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# Developing Optimal Demand Forecasting Models for a Very Short Shelf-Life Item: A Case of Perishable Products in Online's Retail Business

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## Abstract

Demand forecasting is a crucial task for an online retail where has to manage daily fresh foods effectively. Failing in forecasting results loss of profitability because of incompetent inventory management. This study investigated the optimal performance of different forecasting models for a very short shelf-life product. Demand data of 13 perishable items with aging of 210 days were used for analysis. Our comparison results of four methods: Trivial Identity, Seasonal Naïve, Feed-Forward and Autoregressive Recurrent Neural Networks (DeepAR) reveals that DeepAR outperforms with the lowest MAPE. This study also suggests the managerial implications by employing coefficient of variation (CV) as demand variation indicators. Three classes: Low, Medium and High variation are introduced for classify 13 products into groups. Our analysis found that DeepAR is suitable for medium and high variations, while the low group can use any methods. With this approach, the case can gain benefit of better fill-rate performance.

Keywords : Demand Forecasting, Deep Learning, Perishable Products, Online Retail, Case Study

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## 1. Introduction

Demand forecasting is the process of predicting the demand for a product or service in the future. It is a crucial aspect of managing a retail business, as it allows businesses to plan their inventory and operations to meet the expected demand. However, demand forecasting can be especially challenging for businesses that sell perishable products, such as fresh food, meat, and vegetables, due to their limited shelf life and products tend to lose their value overtime they need to carefully manage inventory to avoid waste and excess costs.

In the present, retailers of perishable products include the need to accurately forecast demand to minimize waste and excess inventory costs, as well as the challenges of managing inventory in an environment with rapidly changing consumer demand. These problems can lead to lost opportunities for generating higher revenues and reduced profitability for the business. So, development of machine learning and deep learning models to predict possible demand will be a success key to manage inventory effectively. From author experience in managing inventory with pharmaceutical products found that inaccurate in demand forecasting can lead to oversupply and undersupply. Unnecessary supply in our inventory creates holding costs, on the other hand undersupply makes our company lose the opportunity to generate higher revenue. Therefore, the author would like to use data analytic techniques to forecast demand accurately and select proper inventory policy to manage inventory with maximum efficiency.

According to reasons above, author wants to study about forecasting models to create guidelines for anyone who interested in managing inventory using data analytics.

Objective

1. To optimize weekly demand forecasting model which suitable for perishable product using deep learning models and baseline models.
2. Minimizing loss from decayed goods and oversupply in inventory to improve profit.

Scope

1. The scope of data are 13 perishable products in total that are classified in meat category.
2. The scope of time in our study is 212 days of actual demand data, starting from January 1st, 2022 to July 31st, 2022. This provided a sufficient amount of data for training our forecasting models and allowed us to consider the weekly demand during the model training process.

Framework

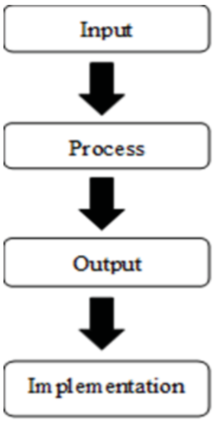
1. ***Input***: Historical demand data of perishable products past 7 months.
2. ***Process***: Classify products into 3 groups using CV (Coefficient of Variation) and training each forecasting model with specific product historical demand data.
3. ***Output:*** Demand forecasting values with 1-week horizons and model's performance compared with evaluation dataset.
4. ***Implementation:*** Implement demand forecasting in business scenario and result of using machine learning and deep learning models.

Benefit

1. Improved inventory management by developing a demand forecasting model

that is specifically tailored to perishable products, the study can help retailers better predict and plan for future demand, leading to improved inventory management and reduced costs associated with waste and excess inventory.

2. Enhanced profitability by minimizing losses from decayed goods and oversupply and maximizing revenues from accurate demand forecasting.




