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Self-Adaptive Newsvendor Model with Information Updated

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Abstract

The use of classical newsvendor model is limited by assumptions and prior probability statistics. Self-adaptive newsvendor model is proposed to divide the sales interval and automatically adjust the differential according to the sales information collected by retailer's information system. Demand interval and its corresponding demand probability value could be adjusted timely to correct the next order prediction quantity. Based on management information system, model calculation tool is designed to improve the feasibility of the model application. Compared to traditional newsvendor model, self-adaptive newsvendor model can effectively meet the needs of short-period, small-quantity, multi-batch products purchasing.

Keywords: Newsvendor model; Self-adaptive; Information Systems; Assisted ordering decisions;

1. Introduction

The classical newsvendor model helps retailers make demand decision for perishable products or innovative products. But, based on conditions assumptions and priori probability statistics, the classical newsvendor model do not adapt to the products procurement strategy of Multi-species, small-quantity, short- cycle and multi-batch, which is now widespread in the retail industry, not to mention those industries which adopt quick response strategy or VMI. This study firstly modifies the basic assumptions of the classical newsvendor model, then uses the sales management

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information system to automatically count sales frequency to correct expectations, and to construct the self-adaptive newsvendor replenishment model.

2. The Relative Theoretical Research

In recent years, many scholars studied widely about the demand decision and inventory problem based on newsvendor model. The newsvendor model is sensitive to sub-optimal ordering decisions, more sensitive than the economic order quantity model. Mean demand is identified as the most influential parameter in deciding order quantity deviation[1]. Price has obvious influence on stochastic demand. A price dependent newsvendor model, in that buybacks is used as a kind of discount policy, is proposed to analyze how the nature of demand uncertainty affects decisions of the supplier and retailer[2]. To maximize the expected total sales, subsidies are used to drive retailer to make more orders. Based on the newsvendor model, there are three kinds of subsidies such as purchase subsidy, sales subsidy and price subsidy for retailers. Price subsidy and sales subsidy have the same stimulation effect[3]. Returns could be another subsidy. But from the perspective of the retailer, deliberate returns could abuse the return policy leading to strong inverse logistics and inventory. By explicitly gauging return probabilities and differentiated salvage values, demand uncertainty and consumer valuation uncertainty are incorporated into a newsvendor model[4].

It could be explained why underorders are typically larger than overorders by defining bounded rationality in terms of probabilistic cost efficiency[5]. According to updating values of information, definitions of two stage rational expectation equilibrium are presented and properties on the equilibrium condition are analyzed. It is proved that payoff of inventory level in rational expectations equilibrium is larger than in nonequilibrium[6]. Considering loss aversion to model the choice preference of the decision maker in the newsvendor problem under recourse option, loss aversion predicts the rational ordering behavior of the newsvendor with respect to the changes in price and cost parameters. It is found that the contract parameter does not depend on the loss aversion[7]. Under the optimal order quantity with the CVaR objective, the loss-averse newsvendor's expected utility decreases in the confidence level. The analysis confirms that high risk implies high return and low risk comes with low return[8-9].

How to get parameter value such as demand probabilities needed in every forecast cycle which is ignored in current literatures but is key to model application. Based on the widely uses of management information system, this study proposes a self-adaptive newsvendor model based on information system. This paper uses computer system to adjust demand intervals and corresponding probability value real-timely, and studies the implementation of the model algorithm.

3. Self-Adaptive Newsvendor Model

3.1. Theoretical Basis of the Model

Classical newsvendor model is a market forecasting model which is suitable for discrete and random product demand. It can be summarized as follow abstract model: for a selling day, under the discrete and random demand, we assume that the probability of sales Ri is P(Ri) which is based on empirical data. If newsboy sales one newspaper, then he earns profit K \$, or if the newspaper cannot be sold out at that day, he will loss H \$ for each. Smart newsboy will use the following eq.1 to determine the optimal order quantity Q*.

$$\sum_{\mathbf{R_i=0}}^{\mathbf{Q^*-1}} \mathbf{P(R_i)} \leq \frac{\mathbf{K}}{\mathbf{K+H}} \leq \sum_{\mathbf{R_i=0}}^{\mathbf{Q^*}} \mathbf{P(R_i)} \tag{1}$$

