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Two-stage replenishment policies for deteriorating items at Taiwanese convenience stores

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ABSTRACT

In the past decade, convenience stores have generally experienced low profit margins due to the intensive competition that exists in the industry. To reduce operating costs, these stores must be able to efficiently control their stock replenishment, especially for deteriorating items such as meal-boxes. To solve this problem, we employed a two-step model to determine the optimal amount of replenishment. In the first step, we obtained the basic reorder quantity by considering three inventory management methods involving the consideration of the probability forecast of demand, hypothesis testing and the newsboy method. In the second step of our model, a novel warning system is established by employing the support vector machine to modify the basic order quantity, which may be varied due to the effect of uncertain factors such as the weather, climate and economic prospects. Using actual data from a convenience store which was a part of the President Chain Store Corporation in Taiwan, the prediction accuracy of the two-step replenishment policies was evaluated. We also apply two methods to enhance accuracy and provide further insights into the model. The results show that the model is workable, and the results can be used as a valuable reference for future practical applications.

1. Introduction

The President Chain Store Corporation (PCSC) is a rapidly growing convenience store chain and as of March 2008, has 4765 stores in Taiwan. During the corporation's initial start-up period, the PCSC was faced with a predicament of a consecutive six-year deficit. However, since then, they have securely built up their foundation and market in the retailing industry. The PCSC believed that the determinant of their competitiveness was not those who were sharing the same market, but actually the threat of a constant change in customer requirements. As such, this guideline alerted managers in each store to be attentive to consumer behavior by providing services attuned to customers' needs, in order to continuously increase customer service and to ensure maximum satisfaction. The key to each stores' success is the ability to make decisions that not only follow consumer trends and needs, but also reduces operational costs. In other words, PCSC stores must be able to efficiently control their stock replenishment, especially for deteriorating items such as meal-boxes. The importance of replenishment is that items that are out of stock greatly diminish service quality. Therefore, decision makers are always faced with the dilemma of balancing the increase of customer satisfaction and the reduction of costs. Convenience stores hold a substantial amount of inventory, of which many perishable goods may become scrap, leading to losses. The application of a scientific method to determine the appropriate order of perishable goods as accurately as possible is greatly needed by decision makers.

Convenience stores generally make their order decisions according to the POS (point of sale) analysis. However, many uncertainties still exist when using the POS system to estimate supply and demand. As product decisions are important and difficult for managers, especially in relation to deteriorating items, a scientific formula to assist managers in making such decisions will not only contribute to the store's profit margin, but also satisfy customers and preserve finite resources.

Stock shortages will cause customers to become unsatisfied and damage the business reputation, especially in the service sector. In most cases, good inventory control can solve any potential shortage problems. However, for deteriorating items, the ordering decision requires a balance between the customer's satisfaction and wastage prevention. Since the prediction problem is complex and changeable in all trades and professions, an optimal decision is not always easy to determine. Based on the research of Silver et al. [1], most firms do not fully understand the complexities of inventory management. For convenience stores, many factors may affect the sale of meal-boxes, including, the

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weather, temperature, festivals, global economical environment and promotions. For items that can be preserved for a long time, oversupplies will only lead to an increase in inventory. However, for perishable goods, overstocking will actually damage the store's profit. As the product life of a meal-box is very short, overstocking may lead to some products passing their expiry date. On the other hand, if there are insufficient stocks, sales opportunities may be lost with a reduction in customer satisfaction.

Currently, general convenience stores' merchandise replenishment strategies still lack a sound scientific basis, with an adverse effect on profit. Convenience store POS systems can provide some information for making order decisions, but cannot accurately predict sales. Therefore, the determination of the most efficient order is an important decision for the store manager. If the decision is based on high-yields, increased quantities may be sold, but with the increased probability of scrap commodities (especially daily products such as sandwiches and meal-boxes), in turn hurting profits. In this study, the ordering, sales and scrapped numbers of the meal-box products of a PCSC store in Taiwan are collected. A two-step model to determine the optimal amount of replenishment is developed so as to achieve higher profits.

1.1. Structure of the proposed algorithms

In the past decade, convenience stores have experienced low profit margins due to the intense competition. As a result, inventory management has become increasingly important to competitive success. There are thousands of items stocked in a convenience store, and they must be managed carefully with a suitable inventory management policy. For perishable goods such as meal-boxes, freshness is always a primary concern for consumers. The decision logic for coping with items subject to obsolescence is even more difficult to handle than those items with a longer shelf-life. As such, making accurate demand forecasting for perishable items is particularly important.

In order to establish the optimal replenishment quantity for the meal-box, this study adopts a two-stage analysis method, as shown in Fig. 1. The first stage is the basic order decision-making, which will attempt to integrate the three types of inventory management model theories, including the consideration of the demand forecast of the probability of order quantity model, hypothesis testing methods and newsboy model. By comparing the results obtained from the three models, we can determine an initial basic order quantity. The second stage is the wastage warning system. As a result of the number of uncertainties, such as weather, temperature and promotions, the basic order quantity derived may result in a supply and demand of error. This study uses a Support Vector Machine (SVM) to increase the predictive accuracy of the approach to supplement the lack of an order prediction model. In general, SVM is often used for binary

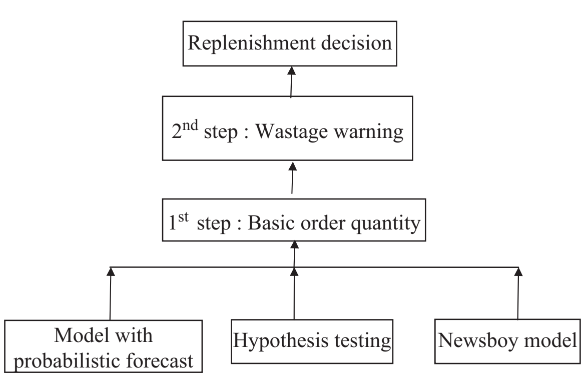

Fig. 1. Two-stage replenishment policies.

judgments. An innovative part of our study is that we suggest that policy makers, whose sales results lead to wastage or no wastage, can also be regarded as binary. Therefore, SVM can be applied to determine whether the initial quantity will induce overstocking, and we can thus establish a wastage warning system.

1.2. Literature review

Convenience store businesses are already operating in Taiwan as the main channels for providing consumers with a variety of quality and stable services. As the number of stores approaches a saturation point, scale development also reaches its peak and each convenience store chains is forced to focus on controlling costs. It is an inevitable trend that the number of unneeded stocks is reduced in order to increase the product inventory turnover rate.

In such a complex and fast changing business environment, coupled with shortened product-life cycles, it is crucial for convenience stores to meet ever-changing customer demands, with the possibility that sales in different stores require different inventory policies. The PCSC thus aims to meet customer demand and to find the lowest inventory costs by using historical data through the existing inventory control and sale information.