<Figure 1> A Framework Used in this Study

## 2. Literature Review

### 2.1 Perishable Products

Perishable products are products whose quality diminishes over time. These products can be further classified into two sub-categories: those with a fixed lifetime and those with a random lifetime. Products with a fixed lifetime, such as canned goods, bottled milk, and pharmaceutical products, have a known expiration date and do not deteriorate until that point. In contrast, products with a random lifetime, such as fresh vegetables, fruits, and blood in blood banks, experience continuous deterioration and must be sold as soon as possible to avoid waste [Madduri, 2009]. The importance of accurate demand forecasting in managing inventory for perishable products has been discussed, as well as the use of time-series forecasting techniques, including traditional methods and neural networks to improve the performance of predictions and reduce forecasting errors.

### 2.2 Demand Forecasting

Forecasting is an essential tool for predicting future values, and it involves the use of historical data combined with mathematical techniques to increase the accuracy of the predictions [Intipeek, 2018]. Demand forecasting is particularly crucial in business planning, as it enables businesses to plan their inventory and operations to meet the expected demand. For companies in the perishable products industry, accurate demand forecasting is even more critical as these products have a short shelf-life and can quickly lose value over time. By having an accurate forecast, companies can minimize waste and excess inventory costs, while maximizing revenue opportunities.

The process of demand forecasting typically falls into three categories: short-horizon forecasting, which predicts values within a three-month period; medium- horizon forecasting, which predicts values between three months and one year; and long-horizon forecasting, which predicts values more than three years into the future [Intipeek, 2018]. In [Barbosa, 2015], the authors use demand forecasting and visualized the results using Minitab software to demonstrate how a food company can use monthly sales predictions to plan their production line, this study show that accurate forecasting is essential for managing inventory.

### 2.3 Time-series Forecasting Technique

In addition to traditional time-series forecasting methods, such as Naïve Forecast and Moving Average which calculated future value based on previous period and season [Sharma, 2015], more advanced techniques like Neural Networks (NNs) are being increasingly used in the field of demand forecasting. NNs, which are modeled after the human brain, can analyze large amounts of historical data and make predictions by processing this data through multiple layers, including an input layer, a hidden layer, and an output layer [Yemane, 2021]. The use of NNs in demand forecasting has been shown to improve the performance of predictions and reduce forecasting errors. For example, in [Intipeek, 2018], Watcharachai used the Moving Average method and other traditional forecasting techniques to predict customer demand for a duck processing factory. In [Yemane, 2021], researchers predicted solar energy production using a Seasonal Naive model, which was compared to deep learning-based time- series forecasting methods, demonstrating the improved performance of these techniques. In [Ghiassi et al., 2008], demand forecasting was done using a feed forward neural network model (NN base model) to predict urban water demand and the study showed that Autoregressive Recurrent Neural Network (DeepAR) had better performance in forecasting energy production [Sharma, 2015].

### 2.4 Performance Metrics

The selection of an appropriate metric for evaluating performance in forecasting is crucial for drawing meaningful conclusions from the results. Many metrics have been proposed and used in different areas of research, but some are more commonly used than others. Studies have been conducted to understand the frequency of use or importance of different metrics among organizations and practitioners. These studies have identified a variety of metrics, but the three most used metrics that have been consistently identified across multiple studies over 25 years are the mean square error (MSE) or root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) [Botchkarev, 2019]. In this study we will focus on using MAPE since it is scale independent and easy to compare with several models.

## 3. Method

In this research we are using "Dataiku" as a platform to do all data preparation, baseline models and deep learning algorithm.

### 3.1 Data preparation

Data preparation is a crucial step in research methodology, as it lays the foundation for the analysis and modeling to come. In this study, we will **sum up historical demand data of perishable products for the past 210 days to 30 weeks** as our primary source of data. This data will be used to classify the products into 4 groups using the Coefficient of Variation (CV) method, which will serve as a basis for our forecasting models.

