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A Statistical Analysis on Forecasting Prices of Some Important Food Commodities in Bangladesh

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ABSTRACT: This paper investigates the best possible forecasting price models for three important agricultural products in Bangladesh namely potato, onion and garlic using time-series and secondary data from January 2000 to December 2014. The main objective of this paper is to find out the appropriate time series models using some of the latest selection criteria that could describe the best price patterns of the above mentioned three crops. To forecast the prices of the crops, the ARIMA models were used, based on model selection criteria and error statistics among the competing models. The overall findings of the study indicate that the fitted models are satisfactory for the respective commodities. The study observed increasing trends in forecasted prices of all three commodities. In particular, the increase in the price of garlic has been observed to be very high compared to that of potato and onion. The study also found that the best fitted SARIMA model for potato is SARIMA (1,0,0) $(0,1,2)_{12,}$ for onion SARIMA (2,0,0) $(0,1,1)_{12,}$ and for garlic SARIMA (2,1,3) $(0,1,3)_{12}$.

Keywords: Box-Jenkins methodology; Forecasting price; Autocorrelation function; ARIMA model; SARIMA model; Estimation; Identification; Akaike information criterion; Bayesian information criterion.

تحليل إحصائي للتنبؤ بأسعار بعض المنتجات الغذائية الهامة في بنغلاديش

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الملخص: درست هذه الورقة البحثية أفضل نماذج أسعار ممكنة للتنبؤ حول ثلاثة منتجات زراعية مهمة في بنغلاديش وهي البطاطا والبصل والثوم، باستخدام متسلسلات زمنية وبيانات ثانوية اعتبارا من يناير 2000 إلى ديسمبر 2014. تهدف هذه الدراسة إلى ايجاد نماذج متسلسلات زمنية مناسبة، باستخدام بعض المعايير المختارة حديثا والتي يمكن أن توصف أفضل أنماط الأسعار للمحاصيل الزراعية الثلاثة المذكورة أعلاه. من أجل التنبؤ بأسعار المحاصيل، فقد تم استخدام نماذج أريما (ARIMA) استناداً على معايير نماذج مختارة وإحصاء الأخطاء بين النماذج المتنافسة. وقد أشارت النتائج الإجمالية للدراسة إلى أن النماذج المركبة مناسبة للسلع المعنية. ولاحظت الدراسة أن الاتجاهات متزايدة في الأسعار المتوقعة لجميع السلع الثلاث. وعلى وجه الخصوص مادة الثوم، حيث لوحظ أن الزيادة في سعرها مرتفعة للغاية مقارنة بالبطاطا والبصل. ووجدت الدراسة أيضًا أن أفضل نموذج مناسب لساريما (SARIMA) يتم الدلالة عليه كما يلي: للبطاطا هو $\mathrm{SARIMA}(1,0,0)(0,1,2)_{12}$ وللبصل هو $\mathrm{SARIMA}(2,0,0)(0,1,1)_{12}$ وللثوم هو $\mathrm{SARIMA}(2,1,3)(0,1,3)_{12}$.

الكلمات المفتاحية: منهجية صندوق جينكنز (Box-Jenkins)، سعر التنبؤ، وظيفة الارتباط التلقائي، نموذج أريما (ARIMA) ، نموذج ساريما (SARIMA)، التقدير، التعريف، معيار معلومات أكيك (Akaike)، معيار معلومات بايز (Bayesian).

1. Introduction

Bangladesh is predominantly an agriculture-based country where more than 80% of the population are engaged in agriculture, of which 70% are purely in the labor force. The agriculture sector is one of the main important sectors for the economic development of the country which contributes 16.33% of the total gross domestic product (GDP) in Bangladesh (Bangladesh Bureau of Statistics (BBS)) [1]. Potato is one of the most important vegetables in

Bangladesh. It contributes 55% of the country's total vegetable production [2]. The market price of potatoes decreases from Tk. 1164/100 kg to Tk. 1077/100 kg (Department of Agriculture Marketing (DAM)) [3]. The onion is also a very important spice crop for the people of Bangladesh. The market price of onion increases from Tk. 1403/100 kg to Tk. 2806/100 kg [3]. Garlic is another important spice crop of the country, which is used for medicinal purposes as well. The market price of garlic decreases from Tk. 3730/100 kg to Tk. 2806/100 kg [3]. Forecasting prices of the heavily consumed major commodities is very essential for the businessmen, planners and policymakers of a developing country like Bangladesh where approximately 40% of the people are living below the poverty line. For many developing countries, primary commodities remain an important source of export earnings, and commodity price movements have a major impact on overall macroeconomic performance. Hence, commodity-price forecasting is a key input to macroeconomic policy planning and formulation [4].

