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Retailer's Optimal Inventory Policies for Cross-Border E-Commerce

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Abstract: This study considers a supply chain formed by multiple suppliers and a cross-border retailer facing a non-stationary demand process. We build a multi-period inventory model with (s, S)-type inventory policy and (s, Q)-type inventory policy. Using this model, demands can be forecasted on the basis of two demand processes, i.e., ARIMA and average demand process. Performances of the two inventory policies, (s, S)-type and (s, Q)-type, are assessed and compared in terms of average delivery time, stock-out frequency, and cost of selling. Through the analysis of 6489 purchase orders of an online shop in Taiwan, covering a period from January 2012 to July 2017, the results present a near-optimal (s, S)-type inventory policy for a cross-border distribution network with multiple suppliers. The model is a synthesis of two components: (i) the inventory policy analysis at a retailer, and (ii) order demand forecasting. We use action research to analyze the performances of inventory models in a cross-border retailer. The results indicate that the semiannual average method using (s, S)-type inventory policy best suits the case company for demand forecasting, as it can decrease the order delivery time from 7.08 days to 0.63 days, and decrease the stock-out frequency from 100.00% to 9.49%. The key contribution of the findings is the seamless integration of the two components to analyze order history data for cross-border supply chains between retailer and suppliers. We anticipate that the research findings may enhance our understanding of inventory control and provide insights into cross-border retailers' future inventory policies.

Keywords: *Inventory management; e-commerce; forecasting; ARIMA demand; cross-border commerce*

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INTRODUCTION

With the widespread application of Information and Communication Technology (ICT), online shopping has become an integral part of modern life. In particular, cross-border shopping has undergone an unprecedented growth amidst the surging demands for overseas products. According to an estimation by (Accenture, 2017), over 2 billion e-shoppers (60% of target global population) would be engaging in global B2C e-commerce trading by 2020, accounting for 13.5% of the total online retail consumption, equivalent to a market value of US$3.4 trillion. As a key engine of the B2C trading market, cross-border e-commerce is estimated to undergo a Compound Annual Growth Rate (CAGR) of 29.3% during 2014 to 2020. Boston Consulting Group also predicts that by 2025, 40% of global cross-border e-commerce sales will take place in the Asia-Pacific region (Heel, Lukic, & Leeuwis, 2014), by then the world's largest cross-border e-commerce market. Therefore, it presents highly promising prospects to provide borderless and globally operated e-commerce and after-sales services through ICT platforms.

Cross-border e-commerce is defined as import and export business activities conducted through electronic means by trading entities belonging to different customs frontiers or jurisdictions (Ali Cross Border E-Commerce Research Center, 2016). In other words, cross-border e-commerce enables trading entities located in different countries or regions

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to conduct business transactions through e-commerce platforms, cross-border payment settlement, and cross-border logistics (Ali Cross Border E-Commerce Research Center, 2016). As such commercial activities involve multiple countries, various issues may arise with respect to language barriers, logistics, regulatory control, tariff costs, and after-sales services. Consequently, even with the convenience of rapid information exchange enabled by the Internet, cross-border online shopping can go far more complex than conventional domestic online shopping.

To circumvent the hassles associated with cross-border e-commerce, many shoppers turn to domestic agents who provide “surrogate shopping services” to purchase products overseas on consumers’ behalf. These agents are also known as “surrogate shoppers”, who profit from charging commissions for buying goods on the customer’s behalf or providing a warehouse in a foreign land as a midway transfer point where purchased goods are shipped to before forwarded to the receiving address of the customer.

Faced with intensified horizontal competition in the surrogate shopping market and uncertainty of consumer’s preference, some shopping agents react by improving shipment efficiency and keeping a small inventory, apart from engaging in price competition. In other words, they seek to shorten the delivery time to attract customers who are “time-sensitive”, and thereby, increase business volume. To this end, many surrogate shoppers build an inventory of their own. As a result, inventory management issues emerge, which need to be addressed in cross-border e-commerce operations.

