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Forecasting onion prices in Pune region of Maharashtra using Dynamic Harmonic Regression

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ABSTRACT

Onion, a staple vegetable, plays a crucial role in both the economy and the livelihoods of people; especially the farmers. Accurate price forecasting is vital for market stakeholders, including consumers, farmers, and policymakers. However, onion prices exhibit fluctuations and multiple seasonal patterns, making prediction challenging. This study delves into a comprehensive analysis of onion prices in the Pune region of Maharashtra using the Dynamic Harmonic Regression (DHR) model, a sophisticated time series technique, adept at capturing multiple seasonalities. The DHR model outperforms traditional forecasting methods, such as Holt-Winters and ARIMA, in predictive accuracy. Furthermore, cointegration analysis examines the relationship between onion prices in the Pune and Vashi markets, providing a deeper understanding of market dynamics. By leveraging historical price data, the study offers valuable insights into future price trends, enabling farmers to make informed decisions and develop strategies to mitigate price fluctuations. To further support farmers, an algorithm is developed to identify the optimal day to sell the produce from the farmer's perspective. Empowering farmers with this forecasting tool can significantly enhance decision-making with actionable price forecasts.

KEYWORDS

Agriculture, Cointegration, Decision Making, Farmer, Time Series Analysis.

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1. Introduction

Onion is an agricultural commodity of significant economic and cultural importance within households and the hospitality sector in India. Fluctuations in onion prices have been a persistent challenge for the agricultural sector [18], especially for farmers. If the farmer reaches the market when the prices are high, he makes substantial profits; however, if he arrives during a price crash, he risks significant losses. Onions, unlike perishable crops, possess the ability to be stored for an extended period of approximately 5-7 months, under appropriate storage conditions [1]. This extended storage window allows the farmer to strategically plan their cultivation, storage, and sales helping them make informed decisions to mitigate the adverse effects of price fluctuations. Consequently, accurate forecasting of onion prices emerges as a valuable tool for farmers and enables them to sell when the profits are being maximized or in the worst-case scenario the losses are minimized.

Researchers have explored the complexities of onion price behavior using various time series analysis techniques. The Auto-Regressive Integrated Moving Average (ARIMA) models can be used to capture the linear dependence present in the onion prices ([8], [7], [5], [13], [11], [9]). Many researchers ([16], [10], [6], [19], [17]) have used the Generalized Auto-Regressive Conditional Heteroskedastic (GARCH) models to model the onion prices where volatility is evident. A few researchers have used machine learning models to model the onion prices (for example see, [22], [20], [21]). Apart from the volatility, the presence of multiple seasonality is also observed in the onion price data. The most effective approach to capture multiple seasonality in data is the Dynamic Harmonic Regression (DHR) model. DHR modeling was initially introduced by [23]. Subsequently, [4] developed a linear method for automated DHR model identification, representing each component as a non-stationary ARMA process. Building upon this foundation, [3] applied a forecasting approach to strain data for damage detection. However, to our knowledge, the DHR model has not been previously used to model onion prices that capture multiple seasonality. Further, the cointegration technique can be used to analyze the relationship between onion prices in two different markets. Cointegration is a statistical property that describes a long-term stable relationship between two or more time series exhibiting trend. Cointegrated variables have a tendency to revert back to their equilibrium relationship over time. Hence, it can be particularly beneficial for making long-term forecasts.

This study focuses on modeling onion prices in the Pune region of Maharashtra using DHR. Maharashtra is India's major onion-producing state; Nashik, Lasalgaon, Pune and Solapur are key production hubs. Pune is a significant onion-producing region and a major market for arrival and consumption of onions. Vashi market is a major consumption center closer to the Pune market, hence it was selected to establish the relationship between onion prices in two markets using the cointegration technique.

The next step is to provide practical advice to farmers by predicting the most suitable day to sell onions. To maximize the profit from selling onion crops, the farmers face a complex decision regarding the optimal time to sell. An algorithm is developed to find the day with the highest expected value of the profit from the farmer's viewpoint.

The rest of the paper is organized as follows: Section 2 describes the data used for analysis, Section 3 explains the data analysis and statistical techniques used for model building, along with the development of the algorithm. Finally, Section 4 discusses the findings of the research.

2. Data Description

Data source:

Secondary data for this study is collected from the government data source "AgMarknet" (http://agmarknet.gov.in) which is consistent with the data available at "NaPanta" (https:// www.napanta.com). These websites provide information on district, market names, commodities (such as variety and grade), daily minimum, maximum, and modal prices (in Rs. per Quintal), and the date on which the information was uploaded. This is real-time data for various agricultural commodities in different markets in India ensuring comprehensive and up-to-date agricultural market information.

