Comparison of Forecasting Performance with VAR vs. ARIMA Models Using Economic Variables of Bangladesh

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Authors' contributions

This work was carried out in collaboration between both authors. Author MSK designed the study, performed the statistical analysis, wrote the protocol, managed the literature searches and wrote the first draft of the manuscript. Author UK managed the analyses of the study and checked grammar of the manuscript. All authors read and approved the final manuscript.

Original Research Article

Abstract

The main concept of this research was forecasting a group of variables simultaneously, thus making use of correlations among the variables. This research aims to check forecasting performance among different VAR and ARIMA models applying some economic indicators of Bangladesh. Data sets were collected from secondary sources of Bangladesh such as Bangladesh bank bulletin, Bangladesh economic review, Monthly economic trends of Bangladesh Bank, and Statistical yearbook of Bangladesh. The stationary VAR and ARIMA models were applied for predicting these financial variables and then checked the accuracy by comparing ME, RMSE, MAE, MPE, MAPE, and MASE of respected the variables. This research found that the VAR model presented a better forecast than ARIMA models for the highly correlated variables such as GDP vs. GNP, Export vs. Import, etc. But ARIMA and VAR models performed almost the same for comparatively low correlated variables. That's means the variables were comparatively low correlated couldn't give a better forecast in the multivariate time series model rather than the univariate time series model. Finally, researchers concluded that before forecasting the authority should check correlations among the variables, and for high correlated variables, the VAR model should be used for forecasting, and otherwise, they can consider any models for both of these correlated and uncorrelated variables.

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1 Introduction

Forecasting is a vital tool of statistical applications for prediction especially for financial variables [1] that have the likelihood of future events based on past and current information. This past and current information are embodied in the form of a model-a single equation structural model or, as it was discussed in parts two- a multi-equation model or a time series model [1,2]. By extrapolating models out beyond the period over which were estimated, it can be used the information contained in them to make forecasts about future events [3,4]. The term forecasting is often thought to apply solely to time-series problems in which we predict the future from given information about the past and the present [4]. Forecasting [5,6] and predicting financial time series [3,7-9] have been a topic of active research for the past few decades. It is a key element of financial and managerial decision making which can be highly utilized in predicting economic and business trends for improved decisions and investments [3,9].

There are several ways to model a time series to make predictions such as moving average (MA), exponential, autoregressive integrated moving average (ARIMA), vector autoregressive (VAR), etc. Here, the researcher considered the VAR model with different orders for multivariate time series model and ARIMA model for univariate time series model [10-12]. Multivariate time series analysis (MVTSA) introduces a way to observe the relationship of a group of variables over time [12], thus making use of all possible information such as correlation [13]. For example, the GDP of Bangladesh is related to Export, Import, Exchange rates, and some other economic variables [14-15]. In such situations, which model can give better results; multivariate or univariate time series models? Multivariate models may contribute better forecast rather than univariate models involving all possible information. MVTSA is an extension of univariate time series analysis (UVTS) [14,16]. Multivariate forecast (MVF) is one kind of forecast that can forecast simultaneously a group of time series variables considering some special issues. Its application is widespread, for example, the medical field where the relationship between exercise and blood glucose can be modeled [17] to the engineering field where the process control effectiveness can be evaluated [18]. On the other hand, the univariate forecast (UVF) is another forecasting process that uses only one variable at a time [19]. In the economy, some variables are highly correlated and some of the variables are low correlated.

Bangladesh is a developing country [20] where the economic condition of the nation depends on different factors; economic variables are the most important factors among these indicators. The development of the financial situation is always threatened by several reasons like a political crisis, natural hazard, inflation, etc. [20,21]. That's why for developing countries like Bangladesh, the government should take some crucial steps to make better financial conditions efficiently. The forecast is not only an essential part of the economy but also a vital part of the socio-economic [22] and agricultural economic [23] prediction. Although the term forecast is often applied solely to time series problems in which it has predicted the future concerning given information about past and present. It should be emphasized for practical computation of the forecasts.

In the economy, one variable is considerably related to each other. There are different variables such as GDP, GNP, Export, Import, and so on that are related to each other [24]. So, for changing one variable may affect other related variables. Based on the correlation among the variables, how can we select a time series model for forecasting? These are the main problems. If the variables are not related to each other, a time series model may be easily selected that can be any type of model. This research aims to check the performance of forecasting models among the highly correlated variables and comparatively low correlated variables along with the behavior of multivariate and univariate time series models for the selected economic variables.

2 Methods and Materials

The VAR model with a different order for multivariate time series analysis and ARIMA models with a different order for univariate time series analysis were discussed in this article. Here we discussed prediction

based on VAR for multivariate and ARIMA for univariate time series models and also considered point and interval forecast [9,12].