To satisfy customers’ expectations for shortened delivery time at a lower cost, this study integrates two demand forecasting techniques with the (s, S) and (s, Q) models in pursuit of an optimal inventory policy for cross-border e-commerce vendors. We aim to assess the performances of the (s, Q)-type and (s, S)-type policies in comparison to cases in which without inventory policies are implemented with respect to average delivery time, stock-out rate, and selling costs. Performances of inventory polices are verified with actual data collected from the case company. It is anticipated that our findings may be used to enhance the quality of order fulfillment procedure in cross-border e-commerce while improving profitability.

LITERATURE REVIEW

Global E-commerce Inventory Management Strategies

Drawing on the research by Chopra and Meindl (2007) and Levi, Kaminsky, and Levi (2003) and Yang (2011) extends the transportation model from order fulfillment to global logistics. In addressing the globalization of orders in e-commerce, Yang (2011) proposes four transportation models coupled by corresponding cost functions taking account of transportation cost, handling cost, warehouse rent cost, and customs duty. Aiming at minimizing the costs, Yang (2011) study empirically verifies the four cost functions, in an attempt to assist optimizing transportation decisions by e-commerce businesses dealing with internationalizing orders.

Addressing issues arising from cross-border logistics, Lin (2015) examines various approaches to meet consumers’ expectations for speedy delivery at minimized total costs. By surveying consumers’ expectations for speed of delivery, his study was aimed to develop order fulfillment solutions under different service levels with transportation cost, handling cost, and warehouse rent cost taken in account.

While most studies mentioned above have endeavored to identify the optimal transportation model for order fulfillment in global e-commerce, there is a paucity of research that taps into devising optimal inventory policies for cross-border inventory management where overseas replenishment is frequently needed.

As highlighted by Stevenson (2014) in their book, operations management, inventory management has two main concerns, namely the level of customer service and the costs of ordering and carrying inventories. Any effective inventory system should include: 1) A system to keep track of the inventory on hand and on order; 2) A reliable forecast of demand that includes an indication of possible forecast error; 3) Knowledge of lead times and lead time variability; 4) Reasonable estimates of inventory holding costs, ordering costs, and shortage costs; 5) A classification system for inventory items. Depending on how inventory purchase, holding, and resale are managed, traditional inventory systems can be divided into two types, i.e., perpetual inventory system and periodic inventory system. The perpetual inventory system, also known as continuous review system, keeps track of inventory balances continuously. Whenever the existing inventory reaches a predefined minimum level, reorders are placed. In contrast, under a periodic inventory system, the inventory is reviewed at fixed intervals. Based on existing inventory level and estimated demands before the next arrival, managers decide the quantity of replenishment orders (Polcharoensuk & Yousapornpaiboon, 2017; Stevenson, 2014).

The disadvantage of periodic inventory is the need to maintain extra inventory to prevent stock-outs between inventory reviews. Furthermore, periodic inventory also entails exceedingly high costs of inventory holding and logistics. Therefore, this study adopts the two strategic models of perpetual inventory system, including continuous review (s, Q)-type and (s, S)-type inventory policies. (s, S)-type policy means that when the inventory level is less than or equal to the reorder point s, reorders should be placed to replenish the inventory to its maximum level of stock S; (s, Q)-type policy means that when the inventory level is less than or equal to the reorder point s, reorders of a fixed quantity Q should be placed.

Furthermore, based on the literature of Just-in-Time (JIT) purchasing (Kelle & Milne, 1999), this study extends the Economic Order Quantity (EOQ) model by assuming deterministic demands and lead times.

Next, drawing on the research of (Silver, Pyke, & Peterson, 1998; Stevenson, 2014), this study summarizes formulas of the (s, S)-type and (s, Q)-type policies by considering the EOQ model and the Reorder Point Level (ROP) model, as shown in Table 1.