The particular interest of this study is to provide suggestions to farmers about the optimal time point for selling onion produce in the market which maximizes their profit. Hence the modal onion prices, which are the most frequent values in the data, are chosen for this study. Daily modal onion prices are collected from the "AgMarknet" website, both for the Pune and Vashi markets, across the time-frame of January 2017 to October 2023. You may note that onion prices for 6 days a week are available in both the markets, with a weekly off.

Missing value treatment:

Every year 15-16 onion price values are not available on account of public holidays, which may fall on different days of a week every year. Additionally, a few data points (ranging from 3 to 5 values) were missing due to disruptions caused by farmer strikes, droughts, and floods that occurred during 2018 and 2019. Since the DHR model considers multiple seasonal patterns with different seasonality parameters, it becomes crucial to impute these missing values to mitigate potential biases and ensure integrity of analysis. The mean imputation technique is therefore used to replace these missing values. Further, data for March, April, and May were missing due to disruptions caused by the COVID-19 pandemic. Given the extended duration of missing values, mean imputation would have resulted in a static price, failing to capture the underlying trends. Therefore, Holt-Winters exponential smoothing was employed for imputation, as it effectively accounts for trend and seasonality, ensuring a more accurate representation of price dynamics.

These steps enhanced the overall data quality, yielding a dataset comprising 2,112 data points. Subsequently, the dataset was partitioned into training and testing sets following an 80:20 ratio for further analysis.

3. Data Analysis

3.1. *Exploratory Data Analysis*

A graphical examination of the time plot reveals very intriguing patterns (Figure 1). A discernible yearly seasonal pattern in onion prices across all years is evident from the data. Furthermore, elevated prices are observed in 2020, primarily attributable to the adverse impacts of the COVID-19 pandemic. Following 2020, the data suggests a

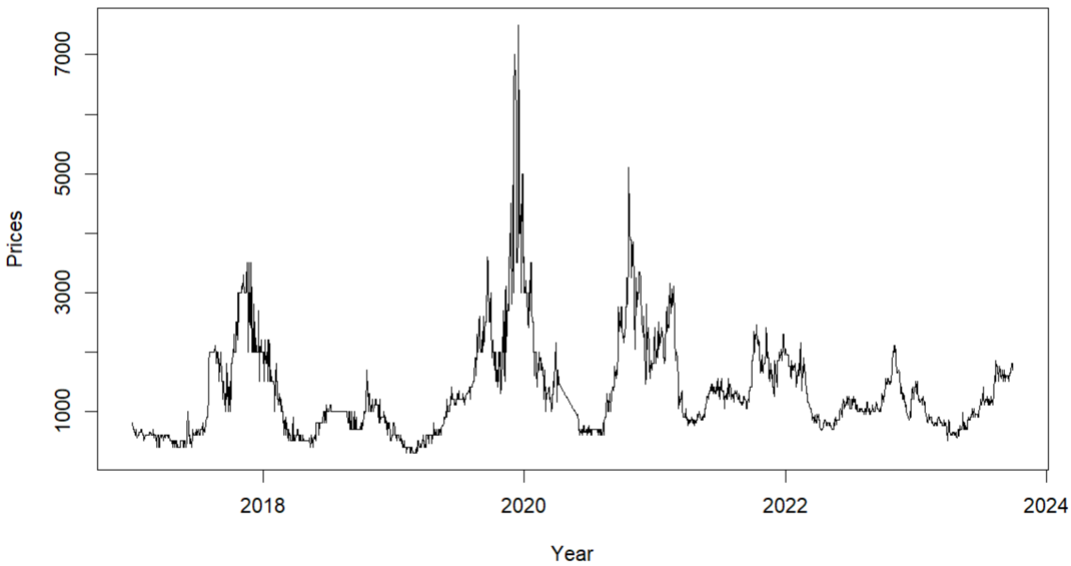

Figure 1.: Time plot of the daily modal onion prices from 2017 to 2023 in Pune market.

return to the historical seasonal trend in onion prices.

To further understand the seasonal patterns present in the data, the monthly, weekly averages, and daily modal onion prices are plotted for every year. The prices are relatively higher at the beginning of the year, tend to fall during March and April, and then increase again in the subsequent period (Figure 2) till end of the year. Similar patterns are observed in the weekly average modal onion prices (Figure 3) and daily modal onion prices (Figure 4). These multiple seasonality patterns present in the data prompts modeling the onion prices using the DHR.

Additional captivating information is revealed via the box plots of the daily modal onion prices in Pune market for each year (Figure 5). It can be observed that the median and the minimum prices have remained approximately at the same level although there is a significant change in the maximum prices over the years. Box plots for all the years are positively skewed which can be noticed from unequal lengths of upper and lower whiskers. Additionally, the median is positioned close to the bottom of the box for every year, indicating very low onion prices 50% of the time. This makes it necessary to advise farmers on the best time to deliver their produce to the market.