We will also be performing data cleaning and transforming to ensure that the data is in a format that is suitable for our models. This includes removing any missing or duplicate values and removing unnecessary features. The data will be split into training and evaluation datasets, with the evaluation dataset being used to measure the performance of our models. By following a thorough data preparation process, we aim to ensure that our models are as accurate and reliable as possible.

### 3.2 Data Characteristics

After data preparation, we classifies the products into 3 groups based on their weekly demand variation using CV (Coefficient of Variation).

Formula as follow:

The given rules used to classify are:

- CV 〈= 0.3: low
- 0.3 〈 CV 〈= 0.6: Medium
- CV 〉 0.6: High

### 3.3 Technique

Time-series forecasting models.

1. Trivial Identity
2. Seasonal Naïve
3. Simple Feed Forward
4. Autoregressive Recurrent Neural Network (DeepAR)

**Performance metric**: use the mean absolute percentage error (MAPE) as a performance metric to evaluate the performance of demand forecasting models.

Formula as Follow:

### 3.4 Model configuration

1. Given the perishable nature of our products, and the need to minimize waste and excess inventory costs, we set the **forecasting horizon at 1 week.** This allowed us to anticipate future demand and make informed decisions on inventory management in a timely manner, to make the most efficient use of our products.
2. For configuration of **Seasonal Naïve** model, we set the **seasonal length 2 weeks**, as our perishable product data was in the meat category, and we observed a significant demand change every 1 or 2 weeks in our data.

| | |
|---|---|
| Seasonal length | 2 weeks |

3. For configuration of our deep learning models in 〈Table 1〉, we used a batch size of 1 and 10 epochs. This meant that our algorithm would work through the entire training dataset 10 times, with each sample being processed in a separate batch. This resulted in the model weights being adjusted 300 times during the training process, as our dataset contained 30 weekly historical demand samples. By using this configuration, we aimed to optimize the models' ability to learn and adapt to the data. We also use dropout as a regularization technique to prevent overfitting and underfitting of our models. Dropout works by randomly setting a certain percentage of neurons to zero during training. This forces the model to learn multiple independent representations of the input data, rather than relying on a small number of neurons. This makes the model less likely to overfit the training data. In our study, we will use a dropout rate of 0.8, which is a typical value used in practice [Srivastava et al., 2014]. This means that during training, 80% of the neurons will be kept and 20% will be dropped out. This will prevent the model from overfitting the training data and improve the generalization performance on unseen data.

〈Table 1〉 Deep Learning Models Configuration

| | |
|---|---|
| Learning rate | 0.0001-0.1 (Search size = 20) |
| Batch size | 1 |
| Epochs | 10 |
| Batch per epochs | 30 |
| NN layer | 2 |
| Cell per layer | 40 |
| Dropout | 0.8 |

## 4. Splitting Strategy

To evaluate the performance of our forecasting models, we will use a K-fold cross-validation method. In this method, the data is randomly divided into k subsets, or "folds", with each fold containing approximately the same number of data points [Oneto, 2012]. The model is then trained on k-1 of the folds and evaluated on the remaining fold. This process is repeated k times, with a different fold being used as the test set in each iteration. The final performance of the model is calculated as the average performance across all k iterations.

In our study, we will use a 6-fold cross-validation, with each fold containing 20% of the data. This means that the model will be trained on 80% of the data and evaluated on the remaining 20% in each iteration. By using this method, we will be able to evaluate the model's performance on different subsets of the data, which will provide a more robust estimate of the model's performance.

## 5. Result

In this study, we examined the effectiveness of different demand forecasting models for perishable products in retail business. Our analysis of 30 weeks of demand data for 13 perishable products revealed several demand patterns in their characteristics. In the following sections, we present the results of our analysis in detail, including the performance of the various forecasting models that we tested. The results of our study have important implications for inventory management and profitability in the perishable products industry, and we discuss these implications in the later section of the paper.

