Nano World Journal

https://doi.org/10.17756/nwj.2023-s1-002

Research Article

Open Access

# Warehouse Product Demand Forecasting Using Time Series Methods

**Sayali Bora*** **and Pushpak Bhonde**

*Symbiosis Statistical Institute, Symbiosis International (Deemed University), Pune, Maharastra, India*

***Correspondence to:**
Sayali Bora
Symbiosis Statistical Institute, Symbiosis International (Deemed University)
Pune, Maharastra, India.
**E-mail:** borasayali11@gmail.com

**Received:** November 24, 2022
**Accepted:** March 04, 2023
**Published:** March 07, 2023

**Citation:** Bora S, Bhonde P. 2023. Warehouse Product Demand Forecasting Using Time Series Methods. *Nano World J* 9(S1): S6-S9.

**Copyright:** © 2023 Bora and Bhonde. This is an Open Access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CCBY) (http://creativecommons.org/licenses/by/4.0/) which permits commercial use, including reproduction, adaptation, anddistribution of the article provided the original author and source are credited.

Published by United Scientific Group

## Abstract

Forecasting plays an essential role in supply chain operations as a lot of critical decisions are dependent on predicted future factors like product demand and sales. It may be necessary to make forecasts years in advance or only a few minutes. Forecasting is a crucial tool for efficient and productive planning, regardless of the situations or time frames involved. Given the significance of warehouses in supply chains, warehouse operations must be productive and profitable. Accurate projections not only help to reduce discrepancies between actual and anticipated sales, but they can also have an impact on other supply chain issues, such as managing excess and obsolete inventories. This paper showcases a comparative analysis of two time series models- Holt-Winters Smoothing Method and Seasonal ARIMA or SARIMA, for better prediction of fluctuating demand of products which in turn will contribute to the company's betterment in multiple ways.

## Keywords

Time Series, Forecasting, Demand, Prediction, Accuracy

## Introduction

Businesses are dealing with more ambiguous demands in numerous industrial scenarios. In order to transport goods over a vast geographic area as client markets become more global, supply chains are becoming more dependent on sophisticated logistical systems. In most firms, operational process optimization is crucial for enabling data-driven decision making, which is made possible through forecasting. Outside of the retail use-case, the rising amount of online, time-stamped activity offers data scientists and analysts a critical new chance to track the overall course of significant social, economic, and other evolutions. In light of ever-growing data sets, the most basic requirements are the effective and successful forecasting of massive time series sequences. Time series analysis refers to techniques for deriving useful statistics and other aspects of time series data through analysis. The process of deploying a model for time series forecasting is to forecast future values based on values that have already been observed.

In the manufacturing industries, warehouses are generally confronted with highly seasonal demand patterns. The service quality provided to clients and the subsequent warehouse performance are driven by personnel capacity. The primary methods to ensure order fulfilment processes are completed on time are workload forecasting and scheduling item production. One must precisely estimate future demand in order to optimize production, necessitating the creation of an accurate model. In this study, various time series models will be compared based on their accuracy measures.

## Literature Review

The primary component of business process optimization is time series forecasting. Faloutsos discussed how classical modelling of time series, scalable tensor methods, and deep learning for forecasting could be used to forecast future demand [7]. Keung discovered how applying machine learning algorithms can be used to acquire a better correlation in forecast and attribute linkages may be obtained [9]. He also discovered that location factors and product category have been determining fluctuating sales or noticeable delays. An artificial neural network was also suggested based on a multilayer feed-forward neural network with backpropagation to forecast demand [6]. The author of [8] explained how a time-series method could be utilised to look into trends as well as seasonal and cyclical elements that can affect the demand for a specific product. Time-series analysis can be done using a number of techniques, such as naïve or random walks, moving averages, exponential smoothing, decomposition, and ARIMA [5]. Aburto and Weber have presented a series of hybrid intelligent systems combining ARIMA and neural networks for demand forecasting [2]. A sophisticated forecasting system was also proposed which was made up of two parts: a statistical pattern recognition process and a variety of exponential smoothing-based forecasting models [4]. The strengths and weaknesses of the moving average, simple exponential, Holt two-parameter, and Holt–Winters methods were detailed by Chase [3].