Inventory control requires the business to maintain and store the items in a business system, including all of the sales and distribution of goods and labor related activities. The issue of concern for inventory management may not be the same in different industries. For example, the inventory for the retail industry is the available sales of finished products, and the inventory for the manufacturing sector includes manufactured goods, raw materials and accessories. Inventory management policy therefore aims to meet customer demand and reduce inventory costs, thus improving the enterprise's return on investment. The purpose for inventory management is the timely replenishment of stock when the inventory level falls below a safe level of stock. The amount of order must also complement the possible exhaustion of the existing stock over time. Inventory control policy is thus one of the most important management topics, that is, the making of the right decision as to order quantities and the timing of such decisions. The different inventory management policies and inventory models are briefly discussed as follows.

Traditionally, orders have been adopted using the decision making model of Harris [2] derived by the Economic Order Quantity (EOQ) model, which states that it is the level of inventory that minimizes the total inventory holding costs and ordering costs. The model assists in determining the optimal number of units to order with a view to minimizing the total cost associated with the purchase, delivery and storage of the product. However, in the EOQ model, many of the basic assumptions, such as a constant and deterministic demand rate and a lack of shortages, are far removed from practice. Hence, the model has been inadequate in coping with this complex and dynamic industrial environment. As such, the EOQ model was further developed by taking more real conditions into account, such as procurement constraints, price discounts and shortages.

The reorder point is an inventory standard practice, which initiates ordering activities when stocks drop below a set reorder point. This ensures the material supply shortage will not occur. The function of "when to order" is a function of the reorder point, that is, when stock falls below the reorder point, orders should be placed immediately. Reorder point decisions must consider the EOQ to avoid high inventory costs and to be able to meet certain service standards. When the product demand is uncertain, the reorder point must take into account the supply lead time as well as the safety stock level. Since convenience stores have a fixed distribution of its daily deliveries, we only need to consider the order quantity irrespective of the reorder point issue. To reduce operating costs, stores must be able to efficiently control their inventory replenishment, especially for deteriorating items with high demand uncertainty such as meal-boxes. The EOQ model is no longer suitable for the determination of the optimal order quantity in this case. We are therefore motivated in this paper to develop a more sophisticated two-stage replenishment policy to solve this problem.

Deterioration means that an item fails to implement its function, or from another point of view, it can also be classified as the time-value of the items' life of inventory [3]. In the real world, especially, in the food industry, deterioration occurs for most items. Ghare and Schrader [4] classified the deteriorating properties of inventory into three categories:

(1) direct spoilage, e.g., vegetable, fruit and fresh food and so on;
(2) physical depletion, e.g., gasoline, alcohol and so on;
(3) deterioration such as radiation change, negative spoiling and loss of efficacy in inventory, e.g., electronic components and medicine.

On the other hand, Nahmias [5] classifies deterioration by the items' inventory lifetime:

(1) fixed lifetime: the items' lifetime is pre-specified and its lifetime is independent of the deteriorating factors. Therefore, it is called *time-independent* deterioration. In fact, the utility of these items decreases during its lifetime, and when it has passed its specified lifetime, the item will perish completely and become of no value, e.g., milk, inventory in a blood bank, food and so on.
(2) random lifetime: There is no specified lifetime for these items. The lifetime for these items is assumed to be a random variable. Items that continue deteriorating in a probability distribution are called *time-dependent* deteriorating items, e.g., electronic components, chemicals, medicine, and so on. The scope of this study covers both fixed and random lifetime deteriorating items.

Goyal and Giri [6] presented a review of deteriorating inventory literature from the early 1990s. The models available in the relevant literature have been classified by the shelf-life characteristic of the inventoried goods. They have further been subclassified on the basis of demand variations and various other conditions or constraints. Most of the literatures relating to the replenishment of deteriorating items deal with an inventory model under a certain type of demand. For example, Jain, Edward [7] present a stochastic dynamic programming model for determining the optimal ordering policy for a perishable product which satisfies a known time-varying demand over a specified planning horizon. Hariga and Benkherouf [8] presented both optimal and heuristic procedures for the inventory replenishment problem in which items deteriorate at a constant rate. The demand rates change exponentially with time over a known and finite planning horizon. Chandra et al. [9] presented the optimal inventory replenishment policy of deteriorating items under inflationary conditions using a discounted cash flow approach over a finite planning horizon. An optimal solution for the proposed model is derived and the effects of deterioration and inflation on the optimal inventory replenishment policy are studied. In contrast, we do not consider the rate of deterioration in our study. For the purposes of our research, during the normal storage period of the meal-box, no deterioration will be observed. However, at the end of the validity period, the meal-box will become worthless.

The literatures identified above have all dealt with demand that follows a certain function. To our knowledge, few papers have focused on the replenishment problem in actual situations where the uncertainty of demand is high. Therefore, statistics have been applied in the past when dealing with such practical cases. For example, based on the operating characteristics of the business cycle and sale forecasting, Chen and Lee [10] proposed an ordinary day and holiday moving average method and a back-propagation neural network method to improve the ordering and discarding rate for fresh foods in convenience stores.

The fresh foods considered in Chen and Lee's paper [10], including sandwiches and sushi, are considered deteriorating items in this paper as they are perishables. The meal-box is similar to a newspaper, which will be considered scrap once it has expired. The analysis of perishable goods has often employed the newsboy theory. There are several relevant literatures that have addressed this issue (see for example [11]). Atkinson [12] determined an optimal order strategy for the generation of the greatest expected profit under the assumptions of a fixed product price and a fixed probability distribution for retail sales. Lau and Lau [13] investigated the newsboy problem with the demands of each subdivision being a function of the prices, and thus included both the order quantity and the sales price as the decision variables.

Chen and Lee [10] determined the optimal order quantity from a statistical point of view, as with most studies. However, in real circumstances, the variance of the optimal order quantity is so great that one must determine the factors which have significant influences on the sales rate. Therefore, in our paper, we applied a two-step approach to determine the optimal order quantity. In the first step, we use several kinds of statistics tools to predict an "averaged" order quantity. In the second step, we developed a mechanism for adjusting the averaged quantity by taking all significant factors into account. The second step is primarily a wastage warning step.

The rest of the paper is organized as follows. In Section 2, we present a description of our optimal replenishment policy under the first step. In Section 3, we present the optimal replenishment policy under the second step of our model. Numerical examples and verification are provided in Section 4. We apply two methods to enhance accuracy and provide further insights into the model in Section 5 and concluding the paper in Section 6.

2. Step I—determination of the basic order quantity

According to the report from the Fair Trade Commission in Taiwan (FTC, R.O.C.), convenience stores in Taiwan reached a total of 9105 stores by the end of 2006. This suggests that there is a convenience store for every 2504 people in Taiwan, which approaches the highest convenience store density in the world. The PCSC has over 4800 stores in Taiwan, with a market share 52%. There are thousands of items stocked in a convenience store, and they must be managed carefully with a suitable inventory management policy. In order to simplify the problem, only four kinds of popular meal-boxes were targeted in this study, and they are denoted as meal-box A, meal-box B, meal-box C and meal-box D. Data relating to the order quantities, sales and scrapped amounts were collected for analysis. As consumer psychology is difficult to fathom, it is difficult to control the amount of scrap from the sale of these products. Due to the characteristics of highly uncertain demand and perishability, it is difficult for the manager to determine the order quantity for meal-boxes.

