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Determination of order quantity for perishable products by using the support vector machine

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Daily meal boxes are perishable goods which, if not sold within their limited lifetimes, will be discarded. Convenience stores generally make their order decisions according to point of sale (POS) analysis. However, due to the effects of uncertain factors, such as the weather, temperature, the number of customers, and promotion activity of substitute products, the order quantity based on POS may not actually match with real demand, especially for perishable items. In this study, a novel warning system is established by employing the support vector machine (SVM) to modify the order quantity; and the Taguchi method is applied to determine the optimal portfolio of the factors that may influence the prediction accuracy of the SVM. Using actual data from a convenience store, which is a part of the President Chain Store Corporation in Taiwan, the prediction accuracy of the warning system was evaluated. Through numerical experiments, that the proposed methodology can significantly raise the profit is confirmed.

Keywords: perishable items; order quantity; support vector machine; Taguchi method

1. Introduction

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 the demands in December, as any cards remaining in January have almost no value. Similarly, daily newspapers and meal boxes are perishable goods which, if not sold within their limited lifetimes, will be discarded. Decision-makers are always faced with the dilemma of balancing the increase of customer satisfaction and the reduction of costs. The application of a scientific method to determine the appropriate order of perishable goods as accurately as possible is greatly needed by decision-makers.

Demand forecasting is one of the major tasks in business administration. Precise forecasting of demand can not only decrease inventory cost, but also increase the quality of customer service and competition advantage. For perishable goods such as meal boxes, freshness is always a primary concern for consumers. Due to the short preservation period, the decision logic for coping with items subject to obsolescence is even more difficult to handle than in the case of those items with a longer shelf life. As such, an effective forecasting approach for catching the information on the demand of perishable items is particularly important in inventory control and marketing.

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. The purpose of inventory management is the timely replenishment of stock when the inventory level falls below a safe level of stock. The amount of an order must also consider the possible exhaustion of the existing stock over time. 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, a good decision is not always easy to determine. Based on the research study of Silver *et al.* [22], most firms do not fully understand the complexities of inventory management. For convenience stores, many factors may affect the sale of meal boxes, such as the weather, temperature, festivals, global economical environment, and promotions. For perishable items, such as meal boxes, a good ordering decision

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for the balance between the customer's satisfaction and wastage prevention is difficult and complex.

Convenience stores generally make their order decisions according to point of sale (POS) analysis. However, many uncertainties still exist when using the POS system to estimate supply and demand. In this study, the ordering, sales, and scrapped numbers of meal box products of a branch of the President Chain Store Corporation (PCSC) in Taiwan are collected. An efficient methodology to determine the suitable amount of replenishment is developed so as to achieve higher profits.

2. Literature review

There are nearly 5000 stores belonging to the PCSC in Taiwan, and each store holds a substantial amount of inventory, of which many perishable goods may become scrap, leading to significant losses. In such a complex and fast-changing business environment, coupled with shortened product-life cycles, the PCSC thus aims to meet customer demand and to find the lowest inventory costs using historical data through the existing inventory control and sale information. 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. Different inventory management policies and inventory models are briefly discussed as follows.

Traditionally, orders have been adopted using the decision-making model of the economic order quantities (EOQ) model [9], which was frequently applied to determine the optimal order quantity. The EOQ problem can be summarized as the determination of the order quantity that minimizes the total costs by balancing the order cost and the holding costs. Li *et al.* [13] developed an EOQ-based model for deteriorating items with a constant deterioration rate to evaluate the impact of a form postponement strategy on the retailer in a supply chain. They assumed that the demand rates of the end products are independent and constant. The EOQ model is simplistic, and thus limited due to several unrealistic assumptions that are rarely encountered in the real world. Since the meal box in this research study is similar to goods with high demand uncertainty, the EOQ model is not applicable in calculating the optimum order quantity. Businesses that have a steady demand for stock are the most suitable for EOQ applications, but they are no longer suitable in this case since the demand uncertainty of the perishable items such as meal boxes is high. Therefore, in this article, we are motivated to develop a more sophisticated methodology to determine an appropriate order quantity.