2.1 Vector autoregressive process

For multivariate analysis, the vector autoregressive (VAR) process is one of the most successful, flexible, and easy processes to use models for time series analysis. The VAR model has proven to be useful especially for describing the dynamic behavior of economic and also financial time series and for forecasting [12,25].

Let $Y_t = (y_{1t}, y_{2t}, ..., y_{nt,})'$ denote a $(n \times 1)$ vector of time series variables. The basic p-order vector autoregressive VAR (p) model has the form-

$$Y_t = \sum_{j=1}^{p} \Phi_j Y_{t-j} + a_t \tag{1}$$

Where: Φ_j is $n \times n$ coefficient matrices, and a_t is $n \times 1$ unobserved zero mean white noise vector (serially uncorrelated or independent) process with time invariant covariance matrix $\sum$ [26]. e.g. $a_t \sim i.i.n(0, \sum)$, $E(a_t) = 0$ and

$$E(a_t a_t') = \begin{pmatrix} E(a_{1t}^2) & E(a_{1t}a_{2t}) & \cdots & E(a_{1t}a_{nt}) \\ E(a_{2t}a_{1t}) & E(a_{2t}^2) & \cdots & E(a_{2t}a_{nt}) \\ \vdots & \vdots & \vdots & \vdots \\ E(a_{nt}a_{1t}) & E(a_{nt}a_{2t}) & \cdots & E(a_{nt}^2) \end{pmatrix} \text{ with } E(a_t a_s') = 0 \text{ for } t \neq s.$$

It can be written as the form-

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + a_t \tag{2}$$

This VAR model can be expressed in matrix notation as VAR(p). Also, $Y_t, a_t, \Phi_j,$ and Y_{t-} can express in the matrix form as [12]:

$$Y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix}, \ a_t = \begin{bmatrix} a_{1t} \\ a_{2t} \\ \vdots \\ a_{nt} \end{bmatrix}, \Phi_j = \begin{bmatrix} \Phi_{11}^j & \Phi_{12}^j & \cdots & \Phi_{1n}^j \\ \Phi_{21}^j & \Phi_{22}^j & \cdots & \Phi_{2n}^j \\ \vdots & \vdots & \vdots & \vdots \\ \Phi_{n1}^j & \Phi_{n2}^j & \cdots & \Phi_{nn}^j \end{bmatrix} \text{ and } Y_{t-j} = \begin{bmatrix} y_{1t-1} & y_{2t-1} & \cdots & y_{nt-1} \\ y_{1t-2} & y_{2t-2} & \cdots & y_{nt-2} \\ \vdots & & \vdots & \vdots \\ y_{1t-p} & y_{2t-p} & \cdots & y_{nt-p} \end{bmatrix}.$$

2.1.1 Vector Autoregressive Model of Order 1

The vector autoregressive model of order 1, VAR(1) is written in the form as:

$$Y_t = \Phi_1 Y_{t-1} + a_t \tag{3}$$

$$Y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \Phi_{11}^1 & \Phi_{12}^1 \\ \Phi_{21}^1 & \Phi_{22}^1 \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix} \tag{4}$$

where,

$$Y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}, \ \Phi_1 = \begin{bmatrix} \Phi_{11}^1 & \Phi_{12}^1 \\ \Phi_{21}^1 & \Phi_{22}^1 \end{bmatrix}, Y_{t-1} = \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} \text{ and } a_t = \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}.$$

In general, the higher-order VAR model like VAR(2), VAR(3), etc. can be expressed similarly with increasing order of coefficients [26].

2.2 Univariate time series model

Autoregressive (AR), moving average (MA), autoregressive integrated moving average models were used for univariate time series prediction. These models were described in the following.

2.2.1 Autoregressive process

Let Y_t represent time series at time t. If the model Y_t as:

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + \mu_t \tag{5}$$

where, δ is the mean of Y and μ_t is an unconditional random error term with zero mean and constant variance σ^2 (i.e., it is white noise), then it can be addressed that Y_t follows a first ordered autoregressive AR(1) process [10,26-28]. This model showed that the forecasting value of Y at time t is simply some proportion $(= \alpha_1)$ of its value at a time $(t - 1)$ plus a random shock or disturbance at time t. Then the model as:

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + \alpha_2 (Y_{t-2} - \delta) + \mu_t \tag{6}$$

In equation (6), Y_t follows a second-order autoregressive or AR(2) process [10,26] where the value of Y at time t depends on its value in the previous two time periods. Here, Y values are being expressed around the mean value of δ. In general,

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + \alpha_2 (Y_{t-2} - \delta) + \cdots + \alpha_p (Y_{t-p} - \delta) + \mu_t. \tag{7}$$

The equation (7) is a pth-order autoregressive or AR(p) process [10,26].