The box plots indicate that there is a great deal of variability in the onion prices. Hence, log transformation is applied to the data to mitigate the variability and the

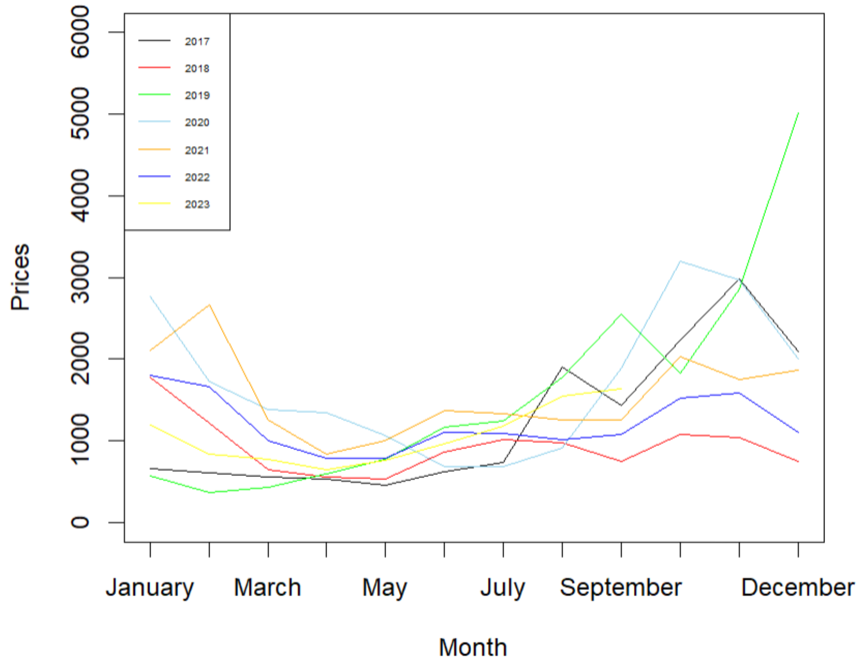

Figure 2.: Time plot showing monthly modal average onion prices for different years.

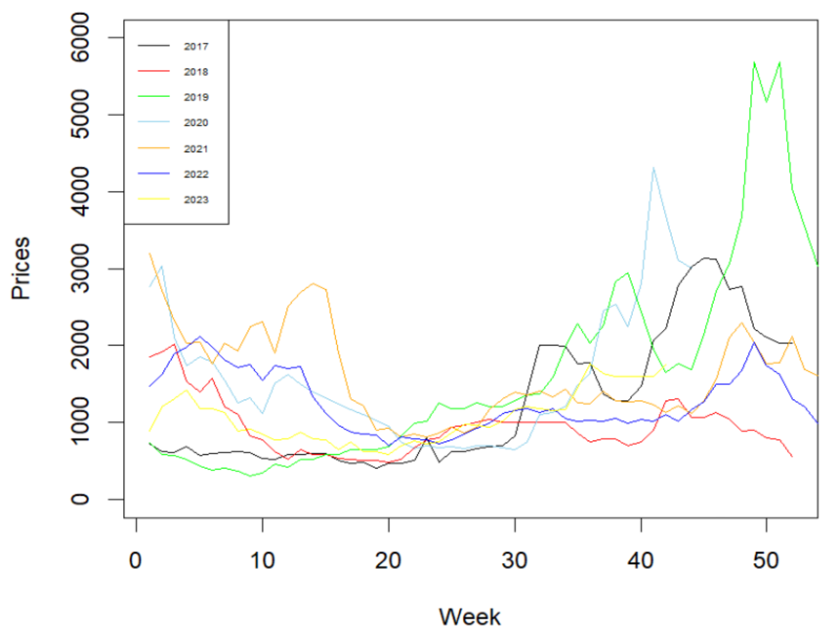

Figure 3.: Time plot showing weekly modal average onion prices for different years.

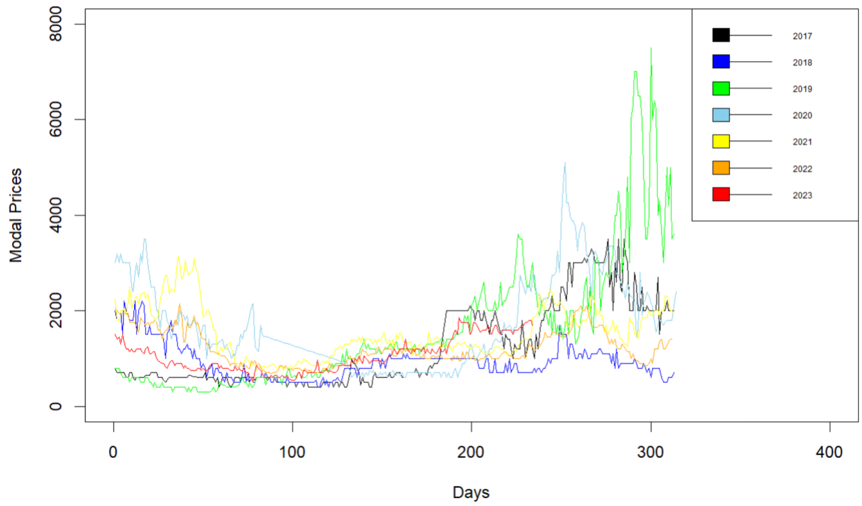

Figure 4.: Time plot of the daily modal onion prices for every year from 2017 to 2023 in Pune market.