Numerous studies have been made on perishable or deteriorating commodities. One may refer to Nahmias [18], Raafat [19], and Goyal and Giri [8] for comprehensive surveys of this literature. The majority of the papers discussed in these surveys involve deterministic demand processes, while stochastic demand inventory models have received considerably less attention [17]. Jain and Edward [10] 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. In the study of Chandra *et al.* [2], 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 our study, the rate of deterioration is not considered, that is, 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 studies identified above have all dealt with the 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, the analysis of perishable goods has often employed the newsboy theory. The meal box is similar to a newspaper, which will be considered scrap once it has expired. There are several relevant studies that have addressed this issue (see, e.g. [11]). Atkinson [1] 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 [12] 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.

To our knowledge, few papers have focused on the replenishment problem in actual situations where the uncertainty of demand is high. Most of the research studies determined the optimal order quantity from a statistical point of view. For example, the analysis of perishable goods has often employed the newsboy theory, and there are several relevant studies that have addressed this issue [12,15,16]. However, as consumer psychology is difficult to fathom, it is difficult to control the amount of scrap simply from the sale of these products. That is, in real circumstances, considering highly uncertain demand and perishability, the variance of the optimal order quantity is so great that one must determine the factors that have significant influences on the sales rate. Therefore, in this study, we applied a support vector machine (SVM) approach to determine the optimal order quantity instead of making a decision simply from a statistical point of view. We develop a methodology for adjusting the order quantity of meal boxes based on a POS decision by taking all influential factors into account. This wastage warning process is accomplished by conducting a SVM analysis. Besides conducting a parameter study to enhance the prediction accuracy of the SVM, we innovatively apply the Taguchi method for control factor screening. Through experiments, we will demonstrate that our proposed algorithm can efficiently reduce wastage, and thus increase the profit.

The SVM, first introduced by Vapnik and his group at AT&T Bell Laboratories [24], has now evolved into an active area of research [21]. Due to many attractive features and excellent generalization performance on a wide range of applications, the SVM is currently considered as one of the most efficient techniques for regression and classification problems [5].

Basically, the SVM can be used to classify objects into two classes based on a series of observations. A number of studies have been announced concerning its theory and applications in 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 also been applied to several new biological problems [7]. Chen *et al.* [3] employed the 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.* [14].

In order to improve the prediction accuracy, it is desirable to determine an optimal combination of factors to construct the SVM model. One way to do this is to employ trial-and-error based experimentations of all possible combinations of factors, i.e. we first remove one of the factors, for example the climate, and reprocess the training model to check the prediction accuracy. Then, this is followed by the number of potential customers, temperature, weather, and other factors. At the same time, we observe the accuracy level affected by each individual factor, and then compare the accuracy of the SVM model with various factors in order to obtain the best combination among the factors. However, since there will be 32 (2^5) kinds of possible combinations for five factors, the testing process may be quite expensive and time consuming. Moreover, the interactions among factors are also being neglected as one factor is changed at one time. Therefore, we are motivated to propose the Taguchi scheme for factor screening before applying SVM.

To the best of our knowledge, none of the prior researchers in this field have applied the 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 can also be regarded as binary. Therefore, the SVM can be applied to make a better decision by adjusting the preliminary order quantity according to whether the quantity will induce overstocking.

The remainder of this article is organized as follows. Section 3 provides a description of our methodology. Numerical experiments and verification are given in Section 4. Analysis of factor screening by the Taguchi method will also be described in this section. Finally, in Section 5, we discuss the limitations of the study and conclude with a summary of the main contributions of the study for research and practice.

3. Methodology

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 determine a suitable replenishment quantity for the meal box, we propose an analysis algorithm as shown in Figure 1. To give a clearer view of the structure of the proposed algorithm, we divided the proposed methodology into four subsections as follows.