2.2.2 Autoregressive integrated moving average

In the case of non-stationary time series, some integration is needed for converting it into stationary series. If a time series is integrated of order 1 (i.e., it is expressed as $I(1)$), after first differentiation it would be stationary, expressed as $I(0)$, that is, stationary time series. Similarly, if a time series expressed as $I(2)$, that means, after the second differentiation it would be $I(0)$. In general, if a time series is $I(d)$, after differentiate it at d times; it would be obtained as stationary series $I(0)$. Therefore for predicting stationary forecast, it is needed to differentiate the series at d times and then it would be applied as the autoregressive moving average time series model such as ARMA(p, q). Also, it can be said that the original time series model is ARIMA(p, d, q), that is an autoregressive integrated moving average time series model, where p denotes the number of autoregressive terms, d is the number of times that the series has to be differentiate before converting it as stationary, and q is the number of moving average terms [10].

2.3 Stationary checking of the models

Equation (2) showed that Y_t is multivariate time series with disturbance term a_t. The time series Y_t will be stable if the eigenvalues of the matrix Φ_1 have modulus less than 1 [26]. The condition is equivalent to-

$$\det (I_{kp} - \Phi_Z) \neq 0, for \ |Z| \leq 1.$$

$$det\left(I_k - \Phi_1 z - \Phi_2 z^2 - \cdots - \Phi_p z^p\right) \neq 0, for |z| \leq 1. \tag{8}$$

There is another condition that determines whether a VAR(p) process is stationary. As we might expect stationary depends on the coefficient of $\emptyset(B)$. Although there is a complication, however, in that case $\emptyset(B)$ is a matrix polynomial and not a scalar polynomial. The appropriate generalization involves the roots of the determinant of $\emptyset(B)$ defined as [12, 26]:

$\alpha(B) = \det[\emptyset(B)]$, which is a scalar polynomial of order $p^* = np$ so that

$$\alpha(B) = 1 + \alpha_1 B + \alpha_2 B^2 + \cdots + \alpha_{p^*} B^{p^*} \tag{9}$$

where, α_i is a scalar.

A necessary condition for a VAR(p) process to be a stationary model, if the scalar polynomial $\alpha(B)$ have all roots greater than 1 in its absolute value or

$$\det[\emptyset(B)] = 0 \implies |B| > 1.$$

For the univariate time series analysis model (ARIMA), the process investigated stationary from the graphical presentation with the pattern of *ACF* or *PACF* graphs. In the case of two or more competing models passing the diagnostic checks, the best model is selected using the criteria multiple R^2, Root Mean Squared Error (RMSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC).

2.4 Performance measures of forecasting

The crucial object in measuring forecasting accuracy is the loss function, $L\left(y_{t+h}, y_{t+h,t}\right)$, often restricted to $L\left(e_{t+h,t}\right)$, which charts the "loss", "cost", or "disutility" associated with various pairs of forecasts and realizations. In addition to the shape of the loss function, the forecast horizon h is of crucial importance. Here a few accuracy measures are mentioned which in actual fact are very important and popular. Accuracy measures are usually defined based on the forecast errors and percent errors showed in the following equations [27,28].

Error: $e_{t+h,t} = y_{t+h} - y_{t+h,t}$

Percent Error: $p_{t+h,t} = \dfrac{(y_{t+h} - y_{t+h,t})}{y_{t+h}}$

Mean Error: $ME = \dfrac{1}{T} \sum\limits_{t=1}^{T} e_{t+h}, t$

Root Mean Squared Error: $RMSE = \sqrt{\dfrac{1}{T} e^2}_{t+h,t}$

Mean Absolute Error: $MAE = \dfrac{1}{T} \sum\limits_{t=1}^{T} \left| e_{t+h,t} \right|$

Mean Percent Error: $MPE = \dfrac{1}{T} \sum\limits_{t=1}^{T} p^2_{t+h,t}$

Mean Absolute Percent Error: $MAPE = \dfrac{1}{T} \sum_{t=1}^{T} \left| p_{t+h,t} \right|$

Mean Absolute Squared Error: $MASE = \dfrac{1}{T} \sum_{t=1}^{T} \left(\left| e_{t+h,t} \right| \right)^2$

2.5 Data and Variables

The data were used in this research was secondary data. The financial data were used in this research. These data were collected from different financial organizations and publications in Bangladesh. These publications and organizations are the Bangladesh bank bulletin [29] (Central bank of Bangladesh), Bangladesh economic review [30], Monthly economic trends of Bangladesh bank [31], and Statistical yearbook of Bangladesh [32]. The economic variables gross domestic product (GDP), gross national product (GNP), the exchange rate (Exch. rate), consumer price index (CPI), export, and import were selected for the study because of its availability and significance of the variables in the economy. These economic variables were collected from the period of 1972 to 2012. The variables were partitioned into two ratios like 70% to 30% and entitled as training and test data set respectively. Here some of the steps were applied for predicting which are- a) partition the variables as training and test data set b) checking the stationary of the model for the variable c) forecast the variables applying the selected model and d) checking accuracy. For checking stationary, the authors used roots of the polynomial according to equations (8) and (9) for multivariate time series analysis and acf and $pacf$ graphs were used for checking stationary in univariate models. But the roots of the polynomial of the selected models and acf and $pacf$ graphs for the variables were not shown in this article because of reducing the length of the article. Also, here predicting values were compared with a test data set that was also not presented in the article. For comparison of forecasting performance, the accuracy measures ME, RMSE, MAE, MPE, MAPE, and MASE were used in this article.