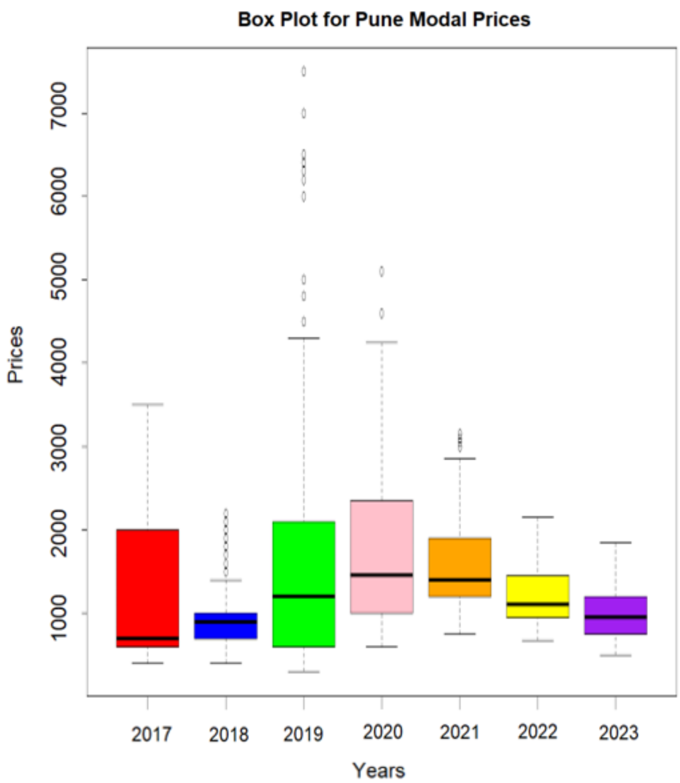

Figure 5.: Box plot for the modal onion prices in Pune market from year 2017 to 2023.

skewness observed in the distribution effectively. This adjustment aims to refine model accuracy and improve the interpretability of data patterns, enhancing the robustness of our research findings. The log-transformed data exhibits stronger seasonal patterns. (Figure 6).

Subsequently, statistical models are fitted to the log-transformed onion prices for forecasting. The forecasts are then exponentiated to restore the original scale, ensuring interpretability. Finally, the anti-log-transformed forecasts are plotted against actual data for visualization.

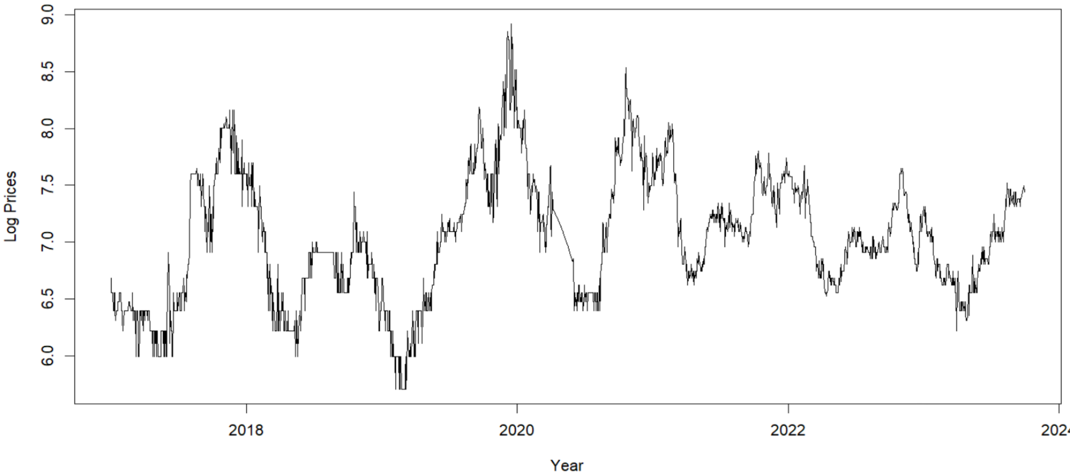

Figure 6.: Time plot of the log-transformed daily modal onion prices for Pune market.