### 5.1 Product Classification

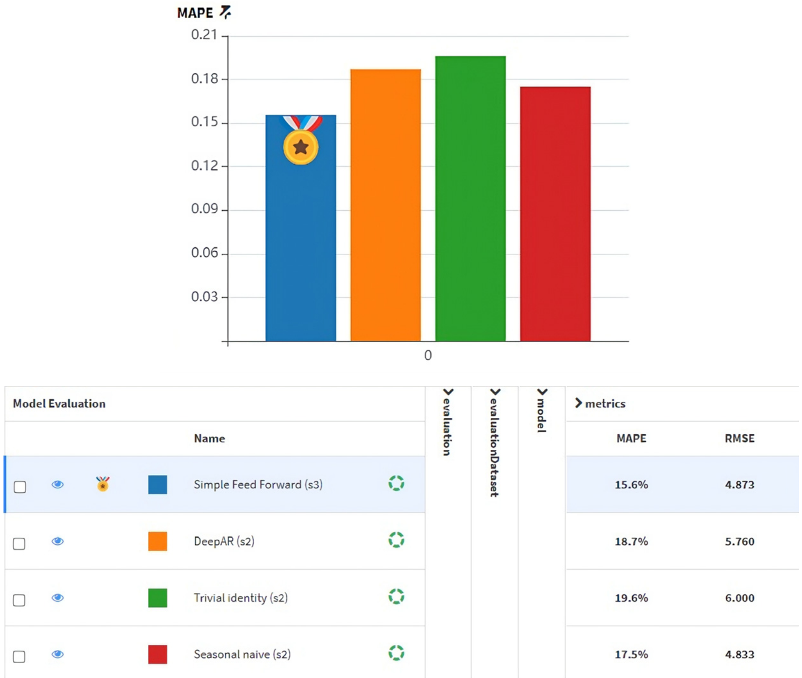
Based on the coefficient of variation (CV) of their weekly demand, our 13 perishable products were classified into three groups: low, medium, and high in 〈Table 2〉.

〈Table 2〉 List of Products and CV Groups

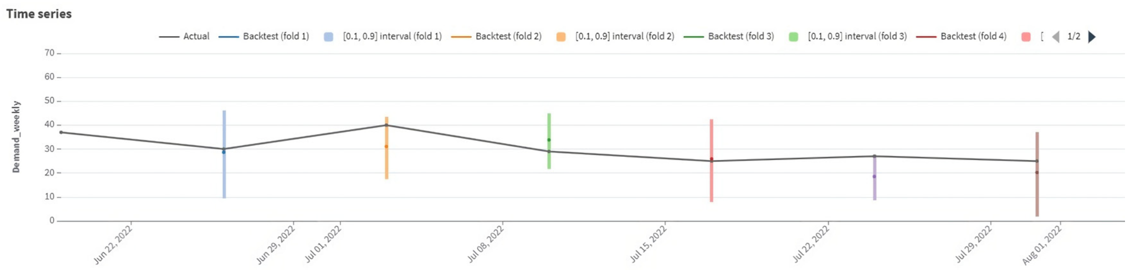
| Group | Products | CV |
|---|---|---|
| low | M3820 | 0.2294 |
| low | M7894 | 0.2621 |
| low | M6138 | 0.2785 |
| low | M3715 | 0.2821 |
| medium | M7325 | 0.3463 |
| medium | M3729 | 0.3725 |
| medium | M1890 | 0.3821 |
| medium | M2806 | 0.3832 |
| medium | M7198 | 0.3958 |
| medium | M6786 | 0.4264 |
| medium | M7635 | 0.5302 |
| medium | M6788 | 0.5528 |
| high | M2917 | 1.1020 |

## 6. Model Performance

In this study, we will analyze the performance of the models for all perishable products in each group using the Mean Absolute Percentage Error (MAPE) as performance metric. 〈Figure 2〉. shows example detailed of all model performance for product M7894 and 〈Figure 3〉. shows model evaluation compare forecasting value and actual value in each




〈Figure 2〉 Model's Performance of Product M7894




〈Figure 3〉 Forecast Values vs Actual Values of M7894

fold using line chart.