The fluctuation of the prices of vegetable and spice crops always makes the government anxious and it has great impact on the millions of the country's producers and consumers. Early forecasting of the probable prices of vegetable and spice crops could help the policy makers to predict the probable fluctuations in their prices [5]. Forecasting prices of commodities is very important in decision making at all levels and sectors of the economy. This is particularly true in the agriculture sector where policy decisions are characterized by risks and uncertainty, largely due to uncertain yields and relatively low price elasticity of demand for most agricultural commodities in order to make good decisions and policies [6].

The farmers are emotionally and financially affected by the fluctuation in prices of agricultural commodities and its adverse effect on the GDP of a country. Prediction of the prices may help the agriculture supply chain in making necessary decisions in minimizing and managing the risk of price fluctuations [7]. Future prices are also used by crop insurance programs to decide their first-stage and harvest prices [8]. Price forecast therefore, is vital to facilitate efficient decisions and it will play a major role in coordinating the supply and demand of farm products. Hence, forecasting cereal prices will be useful to producers, consumers, processors, rural development planners and other stake holders and agencies/institutions involved in the market [9].

The main objective of this paper is to forecast the monthly prices of the selected three most useful agricultural commodities namely, potato, onion and garlic. Four different models on time series data, namely autoregressive (AR) model, moving average (MA) model, autoregressive integrated moving average (ARIMA) model and seasonal autoregressive integrated moving average (SARIMA) model (popularly known as Box-Jenkins methodology) [10] are extensively used in this study.

2. Data and Methodology

Data collection: The monthly secondary data of the prices of the three commodities namely potato, onion and garlic were collected from DAM, BBS and the Food Planning and Monitoring Unit (FPMU) under the Ministry of Food and Disaster Management of Bangladesh. In order to find out the best possible models for forecasting prices of the three items, we used tabular and graphical approaches under descriptive statistics and Box- Jenkins methodology.

Time series analysis: Time series analysis was chosen to analyze the data because this particular analysis requires absolute values of forecast, and it usually produces a better result. The ARIMA process is a mathematical model generally used for forecasting. Under this process, the forecasts are based on linear functions of the sample observations in order to find the simplest models that provide an adequate description of the observed data. The time series process, when differenced, follows both AR and MA models and is known as the autoregressive integrated moving averages (ARIMA) model. The model is often abbreviated as ARIMA (p, d, q) where 'p' stands for AR part, 'd' for integrated part and 'q' for MA part. The ARIMA model as used in this study required a sufficiently large data set and involves four steps within the framework of Box-Jenkins methodology, these being identification, estimation, diagnostic checking and forecasting[11].

Identification: The main tools in identification are the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the resulting correlations, which are simply plots of ACFs and PACFs against the lag length. The ACF and PACF are estimated from the sample data. This estimated ACF and PACF are used as a guide to choose appropriate models. The decision regarding transformation is necessary to stabilize the variance of the series through a time plot and it shows data scattered horizontally around a constant mean; the ACF and PACF drop to, or near to, zero quickly which indicates that the data are stationary. If the time plot is not horizontal, or the ACF and PACF do not drop to zero, then non- stationary is to be implied.

Estimation: At this stage precise estimates of the coefficients, the AR and MA parameters, seasonal and non-seasonal, of the tentative model chosen at the identification stage have to be determined. In other words, having selected appropriate values for non-seasonal (p, d, q) and seasonal (P, D, Q) of the model, parameters are estimated, typically using simple least squares.

Diagnostic Checking: After choosing a particular ARIMA model and having estimated its parameters, the next step is to see whether the chosen model fits the data reasonably well by performing some diagnostic tests. At the diagnostic test one sample test of the chosen model is to see if the residuals estimated from the model are white noise. In this regard, the Portmanteau test can be applied to the residuals as an additional test of fit. The Box-Pierce Q test and Ljung-Box Q tests are the popular portmanteau tests for testing the statistical significance of autocorrelation coefficients. If the portmanteau test is found to be significant, then the model will be inadequate. In such a case, another ARIMA model needs to be considered. Besides the pattern of significant spikes in the ACF and PACF of the residuals, we cannot improve the model. For example, the significant spikes at the small lags suggest increasing the non-seasonal AR or MA component of the model. Similarly, significant spikes at the seasonal lags suggest adding a seasonal component to the chosen model.