3.1 *Estimation of preliminary order quantity*

First of all, we need a roughly estimated order quantity obtained from a POS system, which normally provides figures from a statistical-based tool, such as from a moving average method. Since demand peaks, which may possibly have been incurred due to several accidental events, such as promotion, will be smoothed out through an averaged process, we conduct a SVM analysis to adjust the demand variation due to all the possible uncertain factors. An innovative part of our study is that we suggest that policy makers, whose sales

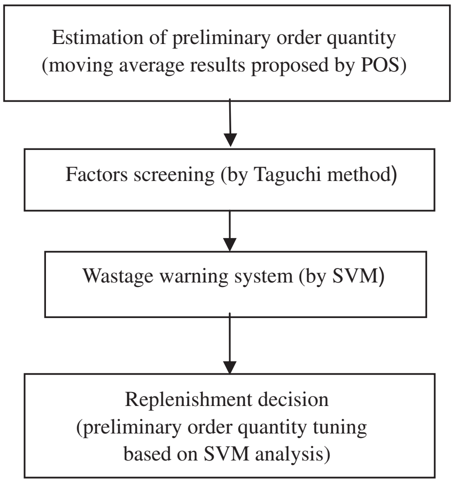

Figure 1. Structure of the proposed algorithm.

results lead to wastage or no wastage, can also be regarded as binary. Therefore, the SVM can be applied to determine whether the preliminary quantity will induce overstocking or not.

Before applying the SVM, we need to determine an optimal combination of factors so as to increase the predictive accuracy of the SVM model. A Taguchi scheme is selected as the perfect tool, since it can not only save the screening efforts but also can check the interaction effects between factors.

3.2 *Factor screening*

For a full-factorial experiment that considers all potential interactions, the experiment numbers of all combinations of the factor levels are required, and it will be extremely time consuming and expensive. To solve this problem, the Taguchi method was developed by Dr Genichi Taguchi at the Electric Communications Laboratory of the Nippon Telephone and Telegraph Company in the late 1950s. As an approach to quality engineering, this method uses a special design of orthogonal arrays to study the entire factor space with only a small number of experiments [20]. The method, which is one of the fractional factorial designs, allows one to statistically and ideally obtain similar information to a full-factorial experimental design, but with fewer experiments. It uses a special design of orthogonal arrays to study the entire parameter space. The origin of the orthogonal array is attributed to Sir Fisher in 1923, who applied the arrays to control error in an experiment. Dr Taguchi has adapted it to determine the influence of each factor on both the mean result and the variation from the result [4].

In this study, we innovatively employ a Taguchi method to screen the significant factors to be used in the SVM method. Usually, there are three categories of quality characteristics in the analysis of the signal-to-noise (S/N) ratio, i.e. the-lower-the-better, the-higher-the-better, and the-nominal-the-better. Since we are going to apply the SVM to determine whether the initial order quantity will induce overstocking and establish a wastage warning system, the quality characteristic is the prediction accuracy from the SVM, and it certainly belongs to the category of the-higher-the-better.

Following the opinions of several experienced managers through in-depth discussions, five possible factors that may affect the prediction accuracy of the SVM are selected, including the consideration of the order quantity, climate, temperature, numbers of customers, and promotion activity of the substitutes for the meal box. Since the Taguchi method is applied for factor screening in this study, each process factor has only two levels, i.e. with or without this factor being included in the SVM analysis.

It is noted that many other factors may also affect the sales of the meal boxes, for instance, the promotion discount of the concerned product and the day of the week. However, in this article, we focused on developing a methodology for adjusting the order quantity of the meal box based on the POS decision. Actually, taking all influential factors into account is not possible, since there are many difficulties in data collection. All the data from the PCSC, such as sales and scrapped numbers of the meal box products, are stored in the computer, and no data can be printed out due to the concerns of business secrecy. Therefore, all the data can only be collected by manually writing down by hand, which is very time consuming. Moreover, some factors may not be activated during our data collection period. For instance, during September to November, no meal box promotion activities were conducted; and only substitutes such as o-nigiri (a rice ball) were on the promotional list. We therefore can only take the effect of promotional activity of substitutes into account.

