



Optimal delivery service strategy for Internet shopping with time-dependent consumer demand

Chaug-Ing Hsu *, Hui-Chieh Li

*Department of Transportation Technology and Management, National Chiao Tung University,
1001 To Hsueh Road, Hsinchu 30010, Taiwan, ROC*

Received 27 August 2004; accepted 25 March 2005

Abstract

This study attempts to optimize a delivery service strategy for Internet shopping by considering time-dependent consumer demand, demand–supply interaction and consumer socioeconomic characteristics. A nonlinear mathematical programming model is formulated for solving the optimal number and duration of service cycles for discriminating strategy by maximizing profit subject to demand–supply interaction. An example is employed to demonstrate the application of the model. Results suggest that discriminating service strategy is a better strategy in response to time-dependent consumer demand than uniform strategy. Finally, the proposed model is demonstrated to yield more profit than models that do not consider variations in consumer demand or demand–supply interaction.

© 2005 Elsevier Ltd. All rights reserved.

Keywords: Internet shopping; Time-dependent consumer demand; Logistics cost; Demand–supply interaction

1. Introduction

Electronic data interchange (EDI) and related technologies have made it more efficient to transmit information to suppliers. At the same time, information flow-based Internet shopping has markedly improved consumer service by reducing order processing time and providing delivery

* Corresponding author. Tel.: +886 3 5731672; fax: +886 3 5720844.
E-mail address: cihsu@cc.nctu.edu.tw (C.-I. Hsu).

information. Since real-time consumer demand is processed via the Internet, operator inventory costs are reduced by ordering goods from wholesalers or manufactures and shipping them directly to consumers. However, high order frequency and small order quantity that characterize consumer Internet shopping behavior make it expensive to deliver goods to individual consumers (Huppertz, 1999). With fixed transportation costs for each shipment, the average logistics cost per item decreases with increasing shipment size. Therefore, a larger quantity of goods will accumulate with longer shipping cycles, which also results in an increased delay in receiving ordered goods, thus reducing consumer intention to shop via the Internet. The above process involves a trade-off between consumer demands and operator logistics costs.

The goal of delivery strategies is to reduce logistics costs and satisfy consumer needs. A crucial factor in optimizing a delivery service strategy is consumer demand. The assumption of constant demand is highly controversial, since in reality demand varies with time, space, and consumer socioeconomic characteristics. For example, peak demand for food products is likely to occur at lunchtime. Serving consumers via uniform shipping cycles without considering variations in cumulative quantities ordered during each shipping cycle may result in high logistics costs under time-dependent consumer demand. Conversely, shipping cycle has a dramatic influence on consumer intention to shop via the Internet because it determines delay in receiving ordered goods. When a consumer orders goods from an Internet store, they typically receive delivery information with respect to each service cycle, which is posted on the Internet. Upon the completion of the service cycle, the goods ordered during that cycle are shipped to consumers. Thus, service cycles coincide with shipping cycles for Internet store operators. In addition to time-dependent consumer demand, consumer demand for Internet shopping is also characterized by socioeconomic characteristics, and temporal and spatial variations. Even when served by the same service cycles, consumers with different characteristics perceive Internet shopping differently, which may further influence consumer demand for Internet store goods and, thus, profit. In summary, how to determine an optimal delivery service strategy for Internet shopping by considering demand–supply interaction, time-dependent consumer demand and consumer characteristics has become important.

Previous empirical studies have investigated the impacts of delivery-related issues on consumer satisfaction with Internet shopping (e.g., Rabinovich, 2004; Esper et al., 2003; Rabinovich and Bailey, 2004). Studies of consumer choices between shopping modes focused primarily on investigating the influences of demand and supply attributes on consumer intention to shop via the Internet (e.g., Sim and Koi, 2002; Bhatnagar and Ghose, 2004). Some studies have quantified consumer demand for Internet store goods and costs under different shipping strategies (Khouja, 2001; Hsu et al., 2003; Chen, 2001). However, few have integrated issues such as consumer socioeconomic characteristics, time-dependent consumer demand, demand–supply interaction and the 24-h nature of Internet shopping into their models.

Discriminating service strategy proposed in this study differs significantly from the traditional and typical uniform service strategy in which all consumers are served according to the same delivery cycle. Periods with considerable consumer demand suggest that frequent and short service cycles are suitable and may stimulate consumer demand for Internet store goods because of reduced delay in receiving ordered goods; this perspective also implies that long service cycles are suitable when demand is very low. Such an approach would reduce logistics costs and boost profit. The Internet store in this study is assumed to operate as a retailer, ordering a batch of goods from

wholesalers or manufactures and distributing these goods to consumers. Delay in receiving ordered goods is determined here as the time between consumers ordering and receiving goods, and depends on delivery cycles which include lead time for processing and handling.

This study explores how to optimize a delivery service strategy for Internet shopping in terms of service cycle frequency and duration by considering time-dependent consumer demand and demand–supply interaction. The model applies mathematical programming methods and compares profit between using discriminating and uniform service strategies thereby identifying the optimal strategy for Internet store operators. This study uses R-company selling flowers via the Internet in Taiwan, as an example to demonstrate the application of the model.

The remainder of this paper is organized as follows. Section 2 reviews the literature on Internet shopping and physical distribution problems. Section 3 formulates the consumer choice probability model for Internet shopping and aggregates consumer demand for Internet store goods in each service cycle. Nonlinear programming problems are formulated in Section 4 for determining the optimal number and duration of service cycles for discriminating service strategy and uniform service strategy by maximizing Internet store profit subject to demand–supply equality. In Section 5, a case study and numerical examples are presented to demonstrate the application of the model and the effects of changing in key parameters on the optimal solution. Finally, Section 6 presents a summary of study findings and conclusions.

2. Literature review

The major issues related to Internet shopping have been extensively examined in numerous studies, including marketing, pricing and payment, etc. (e.g., Pavitt, 1997; Reynolds, 1997; Kiang et al., 2000; Peterson et al., 1997). O’Cass and Fenech (2003) examined Internet user adoption of the Web for retail/purchase behavior. Burke (1997) noted that the home-shopping system eliminated drive time and checkout time and enabled shoppers to access distant stores and showed the retailing technology is most convenient when it matches shopping and media habits. Verhoef and Langerak (2001) identified delivery delay for ordered goods as major disadvantage of Internet shopping.

Previous studies examining the differences in consumer choice in the contexts Internet shopping and conventional shopping focused mainly on analyzing the pros and cons of Internet shopping or the influencing consumer intention to shop on the Internet using collected empirical data (e.g., Manski and Salomon, 1987; Koppelman et al., 1991; Sim and Koi, 2002). Salomon and Koppelman (1988) established a framework of shopping behavior for examining consumer choices among in-home and out-of-home shopping modes. Their framework comprises a description of the shopping–purchasing process and hypotheses relating to influences on individual choices regarding alternative shopping modes. Sherman and Topol (1996) investigated emerging technologies, including electronic retailing and interactive shopping, and their influences on consumers, retailers and manufacturers. Other studies examined the demographic and psycho-graphic characteristics of Internet shoppers using local shopper surveys (e.g., Verhoef and Langerak, 2001; Raijas, 2002). Olson and Boyer (2003) investigated how end user viewpoints and characteristics, such as education and tenure in the workforce, influence use of the Internet as a purchasing avenue. Heim and Sinha (2001) provided an empirical analysis which examined the relationship

between customer loyalty and the order procurement and fulfillment processes of electronic retailers. They found that short delivery times have a significant influence on customer loyalty. Heim and Sinha (2002) further developed a taxonomy of service processes and attempted to link electronic service processes with customer ratings of service performance. They found that a positive and significant correlation between the ordering of the configurations in the taxonomy and consumer satisfaction with web site aesthetics, production selection and product information, etc. Furthermore, Nagurney et al. (2001) proposed a network equilibrium framework for analyzing consumer preference for Internet shopping vs. store shopping under an assumption of multicriteria decision makers.

On the supply side of Internet shopping, Huppertz (1999) concluded that the major problem in electronic commerce is that frequent small-sized orders lead to high transportation costs. Khouja (2001) proposed an optimal mix strategy of drop shipping and in-house inventory for e-retailers, and identified optimal solution of order quantity for in-house inventory to the drop-shipping model under uniform, exponential, and normal demand distributions. Moreover, Hsu et al. (2003) introduced a discriminating shipping strategy for Internet store operators that varies the optimal shipping cycles for different consumer locations and determined the optimal shipping cycles based on consumer demand and distance to the distribution center. In another line of research, numerous studies have investigated physical distribution problems using analytical approaches (e.g., Burns et al., 1985; Blumenfeld et al., 1985). This research typically considered shipping problems under inelastic demand and focused on operating issues such as scheduling, routing, and configuration of physical distribution. However, little research has investigated the influence on logistic costs of time-dependent demand, demand–supply interaction and the 24-h nature of Internet shopping.

