# A Marketing Simulation of a Retail Store with the Consumer Reactions to Stock-outs 

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#### Abstract

In this study, we investigated the difference between sales estimations and actual demands and verified the effectiveness of sales promotions at the retail store, by using agent-based simulations. We developed a store and a customer model, which reflects the consumer reactions to stock-outs such as brand switches. As a result, the deviation between predictions and demands, and also losses of sales were surely observed. Moreover, we found that increasing the shelf capacity of product which tends to be the substitute doesn't necessarily minimize the total sales losses.


Keyword: Agent-based simulation, Demand estimation, Stock-outs, Brand Switches

## 1 Introduction

The occurrance of stock-outs is one of the risks in retail industry. To predict the demands, sales data such as point-of-sales (POS) data has been used. However, the losses of purchase opportunities in stock-outs situations are hardly considered in predictions, because sales data are recorded only when customers purchase some products. Actually the demand estimates almost mean the sales estimates, so retail stores are suffered from the lower sales than expected.
In this research, we investigated the deviation of sales forecasts from actual demands, and also verified the effects of sales promotions in the store, by using agent-based simulation.

## 2 Simulation Model

### 2.1 Store Model

A store, having shelves and back-rooms one-to-one correspondence with the goods, is defined. In every step, the store checks product stock levels, recalculates sales estimates and orders items if stock levels are below order thresholds. These sales estimates are calculated by exponential smoothing, estimates $S_{t}$ is expressed using previous estimates $S_{t-1}$ and sales $x_{t-1}$. Order threshold $k_{t}$ is also defined using sales estimates $S_{t}$ and standard deviation of sales $\sigma_{t}$ as below,

$$
\begin{gather*}
S_{t}=\alpha * x_{t-1}+(1-\alpha) * S_{t-1}  \tag{1}\\
k_{t}=S_{t}+\sigma_{t} \tag{2}
\end{gather*}
$$

The smoothing parameter $\alpha$ is fixed at $\alpha=0.9$ in this simulation. At the end of every step, the store receives new items if ordered in previous step. The lead-times of products are fixed at 2 steps, and the store doesn't make a new order before items arrive.

### 2.2 Customer Model

At the beginning of each step, customers are created and shuffled. According to previous research [1], customers take some actions when they encounter stock-outs. To simplify the model, we defined only "switchers" and "loyal customers", at the ratio of 6 to 4 . When stock-outs occur, switchers substitute the product for another from the same brand, and loyal customers leave the store without buying any product. Switchers confronted with stock-outs of alternative products and loyal customers met stock-outs for 2 times are to refrain from coming to the store, and they visit the store again with a probability of $25 \%$ in every step. The number of customers is given by the sales matrix, which represents sales of products and substitution rates, in reference to [2]. We created and used fictional data in this study.

## 3 Simulation Results

### 3.1 Losses of Sales

At first, we investigated the deviation of sales prediction from actual demands with 2 goods: A and B. We regarded 1 step as 1 day and calculated for 60 days. Capacities of shelves and back-rooms and the sales matrix of the case 1 are shown in table


Figure1: Result of case 1, deviation of sales and actual demands :Goods A

1. Figure 1 shows the result of case 1. The blue line shows the actual demands which are given by the sales matrix as the certain number through the simulation, and the red line shows the real sales. Certainly, the gaps between actual demands and real sales are observed. The losses of sales through day 31 to 60 are $38 \%$ of the actual demand.

| goods | shelf | backroom |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| A | 50 | 100 | goods | A | B |
| B | 50 | 100 | 50 | 80 |  |
| B | 80 | 50 |  |  |  |

Table 1: Specification of store and the sales matrix in case 1.

### 3.2 Verification of the Promotions

Secondly, we examined the effects of sales promotion, changing the size of each shelf when asymmetric item switches occur. We prepared a sales matrix of 4 products, shown in table 2 . The capacity of shelves and back rooms is also set as table 3. Figure 2 shows the losses of sales opportunity in case 2,3 and 4 . Contrary to expectations, it is found that sales losses of the case 4 are smaller than the case 3. This result implies that increasing the shelves' size of products which are likely to be alternatively purchased doesn't necessarily minimize the total sales losses.

## 4 Conclusion

In this research, we investigated the difference of sales estimates and actual demands, and the effect of sales promotion. As a result, we found that there are certain limits in sales predictions. Besides, it was found that expanding the shelves of substitute goods doesn't always lead to minimize the sales losses. As future works, we would like to improve the simulation model more realistically, and use POS data and inventory data of actual stores.

| goods |  | A | B | C | D |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | A | 25 | 30 | 30 | 30 |  |
| B | 37 | 25 | 27 | 26 |  |  |
|  | C | 35 | 29 | 25 | 26 |  |
|  | D | 35 | 29 | 26 | 25 |  |
| goods | case2 |  | case3 |  | case4 |  |
|  | shelf | backroom | shelf | backroom | shelf | backroom |
| A | 35 | 70 | 50 | 100 | 25 | 50 |
| B | 35 | 70 | 40 | 80 | 30 | 60 |
| C | 35 | 70 | 25 | 50 | 40 | 80 |
| D | 35 | 70 | 25 | 50 | 45 | 90 |

Table 2: the sales matrix (upper table) and the specification of the store in case 2,3 and 4 .


Figure2: Comparison of losses of sales among case 2,3 and 4 .

## References

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