Five factors, each at two levels, were considered; therefore, an $L_8(2^7)$ orthogonal array with five columns and eight rows was employed. By choosing an appropriate orthogonal array, the 32 experimental runs can be reduced to 8. Therefore, it is a surprisingly efficient method for process optimization. In Table 1, the "1" symbols represent the properties used in the SVM analysis; otherwise, they are not used.

In the Taguchi method, the S/N ratio is the ratio of the desirable value (mean) for the output

Table 1. Experimental layout using an $L_8(2^7)$ orthogonal array.

Trial number	Factor and level						
	A	B	C	D	E	F	G
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

characteristic to the undesirable value (noise). The S/N ratio, η, for the-higher-the-better quality characteristic can be expressed as

$$\eta = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{1}$$

The influence of each control factor on the prediction accuracy was analyzed from the S/N ratio response table, which expresses the S/N ratio at each level of control factor. The Taguchi method uses the S/N ratio instead of the average to convert the trial result data into a value for the characteristic in the optimum setting analysis. Regardless of the category of the quality characteristic, a greater S/N ratio corresponds to a smaller variance of the output characteristic around the desired value, and hence to a better quality characteristic. Therefore, a bigger level difference of the control factor means a greater influence on the prediction accuracy. Based on analysis of the S/N ratio, the optimal levels of the process factors are determined.

As given in Table 1, five factors, each at two levels, were considered. However, when using the SVM to provide a warning system to compensate for the possible error of the preliminary order quantity, the factors should be independent of each other. Although the full-factorial experiment considers all potential interactions, the experiment numbers of all the combinations of the factor levels are extremely time consuming. The Taguchi method can reduce the testing requirement dramatically and determine the significance of control factors; moreover, it can check the interaction between factors. Intuitively, the climate and temperature may have some kind of relations; hence, potential interaction between these two control factors will be investigated.

3.3 *The SVM*

In order to determine an optimal order quantity for meal boxes so as to maximize profit, a SVM-based replenishment methodology is developed. Based on the information from POS systems, a convenience store can provide order decisions but cannot accurately predict sales. Therefore, in this study, we focus on a wastage warning system for tuning the preliminary order quantity derived from the POS system. An intelligent tool, the SVM, is used to increase the prediction accuracy of the approach by considering influential factors such as the weather, temperature, and promotions.

The principle of the SVM classifier is to project the data into a higher dimensional space, where the classes are separated by a linear model, and the maximum margin hyperplane can give 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 [6]. A simple description of the SVM algorithm is presented 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:

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

where Y is the outcome, y_i the target label of x_i, $x = (x_1, x_2, \ldots, x_N)$ the set of support vectors, and b and α_i the parameters that determine the hyperplane. In general cases where the data are not linearly separated, SVM uses non-linear machines to find a hyperplane that minimizes the number of errors for the training set. A high-dimensional version of Equation (2) for the non-linearly separable case is given as follows:

$$Y = \text{sign}\left(\sum_{i=1}^{N} y_i\alpha_i K(\mathbf{x}, \mathbf{x}_i) + b\right) \tag{3}$$

The function $K(\mathbf{x}, \mathbf{x}_i)$ is the kernel. The SVM classification exercise is to find the support vectors and to determine the parameters b and α_i. For the non-separable case, the SVM can be generalized by placing an upper bound C on the coefficients α_i in addition to the lower bound [25]. Besides the linear kernel, three common types of kernel function for constructing the decision rules are given as follows:

(1) A polynomial kernel of degree d:

$$K(\mathbf{x}\cdot\mathbf{x}_i) = (\mathbf{x}\cdot\mathbf{x}_i + 1)^d \tag{4}$$

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

$$K(\mathbf{x}\cdot\mathbf{x}_i) = \exp(-1/\delta^2(\mathbf{x}-\mathbf{x}_i)^2 \tag{5}$$

where δ^2 is the bandwidth of the RBF kernel.