Recent studies have investigated carriers or provider issues and their effects on consumer services and operating strategies. Most of these empirical studies dealt with these issues by testing hypotheses. Rabinovich et al. (2003) investigated the impacts on supply chain efficiency of information exchanges between e-retailers and end consumers. Rabinovich (2004) later examined an Internet retailer's inventory liquidity and its relationship to the retailer's ability to fulfill its guarantees, and found that Internet retailers should align inventory liquidity and delivery performance to fulfill economically consumer orders. Rabinovich and Bailey (2004) concluded that Internet retailers usually adopt revenue-maximizing strategies for their physical distribution pricing policies that reflect the physical distribution service quality they provide. Esper et al. (2003) found that allowing consumers to choose a carrier leads to increased levels of anticipated satisfaction with the online experience and an increased willingness to buy.

Boyer et al. (2002) developed preliminary frameworks for analyzing e-services and found that the strategic operations choices regarding fit between delivery processes and products must play an important direct role in the consumer perceptions of delivery services. Chen (2001) investigated the benefits of a segmentation strategy in which price-delay combinations were available for several market segments. In Chen's model, Poisson process was employed to describe consumer arrival at the selling process and identified that consumers are segmented according their willingness to pay for one unit of a product. Chen found that the benefit of market segmentation is large if more patient consumers are in the market.

However, the interaction of time-dependent consumer demand and logistics cost related to different delivery service strategies in Internet shopping has seldom been investigated. Furthermore,

while consumer demand for Internet store goods may increase by employing frequent and short service cycles, the extent depends on variations in consumer socioeconomic, temporal and spatial distributions and, furthermore, how Internet store operators set up service cycles during a given operating day. Although these issues have been previously addressed, there is currently no mathematical model that can determine an optimal delivery service strategy by integrating all issues. This study demonstrates how demand–supply interaction can be carefully considered in advance when solving delivery service cycle problems. Specifically, this study formulates a model that can determine an optimal delivery service strategy for Internet store operators by integrating demand–supply interaction, time-dependent consumer demand and consumer characteristics.

3. Consumer demand for Internet store goods

Three key groups of factors influence shopping behavior, namely goods characteristics, shopping mode attributes, and consumer characteristics (Salomon and Koppelman, 1988). Generally, goods that require detailed examination before purchase are considered inappropriate for Internet markets (Liang and Huang, 1998). Thus, the goods discussed here are those that are appropriate for Internet markets. This study designs a consumer choice probability model for choosing between Internet and conventional shopping modes. To capture dynamic and time-sensitive consumer demand, this study considers issues such as differences in consumer socioeconomic characteristics, temporal variations in ordering time of consumer goods, and spatial variations in consumer locations and competitions between Internet stores and retail stores in urban and non-urban areas.

3.1. Individual characteristics

Previous empirical studies have developed logit models to investigate the effects of shopping mode attributes, characteristics of consumer shopping behavior on Internet shopping (Koppelman et al., 1991; Koyuncu and Bhattacharya, 2004; Bhatnagar and Ghose, 2004). Following the formulation of logit models in literature, this study applies a binary logit model to determine consumer choice probabilities for both Internet and conventional shopping. Let $U_{x,k}(t, j)$ represent the total utility of consumer x who orders goods in zone j at time t via shopping mode k . Furthermore, $U_{x,k}(t, j) = V_{x,k}(t, j) + \varepsilon_{x,k}$, where $V_{x,k}(t, j)$ denotes the deterministic component, and $\varepsilon_{x,k}$ denotes a random utility component representing the unobservable or immeasurable factors of $U_{x,k}(t, j)$. Supposing that all $\varepsilon_{x,k}$ are independent and identically distributed as a Gumbel distribution,¹ then the probability of choosing shopping mode k can be estimated using the binary logit model (Ben-Akiva and Lerman, 1985). Let subscripts TS and R denote Internet shopping and conventional shopping, respectively, and the choice probability of choosing Internet stores for consumer x in zone j at time t , $P_{x,TS}(t, j)$, can then be estimated as:

¹ To arrive at the standard logit formulation, it is necessary to assume that the random utility component is independently and identically distributed as a Gumbel distribution (Ben-Akiva and Lerman, 1985).

$$P_{x,TS}(t, j) = \frac{e^{U_{x,TS}(t,j)}}{e^{U_{x,TS}(t,j)} + e^{U_{x,R}(t,j)}}. \quad (1)$$

For simplicity, this study omits subscript x in the following disaggregate choice model in which formulations of the model are also discussed based on individual consumers. The difference in the utility value of consumer shopping via Internet stores and conventional retail stores determines the probability of choosing Internet shopping, which can be rewritten as:

$$P_{TS}(t, j) = \frac{e^{v(t,j)}}{1 + e^{v(t,j)}}. \quad (2)$$

This study assumes technological advances and well-organized facilities in Internet shopping environments enable consumers to access Internet stores with little effort; therefore, search time for goods via the Internet can be ignored. Assume the quality of a good is the same regardless of whether it is purchased via Internet shopping or conventional shopping. The utility function $v(t, j)$ discussed here then has the following specifications:

$$v(t, j) = \beta_0 + \beta_1 \frac{p_{TS}}{I} + \beta_2 T_{TS,t} - \beta_1 \frac{p_R}{I} - \beta_3 T_{t,R,j}, \quad (3)$$

where p_{TS} and p_R denote the prices of goods via Internet shopping and conventional shopping, respectively; $T_{TS,t}$ represents delay in receiving ordered goods for consumers ordering goods via Internet at time t , and includes the goods handling/processing time and transportation time, while $T_{t,R,j}$ denotes access time for consumers purchasing goods via retail stores in zone j at time t . Furthermore, I represents consumer average income per unit time; β_1 , β_2 , β_3 are parameters that express the tastes of consumers; and β_0 reflects alternative specific constant for Internet shopping. The average value of time for delay in receiving ordered goods, VOT, then can be estimated using Eq. (3). Restated,

$$\text{VOT} = \frac{\partial v(t, j) / \partial T_{TS,t}}{\partial v(t, j) / \partial p_{TS}} = I \frac{\beta_2}{\beta_1}. \quad (4)$$

Eq. (4) indicates that the average value of time for delay in receiving ordered goods depends on consumer income per unit of time. Consumers with higher income are more concerned with delay in receiving ordered goods than consumers with lower incomes. The value of time for delay in receiving ordered goods can also be expressed as consumer willingness to pay for one unit of delay savings in receiving ordered goods. Moreover, consumers with higher incomes may be willing to pay higher prices of goods via Internet shopping to receive ordered goods with less delay as Eq. (4) shows.

Since it typically takes longer to receive goods purchased from an Internet store than when purchased at a conventional store, consumers usually prefer to make fewer purchases from Internet stores (Koyuncu and Bhattacharya, 2004). The heterogeneity of consumers implies that consumers may perceive the same delay in receiving goods differently; that is, different consumers have different waiting costs (Chen, 2001). In this study, consumer income distribution is applied to investigate the relationship between consumer socioeconomic characteristics, consumer demand for Internet shopping and delivery service strategies for Internet shopping. Assume that individual consumers with different personal incomes are served by the same supply condition, then the

expected choice probability of selecting Internet shopping for all consumers can be further estimated by aggregating individual consumer choices based on the binary logit model and income distribution. The generalized exponential family of distributions² can describe income distribution (Bakker and Creedy, 2000). This study assumes that personal income I is distributed with a normal distribution,³ with mean μ and standard deviation σ . From Eq. (3), all other things being equal, $v(t, j)$ is a function of I , so the pdf of $v(t, j)$ can be expressed through the transformation of the pdf of I . The pdf of $v(t, j)$, $f_{v(t, j)}(v(t, j))$ then can be expressed as:

$$f_{v(t, j)}(v(t, j)) = f_I \left(I = \frac{\beta_1(p_R - p_{TS})}{\beta_0 + \beta_2 T_{TS, t} - \beta_3 T_{t, R, j} - v(t, j)} \right) \times \left| \frac{\beta_1(p_R - p_{TS})}{(\beta_0 + \beta_2 T_{TS, t} - \beta_3 T_{t, R, j} - v(t, j))^2} \right| \quad \forall t, \forall j. \tag{5}$$

Consequently, taking the expected value of choice probability of selecting Internet shopping yields the following expression for the expected choice probability:

$$E[P_{TS}(t, j)] = \int_0^1 P_{TS}(t, j) f(P_{TS}(t, j)) dP_{TS}(t, j) \quad \forall t, \forall j, \tag{6}$$

where $E[P_{TS}(t, j)]$ represents the expected value of choice probability of selecting Internet shopping in zone j at time t .