Forecasting: If the residuals of the selected model are white noise then the model can be used for forecasting purposes. The reason for the general acceptability of the ARIMA model is its wide successes in forecasting. In this study, we have used the autoregressive (AR) model, moving average (MA) model, autoregressive integrated moving average (ARIMA) model and seasonal autoregressive integrated moving average (SARIMA) in order to find the best suited model and to increase the accuracy of the forecast.

3. The Model

The first-order autoregressive disturbance or AR (l) process is of the form [12]

$$Y_t = \rho Y_{t-1} + u_t$$

where u_t ~ N (0, 1).

Similarly, the second-order AR (2) process is of the form

$$Y_t = \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + u_t.$$

In general, the p[th]-order AR (p) process is considered as

$$Y_t = \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \cdots + \rho_p Y_{t-p} + u_t \ . \quad (1)$$

The first order moving average or MA (1) process is expressed as

$$Y_t = u_t + \theta u_{t-1}.$$

The second- order moving average MA (2) process is of the form

$$Y_t = u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2}.$$

The general form of moving average or MA (q) process is considered as

$$Y_t = u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \ . \quad (2)$$

For time series analysis, the general autoregressive integrated moving average (ARIMA) (P, d, q) model in terms of backward shift operator B is as follows:

$$(1-\varphi_1 \mathrm{B} - \cdots - \varphi_p B^p) W_t = (1-\theta_1 \mathrm{B} - \cdots - \theta_q B^q) A_t \quad (3)$$

where, $w_t = (1-B)^d e_t$ is the first difference of the original time series Y_t and A_t is the random shock which forms a white noise process with mean zero [13]. Similarly, the seasonal ARIMA, often called SARIMA (p, d, q) (P, D, Q)s in terms of the backward shift operator B can be expressed as

$$(1-\varphi_s B^s - \cdots - \varphi_{sp} B^{sp}) W_t = (1-\theta_s B^s - \cdots - \theta_{sQ} B^{sQ}) A_t \quad (4)$$

where, $w_t = (1-B^s)^d Y_t$, s = 12 for monthly data and s = 4 for quarterly data. Contrary to (1.3), here the random shocks A_t do not form a white noise process. Combining (1.3) and (1.4) we obtain

$$(1-\varphi_1 \mathrm{B} - \cdots - \varphi_p B^p)(1-\varphi_s B^s - \cdots - \varphi_{sp} B^{sp}) W_t = (1-\theta_1 \mathrm{B} - \cdots - \theta_q B^q)(1-\theta_s B^s - \cdots - \theta_{sQ} B^{sQ}) A_t \ . \quad (5)$$

As a Final generalization, a constant term θ_0 needs to be added to the model (1.5) in order to accommodate the possibility that the variables w_t may have a non-zero mean. Thus the resulting model can be written as

$$(1-\varphi_1 \mathrm{B} - \cdots - \varphi_p B^p)(1-\varphi_s B^s - \cdots - \varphi_{sp} B^{sp}) W_t = \theta_o + (1-\theta_1 \mathrm{B} - \cdots - \theta_q B^q)(1-\theta_s B^s - \cdots - \theta_{sQ} B^{sQ}) A_t \quad (6)$$

where, $w_t = (1-B)^d (1-B^s)^D Y_t$. Therefore, the equation (1.6) stands as

$$(1-\varphi_1 \mathrm{B} - \cdots - \varphi_p B^p)(1-\varphi_{12} B^{12} - \cdots - \varphi_{12p} B^{12p}) W_t = \theta_o + (1-\theta_1 \mathrm{B} - \cdots - \theta_q B^q)$$
$$(1-\theta_{12} B^{12} - \cdots - \theta_{12Q} B^{12Q}) A_t \quad (7)$$

where, $w_t = (1-B)^d (1-B^{12})^D Y_t$.

This is the multiplicative model of order (p, d, q) $(P, D, Q)_{12}$.

Here the term $(1-\varphi_1 \mathrm{B} - \cdots - \varphi_p B^p)$ is known as the regular autoregressive operator of order p, the term $(1-\varphi_{12} B^{12} - \cdots - \varphi_{12p} B^{12p})$ is known as seasonal autoregressive operator of order p, the term $(1-\theta_{12} B^{12} - \cdots - \theta_{12Q} B^{12Q})$ is the seasonal moving average operator of order Q. The multiplicative model (1.7) represents a common form of most of the seasonal time series models considered in practice.