(3) The Sigmoid kernel,

$$K(\mathbf{x} \cdot \mathbf{x}_i) = 1/[1 + \exp\{v(\mathbf{x} \cdot \mathbf{x}_i) - c\}] \quad (6)$$

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

There are a number of software-related parameters that need to be set for the problem with the SVM. To investigate the effect of the variability in prediction and generalization performance of the SVM, we conduct the experiment with respect to various values of parameters in the SVM such as the kernel parameters and the upper bound C.

3.4 *Replenishment decision*

Once the preliminary order quantity is determined based on the POS system, we use a range of five (or more) to cover the possible variation of the order quantity, and proceed to the SVM analysis. We will tune this number through the SVM by checking the order quantity ranging in ascending order, with the other three control factors left constant. The output of the SVM analysis changes sign from negative to positive, which implies that wastage will occur. Since the marginal cost of a meal box is much higher than the marginal benefit, it is better to order a number that will not incur wastage. Hence, the order number can be determined. A detailed example is presented in Section 4.4.

4. Numerical experiments and verification

4.1 *The preliminary order quantity*

To conduct experiments on the SVM methodology, related data of meal boxes of a PCSC store in Taiwan were collected from September to November 2009, including the ordering, sales, scrapped numbers, cost, profit of meal box, the customer number, promotion activity of substitutes (such as sandwiches or o-nigiri), weather, and temperature. In this study, temperature and weather data were obtained from the Bureau of Meteorology, using the variables of 1, 2, and 3 to represent sunny, cloudy, and rainy weather, respectively. Also, we used the variables of 1 to show that there was promotion activity of a substitute and 2 otherwise. To insure that the larger value input attributes did not overwhelm smaller value inputs, a linear scaling process was conducted before conducting SVM analysis so as to normalize each feature component to the range of $[-1, 1]$.

The predicted meal box order quantity based on the POS system can only provide the manager with a preliminary order quantity. However, in practice, the real number of items sold will be affected by several factors which may change from day to day, and thus induce variability to the demand for the meal box. To resolve this uncertainty, this study introduces the SVM research tool to establish a wastage warning system.

The SVM has achieved high accuracy as a binary judge in applications such as credit risk assessment, airport passenger entry probability assessment, and forecasting. However, the SVM has never been applied to inventory applications. In this study, based on the historical data of order quantities and the number of scrapped items, as well as in-depth discussions with several experienced managers, we found that there are five possible factors (attributes) that may affect the prediction accuracy of the SVM, including consideration of the order quantity, climate, temperature, number of customers, and promotion activity of substitutes for the meal box. But, before we conduct the SVM analysis, we propose the Taguchi scheme for factor screening so as to improve the prediction accuracy of the SVM model.

4.2 *Factor screening*

Since the $L_8(2^7)$ orthogonal array has seven columns, two columns of the array are left empty for the investigation of interaction. According to the Taguchi method, the interaction effect can be measured in column 3 if one inserts the factors to be investigated in columns 1 and 2, respectively. The data of prediction accuracy of the order quantity of the meal box derived from SVM analysis were conducted with the RBF kernel function, the parameters $gamma = 10$, and $C = 1$ (the optimal choice for the related parameters is explained in Section 4.3). In order to calculate the S/N value of the experiment, three groups of data (i.e. the y_1, y_2, and y_3 given in Table 2) are established. Each group of data is a 10-day (randomly selected in November) average value of the prediction accuracy of the meal box.

The S/N value of each trial experiment, as depicted in Table 3, can thus be obtained by Equation (1).

Since the experimental design is orthogonal, it is then possible to separate out the effect of each control factor at different levels. For example, the mean S/N ratio for the temperature at levels 1 and 2 can be calculated by averaging the S/N ratios for the experiments 1–4 and 5–8, respectively.

The influence of each control factor shows the change of the S/N ratio when the control factor is

Table 2. Averaged prediction accuracy of three groups.