The difference in the utility values of Internet shopping and conventional shopping determines the probability of selecting Internet shopping, $P_{TS}(t, j)$, in Eq. (2); that is, $P_{TS}(t, j)$ is a random variable transformed by $v(t, j)$. Consequently, the pdf of $P_{TS}(t, j)$, $f(P_{TS}(t, j))$, is presented as:

$$f(P_{TS}(t, j)) = f_{v(t, j)}(v(t, j)) = \ln \frac{P_{TS}(t, j)}{1 - P_{TS}(t, j)} \left| \frac{1}{P_{TS}(t, j)(1 - P_{TS}(t, j))} \right| \quad \forall t, \forall j. \tag{7}$$

From Eq. (7), since $v(t, j) = \ln \frac{P_{TS}(t, j)}{1 - P_{TS}(t, j)}$, the relationship between the differential of $v(t, j)$, $dv(t, j)$, and that of $P_{TS}(t, j)$, $dP_{TS}(t, j)$, can be further calculated as $dv(t, j) = \frac{1}{P_{TS}(t, j)(1 - P_{TS}(t, j))} dP_{TS}(t, j)$. Then, substituting Eq. (7) for $f(P_{TS}(t, j))$ in Eq. (6), Eq. (6) can be rewritten as:

$$E[P_{TS}(t, j)] = \int_0^1 P_{TS}(t, j) \cdot f(P_{TS}(t, j)) dP_{TS}(t, j) = \int_0^1 P_{TS}(t, j) \cdot f_v \left(v = \ln \frac{P_{TS}(t, j)}{1 - P_{TS}(t, j)} \right) dv(t, j). \tag{8}$$

Similarly, from $I = \frac{\beta_1(p_R - p_{TS})}{\beta_0 + \beta_2 T_{TS, t} - \beta_3 T_{t, R, j} - v(t, j)}$ in Eq. (5), the relationship between dI and $dv(t, j)$ can be expressed as $dI = \frac{-\beta_1(p_R - p_{TS})}{(\beta_0 + \beta_2 T_{TS, t} - \beta_3 T_{t, R, j} - v(t, j))^2} dv(t, j)$. Furthermore, from Eqs. (2), (3) and (5), Eq. (8) can be rewritten as:

² The exponential family includes useful distributions such as the Normal, Binomial, Poisson, Multinomial, Gamma, Negative Binomial, etc. (McCullagh and Nelder, 1989).

³ The probability distribution function (pdf) of I is $f_I(I) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{I-\mu}{\sigma})^2}$.

$$\begin{aligned}
E[P_{TS}(t, j)] &= \int_0^1 P_{TS}(t, j) \cdot f_v \left(v = \ln \frac{P_{TS}(t, j)}{1 - P_{TS}(t, j)} \right) dv(t, j) \\
&= \int_0^\infty \frac{e^{\beta_0 + \beta_1 \frac{PTS - PR}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}}}{1 + e^{\beta_0 + \beta_1 \frac{PTS - PR}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}}} f_I(I) dI \\
&= \int_0^\infty \frac{e^{\beta_0 + \beta_1 \frac{PTS - PR}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}}}{1 + e^{\beta_0 + \beta_1 \frac{PTS - PR}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}}} \cdot \frac{e^{-\frac{(I-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi} \cdot \sigma} dI, \quad \forall t, \forall j.
\end{aligned} \tag{9}$$

3.2. Variations in ordering time of consumer goods and locations

The impacts of ordering time of consumer goods on their choice probabilities are further analyzed. Delay in receiving ordered goods is demonstrated in past studies as an important influence on the probability of choosing Internet shopping (Raijas, 2002; Hsu et al., 2003). Once service cycle lengths are determined, delay in receiving ordered goods decreases with reducing time between ordering time of consumer goods and the end time of the service cycle, and vice versa. Moreover, the smaller the number of retail stores in areas or in regular store closed hours is, the longer access time to retail stores will be. Therefore, it is important to understand how ordering time of consumer goods, which is related to delay in receiving ordered goods and access time to retail stores, influences the utility functions and choice probabilities.

Suppose the entire study period is divided into S consecutive service cycles, and let T_i represent the duration of service cycle i , $T_i = (t_{i,0}, t_{i,m})$, $i = 1, 2, \dots, s$, where s is the last service cycle during the entire study period, $t_{i,0}$ and $t_{i,m}$ represents the start and end times of the service cycle i , respectively. Consequently, the sum of the time duration of all service cycles represents the entire study period, T , namely $\sum_{i=1}^s (t_{i,m} - t_{i,0}) = T$. At each $t_{i,m}$, $i = 1, 2, \dots, s$, Internet store operators begin to deliver ordered goods accumulated during service cycle i .

This study ignores the vehicle routing problem of goods delivery and simplifies the problem by employing T_R to represent average goods delivery time to consumers. Restated, consumers receive ordered goods between $t_{i,m}$ and $(t_{i,m} + T_R)$. Lead time⁴ includes the time required for order transmission, order processing and order preparation. The above definition of lead time influences delay in receiving ordered goods. This study defines “lead time” as the total time used by Internet store operators for preparing goods for delivery, namely handling and processing time at each service cycle. Consequently, a relationship exists among delay in receiving ordered goods, ordering time of consumer goods and lead time. Delay in receiving ordered goods when consumers order goods via the Internet at time t , $T_{TS,t}$, thus can be given by

$$T_{TS,t} = \begin{cases} (t_{i,m} + T_R) - t, t \in (t_{i,0}, (t_{i,m} - T_1)) \\ (t_{i+1,m} + T_R) - t, t \in ((t_{i,m} - T_1), t_{i,m}) \end{cases}, \quad \forall t, \tag{10}$$

⁴ According to Coyle et al. (1996), lead time is the total time that elapses from placing an order until its eventual receipt.

where T_1 represents lead time. Access time to retail stores depends on the density of retail stores opened during different service cycles and different zones. From Eq. (10), delay in receiving ordered goods is influenced by ordering time of consumer goods. Owing to the time required for goods handling and processing, if ordering time of consumer goods falls during $((t_{i,m} - T_1), t_{i,m})$, the ordered goods will not be shipped until the end of service cycle $(i + 1)$.

Access time to retail stores in zone j at time t , $T_{t,R,j}$, can be obtained via $T_{t,R,j} = \frac{R_{t,j}}{V}$, where $R_{t,j}$ ⁵ denotes the average distance to retail stores in zone j at time t , and V represents the average consumer travel speed.

Normally, total consumer demand for Internet store goods can be estimated by multiplying total consumer demand for goods and the expected probability of selecting Internet shopping. Assume total consumer demand for goods in zone j at time t is exogenous and denoted as $q_{t,j}$, then the time-dependent consumer demands for goods of the Internet store at time t for all zones, q_t , can be expressed as $q_t = \sum_{j=1}^n q_{t,j} E[P_{TS}(t, j)]$. Furthermore, total consumer demand for Internet store goods during service cycle i for discriminating service strategy, Q_i , can be further represented as:

$$Q_i = \sum_{t=t_{i,0}}^{t_{i,m}} q_t = \sum_{t=t_{i,0}}^{t_{i,m}} \sum_{j=1}^n q_{t,j} E[P_{TS}(t, j)], \quad i = 1, 2, \dots, s. \tag{11}$$

Furthermore, from Eq. (11), total consumer demand for goods from the Internet store during service cycle i increases with increasing expected value of the probability of selecting Internet shopping, $E[P_{TS}(t, j)]$.

Assume the entire study period is equally divided into S' consecutive service cycles for uniform service strategy, and the duration of each cycle is $\frac{T}{S'}$, where T is the entire study period. The duration of service cycle i for uniform service strategy is denoted using T'_i , namely, $T'_i = (t'_{i,0}, t'_{i,0} + \frac{T}{S'})$, $i = 1, 2, \dots, s'$, where s' is the last service cycle for uniform service strategy, and $t'_{i,0}$ and $t'_{i,0} + \frac{T}{S'}$ represent the start and end times of service cycle i assuming a uniform service strategy, respectively. Total consumer demand for Internet store goods during service cycle i for uniform service strategy, Q'_i , can be calculated as follows:

$$Q'_i = \sum_{t=t'_{i,0}}^{t'_{i,0} + \frac{T}{S'}} q_t = \sum_{t=t'_{i,0}}^{t'_{i,0} + \frac{T}{S'}} \sum_{j=1}^n q_{t,j} E[P_{TS}(t, j)], \quad i = 1, 2, \dots, s'. \tag{12}$$

4. Mathematical programming models for the optimal service cycles

The discussions completed to date deal with dynamic and time-sensitive consumer demand, and demonstrate how service cycle duration influences consumer demand for Internet store goods. This section further investigates how consumer demand for goods from Internet stores influences

⁵ The average distance to retail stores can be approximated using one half of the square root of the average market area per retail store (Hsu and Tsai, 1999); that is, $\frac{1}{2} \sqrt{\frac{A_j}{n_{t,j}}}$, where A_j denotes the area of zone j , and $n_{t,j}$ represents the total number of retail stores in zone j at time t .

logistics costs for Internet store operators. Moreover, this study devises a mathematical programming model for determining the optimal number and duration of service cycles during the entire study period by considering the relationship between consumer demand and logistics costs and assuming that Internet store operators are seeking to maximize profit.