Table 1 *(s, S)-type & (s, Q)-Type Inventory Policies*

Inventory policies	(s, S)	(s, Q)
Reorder point	$\mu L + z\sigma\sqrt{L}, S \geq s$	$\mu L + z\sigma\sqrt{L}, O > \mu L$
Order quantity	$(O + \mu L + z\sigma\sqrt{L}) - (I) \geq O$	$O = \sqrt{2}k\mu/h$
Safety stock	$\mu L + z\sigma\sqrt{L}$	$\mu L + z\sigma\sqrt{L}$
Maximum stock	$O + \mu L + z\sigma\sqrt{L}$	$O + \mu L + z\sigma\sqrt{L}$

Notes: s: reorder point; O: EOQ; S: maximum stock level; μ: demand forecast during average unit time; L: lead time; z: safety stock factor; σ: standard deviation of estimated demand; k: cost per order; h: unit holding cost; I: inventory position.

(s, S)-type and (s, Q)-type policies have been extensively studied and practiced in the field of inventory management. For example, using actual data on sales and purchases by Taiwan's General Welfare Service, Chung (2004) compared the existing rules of thumb inventory policies and how the total costs were affected by the (s, Q)-type and (s, S)-type policies in relation to the three factors, namely, service level, lead time, and unit shortage cost.

Wu (2006) investigated the inventory and distribution policy in cross-docking operating systems. Aiming at minimizing the total cost of the system, her study examined how a central planner determines the optimal (s, S)-type inventory policy to meet pre-specified service levels while maintaining economies of scale in transportation with minimal stock level, thereby minimizing the total cost of the system.

There is, however, a paucity of research that compares the effects of various inventory policies by using empirical data from cross-border logistic operations. To bridge this gap, this study employs an action research method to analyze how (s, Q)-type and (s, S)-type inventory policies could be used to optimize inventory service quality as perceived by customers.

Demand Forecasting Models

Traditional EOQ model assumes that the annual demand is known and evenly distributed along the year. As a result, the average demand per unit time is determined as the parameter of forecasted demand for the (s, Q)-type and (s, S)-type inventory policies.

However, in practice, the demand is usually not evenly distributed. Therefore, retailer employs the ARIMA, a forecasting technique based on a single variable time series, as the model for future demand forecasting.

As a common technique for time series analysis, the ARIMA model was first proposed by Box, Jenkins, Reinsel, and Ljung (2015). Based on time series data, ARIMA identifies an appropriate probability model that represents the interdependency between data and time, so as to predict future points in the series.

In this study, ARIMA model and average demand model are employed comparatively to establish parameters for per-unit-time demand forecasting under the (s, Q)-type and (s, S)-type policies, and to compute forecasted demands as well as standard deviation under the inventory polices. The purpose of this study is to investigate how integration of ARIMA and average demand model with (s, Q)-type and (s, S)-type inventory policies could meet customers' expectations for delivery speed, and affect the stock-out rate.

METHODOLOGY

This study aims to identify the optimal inventory polices for cross-border e-commerce. Using action research method, a total of 6489 historical purchase orders placed to the US-based online shopping website Amazon by Esunfon Company during January 2012 to July 2017 has been analyzed. The flowchart of research is shown in Table 2.

Table 2 *Research Framework*

Flowchart	Purpose	Method	Outcome
Aggregation of purchase orders	Select commodity items that meet the criteria of inventory policies	Establish filtering criteria based on expert interview results; Deal with outliers	Records of purchase orders for commodities that meet the sales criteria
⇓			
Establishing demand forecasting and standard deviation	Establish forecasted demand per unit time μ and predicted standard deviation σ of the forecasted demand under (s, S) and (s, Q) systems	Based on records of order history, two methods are used for demand forecasting: 1) Average demand and standard deviation during the period 2) Construct an ARIMA model Forecasted demand μ	Predicted standard deviation σ
⇓			
Establishing inventory service levels	Establish the safe inventory coefficient z under (s, S) and (s, Q) systems, i.e., the inventory service level within the lead time of replenishments	Based on the probability of stock-out at Esunfon's operations on an online shopping platform, a z-score is obtained by converting the percentile value 1 -stock-out rate into a standardized value	Safe inventory coefficient z
⇓			
Construction and assessment of inventory policies	Construct order quantity and reorder point decision model; assess performance of inventory policies in operation	Populate the (s, S) and (s, Q) systems with forecasted demand μ, predicted standard deviation σ, and safe inventory coefficient z, and assess performance of operations	Inventory models using (s, S) and (s, Q)
⇓			
Inventory policy performance assessment	Assessing performance of inventory policies in operation	Average delivery days Average stockout rate Average stock	Optimal inventory policies for cross-border online shopping vendors