Trial number	y_1	y_2	y_3
1	0.8	0.7	0.6
2	0.6	0.7	0.5
3	0.4	0.4	0.5
4	0.6	0.7	0.5
5	0.7	0.8	0.5
6	0.4	0.4	0.6
7	0.7	0.7	0.5
8	0.6	0.5	0.6

changed from level 1 to 2. As can be seen in Table 4, the effect of the promotion activity of the substitute is the most significant factor.

The influence of each control factor can be clearly observed by a response graph. The power of the influence of each control factor can be determined according to the slope of the lines shown in Figure 2.

By picking up the factors with the higher S/N ratio value, the optimal combination for achieving the best accuracy is determined. It is noted that, according to the results given in Table 4, the interaction effect between temperature and climate cannot be neglected. The interaction effect can be further confirmed by the response graph (Figure 3) between these factors.

The crossed lines shown in Figure 3 imply that the interaction effect between temperature and climate is significant and, therefore, only one of them can be chosen as the control factor. Since the influence of climate is larger than that of temperature, as given in Table 4, the temperature factor is considered to be excluded in the best combination of factors. For confirmation, the S/N ratio is recalculated using climate, preliminary order quantity, customer numbers, and promotion activity of the substitute as the combinatorial factors. The result of the new S/N ratio is -0.915, which is lower than the value (-1.278) with all five control factors included in the combination, as given in Table 3. This result can provide us with a valuable reference when using the wastage warning system as a better decision-making tool in the following section.

4.3 *Wastage warning system by SVM*

The sales data, recorded from September to November in 2009, were provided by a PCSC retail store in Taiwan. For simplicity, only information and data from November are given in Table 5. Among them, the climate data are derived from the Bureau of Meteorology, using the variables of 1, 2, and 3 to represent sunny, cloudy, and rainy weather, respectively. Also, using the variables of 1 to show that there is promotion activity of a substitute, and 2 otherwise. 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 $[-1, 1]$. There are a number of performance-related parameters that need to be set, and our 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 [23], 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 powers $d = 2$ and $d = 3$ are inputted. A total of 30 SVM experiments were performed with three kernels, namely dot (linear), polynomial, and RBF. The experimental results show that the prediction performance of the SVM is sensitive to the various kernel parameters d and the capacity parameter C. As given in Table 6, the accuracy of the training set increases monotonically as C increases for all models. When *gamma* is 10 and C is 1, 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.

A five-fold cross-validation is used, which initially divides the training set into five subsets of equal size, and sequentially one subset is tested using the classifier trained on the remaining four subsets. Thus, each instance of the whole training set is predicted once such that the cross-validation accuracy is the percentage of data that are correctly classified. In this study, the mySVM software system is used to perform the SVM experiments. Note that, if the period of the training data is extended to too great a length, the accuracy of prediction using the cross-training method may not be good enough. For instance, the prediction of November is dependent on the training data from September to October. However, during these 2 months, temperature and climate may be quite different. In addition, some seasonal trends may occur during such a long time, which result in a low-accuracy prediction. It is very important for decision-makers to be cautious in the selection of training data.

4.4 *Demonstrative example*

Here, we will take 1 November as an example to present a step-by-step procedure for the wastage warning system.

Table 3. Experiment for testing the optimal control factors.

Trial number	Temperature (A)	Climate (B)	Interaction A × B	Order quantity (C)	Number of customers (D)	Promotion activity of substitute (E)		*S/N*
1	1	1	1	1	1	1	1	−1.278
2	1	1	1	2	2	2	2	−2.596
3	1	2	2	1	1	2	2	−5.452
4	1	2	2	2	2	1	1	−2.597
5	2	1	2	1	2	1	2	−1.611
6	2	1	2	2	1	2	1	−4.685
7	2	2	1	1	2	2	1	−2.111
8	2	2	1	2	1	1	2	−3.142

Table 4. Response table.