4.1. Logistics cost functions for discriminating service strategy

The average logistics cost functions for discriminating and uniform service strategies are formulated, respectively, by an analytical approach. Because of various numbers of orders accumulating during different service cycles during the entire study period, the average logistics cost during the study period is estimated using the weighting average method based on service cycle number and duration. Logistics cost is divided into transportation cost and inventory cost. This study ignores the problem of fleet capacity, and assumes the fleet to have sufficient capacity to carry all ordered goods. The transportation cost involves both fixed and variable transportation costs. Fixed transportation costs are costs attributable to each shipment regardless of shipment volume, while variable transportation costs involve loading/unloading costs and depend on quantity transported per shipment, namely the number of items ordered during each service cycle. Transportation costs increase with the number of items transported. This study denotes c as a base value of fixed transportation cost, w_t as a multiplier reflecting additional labor cost during different service cycles, such as weekend, night hours, or non-regular hours, because of the 24-h nature of Internet stores and h as variable transportation cost per item shipped. The average transportation cost per item shipped during service cycle i for discriminating service strategy, ATC_i , can be expressed as follows:

$$ATC_i = \frac{1}{Q_i}(c \cdot w_t + hQ_i) = h + \frac{c \cdot w_t}{Q_i}, \quad i = 1, 2, \dots, s. \quad (13)$$

Economies of scale exist, as illustrated in Eq. (13), since ATC_i decreases with increasing total consumer demand for Internet store goods during service cycle i , Q_i . The average transportation cost per item during the entire study period for discriminating service strategy, ATC , can be further expressed as follows:

$$ATC = \frac{1}{S} \sum_{i=1}^s ATC_i = h + \frac{1}{S} \sum_{i=1}^s \frac{c \cdot w_t}{Q_i}, \quad (14)$$

where S denotes the number of service cycles for discriminating service strategy.

Inventory costs discussed here reflect the relationship between the batch ordering of goods by Internet store operators to their suppliers and continuous ordering of goods by consumers. Consider the situation illustrated in Fig. 1, and moreover consider that three curves in the figure represent the cumulative number of goods, which have been: (1) ordered by consumers; (2) delivered and (3) ordered by the operator of the Internet store from suppliers. The shaded area in the figure represents the number of “item-hours” for items carried by the Internet store. Furthermore, denote $t_{i,o}$ as the time when the operator of the Internet store orders batch o of service cycles i and $Q_{i,o}$ as the number of items ordered in batch o of service cycle i .

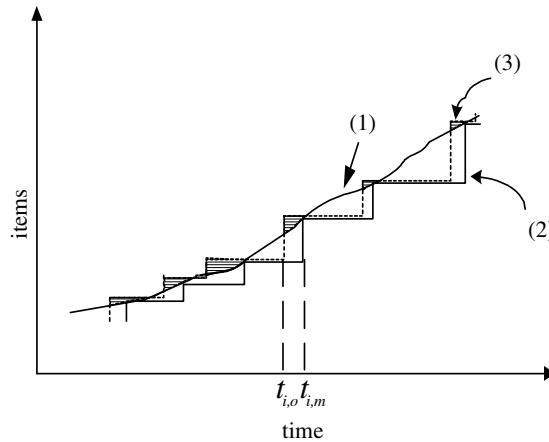


Fig. 1. Inventory cost profile.

The inventory cost per item of goods per unit time can be estimated based on purchasing cost per item, π and inventory carrying rate, ω . Therefore, the total inventory cost of service cycle i for discriminating service strategy, IC_i , results from the difference between the time when the operator ordered the batch and the time when the consumers ordered the goods; that is, $IC_i = \pi\omega \left[Q_{i,o}(t_{i,m} - t_{i,o}) - \sum_{t_{i,o}}^{t_{i,m}} q_t \right]$, $i = 1, 2, \dots, s$. Furthermore, the average inventory cost per item of goods of service cycle i for discriminating service strategy, AIC_i , can be determined by dividing IC_i by the total consumer demand during that cycle, namely:

$$AIC_i = \frac{1}{Q_i} \pi\omega \left[Q_{i,o}(t_{i,m} - t_{i,o}) - \sum_{t_{i,o}}^{t_{i,m}} q_t \right], \quad i = 1, 2, \dots, s. \tag{15}$$

Furthermore, the average inventory cost per item for the entire study period, for discriminating service strategy, AIC , can be presented as follows:

$$AIC = \frac{1}{S} \sum_{i=1}^s AIC_i = \frac{1}{S} \sum_{i=1}^s \frac{1}{Q_i} \pi\omega \left[Q_{i,o}(t_{i,m} - t_{i,o}) - \sum_{t_{i,o}}^{t_{i,m}} q_t \right]. \tag{16}$$

Consequently, the average logistics cost per item during the entire study period for discriminating service strategy, ALC , can be expressed as the sum of the average transportation cost per item and the average inventory cost per item, restated

$$ALC = ATC + AIC = h + \frac{1}{S} \sum_{i=1}^s \frac{1}{Q_i} \left(c \cdot w_t + \pi\omega \left[Q_{i,o}(t_{i,m} - t_{i,o}) - \sum_{t_{i,o}}^{t_{i,m}} q_t \right] \right). \tag{17}$$

4.2. Logistics cost functions for uniform service strategy

The average logistics cost per item for the uniform service strategy is formulated in a manner similar to that for discriminating service strategy, as mentioned above. The average transportation cost per item of service cycle i for uniform service strategy, ATC'_i , can be presented as follows:

$$ATC'_i = h + \frac{c \cdot w_i}{Q'_i}, \quad i = 1, 2, \dots, s', \quad (18)$$

where Q'_i denotes total consumer demand for goods from the Internet store during service cycle i for uniform service strategy, as illustrated in Eq. (12).

Similarly, the average transportation cost per item of goods for the entire study period for uniform service strategy, ATC' , can be formulated as:

$$ATC' = \frac{1}{S'} \sum_{i=1}^{s'} ATC'_i = \frac{1}{S'} \sum_{i=1}^{s'} ATC'_i = h + \frac{1}{S'} \sum_{i=1}^{s'} \frac{c \cdot w_i}{Q'_i}. \quad (19)$$

Similar to the analyses in Section 4.1, the average inventory cost per item of goods of service cycle i for uniform service strategy, AIC'_i , can be formulated as:

$$AIC'_i = \frac{1}{Q'_i} \pi \omega \left[Q_{i,o} \left(t_{i,0} + \frac{T}{S'} - t_{i,o} \right) - \sum_{t_{i,o}}^{t_{i,0} + \frac{T}{S'}} q_t \right], \quad i = 1, 2, \dots, s'. \quad (20)$$

The average inventory cost per item during the entire study period for the uniform service strategy, AIC' , then can be further formulated as:

$$AIC' = \frac{1}{S'} \sum_{i=1}^{s'} AIC'_i = \frac{1}{S'} \sum_{i=1}^{s'} \frac{1}{Q'_i} \pi \omega \left[Q_{i,o} \left(t_{i,0} + \frac{T}{S'} - t_{i,o} \right) - \sum_{t_{i,o}}^{t_{i,0} + \frac{T}{S'}} q_t \right]. \quad (21)$$

4.3. Formulation of the optimal problem

Profit throughout the entire study period can be calculated based on the price of goods via Internet shopping (p_{TR}), purchasing cost per item (π), average logistics cost per item (ALC) and total consumer demand for Internet store goods throughout the entire study period, $\sum_{i=1}^s Q_i$, such as

$$\tau = (p_{TR} - \pi - ALC) \cdot \sum_{i=1}^s Q_i, \quad (22)$$

where τ represents profit throughout the study period. Eq. (22) illustrates the relationship between profit, the average logistics cost per item and total consumer demand for Internet store goods throughout the study period, whereby the larger total consumer demand for Internet store goods during the entire study period or the smaller the average logistics cost per item of goods, larger profit achieved by the Internet store operator. Additionally, profit throughout the entire study period for uniform service strategy, τ' , can be formulated as:

$$\tau' = (p_{TR} - \pi - ALC') \cdot \sum_{i=1}^{s'} Q'_i \tag{23}$$

A nonlinear programming problem is formulated here for determining the optimal number and duration of service cycles for discriminating service strategy by maximizing profit subject to demand–supply equality. From Eqs. (9), (11), (17) and the discussion above, the nonlinear programming problem for maximizing profit throughout the study period given discriminating service strategy is as follows:

$$\text{Max}_{S, T_i=(t_{i,0}, t_{i,m}), t_{i,o}, Q_{i,o}} \tau = (p_{TR} - \pi - ALC) \sum_{i=1}^s Q_i \tag{24a}$$

$$\text{s.t.} \quad ALC = ATC + AIC = h + \frac{1}{S} \sum_{i=1}^s \frac{1}{Q_i} \left(c \cdot w_t + \pi \omega \left[Q_{i,o}(t_{i,m} - t_{i,o}) - \sum_{t_{i,o}}^{t_{i,m}} q_t \right] \right), \tag{24b}$$