***Model performance of models for all perishable products in "Low" group***

〈Table 3〉 MAPE of Each Product in Low Group

| Product | Trivial Identity | Seasonal Naïve | Feed Forward | DeepAR |
|---|---|---|---|---|
| M3715 | 38.4% | 38.5% | 44.9% | **37.4%** |
| M3820 | **22.9%** | 24.5% | 26% | 24.2% |
| M6138 | 13.7% | **13.6%** | 17.2% | 13.8% |
| M7894 | 19.6% | 17.5% | 15.6% | 18.7% |

The results are shown in 〈Table 3〉, all the models have similar performance across all products in the "Low" group. The MAPE values for the Trivial Identity model, the Seasonal Naïve model, the FeedForward model, and the DeepAR model are relatively similar for all products in this group.

For example, product M3820, the Trivial Identity model has a MAPE of 22.9%, the Seasonal Naïve model has a MAPE of 24.5%, the FeedForward model has a MAPE of 26%, and the DeepAR model has a MAPE of 24.2%. For product M7894, the Trivial Identity model has a MAPE of 19.6%, the Seasonal Naïve model has a MAPE of 17.5%, the FeedForward model has a MAPE of 15.6%, and the DeepAR model has a MAPE of 18.7%

These results show that the demand for products in the "Low" group is relatively stable and predictable, and all the models can capture this regularity and produce similarly accurate forecasts.

***Model performance of models for all perishable products in "Medium" group***

〈Table 4〉 MAPE of Each Product in medium group

| Product | Trivial Identity | Seasonal Naïve | Feed Forward | DeepAR |
|---|---|---|---|---|
| M1890 | 36.7% | **22.9%** | 54.7% | 24.4% |
| M2806 | 45.3% | 52.6% | 35.5% | **33.5%** |
| M3729 | 22.7% | 22.6% | 46.1% | **17.3%** |
| M6786 | 36% | 35.5% | 55% | **27.7%** |
| M6788 | 21% | **17.2%** | 66.3% | 17.5% |
| M7198 | 17.6% | 17.6% | 31.3% | **17%** |
| M7325 | 27.3% | 31.5% | 29.8% | **22%** |
| M7635 | 25.7% | 43.5% | 28.2% | **22.6%** |

The results show in 〈Table 4〉, the Trivial Identity and Seasonal Naive models still maintain their performance at a proper level. However, in the medium group, the DeepAR model has the highest performance across all products, except for products M1890 and M6788 which Seasonal Naïve has slightly better performance. For example, for product M1890, the Trivial Identity model has a MAPE of 36.7%, the Seasonal Naïve model has a MAPE of 22.9%, the Feed Forward model has a MAPE of 54.7%, and the DeepAR model has a MAPE of 24.4%.

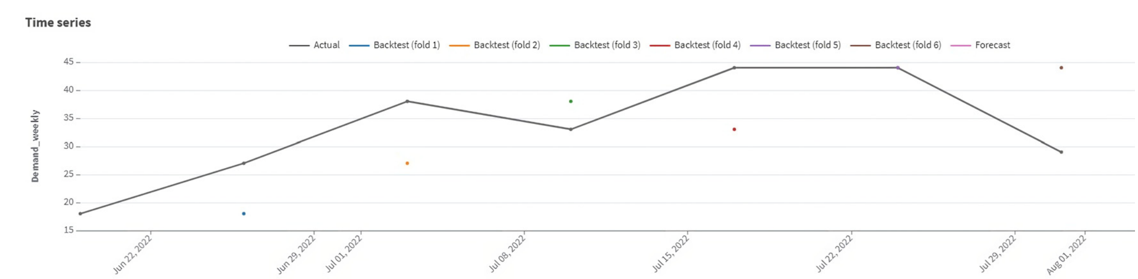
The result is obvious that demand in the "Medium" group is less stable than "Low" group, and more fluctuation in demand, but the DeepAR model has a better performance in capturing this regularity and produces more accurate forecasts than other models.