Case Background of Esunfon Company

Founded in 2006, Esunfon was initially operated as an online retail store in Taiwan. Starting in 2008, its business focus shifted to overseas surrogate shopping services. With a capital investment of 5 million NT dollars, the firm currently employs 10 persons in its business department, which has been engaged in the procurement, warehousing, and sales of nearly 35,000 Stock Keeping Units (SKUs). The surrogate shopping services are operated through various online shopping platforms, such as Rakuten Ichiba Taiwan, Yahoo Kimo Super Mall, Ruten auction, Pchome online, and Taobao. The sources of the goods are primarily from the United States and Japan, with the former accounting for 94.3% of its business operation, totaling 20,755 SKUs approximately. In addition, there are 83.7% of purchase orders from Amazon.com in the US.

Regarding customer's order fulfillment process, Esunfon places orders on customers' behalf upon receipt of the order. The purchased goods are first shipped to a warehousing center in the United States. Subsequently, a notice is sent to the customer informing that the delivery may take approximately 5 to 10 working days. The purchased goods are shipped from the US warehouse to Taiwan in batches through FedEx international economic courier service every Saturday which takes about 4 working days. Upon arrival in Taiwan, the goods are delivered to Taiwanese customers through domestic logistics services or to mainland Chinese customers using China Post's parcel service.

Identifying the Problem

Initially, Esunfon adopted a zero-stock inventory policy. With the popularity of overseas surrogate shopping services, competition intensifies. Customers increasingly require faster delivery speed and improved quality, and thus, prolonged order fulfillment time will lead to decreased customer satisfaction or even transaction termination. To address this challenge, Esunfon started to establish a set of inventory rules. Best-selling commodities are stocked ahead of time to ensure shortened order fulfillment process that meets the customers' expectations for efficient shipment.

Interview results with Esunfon indicate that, given the uncertainties in demands for surrogate online shopping, the firm had to rely on the purchase manager's experience to determine stock levels and replenishment policies. Such decision-making processes are susceptible to unstable inventory, which, in turn, leads to issues, such as capital backlog and extended order delivery time.

Recognizing the demand uncertainties, this study integrates the (s, S)-type and (s, Q)-type policies with ARIMA (Box et al., 2015) and average demand model, in an attempt to alleviate inventory instability, shorten order delivery days, and minimize stock-outs.

Historical Purchase Orders of the Case Company

This study employs two software packages, EView 9.5 student version and SPSS 22.0, as the tools for demand forecasting and outlier detection. All purchase orders placed to the US-based online shopping website Amazon during January 2012 to July 2017 were aggregated as the data source for analysis, totaling 6489 data entries for 1674 commodities.

An interview was conducted with Esunfon's CEO, an expert with years of practical experiences in e-commerce. Whether a commodity item should be stocked is determined by the fact that the commodity has been ordered by customers for 3 months (or longer) during the past 6 months.

Based on the interview results, the filtering criteria for data selection are established, as follows:

1. The commodity has been ordered for three months (or longer) during the past six months.

2. The commodity item has been ordered three times (or more) during the forecasted period starting from January 2017 to July 2017.

After the filtering process, seven commodity items were selected for further analysis.

Subject to interferences, inconsistency may arise from observed values in time series. These anomalies are collectively referred to as outliers, which may affect the estimation of residuals in the forecasting model, which, in turn, affects the evaluation results during diagnosis. Therefore, outlier detection is required.

In this study, presence of extreme outliers is identified using box plots and positions of the inner and outer fence of the Inter Quartile Range (IQR). An outlier must be rectified if it has a significant adverse effect on the prediction results of the time series. In this study, the mean value is used for outlier replacement.