3.2. *Statistical Techniques*

This section discusses the various statistical methodologies employed to analyze onion price data. The primary objective is to develop a robust model for forecasting onion prices. The analysis begins with a rigorous examination of the time series components. The Mann-Kendall test confirms the presence of a trend in the data. Next, time series decomposition reveals a recurring yearly pattern in onion prices. The Holt-Winters' exponential smoothing model is deemed a suitable choice for forecasting given the existence of both trend and seasonality. The fitting of Holt-Winters' model is discussed in Section 3.2.1. The analysis then moves to the ARIMA model to address the non-stationary nature of the onion prices. This ARIMA model fitting is discussed in Section 3.2.2. Furthermore, the presence of multiple seasonality, viz, the daily, weekly, monthly and yearly in the onion prices is observed. Therefore, to capture the effect of multiple seasonality, DHR model is fitted to the data in Section 3.2.3. The DHR model incorporates the residuals of the ARMA process, specifically addressing extended data periodicity such as daily onion prices containing multiple seasonal patterns. The model combines dynamic component given by ARIMA with a harmonic component that uses sine and cosine terms to model seasonality. To investigate if observed price movements in Pune and Vashi markets are driven by a shared underlying trend, cointegraion analysis is performed and discussed in Section 3.2.4.

3.2.1. Holt-Winters' Exponential Smoothing Model

The Holt-Winters' Exponential model is a time series forecasting technique that adeptly identifies and predicts patterns in data characterized by trend, seasonality, and fluctuations. The Holt-Winters' additive model is given by: $F_{t+m} = L_t + mb_t + S_{t+m-s}$, where the values of L_t, b_t, S_t - the series level, slope and seasonality values at time t, respectively - are obtained using following recursive equations:

$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$,

$b_t = \beta(L_t - L_{t-1})$ + (1-β)b_{t-1},

$S_t = \gamma(y_t - L_t)$ + (1-γ)S_{t-s}.

$0 \leq \alpha, \beta, \gamma \leq 1$ are the level, trend, and seasonality smoothing parameters respectively. s is number of seasons in a year and F_{t+m} is the forecast of the time series m period ahead of t. A detailed discussion of this method can be found in [15].

The optimal parameter values obtained after fitting this model to the log-transformed data are as follows: $\alpha = 0.59, \beta = 0$, and $\gamma = 0.81$. The forecasts for the 423 days' test data using this optimal model, along with the training data, are shown in Figure 7. While the training Mean Absolute Percentage Error (MAPE) achieves a favorable value of 1.52%, the model shows a significant difference between actual and predicted values over the test period. This is reflected by a high Root Mean Squared Error (RMSE) of 991.77; although the seasonal pattern in the data is well captured by this model.

3.2.2. ARIMA Model

The ARIMA(p,d,q) model comprises three components: the "Auto Regressive" term (AR(p)), which regresses the current value on its lagged values (p terms); the "Inte-

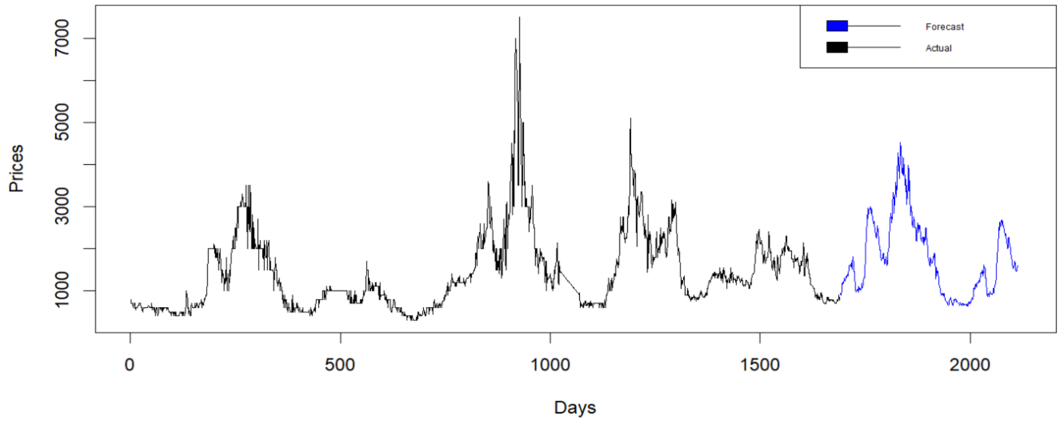

Figure 7.: Actual onion prices and forecast for 423 days using Holt Winters' exponential smoothing method.

grated" term (I(d)), which removes non-stationarity by differencing the data d times; and the "Moving Average" term (MA(q)), which incorporates the impact of q past forecast errors on the current value. [2] provides a comprehensive discussion of this method.