We use arithmetic progression with tolerance D as fluctuation span to predict optimal quantity. As a result, the optimal order quantity meets the following eq.2.

$$\begin{cases} C(Q^*) \geq C(Q^*+D) \\ C(Q^*) \geq C(Q^*-D) \end{cases} \tag{2}$$

Eq.1 can be further modified as eq.3.

$$\sum_{r_i=0}^{Q^*-D} P(r_i) \le \frac{K}{K+H} \le \sum_{r_i=0}^{Q^*} P(r_i) \quad (3)$$

Before the next forecast cycle, by analyzing data from sales information system, retailers can observe the latest market demand distribution, recount the probability P(Ri) of every demand interval and then update. To achieve fast and accurate prediction, the model needs to continuously update three main parameters: commodity demand, the probability of demand, profits and loss function of commodity. Typically, for simplicity, we assume that K and H in formula (3) will increase or decrease at the same proportion when business environment changed. In this case, the value of K/(K+H) will remain unchanged. The key to update the parameter value quickly is: within the sales quarter, retailers use the sales system to automatically count sales with the established segmentation strategy at a certain interval, compute P(Ri) of each range. With the latest P(Ri), we can use formula (3) to predict the optimal order quantity Q*. That's the Self-adaptive Newsboy Model.

3.2. Dividing method of model sales observation point and interval

Fluctuation span D means the length from one forecast interval to another one, which is defined as the following eq.4.

$$D = (\max(R_i) - \min(R_i))/2/(N-1) \quad (4)$$
$$i \in (2, N], N \ge 3$$

$max(R_i)$ means the maximum sales, $min(R_i)$ means the minimum sales, N is the number of predicting nodes. Demand fluctuation is a prediction range. To predict accurately and keep a relatively flat fluctuation, we must collect multiple demand forecasting points to keep N large enough and D small enough.

Table 1 below describes the forecast quantity and its probability distribution of Mengniu dairy at some point in time. It adopted 9 section observation point strategy.

Table 1. The distribution of demand and probability for a commodity

Demand (cans)	R1	R2	R3	R4	R5	R6	R7	R8	R9
	0	12	24	36	48	60	72	84	96
Probability	P(R1)	P(R2)	P(R3)	P(R4)	P(R5)	P(R6)	P(R7)	P(R8)	P(R9)
	0.01	0.07	0.14	0.17	0.22	0.16	0.15	0.07	0.01

Note: the probability is given by the experienced retailer or by way of sharing expert database.

An actual sale quantity R will fall into an interval with 2D span, for example, R1, R2,..., R7 will fall into the corresponding range: $[R_1 - D, R_1 + D)$, $[R_2 - D, R_2 + D)$,..., $[R_7 - D, R_7 + D)$. Then in turn, we can determine the replenishment point by the range which Ri fell in.

Set δ = Ri –R. We use δ as a basis to adjust the demand forecast. If δ is less than 0, it indicates that the last forecast was too low; we need to increase the upper and lower limits of corresponding interval. Otherwise, take the opposite way. We call it as optimistic or pessimistic adjusting strategies. For example, using eq.4, the discrete numbers in Table 1 can be transformed into: [0, 6), [6, 18), [18, 30), [30, 42), [42, 54), [54, 66), [66, 78). If actual sales statistics R = 55 in the range [54, 66), then modify the average value of the range to 55, the interval becomes [49, 61). Upper and lower limits of each other interval reduce by 5 at the same time. This is a pessimistic amendment. If the actual sales statistics is R= 63, then the upper and lower limits of each interval will also increase by 3. This is an optimistic correction. The adjustment method is shown as the eq.5.

$$\begin{aligned} &(R_j - D - \delta,\ R_j + D - \delta),\ \text{if}(R_i > R) \\ &(R_j - D + \delta,\ R_j + D + \delta),\ \text{if}(R_i \le R) \\ &i, j \in (2, N], N \ge 3 \end{aligned} \quad (5)$$

3.3. Adjustment of demand probability

Due to the changeable, competitive market environment, the market forecasting of FMCG is easily affected by market factors, we need to make appropriate adjustments towards forecasting. So, we introduce retailers' expecting error rate ω as eq.6 to market demand.