	Temperature (A)	Climate (B)	Interaction between temperature and climate (A × B)	Order quantity (C)	Number of customers (D)	Promotion activity of substitute (E)
Level 1	−2.981	−2.543	−2.282	−2.613	−2.229	−2.157
Level 2	−2.888	−3.325	−3.586	−3.255	−3.639	−3.711
Effect	−0.093	0.783	1.304	0.642	1.411	1.554

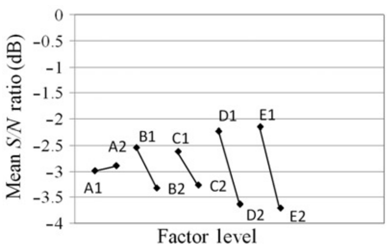

Figure 2. Response graph of all the factors.

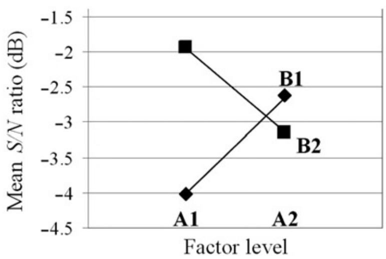

Figure 3. Response graph between temperature and climate.

Step 1: The preliminary order quantity

The preliminary order quantity on 1 November is 17, which is only a number for reference. The optimal order number may be lower or higher than this number depending on the influence of four control factors.

Table 5. Information and data over the November period.

June	Sales unit	Number of customers	Temperature	Climate	Promotion activity of substitute
1	17	720	25.0	2	2
2	14	968	21.5	2	2
3	14	791	20.8	2	2
4	10	761	22.2	1	2
5	14	724	23.8	1	1
6	14	766	24.5	1	1
7	13	965	24.9	2	1
8	12	844	25.5	2	1
9	15	929	25.3	2	1
10	11	879	24.2	3	1
11	13	817	23.5	2	2
12	12	756	24.0	1	2
13	14	830	21.4	3	2
14	13	1014	20.0	2	2
15	10	894	22.0	2	1
16	16	1031	22.4	2	2
17	8	819	19.3	2	2
18	6	761	18.8	2	2
19	4	736	20.1	2	2
20	15	805	19.7	2	2
21	9	908	19.1	2	2
22	11	807	19.7	2	2
23	6	1011	21.6	2	1
24	12	788	22.2	2	1
25	7	786	22.3	1	1
26	10	755	22.1	2	1
27	8	826	22.1	1	1
28	17	967	21.1	1	2
29	9	900	20.8	1	2
30	11	1142	19.6	2	2

Table 6. Classification accuracies (%) of various parameters.

Kernel	Linear	Polynomial $d=2$	Polynomial $d=3$	Radial $gamma=0.1$	Radial $gamma=1$	Radial $gamma=10$
$C=0.1$	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
$C=10$	0.779	0.972	0.990	0.867	0.983	0.994
$C=100$	0.780	0.989	0.992	0.95	0.989	0.994
$C=1000$	0.783	0.989	0.993	0.984	0.989	0.994

Step 2: The SVM
We therefore tune this number through the SVM by changing the order quantity ranging from 12 to 22, with the other three control factors left constant. As given in Table 7, the output values with a negative sign stand for "no wastage occurs." Therefore, the optimal order quantity is determined as the output of the SVM analysis becomes positive.

In this example, the SVM output will change sign as the order quantity is increased from 15 to 16, which means that if we order 16 meal boxes, wastage might occur according to the wastage warning system. On the other hand, if we order 15 meal boxes, there will be no wastage.

Step 3: Replenishment decision
Because the marginal cost of the meal box is much higher than the marginal benefit, it is better to order a number that will not incur wastage. Hence, the order number of 15 is recommended.

4.5 *Verification*

Note that, in this example, we do not choose an order quantity less than 15 simply to reduce the cost, because this number is what we think to be the most precise prediction of demand. A lower order quantity may reduce the possibility of wastage; however, the possible benefit may also be reduced. So, when 15 meal boxes are ordered, the profit is expected to be maximized without sacrificing the customers' rights.