After the literature review, it was observed that there was a lack of comparison between different models for warehouse demand forecasting. An optimal model can only be selected when it is compared with other models, so in this study, we build various time series models for warehouse demand forecasting and compare them using different types of accuracy measures.

## Materials and Methods

This dataset contains information that was recorded from January 2011 to January 2017 for warehouses, and product categories. The company provides a lot of products with more than 30 categories. Four primary warehouses are available for product shipping within the area it oversees. Initially, the data was cleaned and since the amount of missing data was just about 1.07% of the total, the rows were eliminated. The top two product categories that contributed the most to the overall demand were taken into consideration after calculating the category-by-category contribution. The data were then resampled on a monthly basis, and time series data were decomposed in order to examine all of its components. This was followed by stationarity tests for the data. Lastly, taking into account the seasonality component, appropriate models were fit, and accuracy measures were calculated to suggest an optimal model for forecasting.

## Results and Discussion

The demand for all product categories (all four warehouses combined) was calculated and their contribution percentage was plotted. It was observed from figure 1 that 90.29% of demand is from the products labelled as Category_019 and Category_006.

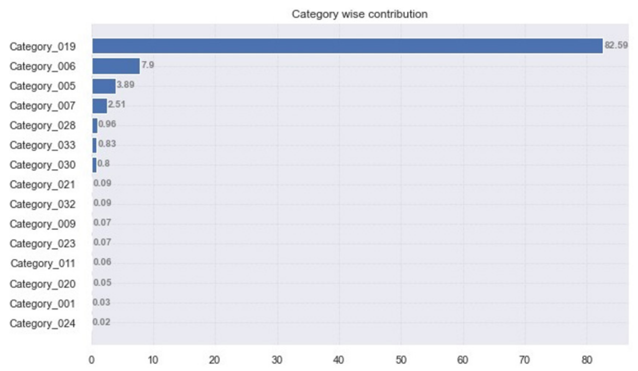


**Figure 1:** Contribution (in %) of the product category in demand.

Considering the contribution percentage of the products, only the top 2 categories i.e., Category_019 and Category_006 were considered for further analysis. A time series is divided into numerous components using a process called time series decomposition. To get a better understanding of the components of time series, decomposition of the time series data was done. Each component represents a pattern category, trend, seasonality, and noise that underlies the time series.

From figure 2 and figure 3 it was observed that both the product Category_019 and Category_006 data had a non-linear increasing trend along with seasonality.

To confirm the stationarity of the data, the following two tests were conducted.

a) Augmented Dickey–Fuller (ADF) test

   Null Hypothesis ($H_0$): Data has a unit root and is non-stationary.

   Alternate Hypothesis ($H_1$): Data does not have a unit root and is stationary.

b) Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

   Null Hypothesis ($H_0$): The data is stationary.

   Alternate Hypothesis ($H_1$): The data is non-stationary.

From table 1 for Category_019, the ADF test concludes non-stationarity, the KPSS test concludes stationarity. In this case, the series is said to be trend stationary. On the other hand, both tests suggest stationarity for Category_006.