In order to determine an optimal order quantity for meal-boxes so as to maximize profit, we develop a two-stage replenishment policy. The first stage outlines the basic needs in relation to the decision-making for the order. In this stage, three inventory management models are tested, including the consideration of the demand forecast of the probability of order quantity model, hypothesis testing methods and the newsboy models. The results from these models are used to establish the basic needs of decision-making patterns.

In the second stage, the study focuses on a wastage warning system for tuning the basic order quantity derived from the first stage of the replenishment policy. In this stage, consideration is focused on the factors that influence the sales number, which includes the weather, temperature, promotions, and so on. An intelligent tool, SVM, is used in this stage to increase the prediction accuracy of the approach and therefore provide a warning system to compensate for the possible error of the basic order quantity, which was obtained simply from a statistics point of view. A summary of the various stages of the replenishment policy are as follows:

2.1. Method 1: model with probabilistic forecast

As with general marketing departments who operate in accordance with past sales history, industry knowledge and the economic situation to predict its probabilistic demand, we incorporate into this study the consideration of probability into the demand function. In the first method, the monthly sales and obsolete volume of meal-boxes are collected and the demand probability can be calculated accordingly. Using this data, the curve of the average profit as against the order quantity of each kind of meal-box can be drawn, and the optimal order amount is the one corresponding to the highest profit. This method is borrowed from Simchi-Levi and Kaminsky's [14] study, which considered a company that designs, produces and sells summer fashion items such as swimsuits. In their study, to assist management in these decisions, the marketing department used historical data from the last five years, the current economic conditions, and other factors to construct a probabilistic forecast of the demand for swimsuits. They identified several possible scenarios for sales in the following season based on such factors as the possible weather patterns and competitors' behavior, and assigned each factor a probability of occurring. In this study, we utilize a similar method, using historical data of the amount of the last purchases, sales and scrapped amounts to predict the best strategy for effectively and quickly responding to market and consumer demand changes. It can be easily verified that profit equals revenue plus the salvage value and minus the associated costs, including ordering costs and purchase costs.

In this case, the ordering costs are relatively small, and are therefore not worth considering. Every meal-box which is past its expiry date will be discarded in PCSC stores, such that the salvage value is zero. Therefore, in this study, the profits of the meal-box are equal to revenue minus purchase costs. The optimal order quantity can thus be determined by the order quantity with the highest average profit. As meal-boxes are delivered everyday and those that have expired will be scrapped, there is no need to consider the effect of the initial inventory levels.

What then is the relationship between optimal order quantity and average demand? One of the important insights derived from the swimsuit case study [14] is that whether the optimal order quantity is equal to, more than, or less than the average demand depends on the difference between marginal profit and marginal cost. In particular, as the marginal cost is greater than marginal profit, the optimal order quantity should be less than the average demand. Similar conditions were observed in our study. As the order quantity increased, average profit typically increased until the production quantity reached a certain value, after which the average profit started decreasing. As production quantity is increased, the associated risk always increases. At the same time, the probability of large gains also increases. The optimal quantity therefore depends on the relationship between the marginal profit achieved from selling an additional unit and its marginal cost. In our study, marginal profit is equal to revenue less the procurement cost, and margin cost is equal to the procurement cost. Since marginal cost will be greater than marginal profit, the optimal order quantity should therefore be less than average demand. Otherwise, excessive items may be discarded as junk when the validity period is over.

2.2. Method 2: hypothesis testing

In order to explore the optimal order quantity of meal-boxes to satisfy consumer demand, we undertook hypothesis testing in the second method. This method required several months of actual sales data to analyze and test the hypothesis of whether the purchase quantities were appropriate. We set up the assumptions as follows. Suppose a certain amount of the daily order will meet all customer demands. We then employ a statistics test, and make conclusions after calculating the *P* value. The upper bound for the basic order quantity to satisfy customer demand of each type of meal-box items can be determined by using the results of hypothesis testing. This analysis was conducted mainly with reference to Lin and Chen's [15] method, which itself is based on the statistics numbers of meal-box sales over several months, particularly at significant levels of $\alpha=0.05$, to analyze whether the needs of consumers will be satisfied.

2.3. Method 3: Newsboy model

Managers often have to make decisions about inventory levels for a very limited sales period. For example, seasonal goods such as Christmas cards should satisfy all demand in December, as any cards remaining in January have almost no value. Similarly, meal-boxes are perishable goods which, if not sold within its limited lifetime, will be discarded. Another example of time-sensitive goods is the daily newspaper, as newspapers not sold on the day of publication will be recycled as scrap. Therefore, this study will also adopt the Newsboy model. Detailed calculation steps can be found in Section 4 of the numerical examples below.

3. Step II—wastage warning system (application of support vector machine)

The theory behind SVM was developed in the 1960s [16], and has now evolved into an active area of research. In its present form, the SVM was developed at AT&T Bell Laboratories by Vapnik and co-workers [17]. Due to its ability to outperform most other classifiers in many applications, SVM is currently considered as one of the most efficient methods in many real-life classification problems. For an introduction to SVMs for pattern recognition, please refer to Burges [18].

Basically, the SVM can be used to classify objects into two classes based on a series of observations. The SVM approach has been introduced to several aspects of real-world practices. For example, the SVM learning algorithm has been used to detect patterns in biological sequences, to classify genes and patients based upon gene expression profiles, and has also been applied to several new biological problems [19,20] employed SVM to improve the prediction accuracy of preventing credit card fraud under the questionnaire-responded transaction approach. A SVM based multi-view face detection and recognition approach was proposed in the study of Li et al. [21]. To the best of our knowledge, none of the prior researchers in this field have applied SVM to solve an inventory problem. Our study is innovative as we suggest that policy makers whose sales results lead to wastage or no wastage at all can also be regarded as binary. Therefore, SVM can be applied to make a better decision by adjusting the basic order quantity according to whether the quantity will induce overstocking.

The principle of the SVM classifier is to project the data into a higher dimensional space. In this higher dimensional space, the classes are separated by a linear model, the maximum margin hyperplane, which gives the maximum separation between decision classes. The training points that are closest to the maximum margin hyperplane define a small set of support vectors. All other training examples are irrelevant for determining the binary class boundaries [22].