Let $\{y_t\}$ be the given time series data. The ARIMA (p, d, q) model is given by

$$Z_t - \beta_1 Z_{t-1} - ... - \beta_p Z_{t-p} = \gamma + \epsilon_t - \theta_1 \epsilon_{t-1} - ... - \theta_q \epsilon_{t-q},$$

where, $Z_t = \nabla^d Y_t$ is d-order differenced stationary series, $\beta_j, 1 \leq j \leq p$ are the AR coefficients, $\theta_j, 1 \leq j \leq q$ are MA coefficients, γ is the drift parameter, and ϵ_t is white noise satisfying the following conditions: $E(\epsilon_t) = 0, V(\epsilon_t) = \sigma^2, Cov(\epsilon_t, \epsilon_{t-k}) = 0$ for $k \neq 0$ and $Cov(\epsilon_t, y_{t-k}) = 0$ for $k > 0$.

A model with an AR component is generally more effective for forecasting purposes as compared to one that exclusively utilizes error terms. Hence, although the ARIMA (0,1,3) model has a smaller BIC value than the ARIMA (4,1,2) model, the latter is selected for checking the accuracy of the fitted model on the test data. The MAPE for both these models is 1.17% while the RMSE for the ARIMA (4,1,2) is 438.29 as compared to 440.09 for the ARIMA (0,1,3) model. The estimated parameters of the ARIMA model fitted to log-transformed data are as follows: $\hat{\beta}_1 = -0.13, \hat{\beta}_2 =$

$0.11, \hat{\beta}_3 = -0.07, \hat{\beta}_4 = -0.01, \hat{\theta}_1 = -0.21, \hat{\theta}_2 = -0.18$. The ARIMA (4,1,2) forecasts for 423 days of test data and the onion price training data are depicted in Figure 8.

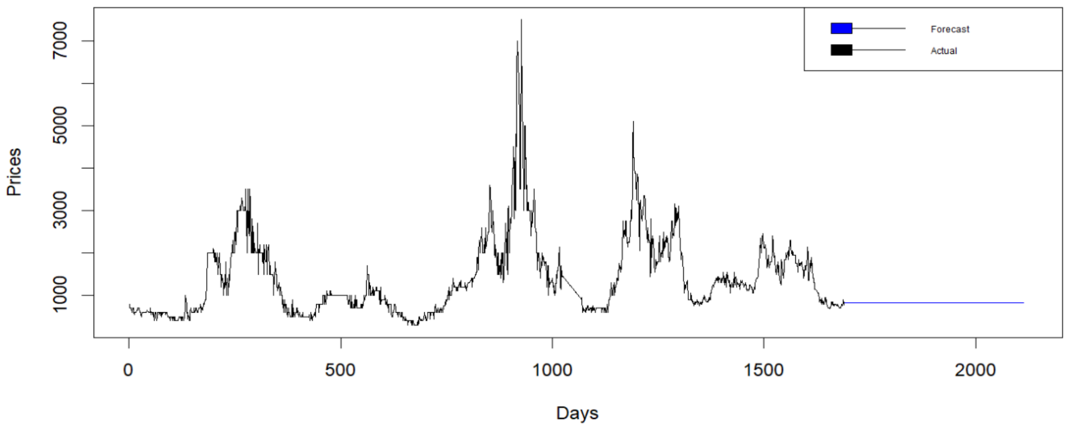

Figure 8.: Actual onion prices and forecast for 423 days using ARIMA (4,1,2) model.

3.2.3. Dynamic Harmonic Regression Model

In ARIMA models, the seasonality is assumed to be fixed. When the data shows more than one seasonal period, one can opt for harmonic regression approach in which the seasonal patterns can be approximated by the Fourier terms. The DHR model approximating the seasonal and cyclic patterns using Fourier terms can be found in [23]. Additionally, the DHR model may incorporate some explanatory variables, such as policies, distance, transportation, and agricultural infrastructure. These variables are excluded from the analysis because they do not show seasonal trends, as DHR in this study is explicitly designed to capture seasonal rather than cyclical or long-term fluctuations. Seasonal fluctuations are primarily driven by recurring factors like climate and planting schedules, which are already well represented in the Fourier terms. A parsimonious approach ensures that the seasonal model remains interpretable and avoids overfitting. Including exogenous variables that do not directly contribute to seasonal patterns would introduce unnecessary complexity without improving predictive performance. Hence, the following DHR model is used to model the onion prices:

$$Y_t = \mu_t + \sum_{j=1}^{k} (\alpha_j c_k(t) + \gamma_j s_k(t)),$$

where Y_t is the log-transformed price of onion at time t, μ_t is the term which follows ARIMA process, k represents the number of harmonic terms included which deals with the number of seasonalities present in the data, $\alpha_j, 1 \leq j \leq k$ and $\gamma_j, 1 \leq j \leq k$ are coefficients for the cosine and sine terms, respectively, m is the period of the harmonic component so that,

$s_k(t) = \sin\left(2\pi \frac{kt}{m}\right)$ and $c_k(t) = \cos\left(2\pi \frac{kt}{m}\right)$.