$$Q_i = \sum_{t=t_{i,0}}^{t_{i,m}} q_t = \sum_{t=t_{i,0}}^{t_{i,m}} \sum_{j=1}^n q_{t,j} E[P_{TS}(t, j)], \quad i = 1, 2, \dots, s, \tag{24c}$$

$$E[P_{TS}(t, j)] = \int_0^\infty \frac{e^{\beta_0 + \beta_1 \frac{p_{TS} - p_R}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}} \cdot e^{-\frac{(t-\mu)^2}{\sigma^2}}}{1 + e^{\beta_0 + \beta_1 \frac{p_{TS} - p_R}{T} + \beta_2 T_{TS,t} - \beta_3 T_{t,R,j}}} \cdot \frac{1}{\sqrt{2\pi} \cdot \sigma} dI, \tag{24d}$$

$$\sum_{i=1}^s (t_{i,m} - t_{i,0}) = T. \tag{24e}$$

Eq. (24a) represents the objective function that maximizes profit throughout the study period. Eq. (24b) defines the average logistics cost per item as Eq. (17). Moreover, Eq. (24c) represents the total consumer demand for Internet store goods during service cycle i . Eq. (24d) expresses expected value of probabilities of selecting Internet shopping. Furthermore, Eq. (24e) constrains that the summation of the duration of all service cycles must be equal to the entire study period. The nonlinear programming model for maximizing profit throughout the study period for uniform service strategy can be formulated in a manner similar to that for discriminating service strategy. This study further compares the objective value between discriminating and uniform service strategies and suggests that with the higher value for adoption by Internet store operators. Furthermore, this study compares the values of profit obtained by the Internet store from discriminating and uniform service strategies using $\xi = \frac{\tau - \tau'}{\tau} \times 100\%$, where τ and τ' represent profit using discriminating and uniform service strategies, respectively. If ξ is positive, discriminating service strategy is suggested; otherwise, uniform service strategy is recommended.

5. Numerical example

A case study is presented to demonstrate the application of the proposed model using data available from R-company selling flowers via the Internet in Taiwan. For simplicity, this study merely chose six cities from all of the cities currently served by R-company as study zones, and

Table 1
The initial values of base demand and supply parameters

Symbol	Definition	Initial value
μ	Mean of the probability distribution of consumer income	353.4 NT\$/h
σ	Standard deviation of the probability distribution of consumer income	199.2 NT\$/h
I	Consumer average hourly income	353.4 NT\$/h
β_0		0.4* (2.02)
β_1		-8.4* (-3.35)
β_2		-0.018* (-2.76)
β_3		-0.095* (-1.98)
V	The average consumer travel speed	25 km/h
p_{TS}	The price of goods via Internet shopping	NT\$ 1050
π	Purchasing cost per item of goods	NT\$ 850
p_R	The price of goods via conventional shopping	NT\$ 1280
h	Variable transportation cost per item	NT\$ 135
c	Base value of fixed transportation cost	NT\$ 850
T_1	Lead time	0.5 h

* Significant at the 5% level; *t*-statistics are reported in parentheses.

assumed one operating day, namely 24 h, as the study period, with the unit of time for study being 1 h. Base values for parameters in the utility were calibrated using data collected via street interviews conducted at Taipei Railway Station and several large shopping districts in Taipei City⁶ and base values for logistics cost functions are estimated from [Ministry of the Interior, ROC \(2001\)](#) as listed in [Tables 1 and 2](#), respectively. [Table 1](#) lists the initial values of base demand and supply parameters while [Table 2](#) lists the related data on study zones. The multipliers reflecting extra cost during different service cycles, w_t are two during AM 0:00–7:00 and PM 9:00–12:00, and one during other times of day. [Fig. 2\(a\)](#) and (b) illustrate time-dependent consumer demand for goods in Taipei City and over the entire study area, respectively. From [Fig. 2\(b\)](#), consumer demand for goods is extremely low during AM 0:00–5:00, and peaks near PM 6:00.

Due to the complexity in solving a nonlinear programming problem, some approximate methods are required and the greedy algorithm is applied in this study due to its simple implementation and speed. In this study, the initial values, including the number and duration of service cycles, are randomly generated. Then the greedy algorithm is applied to obtain the best results for service duration for a specific number of service cycles. To verify this optimal solution, this study tests

⁶ The survey was for three weeks in March 2002. After eliminating incomplete questionnaires, 952 complete questionnaires remained. The questionnaire consists of two data sets. The first set asked shoppers several questions to obtain socioeconomic and demographic data such as income, resident area and Internet experience. The sample had a fair proportion of different-income people, with an average monthly income of NT\$ 55,000, and the residences of the population were spread widely throughout Taipei City. In the second set, respondents were asked whether they purchase via Internet stores based on different values for various attributes of Internet shopping and conventional shopping such as prices of goods via Internet shopping and conventional shopping, delay in receiving ordered goods, access time for purchasing goods via retail stores, etc. The commercial software package LIMDEP ([Econometric Software, 1996](#)) was used to calibrate the model's parameters. Similar to the finding of [Hsu et al. \(1998\)](#), this study found that the most significant factors are price of goods, delay in receiving ordered goods, and access time for consumers purchasing goods via retail stores.

Table 2
The related data about study zones

Zone, j	Area, A_j (km ²)	Number of retail stores, $n_{t,j}$			
		9:00–11:00	11:00–22:00	22:00–23:00	23:00–9:00
Taipei city	272	83	105	76	6
Taipei county	2186	37	97	43	3
Ilan county	2137	11	15	7	1
Taoyuan county	1221	48	68	35	2
Hsinchu county	1428	17	20	9	1
Hsinchu City	104	31	34	17	2

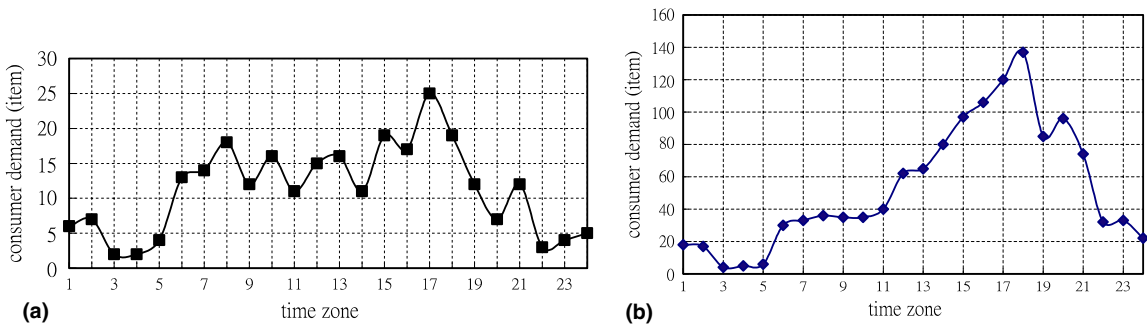


Fig. 2. (a) Time-dependent consumer demand for goods in Taipei City. (b) Total time-dependent consumer demand for goods over the entire study area.

a variety of initial values for the duration of a specific number of service cycles. After several trials, the optimal duration for a specific number of service cycles can then be determined. This procedure is repeated until the optimal durations of service cycles were obtained for each number of service cycle. By comparing the profit values obtained using different numbers of service cycles with the optimal duration, the global optimal number and duration of service cycles that obtain the largest profit can then be determined. The model is programmed using Visual C++, a computer-modeling program developed by Microsoft. Table 4 and Figs. 3 and 4 summarize the initial solution results.

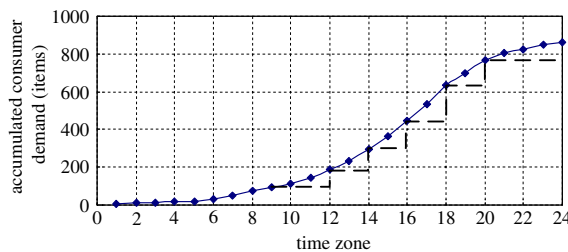


Fig. 3. Accumulated consumer demand for Internet store goods for discriminating service strategy.