3 Results

3.1 Correlation matrix

Table 1 showed the correlation matrix among the selected economic variables. It is shown that Exch. rate vs. GDP, GDP vs. GNP, and Export vs. Import are highly correlated variables among the selected variables whereas CPI vs. GDP, CPI vs. Exch. rate, and CPI vs. GNP are comparatively low correlated variables. In this article, these highly correlated and comparatively low correlated variables are used for forecasting and comparing performance.

Table 1. Correlation matrix among selected economic variables

	Exch. rate	GDP	GNP	CPI	Export	Import
Exch. rate	1.000					
GDP	0.973	1.000				
GNP	0.959	0.994	1.000			
CPI	0.669	0.663	0.675	1.000		
Export	0.835	0.875	0.893	0.814	1.000	
Import	0.840	0.879	0.896	0.829	0.998	1.000

3.2 Forecasting among highly correlated variables

3.2.1 Forecasting among Highly Correlated Variables GDP and GNP

The correlation between GDP and GNP was 0.994 in Table 1 which was a highly correlated value. Fig. 1 represented the forecasting pattern for multivariate and univariate time series models.
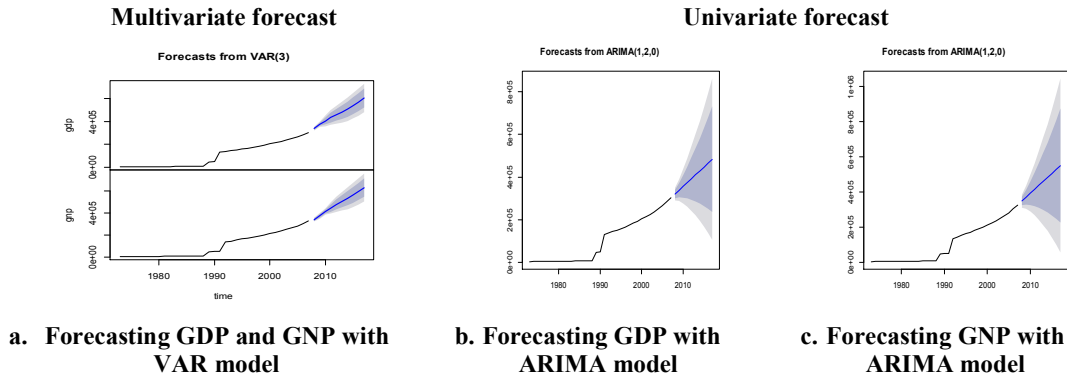
Multivariate forecast   **Univariate forecast**

a. Forecasting GDP and GNP with VAR model   **b. Forecasting GDP with ARIMA model**   **c. Forecasting GNP with ARIMA model**

Fig. 1. Forecasting comparison with VAR vs. ARIMA Model between GDP and GNP

Fig. 1 showed the predicting economic variable, GDP, and GNP in Bangladesh. Fig. 1 (a) depicted forecasting with the VAR model and Fig. 1 (b) and Fig. 1(c) indicated forecasting with the ARIMA model. All these figures depicted here are point forecast and interval forecast at a time. The middle lines of the forecasting patterns portrayed point forecast with the VAR model in Fig. (a) and ARIMA model in Fig. (b-c). The outsides of the middle line of the Fig. (a-c) described interval forecast. Fig. 1 (b & c) indicated a larger area comparatively Fig. 1(a).

3.2.2 Forecasting accuracy measures of VAR vs. ARIMA models for GDP and GNP

Table 2 described all accuracy measures ME, RMSE, MAE, MPE, MAPE, and MASE for a bivariate forecast. It is observed that all measures ME, RMSE, MAE, MPE, MAPE, and MASE were lower in the VAR model than the ARIMA model for both the variables GDP and GNP. All information reported that the forecasting with the VAR model was better than ARIMA models between these two highly correlated variables.