Forecasting Demands and Determining Standard Deviation

Based on historical records of purchase orders, this study determines demand forecasting and standard deviation during the forecasting intervals through two methods:

1. Based on the average value and standard deviation of historical purchase records;

2. Construct ARIMA model based on historical purchase records

Depending on sampling intervals, the data are categorized as shown in Table 3.

Table 3 *Data Categorization*

	Half a year	Two years	Four years
Demand forecasting	Average	Average/ARIMA model	Average/ARIMA model
Predicted standard deviation	Average	Average/ARIMA model	Average/ARIMA model

Notes: Only the average demand model is used because there are too few samples observed to construct the ARIMA model using the half-a-year sampling interval.

Establishing Inventory Service Level

Service level refers to the probability of satisfying demands with existing inventory, therefore service level = 1 - stock-out risks. With respect to the establishment of inventory service level, this study formulates the service level functions with reference to the average service statements by Yahoo! Kimo Super Mall Online Shopping Platform, as follows:

Inventory service level = Z (1 - stock-out rate) Stock-out rate = number of orders canceled (for stock-out + for delay + for not delivered to nearby convenient stores)/ number of orders to be delivered Z: standardized z-score converted by percentile value

On April 15, 2017, Esunfon's stock-out rate on the Yahoo! Kimo Super Mall online shopping platform was 1.15%, and the inventory service level was z (98.5%), i.e., 2.17009.

Establishing the Inventory Policies

The flowchart of inventory policies establishment is illustrated in Figure 1.

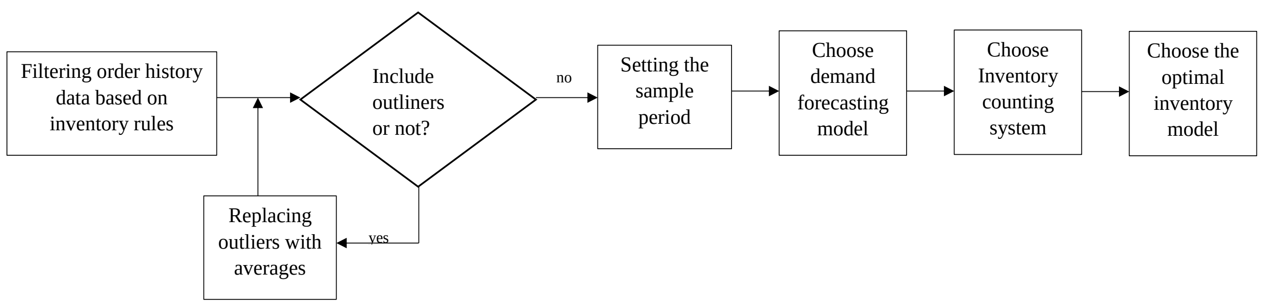

Figure 1 *Flowchart of Establishing Inventory Policies*

INVENTORY POLICY PERFORMANCE ASSESSMENT

The focus of this study is to investigate which inventory model should be adopted to ship commodities originated in the United States to Taiwan. "Average stock-out rate per order", "average selling costs per order", and "average delivery days per order" are used as indicators of inventory performance. Assume the number of orders is ρ, the function for the indicators can be expressed as:

1. Average stock-out rate per order = Average ($\frac{\text{Delayed delivery orders}}{\text{Total orders}}$)
2. Average selling costs per order = Average (commodity cost + international and domestic transportation costs + international and domestic handling costs)
3. Average delivery days per order = Average (the final date of delivery-date of order).

Data Analysis

The results of integrating (s, S)-type and (s, Q)-type inventory policies with the two demand forecasting techniques are shown in Table 4.

It can be observed from Table 4 that when (s, Q)-type inventory policy is implemented, the average stock-out rate per order exceeds 30%. According to Esunfon's CEO, any policy that results in higher than 30% stockout rate is inappropriate for Esunfon. Therefore, subsequent analysis was based on implementation of (s, S)-type policy.