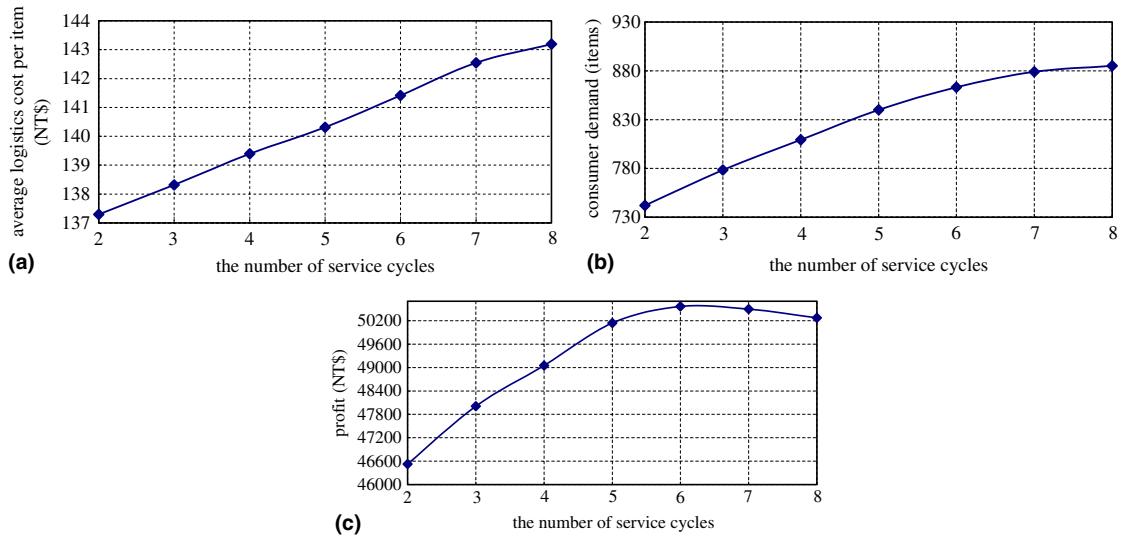


Fig. 4. (a) Average logistics cost per item vs. the number of service cycles for discriminating service strategy. (b) Consumer demand for Internet store goods vs. the number of service cycles for discriminating service strategy. (c) Profit vs. the number of service cycles for discriminating service strategy.

Fig. 3 is time-dependent consumer demand for Internet store goods for discriminating service strategy. From Fig. 3, the solid line represents the accumulated time-dependent consumer demand for Internet store goods for discriminating service strategy, while the dotted line represents the number of goods to be shipped during each service cycle. Moreover, Fig. 3 reveals that numerous items are demanded between 9:00 and 20:00, and a densely spaced service cycle; in contrast, the duration of a single service cycle is 13 h at night, implying extremely low demand during this cycle. Table 3 lists the results and the optimal objective function value for discriminating and uniform service strategies, respectively. The optimal number of service cycles for uniform service strategy is six, and each service cycle lasts approximately 4 h, as listed in Table 3. Consumer demand for goods differs significantly between uniform and discriminating service strategies, namely 818

Table 3
Results and the optimal objective function value for discriminating and uniform service strategies

Strategy	Discriminating	Uniform
Optimal number of service cycles	6	6
Consumer demand for Internet store goods (items)	864	818
Average logistics cost per item (NT\$)	141.41	149.51
Objective function value (Profit, NT\$)	50,569	41,240
Duration of service cycles	9:00–12:00 12:00–14:00 14:00–16:00 16:00–18:00 18:00–20:00 20:00–9:00	0:00–4:00 4:00–8:00 8:00–12:00 12:00–16:00 16:00–20:00 20:00–0:00

and 864 items, respectively. However, the average logistics cost per item for the uniform service strategy is NT\$ 149.51, which exceeds the NT\$ 141.41 for discriminating service strategy. For discriminating service strategy, a high density of service cycles exists during periods with high consumer demand, thus further stimulating consumer demand for Internet store goods. The average logistics cost per item for discriminating service strategy can also be reduced by employing short service cycles during regular hours and long service cycles during late night hours to avoid the high extra cost. Comparing the objective value for discriminating and uniform service strategies yielded a positive value of ζ , namely 18.44%, and indicated that discriminating service strategy is the optimal strategy for Internet store operators.

Fig. 4(a), (b) and (c) individually examine the relationships among average logistics cost per item, consumer demand for Internet store goods, profit and the number of service cycles required to discriminate service strategy. Fig. 4(a) illustrates the average logistics cost per item vs. the number of service cycles required for discriminating service strategy. As illustrated in Fig. 4(a), the average logistics cost per item increases with increasing number of service cycles during a day. Fig. 4(b) displays consumer demand for Internet store goods vs. the number of service cycles required to discriminate service strategy. However, although consumer demand for Internet store goods increases with the number of service cycles but at a decreasing rate, as shown in Fig. 4(b), profit does not continuously increase in the same way. Fig. 4(c) illustrates profit vs. the number of service cycles required to discriminate service strategy, and demonstrated that profit is maximized when a day contains six service cycles. Furthermore, the optimal batch ordering time for the Internet store operator when ordering from the supplier is 0.5 h before the end of each service cycle.

So far, this study has conducted a numerical example for a company selling flowers in Taiwan. Next, this study further explores the influences of changes in key decision parameters on optimal service strategy, along with optimal service cycle number and duration.

The base value of fixed transportation cost includes vehicle depreciation, purchasing cost, and so on. Increased number of service cycles per day leads to more frequent dispatching and thus higher transportation costs. Table 4 lists the optimal objective function values for discriminating

Table 4

Results and the optimal objective function value for discriminating and uniform service strategies under different values of base value of fixed transportation cost

Base value of fixed transportation cost (NT\$)	1200	
Strategy	Discriminating	Uniform
Optimal number of service cycles	6	6
Consumer demand for Internet store goods (items)	859	818
Average logistics cost per item (NT\$)	143.76	155.60
Objective function value (Profit, NT\$)	48,321	36,326
Duration of service cycles	9:00–13:00 13:00–15:00 15:00–17:00 17:00–18:00 18:00–20:00 20:00–9:00	0:00–4:00 4:00–8:00 8:00–12:00 12:00–16:00 16:00–20:00 20:00–0:00
		24.82%

and uniform service strategies under different base values of fixed transportation cost, namely NT\$ 1200. Comparing the results of Tables 3 and 4 reveals that the higher value of the base value of fixed transportation cost produces higher average logistics cost per item for both discriminating and uniform service strategies. The frequencies of service cycles under fixed transportation costs, namely NT\$ 1200 and NT\$ 850, are the same, meaning that rather than serving consumers by reducing frequent service cycles when facing the increased cost, Internet store operators should adopt the original strategy for attracting consumer demand. However, the value of ζ , which indicates the advantage of discriminating regarding uniform service strategies, is larger for higher fixed transportation cost, namely 24.82% vs. 18.44%, as listed in Tables 3 and 4, respectively.

The multiplier reflecting extra costs during different service cycles implies compensation wages because of shipping and handling goods during non-regular hours, for example night hours. Internet store operators can reschedule service cycles to avoid the high logistics costs associated with the increasing values of the multiplier reflecting extra cost. However, such rescheduling may influence the likelihood of individual consumers choosing Internet shopping, and influences consumer demand for Internet store goods.

Table 5 lists the optimal objective function values for discriminating service strategy for different multiplier values reflecting extra costs. As the Table displays, the optimal number of service cycles is six for a multiplier value of two. However, the optimal number of service cycles is seven when the multiplier values are 2.5 and 3.0. The reason for this decision is that because of the logistics costs increase with increasing multiplier, and thus the Internet store operator should employ more frequent service cycles for attracting more consumers to offset the influence of increasing multiplier value on logistics cost. Furthermore, to avoid high additional costs during non-regular hours, the additional service cycle is employed during regular hours, as listed in Table 5.

In this study, consumer income significantly influences demand, which further determines the optimal number and duration of service cycles. Consumer income reflects consumer perceptions regarding delay in receiving ordered goods. Even with the same service cycles and delay in receiving ordered goods, valuations of Internet shopping differ among consumers. Specifically, consumers with different income levels have different levels of concern with delay in receiving ordered goods and price levels. The model captures variations in consumer characteristics by employing

Table 5

Results and the optimal objective function values for discriminating service strategy under different values of multiplier reflecting extra cost

Multiplier reflecting extra cost	2.0	2.5	3.0
Optimal number of service periods	6	7	7
Consumer demand for Internet store goods (items)	864	879	879
Average logistics cost per item (NT\$)	141.41	142.98	144.17
Objective function value (Profit, NT\$)	50,569	50,120	49,074
Duration of service cycles	9:00–12:00	9:00–12:00	9:00–12:00
	12:00–14:00	12:00–14:00	12:00–14:00
	14:00–16:00	14:00–16:00	14:00–16:00
	16:00–18:00	16:00–17:00	16:00–17:00
	18:00–20:00	17:00–18:00	17:00–18:00
	20:00–9:00	18:00–20:00	18:00–20:00
		20:00–9:00	20:00–9:00

consumer income distribution and individual logit model to estimate the expected choice probability of choosing Internet shopping for all consumers. An aggregation bias exists, which affects the accuracy of the optimal decision if variations in consumer income are not considered while using an average customer income value to represent the perceptions of different consumers regarding delay in receiving ordered goods. Table 6 lists the optimal objective function values without and with consideration of variations in consumer characteristics.

