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Winter 12-4-2017

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### Recommended Citation

Chuang, Howard Hao-Chun; Chang, Hsin-lu; and Hsu, Po-Chun, "Improving The Performance of Inventory Control – Taking W Company as an Example" (2017). *ICEB 2017 Proceedings*. 38.

<http://aisel.aisnet.org/iceb2017/38>

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## **Improving The Performance of Inventory Control – Taking W Company as an Example**

*(Work in Progress)*

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### **ABSTRACT**

The W company is facing a problem that their demand is intermittent. Because intermittent demand is difficult to predict, there are some models being created to deal with it. Using these models, such as Bootstrapping, Croston's method, and Discrete-auto-regressive-moving-average model, to predict and compare with the current one if any of them outperforms.

*Keywords:* Intermittent demand, bootstrapping, discrete auto-regressive-moving-average model.

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### **INTRODUCTION**

#### **Introduction of Industry and Company**

Nowadays, the war is no longer between the companies but the supply chains. There are three kinds of companies from upstream to downstream in the semiconductor industry: semiconductor components manufacturers, distributors, and users or system manufacturers. Although the manufacturers can directly deal with users, the distributors have their roles. To the manufacturers, the distributors are like the substituted warehouses and the product promoters. The manufacturers can focus on their professions and progress even faster because of saving the money and the time in marketing and business management. For the users, distributors allow them to buy all components as once and help the ones who are lack of bargaining power to get quantity discount.

W company, the biggest semiconductor distributor in the Asia, has more than 15,000 staffs all around the world and has the offices in more than 71 countries. they also act as an agency for more than 250 companies. Their turnover in 2016 are more than 16 billion US dollars.

Besides the service mentioned in the previous paragraph, W company provides more. For the upstream, they collect information from the market and aggregate them to give the manufacturers suggestions about development and the quantity of demand. For the downstream, they specially provide product maintenance support as the same level of the manufacturers. Not to mention the product design and development. Other services include the financial support and the inventory management.

#### **Research Motivation**

The life cycles of the semiconductor components are short. The semiconductor components often explode unexpectedly. W company are facing to a problem that they have so many kinds of stocks, but they don't know how to keep them in order to make the total cost as low as possible. In fact, the total cost is a tradeoff between the cost of warehousing and the cost of out of stock. Once the W company keeps the quantity of stocks more than what its downstream actually need, the turnover rate of the common items will decrease and the customized item will probably become the dead stock which bringing in the recycle cost. On the contrary, if W company is in the situation that it is out of stock, it will harm the relationship between itself and its downstream. The better case is the retailers decrease the ordering quantities, and the worst case is breaking the partnership. Furthermore, W company has to pay the fine. Nowadays, W company is still using a simple way to predict the demand, which is based on the moving average. To find a more accurate way of making the total cost even lower is the most difficult dilemma that the W company has to face to.

#### **Research Question**

Which replenishment solution has the lowest total cost.

Identify the features of each solution. What are the advantages of each solution?

### **LITERATURE REVIEW**

#### **The Forecasting Method W Company Use Currently**

Although moving-average has neither a scientific approach nor a theoretical foundation, it still the best of all for now. The current replenishment method used in the W company is to calculate the average of demands of the past eight weeks and times the summation of lead time and the adjustment factor. (1) When the amount of the available stock, which is equal to the end of week on hand stock plus the begin of week backlog and minus the order receivable, is less than amount of the safety stock, it will start the replenishment. Sending out an order which has the quantity equal to the difference between the safety stock and

the available stock. Contrarily, the quantity of the available stock is more than the quantity of the safety stock, nothing will happen. (2) It will repeat over and over until the data of the last week has been calculated.

$$S_t = \frac{\sum_{k=t-8}^{t-1} D_k}{8} (LT + r) \quad (1)$$

$$Q_t = \max(S_t - AS_t, 0) \quad (2)$$

Where  $S_t$  is the safety stock at time t, D is the demand from 8 to 1 weeks ago, LT is the lead time and r is the adjustment factor.