$$\omega = \frac{(Q - R)}{Max(Q, R)} \tag{6}$$

If the last actual demand fell into interval I, and the corresponding mean probability of I is P(Ri), we can adjust the probability P(Ri) to (1 + ω) * P (Ri). Assuming there are N observation intervals, starting at 0, we can construct N intervals, only the interval which R has fallen into is the enhanced interval, the other N-1 are all expected to be attenuated intervals, they will reduce by (ω / (N-1)) * P (Ri), N> 1 as eq.7.

$$P'(r_j) = \begin{cases} (1+\omega)\,P(r_j) & j = i \\ \left(1 - \dfrac{\omega}{n-1}\right) P(r_j) & j <> i \end{cases} \tag{7}$$

$$j \in [1, N]$$

4. Self-Adaptive Newsvendor Model Support System

4.1. The system database business model

For discrete stochastic demand, we need to correct demand probability to adapt the changing business environment before every forecast. Self-adaptive newsvendor model needs historical sales data of goods (described as table 2), collected by information systems, and inventory data, to calculate the demand frequency characteristics of the observation point (described as table 3). Finally, we can obtain demand probability distribution of each observation point shown in table 4.

To ensure normal operation of the model, we need to have a corresponding commodity sales profits and losses (gains and losses) data table, such as table 5. As retailers' differences toward drug stores, risk preference, commodity value, and so on, result in differences of product gains and losses, so, in the initial stage, commodity profit and loss value can be decided by retailers themselves. As shown in table 4, it is an initialized commodity gains and losses table.

Probability values can be reflected from product inventory. Zero stocks indicate that the previous forecast was relatively accurate. Otherwise, retailers expect error rate ω necessary to be adjusted. Therefore, we design a list of inventories shown in table 6 below, record the latest replenishment quantity Q' and the current goods quantity S on shelves, and actual sales quantity R = Q'- S.

Table 2. Commodities sales record form

Product ID	Product Name	Unit	Number	Sales time
6923644268503	Mengniu dairy	can	5	2017-8-7 12:12:10
6924187828537	Melon seeds	packet	3	2017-8-7 14:14:13
6923644268503	Mengniu dairy	can	3	2017-8-10 18:12:21
…	…	…	…	…

Table 3. Statistics of commodities demand forecasts point

Sales quantity / Product ID	Product Name	Unit	R_1	R_2	R_3	R_4	R_5	R_6	R_7
6923644268503	Mengniu dairy	can	12	24	36	48	60	72	80
6924187828537	Melon seeds	packet	3	6	9	12	15	18	21
…	…	…	…	…	…	…	…	…	…

Table 4. Probability distribution of commodities possible demand forecasts point

probability / Product ID	Product Name	Unit	$P(R_1)$	$P(R_2)$	$P(R_3)$	$P(R_4)$	$P(R_5)$	$P(R_6)$	$P(R_7)$
6923644268503	Mengniu dairy	can	0.02	0.17	0.23	0.22	0.20	0.15	0.01
6924187828537	Melon seeds	packet	0.03	0.14	0.23	0.20	0.23	0.14	0.03
…	…	…	…	…	…	…	…	…	…

Table 5. Commodity gains and loss assessment form

Product ID	Product Name	H	K	Update time
6923644268503	Mengniu dairy	1.5	0.5	2017-8-1 23:10:10
6924187828537	Melon seeds	1.8	0.3	2017-8-1 23:10:11
…	…	…	…	…

Table 6. Product replenishment and inventory record table

Product ID	Product Name	replenishment quantity Q'	Storage S	Record time
6923644268503	Mengniu dairy	48	0	2017-8-19 7:10:10
6924187828537	Melon seeds	13	2	2017-8-19 7:10:11
…	…	…	…	…

4.2. Model Algorithm Program Analysis

Self-adaptive newsvendor model, as a management model embedded in retailers' logistics information system, will appear as a decision- supporting tool. For each user, this model is transparent. Figure 1 depicts the process that the newsvendor model support systems calculate parameter values.