***Model performance of models for products M2917 in "High" group***

〈Table 5〉 MAPE for Product M2917

| Product | Trivial Identity | Seasonal Naïve | Feed Forward | DeepAR |
|---|---|---|---|---|
| M2917 | **25.7%** | 42.9% | 47.1% | **29.1%** |

From 〈Table 5〉, we can see that the Trivial Identity model has a MAPE of 25.7%, the Seasonal Naive model has a MAPE of 42.9%, the Feedforward model has a MAPE of 47.1%, and the DeepAR model has a MAPE of 29.1%.




〈Figure 4〉 Forecasting Value vs Actual Value of Product M2917

This suggests that for product M2917 in the "High" group, the demand is highly volatile and unpredictable, and none of the models performed well, except for the DeepAR model and Trivial Identity which is our baseline model that has the lowest MAPE among the other 2 models. In this case the DeepAR model can capture the complex patterns and fluctuations in demand for this product more accurately than the other models while Trivial Identity shown that last 6 period demand pattern for product M2917 does not fluctuate like it does before from 〈Figure 4〉.

## 7. Discussion

In this study, we developed demand forecasting models for perishable products in a retail business using baseline models and deep learning models. Our results showed that the performance of the forecasting models varied depending on the product group, with the DeepAR model performing the best overall.

It can be concluded that for most perishable products especially in "Medium" group, DeepAR model has the highest performance compared to other models, and it could be considered as the best model for this category. Since in "Low" group, all models perform similar performance and in "High" group we have only 1 product which we need to study further about models that suitable for perishable products in this group.

The findings of this study indicate that accurate demand forecasting is crucial for managing inventory in the retail business of perishable products. By using the appropriate model for each product group, retailers can minimize waste and excess inventory costs while maximizing revenue opportunities. Our results also suggest that deep learning models such as DeepAR have the potential to improve the performance of demand forecasting for perishable products.

However, it is worth noting that this study has some limitations. For example, we only used data from a single retail business and the results may not be generalizable to other retail businesses. Additionally, our study only focused on weekly demand, future research can be done to expand the forecasting horizon. This study provides evidence for the importance of accurate demand forecasting for managing inventory in retail businesses of perishable products. The results suggest that deep learning models such as DeepAR have the potential to improve the performance of demand forecasting and provide guidelines for anyone interested in managing inventory using data analytics.

## 8. Conclusion

In conclusion, the study aimed to develop and optimize demand forecasting models for perishable products in a retail business. Through data preparation, classification of products into groups, and implementation of various time-series forecasting models, we were able to achieve this goal. Our results showed that the use of deep learning models, specifically the DeepAR model, resulted in the highest performance for forecasting demand for perishable products in the high and medium groups. However, for products in the low group, all models performed similarly.

In our study, we have divided our implementation into two distinct areas: improving financial performance and enhancing service levels.

〈Table 6〉 Cost and Markup for Each Product

| Product | Cost | Holding cost | Markup |
|---|---|---|---|
| M2917 | 64.00 | 6.40 | 32.00 |
| M2806 | 168.67 | 16.87 | 84.33 |
| M7894 | 59.33 | 5.93 | 29.67 |
| M1890 | 806.67 | 80.67 | 403.33 |
| M6786 | 131.33 | 13.13 | 65.67 |
| M3729 | 80.00 | 8.00 | 40.00 |
| M7198 | 148.00 | 14.80 | 74.00 |
| M3715 | 83.33 | 8.33 | 41.67 |
| M3820 | 68.67 | 6.87 | 34.33 |
| M6138 | 140.00 | 14.00 | 70.00 |
| M6788 | 130.00 | 13.00 | 65.00 |
| M7325 | 260.00 | 26.00 | 130.00 |
| M7635 | 30.00 | 3.00 | 15.00 |

