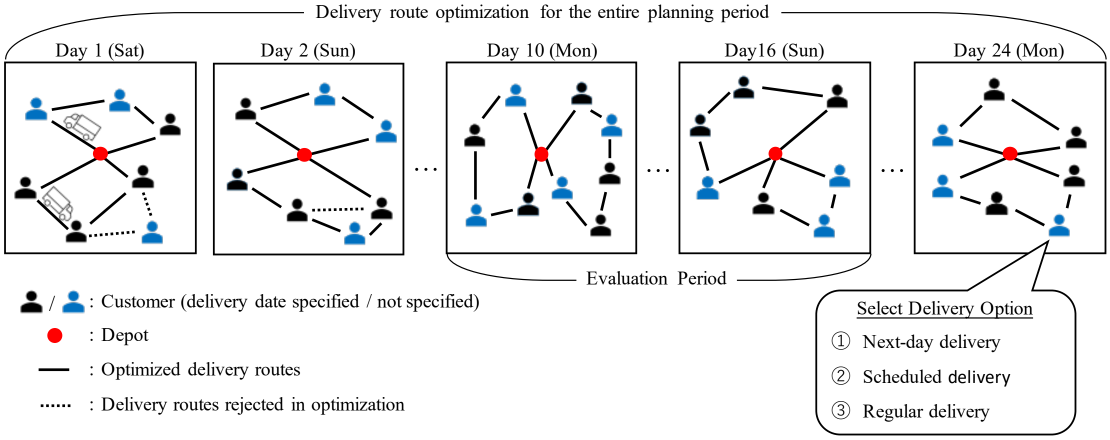

Figure 3: Overview of multi-period vehicle routing problem

$$\sum_{j=0}^{n} x_{ijk}^{t} = \sum_{j=0}^{n} x_{jik}^{t} \qquad (i = 0, 1, 2, \cdots, n), (k = 1, 2, \cdots, K), (t = 1, 2, \cdots, T), \tag{4}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{n} x_{0jk}^{t} \leq m \qquad (t = 1, 2, \cdots, T), \tag{5}$$

$$u_i - u_j + Q \cdot x_{ijk}^{t} \leq Q - q_j \qquad (t = 1, 2, \cdots, T), (k = 1, 2, \cdots, K), (i, j = 1, 2, \cdots, n),\ i \neq j, \tag{6}$$

$$t_i - t_j + M \cdot x_{ijk}^{t} \leq M - c_{ij} \qquad (t = 1, 2, \cdots, T), (k = 1, 2, \cdots, K), (i, j = 1, 2, \cdots, n),\ i \neq j, \tag{7}$$

$$q_i \leq u_i \leq Q \qquad (i = 1, 2, \cdots, n), \tag{8}$$

$$e_i \leq t_i \leq l_i \qquad (i = 1, 2, \cdots, n). \tag{9}$$

The objective function (2) includes transportation and holding costs, respectively represented by the first and second terms. Constraint (3)ensures that the delivery is made within the specified date. Constraint (4) ensures that the number of vehicles arriving at and departing from customer i on each day is equal. Inequality (6) and constraint (7) , which is called the potential (MTZ) formulation (Miller et al., 1960), are constraints on subtour elimination.Note that M in inequality (7) represents a sufficiently large constant.

Indicators for evaluation

To evaluate demand management policies, this study uses two indicators: (i) routing efficiency and (ii) customer satisfaction. The routing efficiency is calculated as the operation cost for delivery, directly obtained as $z(x^*)$ where x^* is the optimal plan for multi-period vehicle routing given a simulated demand. Customer satisfaction is based on the expected maximum utility (EMU), calculated with the estimated choice model. The EMU is defined as follows:

$$\mathrm{EMU}_n = \frac{1}{\mu} \ln \left\{ \exp(\mu V_{n,\text{Next-day}}) + \exp(\mu V_{n,\text{Regular}}) + \frac{\mu}{\mu_g} \left(\sum_{i \in S} \exp(\mu_g V_{ni}) \right) \right\} \tag{10}$$

where S is the collection of six alternatives for scheduled delivery, and μ_g is a scale parameter associated with the subgroup.