Auto-regressive modeling is used because utilizing prices as the regressors helps in incorporating information from past observations making it an effective approach for modelling auto-correlation and capturing short-term time dependencies within the time series. Fourier series of sine and cosine terms are used to model and capture the seasonal or periodic components of a time series. In our case, k=4 depicts the presence of daily, weekly, monthly and yearly seasonality.

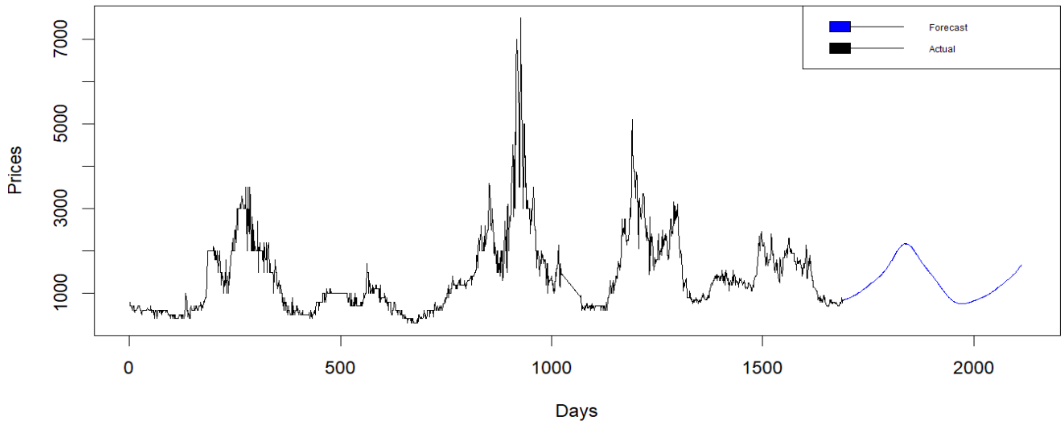

Figure 9.: Actual onion prices and forecast for 423 days using DHR

The MAPE at k=4 is the least with value of 1.17% and the RMSE for the testing set is 357.38. The estimated parameters of the DHR model fitted to log-transformed data are as follows: $\hat{\alpha}_1 = 0.31, \hat{\alpha}_2 = 0.06, \hat{\alpha}_3 = -0.03, \hat{\alpha}_4 = -0.02, \hat{\gamma}_1 = -0.37, \hat{\gamma}_2 = -0.03, \hat{\gamma}_3 = 0.01, \hat{\gamma}_4 = -0.003, m = 313$ and μ_t follows ARIMA (4,1,2) process with parameters $\hat{\beta}_1 = -0.74, \hat{\beta}_2 = 0.29, \hat{\beta}_3 = -.03, \hat{\beta}_4 = -0.17, \hat{\theta}_1 = 0.39, \hat{\theta}_2 = -0.59$. The training data and the forecasts for 423 days test data obtained using the DHR model are plotted in Figure 9.

The MAPE and RMSE values for different models discussed in previous sections are shown in Table 1. One observes that both, the MAPE and RMSE, for the Holt-Winters' model are high as compared to other two models. Although the MAPE values for ARIMA and DHR models are identical, the lower RMSE of the DHR model indicates that the DHR model is more suitable for forecasting the onion prices.

Model	MAPE	RMSE
Holt-Winter's Exponential Smoothing	1.52%	991.77
ARIMA	1.17%	438.29
Dynamic Harmonic Regression	1.17%	357.38

Table 1.: The MAPE and RMSE values for different models fitted to the modal onion prices of Pune region

3.2.4. Cointegration Model

A line chart depicting modal onion prices across the years both for the Pune and Vashi markets is presented in Figure 10. The price patterns in both locations exhibit a high degree of similarity, moving consistently in the same direction throughout the study period. However, prices in the Vashi market are persistently higher, likely due to transportation costs. This price coherence suggests a potential statistical relationship between the two markets, warranting a cointegration analysis. While Pune and Vashi are geographically connected, this study employs standard cointegration analysis rather than spatial cointegration, as key spatial factors—such as transportation costs, storage infrastructure, and associated costs—are not explicitly incorporated.

Cointegration analysis examines whether non-stationary time series can be transformed into a linear combination with a predetermined order of integration ([12, 14]). In simple terms, cointegration seeks to identify a shared stochastic trend across non-stationary variables that may otherwise appear to be individually non-stationary, indicating a long-term equilibrium.