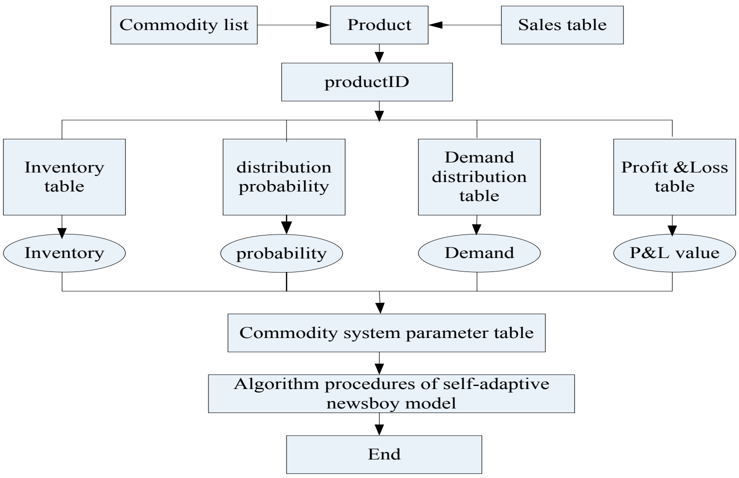

Fig.1. the calculation process of model.

1) Choose any product from sales table and commodity list;

2) According to the commodity code, query the Profit & Loss table 5, inventory table 6, sales table 2, demand table 3 and the corresponding probability distribution table 4, calculate the corresponding profit and loss value, δ - the correction value of demand range, probability value;

3) Update the system parameter table with these new parameter values：demands, probability value, inventory, Profit & Loss value;

4) After getting these new parameter value, use self-adaptive newsboy model algorithm module to compute the optimal predictive value Q*.

4.3. The main function of newsboy model algorithm

Model mainly includes three main adaptive processes: to update the demand forecast point values, update the demand forecast probability, update the income statement. We design three methods: updateParameterValues, updateNeedsQuantity and UpdatingProbabilityOfNeedsQuantities. The first method will invoke the two behind. The main function is as follows:

protected int CmpNewsBoy(string productID, double[] gainLostValue, double[] preQuantityOf_ Needs, double[] probabilityOfNeeds, double[] storageOfGoods)

Result of function is integer type. The functions and types of each parameter are described below:

ProductID: represents product number, described by commodity EAN-13 codes.

gainLostValue: the revenue and loss of commodities, gainLostValue[0] represents earnings, gainLostValue [1] indicates loss.

PreQuantityOfNeeds: represents commodity demand forecasting quantity distribution points. The number of data within the array represents the number of forecast demand points. They are read from the data table.

ProperbilityOfNeeds: commodities probability. they are corresponding with demand array order.

StorageOfGoods: commodity stocks, it is used to determine whether we need to adjust the predict probability.

When the program is running, the five parameters value above is from corresponding table in database. They will be presented in array, as actual parameters.

4.4. The algorithm program flow

Step 1: according to product ID, query the commodity inventories S. If S is zero means that the last forecast is accurate, then turn to the seventh step, otherwise, turn to the second step to adjust demand forecast interval;

Step 2: check the actual demand R of last prediction cycle, calculate the difference δ between the actual demand R with the predicted value Ri ;

Step 3: judge δ, if δ is equal to zero, turn directly into the seventh step, calculate forecast demand, otherwise, calculate tolerance D according to the formula (4), turn to step 4;

Step 4: according to the formula (5), use the gap δ and tolerance D to adjust commodity prediction intervals, update table 3;

Step 5: according to the formula (6), calculate retailers' expecting error rate ω to market demand. If ω is zero, turn to step 7, otherwise enter the next step;

Step 6: based on ω, use the formula (7) to update the prediction probability value of corresponding demand forecasting point in table 4;

Step 7: query commodity profit and loss table to obtain profit K and loss H;

Step 8: according to the latest forecast probability value, use the optimal order quantity formula (3) proposed in this paper to calculate the most quantity Q*. Return the integer value Q*. Then end the algorithm.

5. Conclusions

Compared to the traditional newsvendor model, the step-length used in self-adaptive newsvendor model is more flexible. Probability values of observation point are dynamically variable as the environment changes. The self-adaptive characteristics is mainly reflected in the application of management information system. POS system provides real-time data for accurate demand forecasting and updates dynamically demand probability. We can make this model-supporting system a tool to be embed into the management information system, which can help retailers make quick and accurate prediction for daily purchasing multiple products. To a certain extent, this model may help reduce commodity shortage rate and inventory and improve comprehensive benefit.

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