## 8.1 Financial Performance

〈Table 7〉 Lower, Average and Upper Forecast for Each Product

| Product | Lower forecast | Avg. Forecast | Upper forecast |
|---|---|---|---|
| M2917 | 26.54 | 34.00 | 41.47 |
| M2806 | 10.82 | 13.83 | 16.84 |
| M7894 | 22.099 | 26.50 | 30.90 |
| M1890 | 15.83 | 18.00 | 20.17 |
| M6786 | 25.07 | 28.33 | 31.59 |
| M3729 | 26.53 | 29.33 | 32.13 |
| M7198 | 82.32 | 97.50 | 112.68 |
| M3715 | 20.57 | 25.67 | 30.77 |
| M3820 | 43.673 | 51.33 | 58.987 |
| M6138 | 179.94 | 188.00 | 205.05 |
| M6788 | 96.62 | 109.83 | 123.04 |
| M7325 | 46.9 | 55.50 | 64.1 |
| M7635 | 32.47 | 43.33 | 54.19 |

We postulate that if companies do not utilize forecasting methods and maintain inventory levels that deviate by more than 10% from the predicted lower and upper bounds as shown in 〈Table 7〉, they will incur both cost and opportunity losses for each product as detailed in 〈Table 8〉.

〈Table 8〉 Cost and Opportunity loss for Each Product

| Product | Cost | Opportunity loss |
|---|---|---|
| M2917 | 291.95 | 84.93 |
| M2806 | 769.41 | 223.82 |
| M7894 | 270.66 | 78.74 |
| M1890 | 3679.77 | 1070.45 |
| M6786 | 599.10 | 174.28 |
| M3729 | 364.94 | 106.16 |
| M7198 | 675.13 | 196.40 |
| M3715 | 380.14 | 110.58 |
| M3820 | 313.24 | 91.12 |
| M6138 | 638.64 | 185.78 |
| M6788 | 593.02 | 172.51 |
| M7325 | 1186.04 | 345.02 |
| M7635 | 136.85 | 39.81 |

As detailed shown in 〈Table 8〉, if the company has a total of 13 perishable products that will result in significant costs for holding inventory and wasted products if the inventory level is kept too high. This cost is estimated at ฿9,898 per week. Additionally, if the inventory level is kept too low, the company will also experience opportunity loss, estimated at ฿2,879 per week.

## 8.2 Enhancing Service Level

Our analysis shows that if the company follows a policy of maintaining a fill rate of at least 95%, there are 6 products out of 13 that fall below this standard, as seen in 〈Table 9〉. This indicates a potential opportunity loss and can't satisfy customer needs for the company.

To ensure that the company meets its fill rate policy of being greater than or equal to 95%, we recommend using the upper forecast values rather than the forecast values presented in 〈Table 10〉. This will allow the company to maintain a higher fill rate and avoid any potential losses and improve their service level.

〈Table 9〉 Fill Rate for Each Product

| Product | Forecast | Actual demand | Fill rate |
|---|---|---|---|
| M2917 | 34.00 | 35.83 | 94.88% |
| M2806 | 13.83 | 18.33 | 75.45% |
| M7894 | 26.50 | 29.33 | 90.34% |
| M1890 | 18.00 | 17.50 | 102.86% |
| M6786 | 28.33 | 27.50 | 103.03% |
| M3729 | 29.33 | 32.67 | 89.80% |
| M7198 | 97.50 | 104.00 | 93.75% |
| M3715 | 25.67 | 30.00 | 85.56% |
| M3820 | 51.33 | 52.67 | 97.47% |
| M6138 | 188.00 | 166.83 | 112.69% |
| M6788 | 113.33 | 109.83 | 96.91% |
| M7325 | 55.50 | 53.33 | 104.06% |
| M7635 | 43.33 | 40.83 | 106.12% |