The best model is obtained with the following diagnostics, by lowest values of Akaike's information criteria (AIC) and Schwartz Bayesian criteria (SBC or BIC). To check the adequacy for the residuals, Q statistic is used. A modified Q statistic is the Box-Ljung Q statistic as given below:

$$Q' = n\,(n+2) \sum_{k=1}^{p} \frac{{r_k}^2}{(n-k)} \ .$$

The Q statistic is compared to the critical value of chi-square distribution. If the p-value associated with the Q statistic is small, the model is considered as adequate. Forecasting the future periods using the parameters for the tentative model has been selected.

Trend fitting: For evaluating the adequacy of AR, MA, ARIMA and SARIMA processes, various reliability statistics like R^2, Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE), Mean Absolute Error (MAE) and BIC were used. The smaller the various reliability statistics, the better the efficiency of the model in predicting the future production.

4. Results and Discussion

Accuracy of forecasting depends on the time series data which must be stationary. Apart from the graphical method of using ACF and PACF for determining whether the time series is stationary, a very popular method of determining this is the Augmented Dickey Fuller (ADF) test. In the present study the ADF tests of the three different agricultural commodities such as potato, onion and garlic prices were conducted using EViews software.

The most suitable models were selected based on their ability for reliable prediction. Lower values of RMSE and MAPE were preferable whereas for Normalized BIC, higher values were preferable. Furthermore, the Ljung-Box test (portmanteau test) was conducted to see if the residual ACF at different lag times was significantly different from zero, where not being different from zero was expected. After the best model was identified, forecasts for future values from January 2000 to December 2014 were made. The best fitting model was determined for the three different commodities based on secondary data from January 2000 to December 2014 by using the statistical software SPSS 20. From the following tables, it can be seen that the best SARIMA model for forecasting the wholesale price of potato is SARIMA $(1,0,0)(0,1,2)_{12}$, for onion it is SARIMA $(2,0,0)(0,1,1)_{12}$, and for garlic it is SARIMA $(2, 1, 3)(0,1,3)_{12}$. In the three best models, the ACF and PACF of residuals have no significant spikes and the residuals are found to be white noise. After fitting the best selected models, the prices of three selected commodities were forecasted for January 2015 to December 2015 based on the collected secondary data from January 2000 to December 2014. Overall, the forecast prices of the selected commodities were found to be consistent with some few upturns and downturns of the observed series.

Table 1. Model Selection Criteria for Tentatively Selected SARIMA Models for Onion.

Model	R^2	RMSE	BIC	MAE	MAPE	Ljung-Box(Q-statistics)	P-value
SARIMA$(2,0,0)(0,1,1)_{12}$	.853	478.97	12.49	329.02	16.21	19.88	.176
SARIMA$(2,0,1)(0,1,2)_{12}$	.854	480.24	12.56	327.56	16.15	18.74	.131
SARIMA$(2,0,1)(0,1,3)_{12}$	.853	483.14	12.60	328.94	16.23	16.87	.155
SARIMA$(2,0,1)(0,1,4)_{12}$	.855	480.84	12.62	325.26	16.03	16.22	.133
SARIMA$(3,0,1)(0,1,2)_{12}$	.857	476.40	12.57	327.78	16.26	13.87	.309
SARIMA$(3,0,1)(0,1,3)_{12}$	.858	475.81	12.60	319.63	15.78	13.11	.286

Table 2. Model Parameters of SARIMA (2, 0, 0) $(0,1,1)_{12}$ for Onion.

Type	Coefficient	Standard error	P- value
AR(1)	1.1364	.0724	0.00
AR(2)	-0.3923	.0729	0.00
SMA(12)	0.8587	.0615	0.00
Constant	39.319	6.785	0.00

Table 3. Model Selection Criteria for Tentatively Selected SARIMA Models for Garlic.