$Q_t$  is the order quantity at time t and  $AS_t$  is the available stock before ordering at time t. (Chou & Chuang, 2016) (Chou & Chuang, 2017)

### Model Specially Design for Intermittent Demand

The orders that W company received were intermittent, which means that most of the time the demands were zero. It is really reasonable because we don't have iPhone X presentation frequently, which means the demand of the semiconductor components is not frequently being. Due to this special demand pattern, we can't just take some recent demand to get an average to predict. There are some methods focus on this kind of question and here are five of them.

**Croston's Method:** separate actual demand into two parts, zero or not.

$$\text{If } X_t \neq 0 \text{ then } Z_{t+1} = \alpha X_t + (1 - \alpha)Z_t; V_{t+1} = \alpha q + (1 - \alpha)V_t; Y_{t+1} = \frac{Z_{t+1}}{V_{t+1}} \quad (3)$$

$$\text{If } X_t = 0 \text{ then } Z_{t+1} = Z_t; V_{t+1} = V_t; Y_{t+1} = Y_t \quad (4)$$

Where  $X_t$  is the actual demand at time t.  $Z_t$  is the estimate mean non-zero demand at time t.  $V_t$  is the estimate mean interval size between non-zero demand at time t.  $Y_t$  is the estimate mean demand size at time t.

**Discrete-Auto-Regressive-Moving-Average(DARMA) Model:** The combination of Auto-regressive and moving-average.

The auto-regressive part  $X_t = c + \sum_{i=1}^p \varphi_i X_{t-i} + \varepsilon_t$ . c is a constant,  $\varphi_i$  is a parameter of model and  $\varepsilon_t$  is the error.

The moving-average part  $X_t = \mu + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t$ .  $\mu$  is a constant and  $\theta_i$  is a parameter of model.

$$Y_t = V_t Y_{t-1} + (1 - V_t)Z_t \quad (5)$$

Where  $Y_t$  is the t-th values of the series,  $V_t$  is a random binary variable and  $Z_t$  is a random variable which value equals to  $\{0, 1, 2, \dots\}$

**Bootstrapping:** simultaneously consider demand before and stochastic variation.

$$Y_{jittered} = 1 + INT\{Y + Z\sqrt{Y}\} \quad (6)$$

$$\text{If } Y_{jittered} \leq 0 \text{ then } Y_{jittered} = Y \quad (7)$$

1. Use the demand data from past to estimate the transition probabilities for the Markov chain.
2. Produce a sequence of events from the Markov chain.
3. Replace the non-zero parts with data from past, and jitter them.
4. Sum up forecast values horizontally to get the lead time demand. (Daniel Waller, 2015]

## RESEARCH PLAN

Variables we use are beneath.

Table 1: definition of variables

t	number of weeks within data
SL_t	number of weeks that counts in calculating the service level
LT	Lead time of ordering.
num	Numbers of different kinds of demand.
D	Demand
r	Adjustment factor of ordering quantity.
r_upp	Upper limit of adjustment factor.
r_low	lower limit of adjustment factor.
r_incre	amount that adjustment factor increase.
m	Denominator of moving average.
FR	Fill rate, which is the lower limit of equal to (BOH+OR)/D.

OC	Ordering cycle.
AWU	Average weekly usage.
S	Amount of safety stock.
EOH[t]	End of week on hand stock at t week.
BOH[t]	Begin of week on hand stock at t week.
AS[t]	Available stock before ordering at t week.
BBL[t]	Begin of week backlog at week.
Q[t]	Order quantity at t week.
SL[r]	Service level in r Adjustment factor and demand, equal to number of $(BOH+OR)/D > FR$ divide by $SL_t$
Out_Of_Stock[r]	The total quantity of Out Of Stock.
Final_EOH[r]	EOH on last week

We assume that the demand is known and we separate them into two parts; first part for building model and second for testing. The orders before are all received so there is no beginning backlog at first.