Table 2. Forecasting accuracy measures of VAR vs. ARIMA Models for GDP and GNP

Model	Variable	ME	RMSE	MAE	MPE	MAPE	MASE
VAR model	GDP	-2.44×10^{-13}	7472.52	4254.99	515.48	954.82	0.315
	GNP	-2.08×10^{-13}	7268.36	3703.54	350.26	493.19	0.247
ARIMA model	GDP	992.023	14077.3	5389.67	1.406	6.387	0.518
	GNP	1055.51	16935.9	6782.40	0.6211	7.659	0.594

3.2.3 Forecasting among highly correlated variables export and import

The correlation between the other two highly correlated variables Export and Import was 0.998 which was a very highly correlated value. Fig. 2 represented the forecasting patterns of these two variables with VAR and ARIMA models.
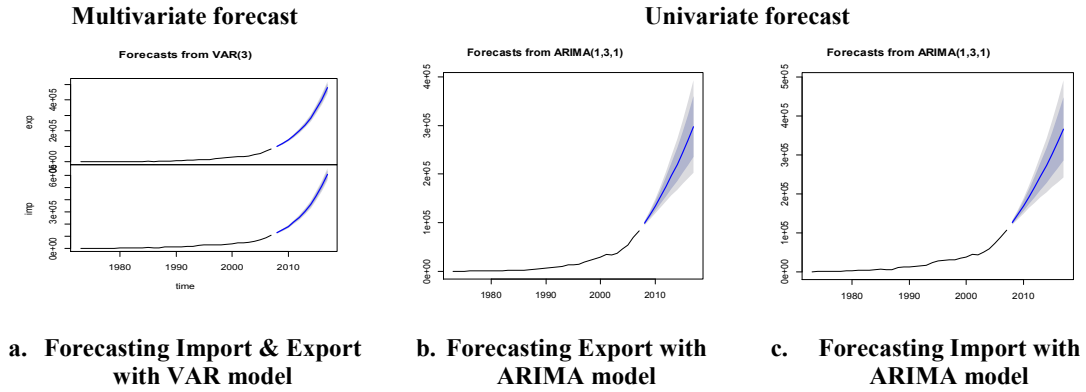
Multivariate forecast   **Univariate forecast**

| a. Forecasting Import & Export with VAR model | b. Forecasting Export with ARIMA model | c. Forecasting Import with ARIMA model |

Fig. 2. Forecasting comparison with VAR vs. ARIMA Models between export and import

Fig. 2 showed the prediction of the economic variable Export and Import in Bangladesh. Fig. 2(a) depicted forecasting with the VAR model, similarly, Fig. 2(b) and Fig. 2(c) indicated forecasting with the ARIMA models. All these figures described point and interval forecast at a time. The middle lines of the forecasting patterns portrayed point forecast with the VAR model in Fig. (a) and ARIMA model in Fig. (b-c). The outside of the middle line of the Fig. 2(a-c) described interval forecast. Fig. 2(b & c) indicated a larger area comparatively Fig. 2(a).

3.2.4 Forecasting accuracy measures of VAR vs. ARIMA models for export and import

Table 3 described all the accuracy measures ME, RMSE, MAE, MPE, MAPE, and MASE for these two highly correlated variables. All the measures were described as minimum in the VAR model than ARIMA models. All information concluded that the forecasting with the VAR model was better rather than the ARIMA models comparing these two highly correlated variables.

Table 3. Forecasting accuracy measures of VAR vs. ARIMA models for export and import

Model	Variable	ME	RMSE	MAE	MPE	MAPE	MASE
VAR model	Export	1.32×10^{-13}	3873.42	2253.03	11.26	12.75	0.362
	Import	2.24×10^{-13}	5759.99	2144.86	10.51	10.55	0.426
ARIMA model	Export	1127.65	7377.86	2542.64	0.593	10.806	0.501
	Import	1417.10	10599.97	4305.88	1.079	11.616	0.651

3.2.5 Forecasting among highly correlated variables Exch. rate, GDP, and GNP

Fig. 3 showed the prediction of economic variables Exch. rate, GDP, and GNP in Bangladesh. Fig. 3(a) depicted forecasting with the VAR model, and similarly, Fig. 3(b), Fig. 3(c), and Fig. 3(d) outlined forecasting with the ARIMA model. All these figures were described as point and interval forecasts at the same time. The middle lines of the forecasting patterns portrayed point forecast with the VAR model in Fig. (a) and ARIMA model in Fig. (b-d). The outside of the middle line of the Fig. 3(a-d) described interval forecast. Fig. 3(b-d) indicated larger areas in comparatively Fig. 3(a).