Table 2: Parameter estimation results

	MNL		NL	
Parameter	Estimate	t-stat	Estimate	t-stat
$\mathrm{ASC}_{\text{Next-day}}$	0.628	15.21^{**}	0.638	16.68^{**}
$\mathrm{ASC}_{\text{Holiday-Morning}}$	0.427	5.68^{**}	0.590	7.59^{**}
$\mathrm{ASC}_{\text{Holiday-Daytime}}$	-1.152	-1.50	0.150	1.76
$\mathrm{ASC}_{\text{Holiday-Night}}$	0.172	2.19^{*}	0.441	5.11^{**}
$\mathrm{ASC}_{\text{Weekday-Morning}}$	-1.054	-12.74^{**}	-0.616	-6.02^{**}
$\mathrm{ASC}_{\text{Weekday-Daytime}}$	-1.190	-14.10^{**}	-0.726	-6.87^{**}
$\mathrm{ASC}_{\text{Weekday-Night}}$	-0.922	-10.58^{**}	-0.452	-4.21^{**}
β_{day}	-0.221	-18.50^{**}	-0.213	-19.87^{**}
β_{fee}	-0.010	-81.91^{**}	-0.009	-77.51^{**}
$\beta_{\text{slot\_range}}$	-0.068	-3.16^{**}	-0.066	-3.08^{**}
μ_g			1.231	28.03^{**}
Sample size		18928		18928
Initial log likelihood		-39359.67		-39359.67
Final log likelihood		-25503.85		-25489.04
Adjusted rho-square		0.3520		0.3524
Likelihood-ratio test	$-2\{L(\hat{\beta}_{\text{MNL}}) - L(\hat{\beta}_{\text{NL}})\} = 29.62 > 3.84 = \chi^2_{1,0.05}$			

3 Results and discussion

Table 1 shows an aggregate result, the percentage of each delivery option being chosen. Approximately 45% of observations chose next-day delivery, and among those for scheduled delivery, 46% selected morning delivery. Note that the survey period coincided with "Golden Week" (a major holiday period in Japan), which resulted in approximately 81% of observations choosing a holiday to receive the ordered items.

The estimation result of the delivery option choice model is shown in Table 2, compared with the result of the standard multinomial logit (MNL) model. Both models suggest the same signs for delivery attributes, and the likelihood ratio test suggests the statistical preference of the NL model over the MNL model. The scale parameter μ_g was estimated to be 1.231, which gives $1/\mu_g = 0.812$, confirming an appropriate nest structure. The value of delivery time (VODT) for e-commerce users was calculated as approximately 23.67 JPY/day (0.17 EUR/day at the rate of 140 JPY to 1 EUR). This describes the customer's willingness to pay for a shorter delivery day, implying that, on average, customers are willing to wait one additional day if the delivery fee is about 24 JPY higher. The VODT has been analyzed in different contexts (e.g., Hsiao, 2009; Meister et al., 2023), and ours was calculated in the context of delivery option choice of e-commerce users as in Oyama et al. (2022). Moreover, our estimation result suggests that an increase in the range of time slots decreases the utility. This is because customers have to be at home for a longer period of time.

In this study, we evaluate the following two policies that can change the delivery option choice behavior of customers and have impacts on delivery efficiency.

1: Additional charge of 100 JPY for morning delivery

The SP survey results show that about 45% of those who chose scheduled delivery specified morning delivery, indicating that there is a high demand for morning time slots. Therefore, the number of vehicles in operation may be unevenly distributed depending on the time of day. The pricing is expected to reduce the demand for morning slots and thus may improve the routing efficiency.

2: Change of the time slot range from 2 to 4 hours.

The current service provided by Yamato Holdings Co., Ltd. has a 2-hour time slot for afternoon deliveries. In addition to this, we evaluate the cases with a time slot range of 3 or 4 hours. A longer time slot relaxes the time window constraints for delivery to be satisfied in finding the optimal route, thus improving the efficiency of the delivery route. However, on the other hand, longer slot ranges increase the uncertainty of the delivery time, which is

Table 3: Scenario evaluation result

Scenario	AM +100	Slot range	Cost[a]	ΔCost[b]	ΔSatis[c]	ΔCost/ΔSatis[d]
Bm	×	2h	3300.54	—	—	—
1	∘	2h	3200.67	3.03%	-0.129	23.54
2	×	3h	3246.39	1.64%	-0.029	56.75
3	∘	3h	3170.72	3.93%	-0.154	25.56
4	×	4h	3202.21	2.98%	-0.057	52.22
5	∘	4h	3162.10	4.19%	-0.179	23.50