Model	R^2	RMSE	BIC	MAE	MAPE	Ljung-Box(Q-statistics)	P- value
SARIMA$(1,1,4)(1,1,5)_{12}$	.904	973.622	14.16	519.00	10.86	10.00	.188
SARIMA$(2,1,5)(1,1,5)_{12}$	.906	971.621	14.21	511.59	10.61	8.11	.150
SARIMA$(2,1,3)(0,1,3)_{12}$	.906	953.208	14.02	513.93	10.64	10.54	.394
SARIMA$(2,1,4)(0,1,3)_{12}$	.905	964.886	14.08	519.80	10.84	7.81	.553
SARIMA$(2,1,4)(0,1,4)_{12}$	.905	968.313	14.11	518.50	10.81	7.77	.456
SARIMA$(2,1,4)(0,1,5)_{12}$	.907	959.466	14.13	506.96	10.48	7.24	.404

Table 4. Model Parameters of SARIMA (2, 1, 3) $(0,1,3)_{12}$ for Garlic.

Type	Coefficient	Standard error	P-value
AR(1)	0.3127	0.0730	0.00
AR(2)	-0.8822	0.0631	0.00
MA(1)	0.2857	0.1000	0.00
MA(2)	-O.8862	0.0629	0.00
MA(3)	-0.1551	0.0856	0.07
SMA(12)	0.9894	0.0822	0.00
SMA(24)	0.1812	0.1276	0.15
SMA(36)	-0.3005	0.1105	0.00
Constant	16.87	-0.18	0.85

Table 5. Model Selection Criteria for Tentatively Selected SARIMA Models for Potato.

Model	R^2	RMSE	BIC	MAE	MAPE	Ljung-Box(Q- statistics)	P- value
SARIMA$(0,1,1)(0,1,1)_{12}$	.829	217.159	10.884	138.89	13.70	16	.453
SARIMA$(0,1,2)(0,1,2)_{12}$	.844	208.651	10.865	132.20	13.12	7.78	.900
SARIMA$(0,1,3)(0,1,2)_{12}$	.844	209.210	10.901	132.41	13.14	7.69	.863
SARIMA$(0,1,4)(0,1,3)_{12}$	.846	209.102	10.961	131.46	13.21	7.40	.765
SARIMA$(0,1,5)(0,1,3)_{12}$	.846	209.658	10.997	131.35	13.20	7.46	.681
SARIMA$(1,0,0)(0,1,2)_{12}$	.848	205.002	10.779	134.58	13.22	10.84	.764

Table 6. Model Parameters of SARIMA (1, 0, 0) $(0,1,2)_{12}$ for Potato.

Type	Coefficient	Standard error	P- value
Constant	6.080	1.704	0.00
AR(1)	0.893	0.035	0.00
SMA(12)	1.268	0.086	0.00
SMA(24)	-0.3608	0.091	0.00