3.2.6 Forecasting accuracy measures of VAR vs. ARIMA Models for Exch. rate, GDP, and GNP

Table 4 described all the accuracy measures; ME, RMSE, MAE, MPE, MAPE, and MASE for forecasting of these three variables. It was found that all the measures were minimum in the VAR model in comparison to ARIMA models. All information concluded that the forecasting with the VAR model was better than ARIMA models among these highly correlated variables, Exchange rate, GDP, and GNP.
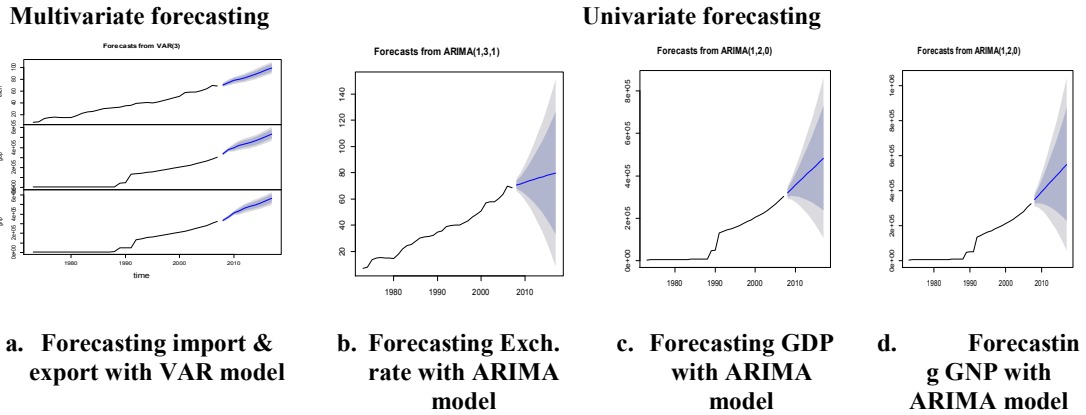
Multivariate forecasting   **Univariate forecasting**

| a. Forecasting import & export with VAR model | b. Forecasting Exch. rate with ARIMA model | c. Forecasting GDP with ARIMA model | d. Forecasting GNP with ARIMA model |

Fig. 3. Forecasting comparison between VAR vs. ARIMA Model among Exch. rate, GDP, and GNP

Table 4. Forecasting accuracy measures of VAR vs. ARIMA models for Exch. rate, GDP, and GNP

Model	Variables	ME	RMSE	MAE	MPE	MAPE	MASE
VAR model	Exch. rate	-2.20×10^{-16}	1.446	1.142	-0.082	2.910	0.571
	GDP	-8.61×10^{-14}	6576.40	4832.01	-10.85	32.095	0.464
	GNP	1.622×10^{-12}	6575.95	3960.77	-2.852	14.019	0.346
ARIMA model	Exch. rate	-0.018	2.989	2.121	-0.753	6.453	1.050
	GDP	992.023	14077.31	5389.67	1.406	6.387	0.518
	GNP	1055.51	16935.93	6782.40	0.621	7.659	0.594

3.3 Forecasting of comparatively low correlated variables

Table 1 showed the correlation between exchange rate vs. CPI, CPI vs. GDP, and CPI vs. GNP was comparatively low in correlation with each other. Here, at first, we applied bivariate forecast and after then three variables forecast for the multivariate forecast. And, next, the ARIMA model is used for each variable separately for the univariate forecast.

3.3.1 Forecasting of two low correlated variables Exch. rate and CPI

The correlation between CPI and the exchange rate was 0.669 which was moderately low. Fig. 4 demonstrated the forecast of these low correlated variables.
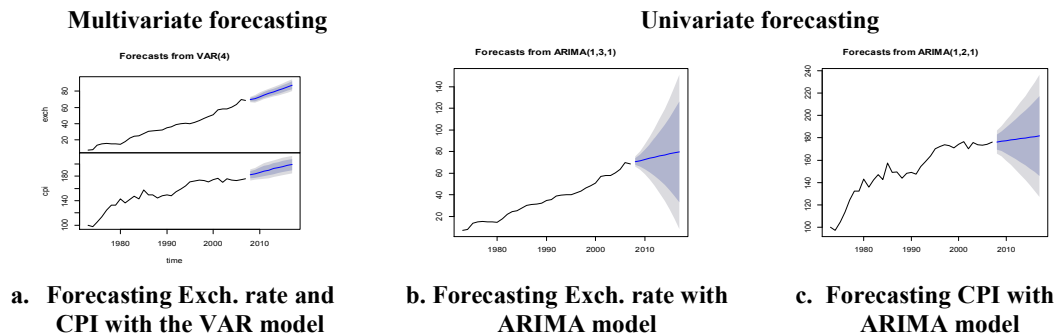
Multivariate forecasting   **Univariate forecasting**

| a. Forecasting Exch. rate and CPI with the VAR model | b. Forecasting Exch. rate with ARIMA model | c. Forecasting CPI with ARIMA model |

Fig. 4. Forecasting comparison with VAR and ARIMA Model between Exch. rate and CPI

Fig. 4 showed the prediction of economic variables, Exch. rate, and CPI in Bangladesh. Fig. 4(a) depicted forecasting with the VAR model, similarly, Fig. 4(b) and Fig. 4(c) outlined forecasting with the ARIMA model. All these figures described point and interval forecast at the same time. The middle lines of the forecasting patterns portrayed point forecast with the VAR model in Fig. (a) and ARIMA model in Fig. (b-c). The outside of the middle line of the Fig. 3(a-c) described interval forecast. Fig. 3(b-c) indicated a larger area comparatively in Fig. 3(a).