As listed in Table 6, owing to considering variations in consumer characteristics, operators of Internet stores employ more frequent service cycles to serve various consumers and thus satisfy more demand. The optimal number of service cycles from models without considering variations in consumer characteristics is two, less than for models that do consider variations. Because of many shipments during the entire study period, the average logistics cost per item for models that consider variations in consumer characteristics exceeds that for models that merely use an average consumer income value; however, the operator gains more profit for models that consider variations in consumer characteristics, as illustrated in Table 6.

Besides socioeconomic characteristics such as income, consumer demand for Internet shopping is also characterized by temporal and spatial variations, which could influence the optimal decision regarding the number and duration of service cycles. Spatial variations reflect various competitions between Internet stores and retail stores in different zones. Besides spatial variations, consumer demand also displays time-dependent distribution. Serving consumers with service cycles without considering time-dependent consumer demand may incur high logistics cost and low consumer demand. This study compares profit, average logistics cost per item and consumer demand for Internet store goods from models that do and do not consider temporal and spatial variations in consumer demand of Internet shopping, respectively. For models that do not consider spatial variations in consumer demand of Internet shopping, the average time required to access retail stores during each hour is obtained by averaging access time to retail stores across all zones. Additionally, consumer demand for goods during each hour for zones is uniform and obtained by dividing total consumer demands for goods by the entire study period, namely 24 h.

Table 6

Results and the optimal objective function values without and with consideration of variations in consumers' characteristics

	Without consideration of variations in consumers' characteristics	With consideration of variations in consumers' characteristics
Optimal number of service cycles	2	6
Consumer demand for Internet store goods (items)	742	864
Average logistics cost per item (NT\$)	137.30	141.41
Objective function value (Profit, NT\$)	46,545	50,569
Duration of service cycles	14:00–19:00 19:00–14:00	9:00–12:00 12:00–14:00 14:00–16:00 16:00–18:00 18:00–20:00 20:00–9:00

Table 7

Comparisons of results from models with and without consideration of temporal and spatial variations in consumer demand of Internet shopping

	Without consideration		With consideration of spatial and temporal variations
	Temporal	Spatial	
Optimal number of service cycles	6	5	6
Consumer demand for Internet store goods (items)	847	840	864
Average logistics cost per item (NT\$)	142.91	140.31	141.41
Objective function value (Profit, NT\$)	48,355	50,139	50,569
Duration of service cycles	3:00–7:00	9:00–13:00	9:00–12:00
	7:00–10:00	13:00–16:00	12:00–14:00
	10:00–13:00	16:00–18:00	14:00–16:00
	13:00–18:00	18:00–20:00	16:00–18:00
	18:00–22:00	20:00–9:00	18:00–20:00
	22:00–3:00		20:00–9:00

Table 7 compares the results from models with and without consideration of temporal and spatial variations in consumer Internet shopping demand, respectively. As listed in Table 7, though the optimal number of service cycles from models with and without considerations of temporal variations in consumer Internet shopping demand is the same, the durations of service cycles differ considerably. For models that consider time-dependent consumer demand, demand increases and logistics cost reduces because of the service cycle being densely spaced during periods with larger demands and long duration of service cycles during night hours. Consequently, the Internet store operator achieves increased profit. As for comparisons between model with and without considerations of spatial variations, service cycles are less frequent for models that do not consider spatial variations in consumer demand for Internet shopping. Moreover, profit is lower because of issues regarding spatial variations in consumer locations and competition between Internet and retail stores in urban and non-urban areas being ignored in optimizing the service cycles.

Delivery service strategies must not only minimize logistics costs, but also must satisfy consumer needs. Previous investigations have considered physical distribution problems other than demand–supply interaction by assuming exogenous consumer demand. This study compares the number and duration of service cycles determined with and without demand–supply interaction. A nonlinear mathematical programming model without demand–supply interaction, namely Eqs. (24a), (24b) and (24e), is applied to optimize the service cycles, where data on consumer demand for goods from Internet stores is given and displays time-dependent consumer demand for goods, as illustrated in Fig. 2(b). For comparison, the operator is assumed to adopt an identical market share that in models with demand–supply interaction, namely 68%.

Table 8 compares the results from models with and without demand–supply interaction. The table shows that the optimal number of service cycles using models without demand–supply interaction is two, which is less than that using models with demand–supply interaction. This finding implies that without considering demand–supply interaction, the Internet store operator seems to minimize average logistics cost per item by assuming inelastic demand and applying the least frequent service cycles. However, further applying the proposed model to calculate the revised re-

Table 8
Comparisons of results from models with and without demand–supply interaction

	Model with demand–supply interaction	Model without demand–supply interaction	
Duration of service cycles	9:00–12:00 12:00–14:00 14:00–16:00 16:00–18:00 18:00–20:00 20:00–9:00	8:00–17:00 17:00–8:00	
		Initial results	Revised results
Consumer demand for Internet store goods (items)	864	864	720
Average logistics cost per item (NT\$)	141.41	136.97	137.36
Objective function value (Profit, NT\$)	50,569	54,330	45,106
Market share	68%	68%	58%

sults, namely Eqs. (11), (17) and (22), yields lower demands because of higher delay in receiving ordered goods with the service cycles, and implies that the operator overestimates the market demand. As for models dealing with demand–supply interaction, the influence of service cycles on consumer demands is examined in such a way that demands reduce with increasing delay in receiving ordered goods. Furthermore, consumer demands then influence operator logistics cost. Finally, the optimal number and duration of service cycles from the demand–supply convergent state leads to higher profit than for models without demand–supply interaction, as listed in Table 8.

As Chen (2001) indicated, consumers may be willing to pay a higher price for goods to receive them faster and that different consumers have varying waiting costs. Since consumer income is positively related to the price consumers are willing to pay for goods as Eq. (4) shows, the Internet store operator may increase profit by serving high-income consumers with frequent service cycles and high-priced goods. However, consumer intention to shop via the Internet may be reduced due to the high price of goods and, thereby, influence profit. This study further investigates the relationship between consumer average hourly income, the price of goods via Internet shopping and the optimal frequency of service cycles.

Table 9(a) lists two scenarios based on consumer average hourly income and the price of goods via Internet shopping. The price of goods and consumer average hourly income are higher under scenario 2 than those under scenario 1, in which the standard deviation of the probability distribution of consumer income remains the same. Moreover, the percentage change in consumer average hourly income and in the price of goods via Internet shopping between scenario 1 and 2 are both 11.65%.

Table 9(b) presents a comparison of the objective function values from scenarios 1 and 2. The optimal number of service cycles in scenario 2 is 7, which is larger than that in scenario 1. Due to

Table 9(a)
Scenarios based on consumer average hourly income and the price of goods via Internet shopping

	Scenario 1	Scenario 2
Consumer average hourly income (NT\$/h)	353.4	400.0
The price of goods via Internet shopping (NT\$)	1050	1188

Table 9(b)
Comparisons of results from different scenarios

	Scenario 1	Scenario 2
Optimal number of service cycles	6	7
Consumer demand for Internet store goods (items)	864	865
Average logistics cost per item (NT\$)	141.41	145.84
Objective function value (Profit, NT\$)	50,569	166,218
Duration of service cycles	9:00–12:00	10:00–13:00
	12:00–14:00	13:00–15:00
	14:00–16:00	15:00–16:00
	16:00–18:00	16:00–17:00
	18:00–20:00	17:00–19:00
	20:00–9:00	19:00–22:00
		22:00–10:00

the frequent service cycles in scenario 2, the average delay in receiving ordered goods in scenario 2 is less than that in scenario 1. Additionally, consumer demand for Internet store goods in scenario 2 is not reduced by the high price of goods. This finding indicates that as consumer average hourly income increases, consumer demand for Internet store goods becomes less price sensitive and, thereby, an increase in price will increase profit. Conversely, this finding also demonstrates that consumers with high incomes are more sensitive to delay in receiving ordered goods than the price of goods; that is, these consumers may be willing to pay more to receive ordered goods faster. Therefore, profit in scenario 2 is increased.

6. Conclusions

Recent studies have investigated Internet shopping carriers and provider issues and their effects on consumer services and operating strategies. Most of these empirical studies dealt these issues by collecting empirical data and testing hypotheses. This study further develops a mathematical programming model that can determine the optimal number and duration of service cycles for Internet shopping by exploring demand–supply interaction and time-dependent consumer demand. This study shows how demand–supply interaction can be carefully considered in advance of solving delivery service problems. This study also shows how variations in consumer socioeconomic, temporal and spatial distributions influence consumer demand for Internet store goods and, thereby, profit.

The results show discriminating service strategy yields better objective values than uniform service strategy, from which indicates that the Internet store operator and consumers may benefit from spacing service cycles according to time-dependent consumer demand. This finding also suggests that in practice an Internet store operator should employ frequent and short service cycles for periods with increased demand and long service cycles when demand is very low. The results further show that when transportation cost increases, the optimal frequent service cycles remains the same or increases. This finding indicates that the impact of reduced consumer demand for Internet store goods on profit is more significant than the increased logistics cost and, therefore,

Internet store operators should employ more frequent service cycles to attract consumers and offset the influence of increasing costs.