A simple description of the SVM algorithm is provided as follows. First, we define the labeled training examples $[\mathbf{x}_i, y_i]$, an input vector $\mathbf{x}_i \in R^n$, and target labels $y_i \in \{+1, -1\}$, $i=1,\ldots,N$. For the linearly separable case, the decision rule defined by an optimal hyperplane is given as follows:

$$Y = sign\left(\sum_{i=1}^{N} y_i \alpha_i (\mathrm{x} \cdot \mathrm{x}_i) + b\right) \tag{1}$$

where Y is the outcome, y_i is the target label of x_i, $\mathbf{x}=(x_1, x_2,\ldots, x_n)$ represent the set of support vectors and b and α_i are parameters that determine the hyperplane. In general cases where the data is not linearly separated, SVM uses non-linear machines to find a hyperplane that minimize the number of errors for the training set. A high-dimensional version of Eq. (1) for the non-linearly separable case is given as follows:

$$Y = sign\left(\sum_{i=1}^{N} y_i \alpha_i K(\mathrm{x}, \mathrm{x}_i) + b\right) \tag{2}$$

The function $K(\mathbf{x}, \mathbf{x}_i)$ is the kernel. Besides the linear kernel, three common types of kernel function for constructing the decision rules are given as follows:

(a) A polynomial kernel of degree d

$$K(\mathrm{x} \cdot \mathrm{x}_i) = (\mathrm{x} \cdot \mathrm{x}_i + 1)^d \tag{3}$$

(b) A radial basis function (RBF) with kernel function

$$K(\mathrm{x} \cdot \mathrm{x}_i) = \exp(-1/\delta^2 (\mathrm{x} - \mathrm{x}_i)^2 \tag{4}$$

where δ^2 is the bandwidth of the radial basis function kernel

(c) The Sigmoid kernel

$$K(\mathrm{x} \cdot \mathrm{x}_i) = 1/[1 + \exp\{v(x \cdot \mathrm{x}_i) - c\}] \tag{5}$$

where v and c are parameters of a sigmoid function satisfying the inequality $c \geqq v$.

The SVM classification exercise is to find the support vectors and to determine the parameters b and α_i. The details of the optimization are discussed in Cristianini and Shawe-Taylor [22].

To investigate the effectiveness of the SVM approach, we conduct the experiment with respect to various kernel parameters and the upper bound c, and compare the prediction performance of SVM with various parameters.

In our study, the optimal order quantity is defined as a classification problem of classifying between wastage or non-wastage conditions. The estimation of a boundary which robustly separates the two classes of conditions is similar to the underlying characteristic of SVMs, motivating us to employ SVM to establish the second stage of the replenishment policy. The problem with SVMs is the same as with other techniques, e.g. Partial Least Squares (PLS) and Neural Networks (NN), namely that there are a number of software-related parameters that need to be set. In this study, the performance and predictive capability of SVM algorithms are investigated within the area of the order quantity for retailers. The research in this paper clearly indicates the importance of SVM parameter optimization as well as variable selection in order to develop statistical models with good predictive capabilities.

4. Numerical experiments and verification

Convenience stores are located on almost every block in Taiwan, with each store providing two to three thousand products that can be roughly divided into 35 categories of merchandise. The potential gross profit in the convenience store market is limited not only by the gradual saturation of demand and rising operation costs, but also the holding cost of various items. As such, inventory management has assumed an increasingly greater importance. To conduct experiments on the two-stage replenishment policy, the ordering, sales and scrapped numbers of the targeted meal-box products of a PCSC store in Taiwan are collected from June to October 2009. Detailed computation results are given in the following subsections.

4.1. Decision of the basic order quantity

Although, according to Chen and Huang's [23] study, using an average demand substitution analysis with the EOQ model can show proportional trends in demand, the EOQ model is limited due to several unrealistic assumptions that are rarely encountered in the real world. To establish a particular store selling the meal-box under the basic inventory management model, this study does not employ the EOQ model, but rather analyzes three kinds of inventory management models as described below.

4.1.1. Model with probabilistic forecast

Retailers generally use the historical purchases, sales volume and scrap amounts data to predict future market demand and establish efficient strategies for replenishment. This allows for the rapid response to market changes in order to meet consumers' changing demands. In this section, we construct a demand prediction probability curve using the meal-box sales volume collected from a PCSC store since June to October 2009 as a sample. We choose four popular meal-boxes for the purposes of our study, and the relevant information is shown in Table 1 below.

The sales volume corresponding to the occurrences of four kinds of meal-boxes sold in June are listed in Table 2. Based on this data, the average profit of each order quantity can be calculated.

In Table 2, the occurrence day means the amount of days that will be counted for certain unit sales for a certain type of meal-box. For example, in June, there are 10 days in total that meal-box A has sold 3 units per day. To determine the probability values for each type of meal-box corresponding to sales unit, we divide the occurrence days of each meal-box corresponding to unit sales by the total number of days as shown in Table 2. For example, in

Table 1
Information of four kinds of most popular meal-boxes.

	Price	Cost	Profit
Meal-box A	45	37	8
Meal-box B	50	40	10
Meal-box C	60	48	12
Meal-box D	65	49	16

Table 2
The sales volume corresponding to the occurrence of four kinds of meal-boxes sold in June.

Occurrence day	Unit sales						
	0	1	2	3	4	5	Total (days)
Meal-box A	2	2	15	10	1	0	30
Meal-box B	0	4	7	15	2	2	30
Meal-box C	1	11	13	4	1	0	30
Meal-box D	4	19	7	0	0	0	30

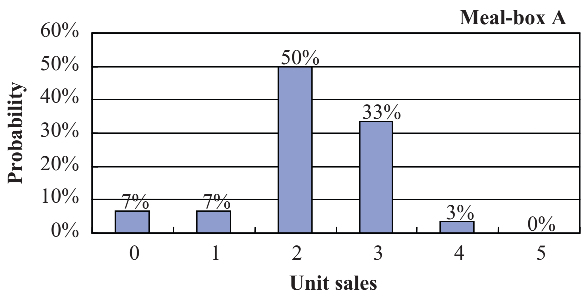

Fig. 2. Probability distribution of meal-box A in June.

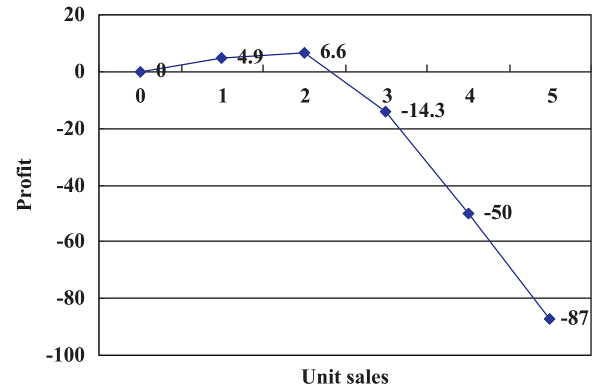

Fig. 3. Average profit as a function of order quantity.

Table 3
The average and standard deviation of meal-box A from June to October.

	June	July	August	September	October
Average	2.2	1.4	1.4	1.3	1.3
Standard deviation	0.87	0.79	0.55	0.98	0.82

June, the probability that demand of meal-box A is 3 units per day is 33% (=10/30). Each type of meal-box has a different probability distribution in each month. Fig. 2 below provides an example of the probability distribution of meal-box A in June.