Convenience stores generally make their order decisions according to POS analysis. The order quantity determined by POS and SVM may be different, and therefore the net profit will be not the same. Using the averaged cost ($44.03) and averaged profit ($12.23) of the overall meal boxes, the net profit between these two methods is compared. As can be seen from the experimental results, the improvement in the net profit made by SVM is significant. For October, the net profits obtained by following the decision policy from POS and SVM are $907.32 and $2707.72, respectively. While, as given in Table 8, the net profits of POS and SVM for November are $400.98 and $2174.43, respectively.

It seems that most of the order quantity determined by POS is higher than that of SVM. Hence, the profit made according to the decision of POS is high; however, its loss is also high due to more wastage. Clearly, the improvement of the net profit made by SVM is significant.

5. Conclusions and recommendations for future research

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. As the product life of a meal box is very short, overstocking may lead to some products passing their expiry dates. On the other hand, if there are insufficient stocks, sales opportunities may be lost with a reduction in customer satisfaction. Accurate predictions of the order quantity of a perishable product are of interest to many scholars, but there are many uncertain factors affecting the forecast results. In this study, a SVM-based replenishment methodology is developed to determine an optimal order quantity for perishable items so as to maximize profit. The optimal combination of control factors for achieving the best prediction accuracy of the SVM is determined by the Taguchi method. The results show that the model is workable, and the results can be used as a valuable reference for future practical applications.

Before this novel approach is applied in corporations across Taiwan or even mainland China in the future, it is suggested that more factors should be identified that may affect the prediction accuracy of the SVM such as festivals, the effect of substitutes, and promotional activities from the competitors of the President stores company.

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Table 7. Analysis results from mySVM.

Preliminary order quantity	8	9	10	11	12	13	14	15	16	17	18
Output of SVM	−1.96	−1.72	−1.49	−1.25	−1.02	−0.78	−0.54	−0.31	0.07	0.16	0.39

Table 8. Performance comparison between POS and SVM.

Date	Order quantity determined by POS	Order quantity predicted by SVM
1 November	17	15
2 November	14	15
3 November	14	15
4 November	14	9
5 November	15	9
6 November	18	9
7 November	20	11
8 November	19	11
9 November	15	11
10 November	12	12
11 November	12	11
12 November	13	9
13 November	15	12
14 November	14	12
15 November	13	11
16 November	16	11
17 November	17	11
18 November	17	10
19 November	13	10
20 November	14	11
21 November	9	11
22 November	11	11
23 November	10	11
24 November	10	10
25 November	8	9
26 November	9	10
27 November	14	9
28 November	14	9
29 November	11	9
30 November	12	11
Sales unit	328	293
Wastage	82	32
Loss	$3610.46	$1408.96
Profit	$4011.44	$3583.39
Net profit	$400.98	$2174.43

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支援向量機於超商易腐性商品補貨策略之應用

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摘要

企業的訂購和存貨政策與其營運成本有密切的關聯。訂貨不足會導致銷售機會的喪失，過多的存貨則會造成企業成本上升。如何決定合適的訂購量，一直以來都是企業所重視的一環。本研究以統一超商的便當爲分析對象，發展出一套有效的易腐性商品補貨策略。首先，以移動平均法求得粗估的整體數量。其次，運用支援向量機(SVM)所建立之報廢預警系統微調數量，以決定整體便當最佳訂購量。在面對不確定的環境下，許多因素都會影響到預測的準確性。因爲支援向量機能考慮現實環境中許多不確定的因素，而這些因素是往往是會影響到預測的準確度，例如來客數、天氣、促銷活動等，因此加入SVM後，可以使訂購量更符合實際情況。爲提高SVM預測的準確度，本文運用田口實驗設計法以找出影響訂購決策中的關鍵因素組合。經實驗比較，本研究所提的方法，遠比統一超商所使用的人爲預測來得有效率，證明此套預測工具能有效地決定最佳訂量，並提高便利商店的獲利能力。

關鍵詞: 易腐性商品；補貨策略；支援向量機；田口實驗設計

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