Table 4 *The Results of Integrating (s, S)-Type and (s, Q)-Type Inventory Policies*

Inventory policies	Demand forecasting techniques	Average delivery days per order	Stock-out rate
Esunfon	-	7.08	100.00%
(s, S)	Semiannual average	0.63	9.49%
	2-year ARIMA	2.43	27.69%
	2-year average	1.96	23.78%
	4-year ARIMA	2.61	31.76%
	4-year average	2.50	32.61%
(s, Q)	Semiannual average	2.17	32.13%
	2-year ARIMA	2.87	32.38%
	2-year average	2.71	34.28%
	4-year ARIMA	3.29	42.37%
	4-year average	3.10	39.32%

Table 5 *The Detailed Results of Adopting (s, S)-Type Policy*

Inventory policies	Demand forecasting techniques	Average delivery days per order	Stock-out rate	Selling cost (in NTD)	Average daily stock
Esunfon	-	7.08	100.00%	$1,080.17	-
(s, S)	Semiannual average	0.63	9.49%	$1,064.09	4.30
	2-year ARIMA	2.43	27.69%	$1,065.55	3.17
	2-year average	1.96	23.78%	$1,067.56	3.42
	4-year ARIMA	2.61	31.76%	$1,066.22	3.23
	4-year average	2.50	32.61%	$1,065.65	2.42

It can be observed from Table 5 that the selling costs are rather constant regardless of the demand forecasting techniques used. When ARIMA is employed for establishing demand forecasting and standard deviation, the carrying stock levels are relatively low while the average delivery time is longer. In addition, with respect to sampling, longer sample intervals ensue higher stock-out rates and longer delivery time.

Expert's Assessment on Inventory Performance

Esunfon's CEO, who has over 10 years of experience in order fulfillment process, estimates that approximately 90% of the customers are willing to wait for up to one week. A one- or two-day delivery time is the most desired by customers, nevertheless.

In addition, data of service quality at Esunfon's operations on Yahoo! Kimo Super Mall online shopping platform on April 15, 2017 indicate that the stock-out rate was 1.15% and the delivery speed was 2.0 days. Concerning cross-border replenishment, Esunfon's CEO thinks that any good inventory policy would ensure that the average delivery time be kept under 2 days, and the stock-out rate less than 10%.

Based on the expert assessment criteria described above, the (s, Q)-type inventory policy is deemed unsuitable for Esunfon because it invariably leads to a stock-out rate higher than 30%; in contrast, the (s, S)-type inventory policies could bring the average delivery time down to 2 days and stock-out rate under 10% only when a semiannual average method is used for demand forecasting. Therefore, the (s, S)-type policy meets the conditions of expert assessment, and, thus, qualifies to be the most suitable inventory policy for Esunfon.

CONCLUSION

This study addresses the issue of order fulfillment in the context of cross-border surrogate online shopping and investigates order fulfillment issues arising from long lead time for replenishment and increased customer demand for shortened delivery time and fast delivery quality in cross-border e-commerce. By examining the issue of cross-border logistics under an inventory management perspective, this study seeks to satisfy customer's expectations for shortened order delivery time with minimal stock-outs.

To identify the optimal inventory policy in the context of cross-border surrogate online shopping, this study employs expert interview method to determine inventory levels for cross-border replenishments. The ARIMA demand forecasting model and average demand model are integrated into (s, Q)-type and (s, S)-type, the two common inventory policies used in continuous review systems. Average delivery days per order, stock-out rate, and selling cost were used as performance indicators for optimal inventory policies in cross-border surrogate shoppers.

Based on actual data of purchasing orders by cross-border e-commerce retailer Esunfon and the expert opinions provided by Esunfon's CEO, who has more than10 years of experience in e-commerce, an optimal inventory model for cross-border e-commerce was established, which is capable of keeping the average delivery time under 2 days and stock-out rate lower than 10%. The (s, Q)-type policy proves unsuitable for Esunfon because it leads to more than 30% stock-out rate; the (s, S)-type policy could keep average order delivery under 2 days and stock-out under 10% only when the demand forecasting is made with semiannual average method. Therefore, it best meets the expert assessment criteria and customers' expectations for order delivery time, with validated reliability and effectiveness.

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