Using the unit sales to calculate the probability value and construct a probability prediction curve, we can then find the most profitable order quantities. As an example, if the store orders three units of meal-box A, the cost is NT$111 (according to Table 1). If none are sold, the store carries a loss of NT$111, with this situation occurring 7% of the time. If one meal-box is sold, the store will gain NT$8 for one meal-box sold, but the remaining boxes will carry a loss of NT$74 if they are not sold, leading to a loss of $66. Similarly, if two meal-boxes are sold, the store will lose $21, and this situation has a 50% probability of occurring. If all the meal-boxes are sold, the store will make a profit of $24, and this situation has a 33% probability of occurring. This allows us to determine the expected profit from ordering 3 units. The expected profit is the total profit of all the scenarios weighted by the probability that each scenario will occur. Fig. 3 plots the average profit as a function of the ordering quantity.

As the order quantity increases, the average profit typically increases until the ordering quantity reaches a certain value, after which the average profit starts decreasing. Fig. 3 shows that the optimal order quantity that maximizes average profit is two units in that specific situation. One can then calculate the optimal profit associated with other types of meal-box in a similar manner.

Since the marginal cost is much higher than the marginal profit, as can be seen from Table 1, the optimal ordering quantity should be less than the average demand, which in this example is 2.2 units. This is consistent with the conclusion presented in Simchi-Levi and Kaminsky's [14] study of swimsuit production.

4.1.2. The hypothesis testing

To study the order quantity for meal-boxes and to examine customer satisfaction, we analyzed the sales information from June to October (2009), and tested hypotheses to determine the correct order quantity for each convenience store.

In this study the statistics for the 4 types of meal-box sales information were used. Among them, meal-box A (Table 3) is used as an example to analyze whether the order quantity meets consumer demand, at the significance level of $\alpha = 0.05$.

We use the data in June as a demonstrative example. As shown in Table 3, the average demand $\overline{X}$ is 2.2 units and standard deviation is 0.87. The detailed analysis steps for hypothesis testing are shown as follows.

(1) The establishment of assumptions
Suppose that two meal-boxes a day will satisfy customer needs.

$$H_0 : \mu \leq 2$$
$$H_1 : \mu > 2$$

(2) Select test statistic
We used $\overline{X}$ as the test statistic. Because the sampling number is 30, the sampling distribution can be treated as a normal distribution according to the central limit theorem.

(3) Calculate P values
According to the symbol of the alternative hypothesis, the analysis should be conducted using a right-tailed test. The probability for $\overline{X}$ to be greater than 2.2 is

$$P \text{ value} = P(\overline{X} \geq 2.2 | \mu = 2) = P\left(\frac{\overline{X}-2}{0.87/\sqrt{30}} \geq \frac{2.2-2}{0.87/\sqrt{30}}\right)$$
$$= P(Z \geq 1.26) = 0.5 - 0.3962 = 0.1038$$

(4) Conclusion
As the P value is greater than α (0.05), we do not reject the null hypotheses, namely that the average quantity of daily demand for the meal-box A in June is no more than 2.

In the same manner, the four different types of meal-boxes can be analyzed in accordance with the hypothesis testing of the individual results, which will indicate whether each type of meal-box is set at a volume satisfying the needs of customers' demand. The results of the above hypothesis testing are shown in the table below (Table 4).

The results of hypothesis testing practically set an upper bound for the ordering quantity. As long as the store does not

Table 4
The results of the above hypothesis testing from June to October.

	Meal-box A	Meal-box B	Meal-box C	Meal-box D
June	≦2	≦3	≦2	≦1
July	≦2	≦2	≦1	≦1
August	≦2	≦2	≦1	≦1
September	≦2	≦2	≦1	≦1
October	≦2	≦2	≦2	≦1

Table 5
The underage and overage costs of each kind of meal-box.

	Overage cost C_1	Underage cost C_2	$C_2/(C_1+C_2)$
Meal-box A	37	8	0.177778
Meal-box B	40	10	0.2
Meal-box C	48	12	0.2
Meal-box D	49	16	0.25

order amounts higher than these values, it will not be required to scrap items or suffer unnecessary financial losses.

4.1.3. The Newsboy model

For an owner of a newsstand who faces an uncertain demand everyday, the owner must decide on the number of copies of a particular paper to buy from the supplier. If the owner buys too many papers, there may be unsold papers remaining which have no value at the end of the day. If too few papers are purchased, the owner may have lost the opportunity of making a higher profit. The newsboy model is a mathematical model used to determine optimal inventory levels under the conditions of a single product with a fixed-price and uncertain demand. Similar to Lin's study [24], we denote C_1 as the overage cost associated with each demand that cannot be sold, and C_2 as the underage cost due to understocking, as shown in Table 5. In this study, the overage cost is higher than the underage cost. The decision rule is to select the Q^* value (i.e. the optimal number of meal-boxes to order) that satisfies

$$P(x<Q^*)=\frac{C_2}{C_1+C_2} \tag{6}$$

where $P(x<x_o)$is the probability that the total demand x is less than the value x_o.

In this study, the probability that the demand is equal to a certain order quantity x, denoted as $P(x)$, can be calculated by dividing the number of days that have x units sold with the total days in a month (for example, there are 30 days in June). Table 6 shows the probability of meal-box A in June.

The total expected cost of order quantity of Q is

$$TEQ(Q)=C_1\sum_{x=0}^{Q}P(x)(Q-x)+C_2\sum_{x=Q+1}^{\infty}P(x)Q(x-Q) \tag{7}$$

where the first term is the cost of being overstocked, and the second term is the cost of being understocked. The optimal value of order quantity Q^* can be determined by the following equation:

$$P(X\leq Q^*-1)\leq\frac{C_2}{C_1+C_2}\leq P(X\leq Q^*) \tag{8}$$

Taking meal-box A as an example and using the data shown in Tables 5 and 6, we found that $0.14<0.177778<0.64$, which shows that the value of $C_2/(C_1+C_2)$ is located within demand $x=1$ and demand $x=2$. Whether the optimal order quantity, Q^*, should be 1 or 2 can be determined by the following considerations:

For $Q=1$, $TEC(Q)=37*(0.07*1+0)+8(0.5*1+0.33*2+0.03*3)=12.59$

Table 6
The probability of meal-box An in June.

Demand	0	1	2	3	4	5
$P(x)$ (%)	7	7	50	33	3	0
Cumulative probability $P(x\leqq Q^*)$ (%)	7	14	64	97	100	0

Table 7
The optimal order quantity predicted by the different methods for four kinds of meal-boxes in June.

	Meal-box A	Meal-box B	Meal-box C	Meal-box D
Probabilistic forecast	1	2	1	0
Hypothesis testing	≦2	≦3	≦2	≦1
Newsboy model	1	1	1	0

For $Q=2$, $TEC(Q)=37*(0.07*2+0.07*1)+8(0.33*1+0.03*2)=10.89$

Since the total expected cost for $Q=2$ is less than that of $Q=1$, we select $Q^*=2$ as the optimal order quantity.