3.3.2 Forecasting accuracy measures of VAR vs. ARIMA Models for Exch. rate and CPI

Table 5 described all the accuracy measures of forecasting such as ME, RMSE, MAE, MPE, MAPE, and MASE which were nearest in both VAR and ARIMA models; some of these values were found to be almost equal in corresponding model showed in Table 5. All of this information suggested that the forecasting with the VAR model was not so better than ARIMA models for these two comparatively low correlated variables.

Table 5. Forecasting accuracy measures of VAR vs. ARIMA Models for Exch. rate and CPI

Model	Variables	ME	RMSE	MAE	MPE	MAPE	MASE
VAR model	Exch. rate	4.88×10^{-17}	2.994	2.125	111.84	142.70	0.323
	CPI	1.760	22.311	13.328	270.93	601.96	0.349
ARIMA model	Exch. rate	-0.018	2.989	2.121	-0.753	6.453	0.050
	CPI	1.669	16.46	8.996	0.249	6.584	0.284

3.3.3 Forecasting of three variables which are comparatively low correlated

Multivariate forecast   **Univariate forecast**

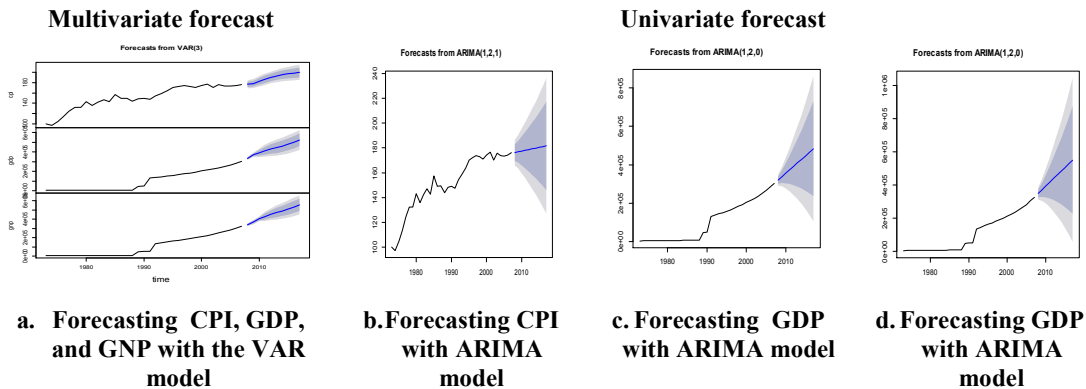| a. Forecasting CPI, GDP, and GNP with the VAR model | b. Forecasting CPI with ARIMA model | c. Forecasting GDP with ARIMA model | d. Forecasting GDP with ARIMA model |

Fig. 5. Forecasting comparison with VAR vs. ARIMA Model among CPI, GDP, and GNP

Fig. 5 showed the predicting of economic variables CPI, GDP, and GNP in Bangladesh. Fig. 5(a) depicted forecasting with the VAR model and Fig. 4(b) to 4(d) outlined forecasting with ARIMA models. All these figures described point and interval forecast at the same time. The middle lines of the forecasting patterns portrayed point forecast with the VAR model in Fig. 5(a) and ARIMA model in Fig. 5(b-d). The outside of the middle line of the Fig. 5(a-d) described interval forecast. Fig. 5(b-d) indicated a larger area comparatively in Fig. 3(a).

3.3.3 Forecasting accuracy measures VAR vs. ARIMA Models for CPI, GDP, and GNP

Tables 6 showed all the accuracy measures ME, RMSE, MAE, MPE, MAPE, and MASE of forecasting of these three low correlated variables. The ME, RMSE, MAE, MPE, MAPE, and MASE all were not varied in the multivariate and univariate forecast for each corresponding variable. According to all of this information,

it can be concluded that selecting a univariate forecast model would not be worse than the multivariate model regarding these low correlated economic variables CPI, GDP, and GNP of Bangladesh.

Table 6. Forecasting accuracy measures of VAR vs. ARIMA Models for CPI, GDP, and GNP

Model	Variables	ME	RMSE	MAE	MPE	MAPE	MASE
VAR model	CPI	1.722	16.56	9.45	1.042	9.94	0.894
	GDP	-2.95×10^{-13}	7757.60	5802.20	-27.28	28.94	0.557
	GNP	-2.94×10^{-12}	6905.62	3577.70	-3.527	11.868	0.313
ARIMA model	CPI	92.02	17.31	5389.67	1.406	6.387	0.518
	GDP	105.51	6935.93	6782.40	0.621	7.659	0.594
	GNP	1.609	616.46	8.996	0.249	6.584	0.884