〈Table 10〉 Fill Rate for Each Product Using Upper Forecast Values

| Product | Upper Forecast | Actual demand | Fill rate |
|---|---|---|---|
| M2917 | 41.47 | 35.83 | 115.73% |
| M2806 | 16.84 | 18.33 | 91.85% |
| M7894 | 30.9 | 29.33 | 105.34% |
| M1890 | 20.17 | 17.50 | 115.26% |
| M6786 | 123.04 | 27.50 | 108.56% |
| M3729 | 32.13 | 32.67 | 98.36% |
| M7198 | 112.68 | 104.00 | 108.35% |
| M3715 | 30.77 | 30.00 | 102.57% |
| M3820 | 58.987 | 52.67 | 112.00% |
| M6138 | 205.05 | 166.83 | 122.91% |
| M6788 | 31.59 | 109.83 | 114.87% |
| M7325 | 64.1 | 53.33 | 120.19% |
| M7635 | 54.19 | 40.83 | 132.71% |

By applying the upper forecast values in place of the forecast values, the company's fill rate surpasses its policy for 12 out of 13 products, thus enhancing customer satisfaction and improving overall service level.

Overall, the study provides valuable insights for retailers of perishable products, as it demonstrates the benefits of using advanced forecasting models and techniques to improve inventory management and increase profitability. In addition, it highlights the importance of considering product characteristics and variation in demand when developing forecasting models, as this can greatly affect their performance. As an extension of this research, it would be beneficial to test the developed models on different product groups, and to consider other factors such as weather, economic conditions, and promotional activities that may impact demand.

In summary, the study proposed an effective forecasting model for perishable products and provided a practical guideline for retailers. Implementing the developed model and inventory policy will improve inventory management and increase profit.

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## Author Profile

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Wiwat holds a bachelor's degree in business administration (BBA) with a concentration in Supply Chain and Logistic Management. With a passion for data analysis and process improvement, Wiwat has accumulated valuable work experience in the pharmaceutical industry, where he successfully managed inventory and implemented process enhancements over a period of two years. While pursuing M.S. degree in Management of Analytics and Data Technologies at the prestigious National Institute of Development Administration (NIDA), Wiwat further honed his analytical skills by working as an analytic facilitator for Datacafe, a part-time role that allowed him to contribute his expertise in data analysis. Currently, Wiwat holds a full-time position as a data analyst and system designer in a hemp extraction company, where he continues to leverage his talents to optimize operations and drive efficiency.

Songwut Ahmornahnukul

Songwut Ahmornahnukul is a scholarship holder and graduate with a master's scholarship from the Graduate School of Applied Statistics (GSAS), National Institute of Development Administration (NIDA), Thailand. And, a Bachelor of Science from the School of Information Technology, King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand. Songwut has work experience in management trainee in Retail, Marketing, Supply Chain, Finance, Accounting and Human Resource Management at Charoen Pokphand Group Company, Ltd. He is currently Manager and Data Scientist at the Management of Analytics and Data Technologies Center, GSAS, NIDA. His current research interests include data science, data management, data simulations, business analytics.

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Akkaranan Pongsathornwiwat is currently working as a full-time faculty member in Graduate School of Applied Statistics, National Institute of Development Administration (NIDA), Thailand. He received the B.S. degree in petrochemicals and polymeric materials form Silpakorn University, and M.S. degree in Industrial Engineering from Chulalongkorn University, Bangkok, Thailand, in 2007 and 2010, respectively. He received his Ph.D. in Knowledge Science from Japan Advanced Institute of Science and Technology, Nomi, Japan, in 2016 and another Ph.D. in Engineering and Technology from Sirindhorn International Institute of Technology, Thammasat University, Thailand in 2018 under SIIT-JAIST-NECTEC Dual Doctoral Degree scholarship. His current research interests include multiple criteria decision making under uncertainty and its applications, information integration and computational intelligence, engineering management and supply chain management, and applications of operations research.