The optimal order quantity determined by the model with probabilistic forecast is based on the considerations of maximum profit, while the newsboy model calculation is based on the lowest cost considerations. As can be seen from the above calculations, the demand probability of the order quantity model and the news model have consistency with regards to the conclusions of cost and profit minimization under the optimal order quantity model. Hypothesis testing may be used to provide a bound for the optimal order quantity, which can be used to verify the conclusions drawn from the other two methods. For example, in June, whether the optimal order quantity of meal-box A is 1 can be determined by both the model with probabilistic forecast and the newsboy model. On the other hand, hypothesis testing reveals that a daily order amount of ≦2 is recommended, which sets an upper bound for ordering. Similar examples can also be seen for other kinds of meal-boxes shown in Table 7.

The store manager can thus choose whether to apply the demand model or newsboy model to determine the order quantity. If the manager wishes to order more units to fulfill an expected increase in demand, hypothesis testing can be used to set an upper bound for the order amount, as otherwise overstocking may result.

Basically, the probabilistic forecast method and the theoretical newsboy method can produce similar results. This value, bounded by the answer obtained from the hypothesis testing method, can be treated as the basic quantity orders. In addition to the three analytical models above, there are still many uncertain factors that can affect the sales forecasts, such as climate, festivities, popularity, economic prospects, promotions and so on. As such, this study proposes and includes the support vector machine research methods in order to enhance the predictive accuracy of the related research.

4.2. Wastage warning system—Support Vector Machine model

4.2.1. Data collection and preprocessing

In the previous section, the methods for obtaining a basic order quantity using three kinds of methods were presented. We regard the previous process as the first step in the analysis. However, in practice, the real number of items sold maybe affected by temperature, climate change, the number of customers and the economic outlook. To resolve this uncertainty, this research introduces the SVM research tool to establish a wastage warning system.

Table 8
Definition of variables.

Variable	Definition
x_1	economic outlook
x_2	the number of customers
x_3	temperature
x_4	climate
x_5	order quantity

Table 9
Information and data over the June period.

June	Wastage quantity	Economic outlook	Number of customers	Temperature	Climate	Order quantity
1	0	104	1197	29	2	3
2	0	0	1707	30	2	3
3	0	0	2160	28	3	3
4	0	45	1356	25	3	3
5	0	9	1068	26	3	3
6	0	11	988	26	3	3
7	0	41	1040	25	3	3
8	0	−55	909	24	3	3
9	0	0	1158	24	3	3
10	0	0	1610	25	3	3
11	1	38	1252	26	3	4
12	2	31	901	25	3	3
13	1	−24	939	27	2	3
14	2	104	996	29	2	3
15	0	123	1170	28	3	3
16	1	0	1572	27	3	3
17	1	0	1896	28	2	3
18	0	0	1724	29	2	3
19	0	0	1625	29	1	2
20	0	182	1324	28	1	2
21	0	96	1095	29	2	2
22	2	−6	1094	30	2	2
23	1	−33	1203	28	1	3
24	2	0	1362	29	2	2
25	0	126	1124	29	2	2
26	0	−73	983	27	3	2
27	0	−22	1019	29	1	2
28	0	49	1225	29	2	2
29	0	−10	2108	28	3	2
30	1	0	2615	29	2	2

SVM applications in various fields have been very extensive. SVM has achieved a high accuracy as a binary judge in applications such as credit risk assessment, airport passenger entry probability assessment and forecasting. However, SVM has not been previously applied to the inventory applications. In this study, based on the historical data of order quantities and the amount of scrapped items, as well as consideration of the climate, temperature, numbers of customers and the economic situation, SVM can be trained to provide the basis for demand patterns. The selected variables for this research are shown in Table 8.

We select four kinds of major meal-boxes sold in the chain store for this experiment. The sales data, which is provided by a PCSC retail store in Taiwan, have been recorded from June to October, 2009. For simplicity, this article only shows information and data in June, as shown in Table 9, to illustrate the application of SVM methods. Among them, the economic situation is based on the daily stock market index, and temperature and weather data are derived from the Bureau of Meteorology, using the variables of 1, 2 and 3 to represent sunny, cloudy and rainy weather, respectively.

To ensure that the larger value input attributes do not overwhelm smaller value inputs, a linear scaling process was conducted so as to normalize each feature component to the range of $[-1,\ 1]$. The prediction performances of SVM with various parameters are compared, including the parameters related to the three kinds of models, i.e., the linear model, polynomial model and the radial model. The goal is to identify the optimal choice for the kernel model and related parameters, such that the classifier can accurately predict the unknown wastage data. Based on the results proposed by Tay and Cao [25], we set an appropriate range of parameters as follows: a range for the kernel parameter *gamma* is set between 0.1, 1 and 10; a range for the capacity parameter C is set between 0.1 and 1000; and for the polynomial model, the power $d=2$ and $d=3$ are inputted. A total of 30 SVM experiments were performed with three kernels, namely dot (linear), polynomial, and radial basis function. As implemented in mySVM, C is scaled by 1/number of training examples. Each cell of Table 10 contains the accuracy of the classification techniques and that with the best cross-validation accuracy is selected. The experimental results show that the prediction performance of SVM is sensitive to the various kernel parameters d and the capacity parameter C. As shown in Table 10, the accuracy of the training set increases monotonically as C increases for all the models. When d is 3 and C is 10, prediction performance is the best, and it maintains an almost constant value as C becomes greater than 10. We therefore choose this parameter combination for the following analysis.

Table 10
Classification accuracies (%) of various parameters.

Kernel	Linear	Polynomial		Radial (RFB)		
		$d=2$	$d=3$	$gamma=0.1$	$gamma=1$	$gamma=10$
$C=0.1$	0.739	0.828	0.961	0.711	0.711	0.711
$C=1$	0.761	0.922	0.983	0.75	0.867	0.994
$C=10$	0.789	0.972	0.994	0.867	0.983	0.983
$C=100$	0.789	0.989	0.994	0.95	0.989	0.983
$C=1000$	0.783	0.989	0.994	0.994	0.989	0.983

In this study, a fivefold cross-validation is used which initially divides the training set into 5 subsets of equal size, and sequentially one subset is tested using the classifier trained on the remaining 4 subsets. Thus, each instance of the whole training set is predicted once such that the cross-validation accuracy is the percentage of data that is correctly classified. In this study, the mySVM software system is used to perform the SVM experiments.

Using the SVM model trained from the data in June, the possible wastage of goods in July can be estimate. For example, two units of meal-boxes were ordered on July 10, as shown in Table 11. On the same day, the stock index rose 15 points, there were 1154 customers, and the temperature was 30 °C with a sunny climate. The predictions calculation is -0.9991, which indicated that there was no excessive ordering. The actual number of discarded items was indeed zero. On July 11, for example, two meal-boxes were ordered. On the same day, the stock index fell 94 points, there were 1456 customers, the temperature was 30 °C, and climate was cloudy. The prediction result was 0.0474, which indicated an excessive ordering situation. Indeed, the actual number of items scrapped was one.