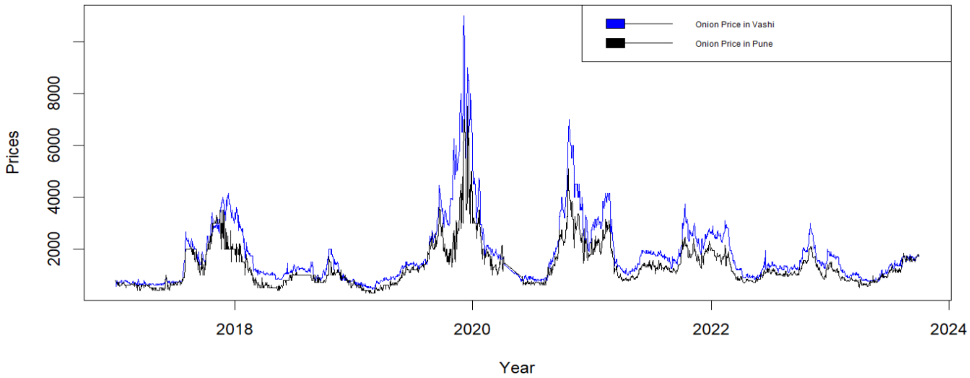

Figure 10.: Line plot of the daily modal onion prices from 2017 to 2023 in Pune and Vashi markets

To investigate the presence of a long-term equilibrium relationship between onion prices in Pune and Vashi, the initial step is to establish the order of integration for both series. The results confirm an integrated order of one (I(1)), implying non-stationarity in levels but achieving stationarity through differencing of order 1. Subsequently, a linear model is build with onion prices in Vashi market as the dependent variable and onion prices in Pune market as the independent variable. The estimated linear model, $P_V(t) = -102.38 + 1.41.P_P(t)$, where $P_V(t)$ and $P_P(t)$ denote the prices in Vashi and Pune markets at time t respectively, represents the two markets' linear relationship. The residuals of this model are tested for stationarity to ensure the long-term stability of the relationship. The results support the residuals' stationarity, fulfilling the second condition for cointegration, indicating that onion prices in Pune and Vashi markets are cointegrated. This new notion of cointegration adds to our knowledge of the two markets' long-term correlation.

3.3. *An Algorithm to Predict the Best Day to Sell the Produce*

As mentioned in Section 3, analysis of past data reveals that farmers receive extremely low prices for onions half the time. However, farmers should receive fair prices for their products to ensure that they are compensated for their labor and investment, encouraging sustainable agricultural production. Without fair prices, farming may become unsustainable. Hence, it becomes essential to advice the farmers when to take the product to the market for selling. The goal is to equip farmers with actionable information so that they can make informed decisions about the optimal time to sell their onion produce.

Here, an algorithm is developed for facilitating this decision. Since this decision is based on the onion storage capacity, the farmer is required to specify the number of days the onions can be stored before selling, as input to the algorithm. The output generated by the algorithm provides the farmer with the exact date to sell their produce, ensuring they achieve the highest possible return. Using the forecasting capabilities of the most effective DHR model, the most profitable selling day within a user-defined time window is determined.

This approach not only enhances the farmer's profitability but also tries to mitigate the risks associated with volatile agricultural markets. Empowering farmers with this forecasting tool can significantly simplify decision-making by providing real-time price insights.

4. Discussion

The present study delves into the intricate dynamics of onion price behaviour in the Pune and Vashi markets. A pronounced seasonal pattern, characterized by price surges at the year's commencement followed by a decline during March and April, and subsequent recovery is evident. This short-term periodic behavior is mainly attributed to the interplay of supply and demand factors associated with the onion cultivation cycle and offers opportunities for farmers to plan strategic harvest and sales. However, the presence of outliers in 2018 and 2019, linked to extreme weather events and labor disruptions, underscores the vulnerability of the onion market to external shocks. Box plot analysis reveals a consistent positive skew in price distributions across all years, indicating that farmers receive lower prices most of the time in a year.

While traditional time series models such as ARIMA have been widely employed in previous studies as well as this study, the inherent limitations in capturing multiple seasonality patterns and the constant forecast restrict their predictive accuracy. In this context, the DHR model demonstrates superior performance by effectively incorporating these complex seasonal variations. The model's ability to account for multiple seasonality significantly enhances its predictive capabilities and it outperforms traditional methods in terms of prediction accuracy.

Furthermore, the analysis reveals a similarity in the movements of onion prices in Pune and Vashi markets, suggesting a potential long-term equilibrium relationship. The application of cointegration analysis confirms this hypothesis, indicating that the two price series are bound by a common stochastic trend. This finding offers a valuable opportunity to develop more efficient and accurate forecasting models by leveraging these interconnected price dynamics. By integrating these insights into decision-making process, farmers and market participants can potentially mitigate the adverse impacts of price fluctuations and enhance the overall efficiency of the onion market.

Although this study provides valuable information on onion price dynamics, more research is warranted to deepen the understanding of the factors influencing price fluctuations. Exploring the impact of government policies, storage facilities, and alternative crop choices on onion production and pricing could provide additional information.

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