The results show that variations in consumer socioeconomic, temporal and spatial characteristics play important roles in determining the optimal number and duration of service cycles and that not considering these variables yields reduced profit. This finding implies that the Internet store operator should carefully investigate the temporal and spatial distribution of consumer demand, income and needs and provide a delivery service strategy tailored to these criteria. For example, service cycles could be intensely spaced for a consumer area or region with numerous retail stores or during periods of large consumer demand. The finding also implies that consumers with high income are more sensitive to delivery delay than to the price of goods and, thus, serving these consumers with frequent service cycles for high price of goods could yield increased profit.

Conversely, this study shows that without considering demand–supply interaction, the Internet store operator typically minimizes average logistics cost per item by assuming inelastic demand and then applying least-frequent service cycles. However, this strategy yields lower profit than strategies that consider demand–supply interaction. In this study, demand–supply interaction is examined in a way that reduces logistics cost due to a large accumulation of goods based on long and less frequent service cycles; however, this strategy also results in an increased delay in receiving ordered goods, thus reducing consumer intention to shop via the Internet. Consequently, this finding in this study implies that the delivery service strategy may not only affect consumer demand for Internet store goods, but also operator logistics costs. In practice, Internet store operators may investigate the effects of service cycles on consumer demand for Internet store goods and its relationship with logistics costs.

This study can be extended in several ways. On the demand side, this study focused only on choice probabilities for two shopping modes rather than that among shopping stores within each mode. Future studies may use the joint or nested logit models to determine consumer choice probabilities for a specific Internet store. Second, the case study is based on an Internet store selling flowers in Taiwan with a study period of one operating day. Future studies may apply the model to different goods, such as computers and extend the study period beyond one day. Such studies would need to examine the impact of different characteristics of goods on consumer intention toward Internet shopping and calibrate a consumer demand function. Finally, as [Chen \(2001\)](#) suggested, profit may be improved by segmenting the market and then serving different market segments with different combinations of prices and service cycle frequencies. Future studies may expand this study's model and address this issue by determining an optimal segmenting strategy and investigating the relative influences of the price of goods and delay in receiving ordered goods on consumer intention to shop via the Internet in the contexts of these different segments.

Acknowledgement

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC 93-2416-H-009-005.

References

- Bakker, A., Creedy, J., 2000. Macroeconomic variables and income distribution—conditional modeling with the generalized exponential. *Journal of Income Distribution* 9, 183–197.
- Ben-Akiva, M., Lerman, S.R., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, Massachusetts.
- Bhatnagar, A., Ghose, S., 2004. Segmenting consumers based on the benefits and risks of Internet shopping. *Journal of Business Research* 57, 1352–1360.
- Blumenfeld, D.E., Burns, L.D., Diltz, J.D., Daganzo, C.F., 1985. Analyzing trade-offs between transportation, inventory and production costs on freight networks. *Transportation Research B* 19, 361–380.
- Boyer, K.K., Hallowell, R., Roth, A.V., 2002. E-services: operating strategy—a case study and a method for analyzing operational benefits. *Journal of Operations Management* 20, 175–188.
- Burke, R.R., 1997. Do you see what I see? The future of virtual shopping. *Journal of the Academy of Marketing Science* 25, 352–360.
- Burns, L.D., Hall, R.W., Blumenfeld, D.E., Daganzo, C.F., 1985. Distribution strategies that minimize transportation and inventory costs. *Operation Research* 33, 469–490.
- Chen, F., 2001. Market segmentation, advanced demand information, and supply chain performance. *Manufacturing & Service Operations Management* 3, 53–67.
- Coyle, J.J., Bardi, E.J., Langley, C.J., 1996. *The Management of Business Logistics*. West Publishing Company, Minneapolis.
- Econometric Software, 1996. LIMDEP V7.0. Econometric Software, Bellport NY.
- Esper, T.L., Jensen, T.D., Turnipseed, F.L., 2003. The last mile: an examination of effects of online retail delivery strategies on consumers. *Journal of Business Logistics* 24, 177–203.
- Heim, G.R., Sinha, K.K., 2001. Operational drivers of customer loyalty in electronic retailing: an empirical analysis of electronic food retailers. *Manufacturing & Service Operations Management* 3, 264–271.
- Heim, G.R., Sinha, K.K., 2002. Service process configurations in electronic retailing: a taxonomic analysis of electronic food retailers. *Production and Operations Management* 11, 54–74.
- Hsu, C.I., Tsai, I.J., 1999. Logistics cost, consumer demand, and retail establishment density. *Papers in Regional Science: the Journal of the RSAI* 78, 243–263.
- Hsu, C.I., Chiang, H.Y., Pai, J.T., 1998. Analyzing consumers' choice behavior between teleshopping and store shopping. *Transportation Planning Journal* 27, 435–464 (in Chinese).
- Hsu, C.I., Chiang, H.Y., Lee, W.C., 2003. Shipping strategies for Internet shopping goods under non-homogeneous demand pattern. *Journal of the Eastern Asia Society for Transportation Studies* 5, 2341–2354.
- Huppertz, P., 1999. Market changes require new supply chain thinking. *Transportation & Distribution* 40, 70–74.
- Khouja, M., 2001. The evaluation of drop shipping option for e-commerce retailers. *Computer & Industrial Engineering* 41, 109–126.
- Kiang, M.Y., Raghu, T.S., Shang, K.H.M., 2000. Marketing on the Internet—who can benefit from an online market approach? *Decision Support System* 27, 383–393.
- Koppelman, F., Salomon, I., Prousaloglou, K., 1991. Teleshopping or store shopping. A choice model for forecasting the use of new telecommunications-based services. *Environment and Planning B: Planning and Design* 18, 473–489.
- Koyuncu, C., Bhattacharya, G., 2004. The impacts of quickness, price, payment risk, and delivery issues on on-line shopping. *Journal of Socio-Economics* 33, 241–251.
- Liang, T.P., Huang, J.S., 1998. An empirical study on consumer acceptance of products in electronic markets: a transaction cost model. *Decision Support Systems* 24, 29–43.
- Manski, C., Salomon, I., 1987. The demand for teleshopping: an application of discrete choice models. *Regional Science and Urban Economics* 17, 109–121.
- McCullagh, P., Nelder, J.A., 1989. *Generalized Linear Models*. Chapman and Hall, London.
- Ministry of the Interior, ROC., 2001. MOI statistical information service. Available from: <<http://www.moi.gov.tw/W3/stat>>.
- Nagurney, A., Dong, J., Mokhtarian, P.L., 2001. Teleshopping versus shopping: a multicriteria network equilibrium framework. *Mathematical and Computer Modelling* 34, 783–798.

- O’Cass, A., Fenech, T., 2003. Web retailing adoption: exploring the nature of Internet users Web retailing behaviour. *Journal of Retailing and Consumer Services* 10, 81–94.
- Olson, J.R., Boyer, K.K., 2003. Factors influencing the utilization of Internet purchasing in small organizations. *Journal of Operations Management* 21, 225–245.
- Pavitt, D., 1997. Retail and the super high street: the future of the electronic home shopping industry. *International Journal of Retail & Distribution Management* 25, 38–43.
- Peterson, R.A., Balasubramanian, S., Bronnenberg, B.J., 1997. Exploring the implication of the Internet for consumer marketing. *Journal of the Academy of Marketing Science* 25, 329–346.
- Rabinovich, E., 2004. Internet retailing intermediation: a multilevel analysis of inventory liquidity and fulfillment guarantees. *Journal of Business Logistics* 25, 139–169.
- Rabinovich, E., Bailey, J.P., 2004. Physical distribution service quality in Internet retailing: service pricing, transaction attributes, and firm attributes. *Journal of Operations Management* 21, 651–672.
- Rabinovich, E., Bailey, J.P., Carter, C.R., 2003. A transaction-efficiency analysis of an Internet retailing supply chain in the music CD industry. *Decision Sciences* 34, 131–172.
- Raijas, A., 2002. The consumer benefits and problems in electronic grocery store. *Journal of Retailing and Consumer Services* 9, 107–113.
- Reynolds, J., 1997. Retailing in computermediated environments: electronic commerce across Europe. *International Journal of Retail & Distribution Management* 25, 29–37.
- Salomon, I., Koppelman, F., 1988. A framework for studying teleshopping versus store shopping. *Transportation Research A* 22, 247–255.
- Sherman, E., Topol, M.T., 1996. Anticipating the impact of new technologies on retailing. *Journal of Retailing and Consumer Services* 3, 107–111.
- Sim, L.L., Koi, S.M., 2002. Singapore’s Internet shoppers and their impact on traditional shopping patterns. *Journal of Retailing and Consumer Services* 9, 115–124.
- Verhoef, P.C., Langerak, F., 2001. Possible determinants of consumers’ adoption of electronic grocery shopping in the Netherlands. *Journal of Retailing and Consumer Service* 8, 275–285.