The process of generating data:

1. Use the demand ( $D_{t-1-t-8}$ ) before to create safety stock.
2. Once the safety stock ( $S_t$ ) is less than available stock on hand before ordering ( $AS_t$ ), launch the replenishment. The order quantity ( $Q_t$ ) is equal to  $S_t$  minus  $AS_t$ .
3. Fulfill the demand with begin of the week stock on hand ( $BOH_t$ ) and the order receivable ( $OR_t$ ).
4. Update the begin of week stock on hand ( $BOH_t$ ), which equals to the end of week stock on hand last week( $EOH_{t-1}$ ).
5. Update  $EOH_t$ , which equals to the maximum value between  $(BBL_t + OR_t - D_t)$  and zero.
6. Update  $BBL_t$ , which equals to  $(BBL_{t-1} - OR_{t-1} + Q_{t-1})$
7. Update  $AS_t$ , which equals to  $(EOH_t + BBL_t - OR_t)$
8. Once  $D_t$  more than  $(BOH_t + OR_t)$ , save the difference in Out\_Of\_Stock<sub>t</sub>
9. When  $D_t > 0$  and  $(BOH_t + OR_t)/D_t > FR$ , increases Fullfill by one unit. The situation  $D_t = 0$  also increases Fullfill by one unit because it still satisfying the demand.

After testing Croston's method, Discrete-ARMA (DARMA) model and bootstrapping, we should compare them one by one. At first, calculating the quantity of each Final\_EOH times its own warehousing cost, we will get the total warehousing cost of all components we have. Second, calculating each Out\_Of\_Stock times its own cost of out of stock, we will get the total cost of out of stock of all components we have. Now we sum these two costs up and get the total cost. The one that has the lowest total cost is the optimal solution of our question. The following figure indicates the aforementioned steps.

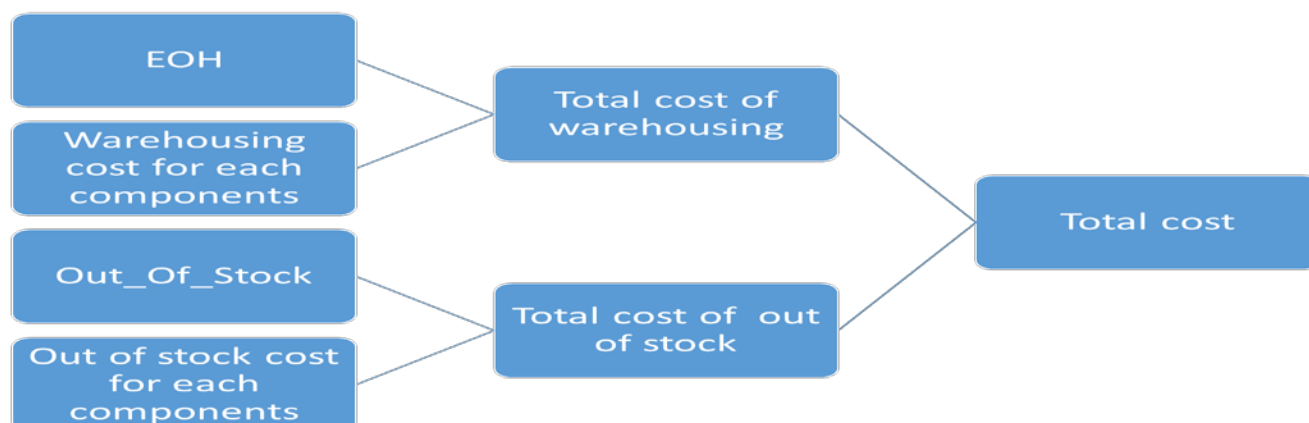


Figure 1: components of total cost

### EXPECTED CONTRIBUTION

We expect to find at least one model which produces lower total cost than the current one. Although the one that has the lowest cost is the optimal solution, we classify the advantages of other models. If the customers of W company have emergency order will change the constraints, we don't have to try all these models again. Instead, we can just choose the one that has the lowest total cost on that component(s). Eventually we will decrease the total cost and simultaneously maintain service level as good as that in the past.

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