The results of Table 12 show that over 31 days the forecast error only occurred on 10 days with a forecast accuracy of 68%. We also found that the higher the predicted wastage value, the higher the chance that there will be scrapped quantities, as can be seen on July 23 and July 29. Prediction accuracies for each month are shown in Table 12. Based on the experiments, we have developed a SVM that does provide a wastage warning system for store managers, allowing them to adjust the order quantity in order to reduce scrap.

As described in subsection 4.2, we have identified the optimal choice for the kernel model and related parameters such that the

Table 11
Information and prediction results in July.

July	Precision	Prediction result	Wastage quantity	Economic outlook	Number of customers	Temperature	Climate	Order quantity
1	○	1.0003	1	0	2581	30	2	2
2	×	0.2082	0	56	2046	29	1	2
3	×	−0.1110	0	57	1487	29	1	2
4	○	0.1269	0	73	1339	30	1	2
5	○	0.1038	0	80	1340	30	1	2
6	×	0.2879	0	40	1427	30	1	2
7	○	0.5358	0	0	1627	30	1	2
8	○	0.8759	1	0	2229	30	1	2
9	×	−0.288	0	182	1519	30	3	2
10	×	0.2179	0	15	1154	30	1	2
11	○	0.6816	1	−94	1456	30	2	2
12	○	0.3076	1	63	1863	30	3	2
13	×	0.4665	0	117	1538	31	1	2
14	○	−0.5679	0	0	2052	30	1	1
15	○	−0.8308	0	0	2515	29	3	1
16	○	0.2300	0	−54	1692	29	3	2
17	×	−0.0218	1	92	1321	30	2	2
18	×	−1.0006	0	−24	1275	30	2	1
19	○	−1.0665	0	−12	1098	30	1	1
20	○	−1.4128	0	113	1231	30	1	1
21	○	−0.2042	0	0	2031	31	1	1
22	○	1.4396	0	0	2562	31	1	2
23	○	0.8402	2	36	1848	31	2	2
24	×	−0.5572	1	122	1349	29	3	2
25	○	−1.4577	0	−4	1118	29	1	1
26	○	−0.4953	0	−174	1274	30	2	1
27	○	1.6166	0	−404	1129	30	1	2
28	○	0.6392	1	0	1810	30	1	2
29	×	−0.1297	2	0	2042	28	3	2
30	○	−0.0320	0	−90	1546	28	2	2
31	○	−0.7183	0	215	1355	29	1	2

Table 12
Accuracy of precision in each month.

	July	August	September	October
Accuracy (%)	68	71	70	74

Table 13
Prediction accuracy of each month.

	June	July	August	September	October
Accuracy (%)	67	71	58	57	58

classifier can obtain an accurate prediction. However, the experiment found an accuracy prediction rate of 68% in July as shown in Table 12. Obviously, there is clearly room for improvement. We therefore are motivated to conduct a series of studies to enhance prediction accuracy in the following section.

5. Improvement of the prediction accuracy

The accuracy of the SVM experiment can be improved so as to confirm its utility in establishing a wastage warning system for decision-makers. We provide two ways to meliorate accuracy in this section, that is, the implementation of the moving average method in the training process and factor screening.

5.1. Moving average

To study the impact of the selection of testing data on the prediction accuracy, we use the data from June to October as the main cross-training data. That is, four out of five months are randomly selected for the training usage, and the remaining month will be predicted and compared with the real sales results. For example, if we want to predict the accuracy of October, we use the data from June to September for the training, and so on. The results are shown in Table 13.

Although the accuracy of prediction reached over 50% using the cross-training method, it is obviously not good enough. The reason for the inaccuracy may be due to the scale of the training data extending over too long a period. For instance, the prediction of October is dependent on the training data from June to September. However, during these four months, the temperature and the climate may be quite different. In addition, some seasonal trends may occur during such a long time, which results in a low accuracy prediction. It is very important for decision-makers to be cautious in the selection of training data. Therefore, we propose a moving average method in the following subsection.

We collected information between June to October in the previous training period, and noticed the weather pattern was susceptible to a change in seasons. Therefore, the forecast data may be distorted, making it difficult to improve predictive accuracy. As such, we attempted to implement a moving average method for training purposes. This is an improvement over the arithmetic average method, which is one of the most simple adaptive prediction models. The fewer the number of periods used in a moving average forecasting method, the more reactive the forecast is to the most recent demand changes. To achieve the best predictive accuracy, we use a weekly time period to calculate the moving average, and only the information in June will be used to train the SVM so as to make a prediction for July.

For example, the predictive value of the 1st of July will be based on the training materials between the 24th to the 30th of

Table 14
The forecast accuracy rate in July by using the moving average method.

Date	Comparison result	Date	Comparison result	Date	Comparison result
7/1	○	7/11	×	7/21	○
7/2	○	7/12	○	7/22	○
7/3	○	7/13	○	7/23	×
7/4	○	7/14	×	7/24	○
7/5	○	7/15	×	7/25	○
7/6	○	7/16	×	7/26	○
7/7	○	7/17	○	7/27	○
7/8	×	7/18	○	7/28	×
7/9	○	7/19	○	7/29	○
7/10	○	7/20	○	7/30	×
				7/31	○
Accuracy 74%					

Table 15
Accuracy of portfolio analysis of factors.

Accuracy (%)	Economic outlook (stock market change)	Number of customers	Temperature	Climate	Basic order quantity
68	○	○	○	○	○
71	×	○	○	○	○
48	○	×	○	○	○
45	○	○	×	×	○
74	○	○	○	×	○
45	×	×	×	×	○
45	×	×	○	○	○
45	○	○	×	×	○
45	×	×	×	○	○
45	×	○	×	○	○
45	○	×	×	×	○
55	○	×	○	×	○
84	×	○	○	×	○
45	○	×	×	○	○

June, and the predictive value of the 2nd of July will be based on the training materials between the 25th of June and July 1st, and so on. The July average forecast accuracy rate for each day is shown in Table 14. There are only eight inaccurate predictions happened out of 31 testing. The implementation of the moving average method resulted in the experiment achieving a calculated average accuracy rate of up to 74%.

5.2. *Factor screening*

The other way to improve the prediction accuracy is to find an optimal combination of factors (attributes) to construct the SVM model. In Section 4, five factors were considered in the SVM model to predict whether overstocking would occur. These factors include economic outlook (based on the daily stock market index), climate, weather, the number of customers, and the basic order quantity that was obtained from step one of the process. In this section, we will verify if these five factors are appropriately selected.

We again use the data relating to meal-box A in June as an example. We first removed the stock market factors and reprocessed the training model. This was followed by the number of potential customers, temperature, weather and other factors relevant to the re-training. At the same time, we observed the accuracy level affected by each individual factor. We then compare the accuracy of SVM model with various factors in order to obtain the best combination among the attributes. The accuracy results of the portfolio analysis of factors are shown in Table 15. The "○" symbols in this table represent the properties used in the SVM analysis; otherwise, they are not used. Whether overstocking will occur is closely related to the factor of "basic order quantity", and therefore we use this option throughout the table (as represented by the "○").