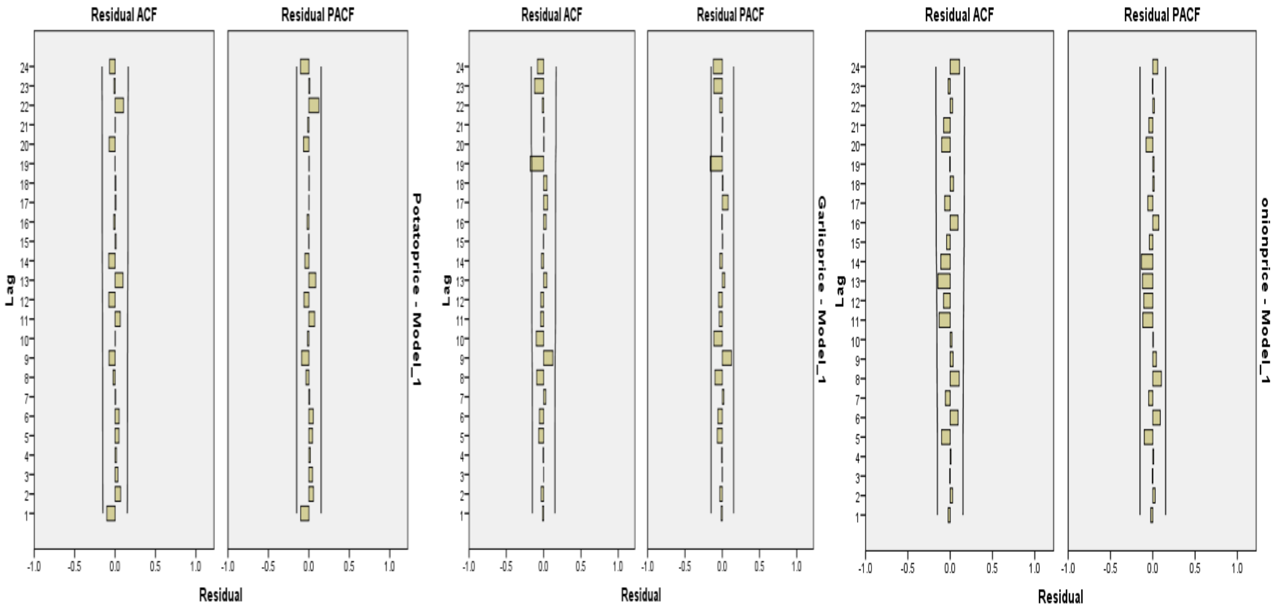

Figure 1. Residual of ACF and PACF for the best SARIMA models for Potato, Garlic and Onion.

The actual and fitted prices using the best fitted model of the respective commodities are presented below for one year (March 2009 – February 2010) to check the validity of the models employed in our study.

Table 7. Comparison of Actual and Fitted price of the Commodities per 100 kg.

	Potato		Onion		Garlic	
Month	Actual price	Fitted price	Actual price	Fitted price	Actual price	Fitted price
Jan-14	632	1068	3430	5703	7898	7767
Feb-14	1514	548	1938	1896	6951	7695
Mar-14	784	1579	2166	1535	4658	4516
Apr-14	1124	983	2156	2208	4650	4550
May-14	1264	1329	1928	2624	4522	5683
Jun-14	1511	1406	2825	2071	5795	5034
Jul-14	1713	1619	3251	3496	6279	6107
Aug-14	1756	1768	3380	3581	5812	6370
Sep-14	1760	1808	3472	3584	6853	5824
Oct-14	1847	1830	3252	3900	7566	7367
Nov-14	1850	1893	3299	3554	7218	7731
Dec-14	1952	1818	2752	3003	6970	7083

Figure 2. Plot of Actual and Predicted Prices of Potato, Onion and Garlic.

The forecasted prices of the selected commodities are given below Table 8.

Table 8. Forecasted Prices per 100 kg of Potato, Garlic and Onion.

Forecasted price per 100kg			
Month	Potato	Onion	Garlic
Jan-15	1700	2167	7034
Feb-15	1170	2360	6306
Mar-15	1370	2579	4339
Apr-15	1454	2546	4607
May-15	1600	2896	5159
Jun-15	1664	3099	5364
Jul-15	1738	3453	5793
Aug-15	1780	3730	6231
Sep-15	1799	3932	6589
Oct-15	1822	4280	6905
Nov-15	1940	4554	6858
Dec-15	1898	4038	6655

4. Conclusion

During the last few decades, a huge amount of work has been done by using time series data on the major crops of Bangladesh such as rice, wheat, tea, jute, lentil, etc. See for example, [14] and [15]. We used three important food crops, i.e. potato, onion and garlic, for our analysis. We observed from Table 8 that the forecasted price for potato rose from Tk.1700 per 100 kg in January 2015 to Tk.1898 by the end of the year 2015. For onion, the forecasted price of onion rose from Tk. 2167 per 100 kg in January 2015 to Tk. 4038 by the end of the year 2015. The table reveals that the price fluctuations had erratic trends in nature. The forecasted price of garlic decreased greatly from Tk. 7034 per 100 kg in January 2015 to Tk. 5793 in July 2015. After this, the price slightly increased from Tk. 5793 per 100 kg in July 2015 to Tk. 6655 in December 2015. Based on the above numerical figures, we may conclude that the overall prices for the selected three important food commodities are expected to increase in the next one year. This could be very helpful information to businessmen, policy makers and planners in order to make future economic decisions regarding these types of agricultural food commodities.

The seasonal autoregressive integrated moving average model traces out the seasonal effect of the desired variable. The current research identified SARIMA (1,0,0) $(0,1,2)_{12}$ for potato, SARIMA (2,0,0) $(0,1,1)_{12}$ for onion and SARIMA (2,1,3) $(0,1,3)_{12}$ for garlic have been proved to be the best possible models for forecasting purposes on the basis of the latest model selection criteria. The forecasting performances of the chosen models were found to be satisfactory, as shown by Figure 2. As we know, more reliable results on forecasting accuracy mainly depend on accuracy of data on the selected variables. Thus, we recommend that data banks in Bangladesh should be better organized and of better quality in order to obtain the best possible outcomes through forecasting models.

Conflict of Interest

The authors declare no conflict of interest.

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