# Integration of Sales Forecast Model and (r,Q) Inventory Model for Perishable Products in Restaurant Scenarios

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## 1. INTRODUCTION

Inventory modeling has also been one of the most developed field of operations management and operational research journals. The term “deterioration” can relate to damage, spoilage, dryness, vaporization, etc. According to Goyal and Giri [1], products like foodstuff, green vegetables, which have a maximum usable lifetime, are known as perishable products. However, most existing studies on inventory modeling focus on one-period mathematical modeling [4], which might not be versatile enough to the changing demand patterns. This study refer to previous studies on restaurant sales forecast and inventory modeling [2], [3] to develop a combined model of sales prediction and inventory management, in which the forecast results are used to update inventory model parameters to achieve less total cost.

## 2. MODEL DESCRIPTIONS

We study a dynamic perishable inventory system. Products have a fixed lifetime of m units of time, after which they will be disposed if not consumed. The inventory is controlled under a (r,Q) policy. Parameter r, Q both have a fixed base by basic inventory theory and dynamic term directly correlated to sales prediction. We assume the model begins when a new order arrived (inventory level of r) and there is no decrease of value of products during its lifetime. The lead time L is assumed to be fixed and known. The inventory is depleted under FIFO policy. Notations also include fixed ordering cost K, holding cost per unit item per unit time h, purchase cost per unit c, outdated cost per unit w, lost sales cost per unit p.

### 2.1 Sales Forecast Model

Sales forecast model is developed based on studies of Austin and Kabir [2], in which the open source datasets are used to train the model and conclusions are used for feature selection and algorithms choosing. Models include LTSM, GRU, top NonRNN models from original study, and an additional transformer model is added for better performance and feature selection for NonRNN models.

The datasets contains sales data from 31 Dec 2017 to 1 Mar 2018, and we also used windowing and batching techniques to use past 14 days as a feature to predict the future 7 days sales. Other features includes time elements includes date, month, year, events like holidays, Christmas, time span functions like daily average, weekly average, etc. Top importance features are selected according to original study for efficiency MAE, MAPE are used as performance metric which can be verified to be the best one in this case, and the aggregation of chosen models and parameters turns out to be better than original study with MAE of 203 compared with 235.

### 2.2 Simulation for Optimal Solution

Refer to methods of Chaaben and Zied [3], simulations of solutions generated by scatter search and tabu search are conducted to obtain optimal (r,Q), which has the least total cost during 20000 sim time. However, the random demand generator of original study is a fixed gamma distribution with mean of 10 and cv^2 from 0.32 to 1, which firstly is not appropriate in this study because the forecast model result is timely dependent, which has worse performance in independent random number generation. Thus, we roughly fit the demand with three components: trend, weekly seasonality, holidays, and the function has R square of 0.25, which can be eligible for demand generator with noise term to ensure stochastic nature. Secondly, the scale and unit of demand generator regressed from studied datasets is not aligned with demand in simulation, which can lead to explosions in result. We solve it by multiplying the generated demand a scale factor, which decreases the values to certain extent for reasonable results. It can be verified because the relationship between overall sales and single ingredient demand is an aggregation of relationships between dishes and ingredients and relationships between sales and dishes, which are all linear and according to CLT, to certain scope, such relationships can be formulated as normal and transformed to be linear, which is the method used in this study.

Due to computational resources limitations, we run three scenarios with 3 different settings of K, c, p, w with 5 replications, with a python script. The results are shown in Table 1.

## 2.2 Simulation for Proposed Model

In the proposed model, the base part of parameter r, Q is calculated firstly with EOQ formula and expected lead time demand, then adjusted for perishbility by ensuring that the order quantity will not exceed life cycle demand. Then, in real situations, every 7 days a forecast will be processed and output next 7 days predicted sales, and the dynamic part is that the Q will adjust based on the error and values of prediction to align the r to be lead time demand and D to be life cycle demand.

In terms of actual implement, the IO might be tricky since the forecast model is too complicated to nest in another file. However, since the inventory control process is independent from demand series, the demand can be imported as a pre-generated array by the demand generation function into forecast model and the inventory behavior can be defined via the array output as forecast results. Thus, we can combine and align two models.

## 3. Results and Discussions

In the forecast model, the MAE of aggregation of models has a best value of 203, which is better than the best model of original study of 235.

In simulation, the results require discussion:

Table 1: Results of Simulations

| K | c | p | w | solution | optimal | proposed |
|---|---|---|---|---|---|---|
| 100 | 5 | 20 | 5 | (3.14, 16.29) | 298 | 0.1 |
| 100 | 15 | 20 | 5 | (4.24, 22.01) | 298 | 2 |
| 200 | 5 | 20 | 5 | (34.52, 169.94) | 298 | 10 |

The optimal column represents optimal cost obtained by optimal simulation and proposed means relative difference in total cost in percentage. Scale factor=829.59. Obviously, the last setting is not ideal compared with 3.8% of original mathematically model, it can be explained with variations of forecast model or the assumption of linear relationship cannot stand in certain circumstances. However, the simulation of original study with fixed distribution may not work well in real world where the demands are mostly changing and time dependent, which means our model may prevail with same differences

In the future, more scenarios can be explored, while the transformation can be more complex like normalization.

## 4. REFERENCES

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## 5. ACKNOWLEDGEMENTS

This research is funded by Swanson School of Engineering and Office of the Provost at the University of Pittsburgh.

Thanks to the instructions and support of Dr. Bo Zeng, we can conduct this study.