Considering the seasonality component of the time series, as seen in figure 2 and figure 3, the following two models were fitted. For Category_019 Holt-Winters' model and Seasonal

**Table 1:** Results for stationarity tests.

| | | |
|---|---|---|
| ADF TEST | | |
| Category_019 | p value: 0.72 | Result: Data has a unit root and is non-stationary |
| Category_006 | p value: 0.009 | Result: Data has no unit root and is stationary |
| KPSS TEST | | |
| Category_019 | p value: 0.39 | Result: The data is stationary |
| Category_006 | p value: 0.08 | Result: The data is stationary |

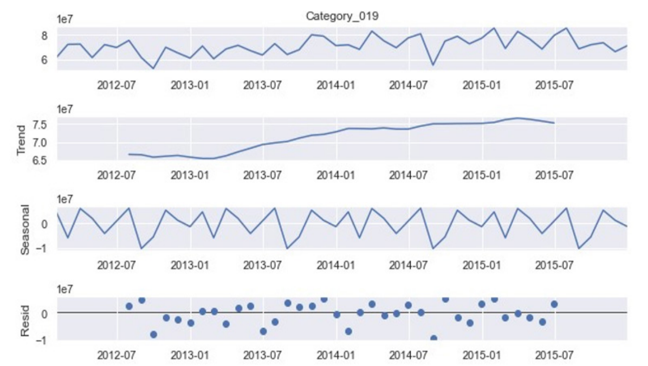

**Figure 2:** Decomposition plot for product Category_019.

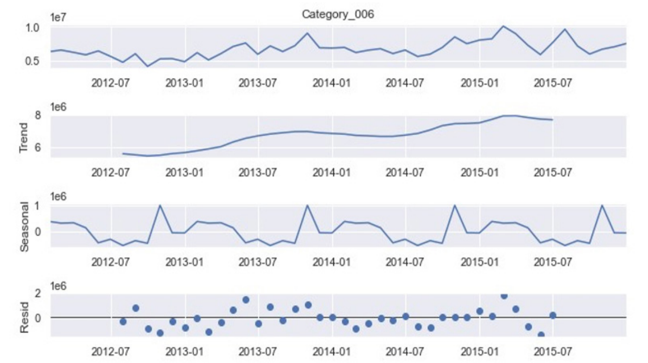

**Figure 3:** Decomposition plot for product Category_006.

ARIMA or SARIMA model. [SARIMA (0,1,2) (0,1,0,12)] similarly for Category_006 Holt-Winters' model and Seasonal ARIMA or SARIMA model. [SARIMA (0,0,1) (0,1,0,12)].

The data was split into 80% training and 20% testing sets and accuracy measures were calculated. The accuracy measures of the models can be seen in table 2 and table 3 for Category_019 and Category_006 respectively.

From table 2 and table 3 it was observed that the SARIMA model had lower AIC and BIC values. Also, the MAPE value was slightly lesser for the SARIMA model as compared to HW's model.

## Conclusion

Making the best business decisions requires the ability to forecast the future, not just the ability to analyse and comprehend historical facts. Data patterns are found through time series analysis, and these patterns can subsequently be used to forecast the upcoming demand for the required products. The primary distinction between warehouses and manufacturing facilities is the demand, which is highly variable daily and necessitates maximum flexibility. Rather than always using AI techniques, a simply applicable SARIMA model can reduce complexity, and make computation simpler. The above analysis suggests that the seasonal ARIMA model works with better accuracy as compared to Holt-Winter's model for the prediction of product demands at different warehouses. ARIMA captures seasonality much better here. It generally takes more than a month to ship goods by the ocean to various central warehouses, so it will be helpful to predict demand in advance. Since the warehouse environments are distinct from production environments due to the daily demand fluctuations, forecasting future demand by fitting the above model can help improve customer service and fulfil the required demand for the products.