[a]Average cost of delivery for 100 simulations
[b]Reduced delivery costs
[c]Changes in customer satisfaction
[d]Cost savings divided by reduction in customer satisfaction

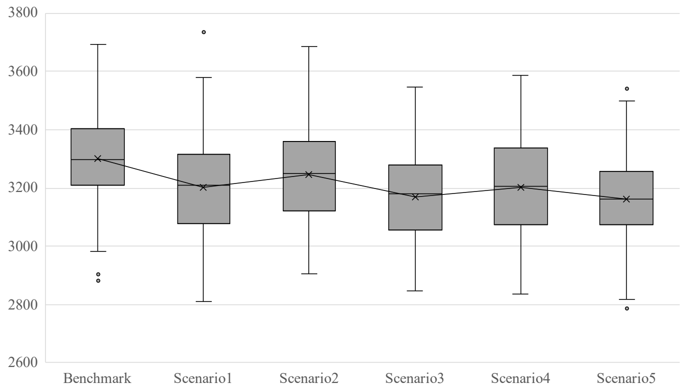

Figure 4: Delivery cost variation of different scenarios

expected to decrease customer satisfaction.

Regarding the multi-period VRP, we set the planning horizon to 24 days, with the first day being Saturday. The demand for home delivery is generated at a random point in a square with side lengths of 100 on each day of the planning horizon. Each customer's choice of delivery options is simulated according to the choice probability of the NL model. Given the simulated delivery demand, we optimize the delivery schedule for a multi-day period and calculate the operation cost by solving the multi-period VRP, as shown in Figure 3. We implemented the optimization using the Gurobi Optimizer mathematical optimization solver. Since the demand that occurred before the planning period cannot be considered in the early stages of the planning horizon, the evaluation focuses on the seven days from the 10th day (Monday) to the 16th day (Sunday). We summed up the operation costs of the seven days, which is defined as the delivery cost and computed for different policies. For each scenario, we performed 100 runs of the demand simulation and routing optimization.

Table 3 reports the average indicator values over 100 runs, and Figure 4 shows the variation of operation costs, for different scenarios. As a result, both the policies implemented reduced the cost of delivery. In particular, Scenario 5 which introduced the morning slot pricing and expanded the time slot to four hours lowered costs the most, but it also caused the most significant decrease in customer satisfaction. Although charging an additional fee for morning delivery is more effective than expanding the range of time slots in terms of reducing costs, it is not the optimal policy because of the large decrease in customer satisfaction.

To evaluate the balance between delivery efficiency and customer satisfaction, we calculated the cost reduction rate divided by the decrease in customer satisfaction, which is shown in the rightmost column of Table 3. The result shows that Scenario 2 has the best value. In conclusion, it is clear that the policy of expanding the range of time slots is more effective than the policy of charging an additional fee for morning deliveries.

4 Conclusions

This study evaluated policies for day-to-day delivery demand management based on the balance between delivery routing efficiency and customer satisfaction. For such evaluation, we first estimated a delivery option choice model and analyzed the customer preferences. Moreover, the multi-period VRP was formulated and optimized to evaluate the impact of the option choice behavior on the day-to-day delivery efficiency.

Specifically, two policies were considered: an additional charge of 100 JPY for morning deliveries, and the change in time slot range from 2 to 4 hours. While the surcharge policy for morning delivery reduced delivery costs, it also significantly decreased customer satisfaction. The best value was obtained in terms of the balance when the time slot range was 3 hours, regardless of whether the surcharge policy was implemented or not. From the above, we conclude that the optimal time slot range for this case study is 3 hours and that the morning delivery surcharge policy should not be implemented.

Future work includes the improvement of simulation setup conditions. This study assumed all demand during the planning horizon to be generated a priori and did not consider demand dynamically occurring on a day-to-day basis. Therefore, it is not possible to reflect a decrease in delivery efficiency due to sudden demand for next-day delivery. Therefore, a more advanced policy evaluation is needed in the future by incorporating the day-to-day dynamic nature of demand and optimizing the delivery plan with uncertainty.

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