From the testing results shown in Table 15, we found that the best combination of factors was to exclude stocks and weather factors. By using the basic order quantity, customer numbers and temperature as the combinatorial factors, the accuracy was 84%, which means that only 5 out of 31 days were incorrectly predicted in July. Compared to the previous experimental results which resulted in an accuracy of 68%, this is quite a substantial increase. These results can provide the store manager with a valuable reference when using the wastage warning system as a better decision making tool.

6. Conclusion

While the POS system is able to provide information for ordering decisions in convenience stores, it cannot accurately forecast demand. This is particularly so in relation to perishable and deteriorating items, which if not sold before the expiry date, will be scrapped, incurring a loss for the store. As such, accurate predictions are of interest to many scholars, but there are many uncertain factors affecting the forecast results. At present, convenience stores in Taiwan are ranked number one worldwide in terms of density. However, due to the intense competition, store managers have a crucial role in making the important decisions regarding replenishment policies. This study proposes a two-stage replenishment management model, and by collecting data over from June to October 2009 period at a single convenience store in Taiwan, it was confirmed that such a management model can accurately determine the optimal order quantity.

In the first phase of the basic order quantity decision model, the integration of probabilistic forecast model, hypothesis testing and the newsboy theory method provided estimates of the order amount in order to achieve the basic quantity. The second phase is related to the use of the SVM in order to determine the effect of other relevant considerations which might alter the order quantity. Through numerical analysis and verification, the conclusions reached are as follows:

(1) The probabilistic forecast model and the newsboy model are consistent in terms of the conclusions as to cost minimization and profit maximization under the basic order quantity. By using the results of hypothesis testing, the upper bound of the basic order quantity of each type of meal-box items to satisfy customer demand can be set. Through these methods, the basic order quantity in the first stage can be determined.
(2) The optimal order quantity does not necessarily equal the basic or average demand forecast due to the fact that the marginal cost of a meal-box is much greater than the profit margin. As such, the optimal order quantity should be lower than the average demand. Through the probabilistic forecast model, this argument has also been confirmed.
(3) In practice, apart from the three kinds of analysis models above, there should still be room for improvement of the order quantity decisions. There remain many uncertain factors that may affect the sales forecasts, such as climate, temperature, customer number, the economy and so on. In this study, the support vector machine method is innovatively applied to build the second phase of the model, that is, the wastage warning system. This study utilized a fivefold cross-validation technique in training data sets in order to filter out the best parameter combinations, constructing a practical support vector regression prediction model.
(4) The prediction accuracy of the wastage warning system is closely related to the selection of the period of training data

and factors used for the SVM model. To build a robust and reliable prediction model, we propose a moving average method and factor screening analysis to improve the prediction accuracy.

Due to the difficulty in obtaining the data from a POS system, the experimental data is restricted to single store, which makes the figures shown in this study appear smaller. However, it can be confirmed from the experimental data that the novel two-stage approach of the replenishment decision-making system can accurately predict order quantities. Future research will focus on the order decision of multiple stores by taking the effect of risk pooling into account. Moreover, before this novel approach is applied in corporations across Taiwan, it is suggested that more factors should be identified which may affect the prediction accuracy of SVM, such as the promotional activities from the President stores and its competitors.

References

[1] Silver EA, Pyke DF, Peterson R. Inventory Management and Production Planning and Scheduling. 3rd ed. NY: Wiley & Sons; 1998.
[2] Harris FW. Operations and cost, factory management. Production and Operation Management 1915;5:1–6.
[3] Raafat F. Survey of literature on continuously deteriorating inventory models. Journal of Operational Research Society 1991;42:27–37.
[4] Ghare PM, Schrader GF. A model for an exponentially decaying inventory. Journal of Industrial Engineering 1963;14:238–43.
[5] Nahmias S. Perishable inventory theory: a review. Operations Research 1978;30:680–708.
[6] Goyal SK, Giri BC. Recent trends in modeling of deteriorating inventory. European Journal of Operational Research 2001;134(1):1–16. 1 October.
[7] Jain K, Edward AS. Lot sizing for a product subject to obsolescence or perishability. European Journal of Operation Research 1994;75:287–95.
[8] Hariga MA, Benkherouf L. Optimal and heuristic inventory replenishment models for deteriorating items with exponential time-varying demand. European Journal of Operation Research 1994;79:123–137.
[9] Chandra KJ, Aggarwal KK, Goel SK. Optimal order policy for deteriorating items with inflation induced demand. International Journal of Production Economics 2006;103(2):707–14 .
[10] Chen, KH & Lee WI, The convenience stores' fresh food commodity sales forecasting model, Master thesis, National Kaohsiung First University of Science and Technology; 2006.
[11] Kabak I, Schiff. A. Inventory models and management objectives. Sloan Management Review 1978;10:53–59.
[12] Atkinson A. Incentives, uncertainty, and risk in the Newsboy Problem. Decision Sciences 1979;10:341–57.
[13] Lau AHL, Lau. HS. The newsboy problem with price-dependent demand distribution. IIE Transactions 1988;20:168–75.
[14] Simchi-Levi D, Kaminsky P. Designing and managing the supply chain. 3rd ed.. McGraw-Hill; 2009.
[15] Lin HL, Chen GC. Applied Statistics. 3rd. Yeh Yeh Book Gallery; 2006.
[16] Vapnik V, Chervonenkis A. A note on one class of perceptrons. Automation and Remote Control 1964;25.
[17] Vapnik V. The Nature of Statistical Learning Theory. New York: Springer Verlag; 1995.
[18] Burges CJC. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery 1998;2(2):955–974.
[19] Furey TS, Cristianini N, Duffy N, Bednarski DW, Schummer M, Haussler D. Support vector machine classification and validation of cancer tissue samples using microarray expression data. Bioinformatics 2000;16(10):906–14.
[20] Chen RC, Chen TS, Chien YE, Yang YR. Novel questionnaire -responded transaction approach with SVM for credit card fraud detection. Lecture Notes in Computer Science (LNCS) 2005;3497:916–921.
[21] Li Y, Gong SG, Sherrah J, Liddell H. Support vector machine based multi-view face detection and recognition. Image and Vision Computing 2004;22(5):413–27.
[22] Cristianini N, Shawe-Taylor J. An introduction to support vector machines. Cambridge, England: Cambridge University Press; 2000.
[23] Chen, GH, Huang JY, Inventory management of president chain store by support vector machine. In: Proceedings of the 2008 International Conference on Management and Technology, Yunlin, Taiwan; June 2008.
[24] Lin CH. Material Management. Haw-Tai Book; 2006.
[25] Tay FEH, Cao L. Application of support vector machines in financial time series forecasting. Omega 2001;29:309–17.