**Table 2:** Accuracy measures for Holt-Winters and SARIMA model fitted for Category_019.

| Category_019 | Accuracy measures | | | | |
|---|---|---|---|---|---|
| Model Name | MAE | RMSE | MAPE | AIC | BIC |
| Holt-Winters | 9293974.92 | 10410939 | 0.13 | 1536.80 | 1566.74 |
| SARIMA | 5331573.56 | 6947122 | 0.07 | 1226.31 | 1230.98 |

**Table 3:** Accuracy measures for Holt-Winters and SARIMA model fitted for Category_006.

| Category_019 | Accuracy measures | | | | |
|---|---|---|---|---|---|
| Model Name | MAE | RMSE | MAPE | AIC | BIC |
| Holt-Winters | 1637630.38 | 1812914 | 0.255 | 1373.60 | 1403.53 |
| SARIMA | 1594927.65 | 1856554 | 0.23 | 1127.15 | 1130.31 |

## Limitations and Further Scope

There is no model which perfectly fits the data, so we have to consider an optimal model with lower error rates. The test data is not sufficiently large, so the accuracy measures may vary for actual forecasts. Additional models that better capture seasonality and trend can be fitted. A similar approach can be used to forecast demand for the remaining product categories. Further, the warehouse-wise demand for each category can be forecasted for the betterment of the company. Other models apart from Holt-Winter and SARIMA can be tried and compared to for better forecasting.

## Acknowledgments

Sincere thanks to Symbiosis Statistical Institute, Symbiosis International (Deemed University) for this opportunity. We really appreciate the direction provided by our director, Prof. Dr. Sharvari Shukla, and the research committee.

## Conflict of Interest

None.

## Credit Author Statement

Sayali Bora: Framed the problem statement, Investigation, Analysis; Pushpak Bhonde: Analysis, Writing - original draft preparation, Writing - review and editing. All the authors read and approved the manuscript.

### References

1. Taylor JW. 2003. Exponential smoothing with a damped multiplicative trend. *Int J Forecast* 19(4): 715-725. https://doi.org/10.1016/S0169-2070(03)00003-7
2. Aburto L, Weber R. 2007. Improved supply chain management based on hybrid demand forecasts. *Appl Soft Comput* 7(1): 136-144. https://doi.org/10.1016/j.asoc.2005.06.001

3. Chase CW. 2013. Demand-Driven Forecasting: A Structured Approach to Forecasting. John Wiley & Sons.

4. Jomaa D, Monteiro T, Besombes B. 2013. Design and development of a forecasting module: case of a warehouse management system. In IFAC Proceedings Volumes *46*(24): 177-182. https://doi.org/10.3182/20130911-3-BR-3021.00013

5. Box GE, Jenkins GM, Reinsel GC, Ljung GM. 2015. Time Series Analysis: Forecasting and Control. John Wiley & Sons.

6. Praveen U, Farnaz G, Hatim G. 2019. Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling. *Procedia Manuf* 38: 256-263. https://doi.org/10.1016/j.promfg.2020.01.034

7. Faloutsos C, Gasthaus J, Januschowski T, Wang Y. 2019. Classical and contemporary approaches to big time series forecasting. In *Proceedings of the 2019 international conference on management of data*, pp 2042-2047. https://doi.org/10.1145/3299869.3314033

8. Darmanyan A, Rogachev A. 2020. Modeling and forecasting seasonal and cyclical events using retrospective data. In *E3S Web of Conferences* Vol. 217, pp 06007. EDP Sciences. https://doi.org/10.1051/e3sconf/202021706007

9. Keung KL, Lee CK, Yiu YH. 2021. A machine learning predictive model for shipment delay and demand forecasting for warehouses and sales data. In *IEEE international conference on industrial engineering and engineering management*, pp 1010-1014. https://doi.org/10.1109/IEEM50564.2021.9672946

10. Dubey AK, Kumar A, García-Díaz V, Sharma AK, Kanhaiya K. 2021. Study and analysis of SARIMA and LSTM in forecasting time series data. *Sustain Energy Technol Assess* 47: 101474. https://doi.org/10.1016/j.seta.2021.101474

11. Aurna NF, Rubel MTM, Siddiqui TA, Karim T, Saika S, et al. 2021. Time series analysis of electric energy consumption using autoregressive integrated moving average model and Holt Winters model. *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 19(3): 991-1000. http://doi.org/10.12928/telkomnika.v19i3.15303