4 Discussion

This research considered forecasting performance with different time series models like vector autoregressive (VAR), autoregressive integrated moving average (ARIMA. The main concept of this study is to find the best forecasting models, where a group of variables is highly associated and some of the variables are comparatively low associated. This article found that the multivariate models like VAR models were best where correlation is higher but ARIMA models were not so inappropriate where the correlation was low. In low correlated variables, both the VAR model and ARIMA model were not worse for the financial variables. Both multivariate time series modes and ARIMA models were used for health care research. ARIMA models were used for diabetes before and after being placed on a regimen of chlorpropamide and VAR models were used for modeling the relationship between exercise and blood glucose and psychosocial distress and lymphocyte [17]. In another study, Seng Sothan [21] emphasized that foreign aid for long periods did not contribute fairly to investment and growth using univariate time series with distributive lag order. Also, Robert J. Barro [31] found the relationship between GDP and fertility rate and growth rates were positively related to political stability. ARIMA models with different orders were applied for showing rice production patterns in Bangladesh [23]. The researcher found that short-term forecasting was more efficient for ARIMA models compared to other models. VAR models were strongly related to the interrelationship of interest rates, money, etc. [25]. Swedish unemployment was forecasted [32] with ARIMA and VAR models which showed that the ARIMA model was performed better forecast. Masayoshi Hayashi [33] emphasized the VAR model for forecasting welfare caseloads in Japan; found that VAR and forecast combinations tend to outperform the other methods of investigation. Forecasting women, infants, and children caseloads, the VAR model predicted fewer errors compared to ARIMA models [34]. Based on this research [34], the cost savings to using the VAR model were high. If the costs of estimating these models were high, this may not represent a large cost saving. Stationary autoregressive moving average processes (ARMA) were used [35] for a real lifetime series of data that found the analysis of time series data exhibiting non-stationary behavior and handling easily missing data and that was computationally efficient. Also, Hyun Joo Chang [36] applied the ARIMA model for explaining welfare caseload reduction in New York State. He studied an ARIMA model with intervention analysis using the gross state product as an economic force that reflected labor demand and supplies with policy development. VAR models were designed to analyze the monetary policy transmission mechanism in the USA by considering specification, identification, and the effect of the omission of the long-term interest rate [37]. Here VAR model delivered a more precise estimation of the structural parameters capturing behavior in the market for reserves and showed that contemporaneous fluctuations in long-term interest rates.

However, there were some limitations to this study. Secondary data were used in this study and also the outputs of the study were considered into three decimal places. The forecasting values were not presented in the article because of the large number of tables. Also to minimize the number of tables, we avoid some of the tables which represented forecasting values as well as model identifications criteria. For VAR model selection, we used only for eigenvalues, not graphical presentation. Similarly, in ARIMA models, we used only graphical presentation of ACF and PACF curve but it would not possible to present the article.

5 Conclusions

This article considered forecasting performance in multivariate and univariate time series models under consideration of correlation. The researchers used some financial variables of Bangladesh such as GDP, GNP, Export, Import, CPI, and Exchange rate for showing the performance of forecasting. These all are numerical variables. For checking forecasting error, the researcher divided the entire data set into two parts 70:30 ratios named training and test data set. Then it was checked the forecasting accuracy by using ME, RMSE, MAE, MPE, MAPE, and MSPE. This research indicated that the VAR model presented a better forecast than ARIMA models for the highly correlated variables such as GDP vs. GNP, Export vs. Import, etc. But when the variables were comparatively low correlated like CPI vs. exchange rate, CPI vs. GDP, etc. then both ARIMA and VAR models gave almost the same performances which expressed that the variables were comparatively low correlated and couldn't give a better forecast in the multivariate time series model rather than the univariate time series model.

Finally, it can be concluded that before forecasting the researchers should check correlations among the variables, and applying the VAR model if their presence a high correlation among the variables. If there does not exist a high correlation among variables then we can use any techniques; like univariate or multivariate time series models. The authorities of a nation can apply this concept for predicting economy and weather forecast as well as forecasting agricultural production.

Competing Interests

Author has declared that no competing interests exist.

References

[1] Clements M, Hendry D. An overview of economic forecasting. A Companion to Economic Forecasting. Oxford: Blackwell. 2002;15:1-8.

[2] Akadiri AC, Gungor H, Akadiri SS, Bamidele-Sadiq M. Is the causal relationship between foreign direct investment, trade, and economic growth complement or substitute? The Case of African Countries. Journal of Public Affairs. 2020;20(2):e2023.

[3] Chaudhuri A. Forecasting financial time series using multiple regression, multi-layer perception, radial basis function, and adaptive neuro fuzzy inference system models: A comparative analysis. Computer and Information Science. 2012;5(6):13-24.

[4] Pindyck RS, Rubinfeld DL. Econometric Models and Economic Forecasts Mcgraw-Hill Book Company. New York; 1981.

[5] Armstrong JS. Editor. Principles of forecasting: A handbook for researchers and practitioners. Springer Science & Business Media; 2001.

[6] Chen SM. Forecasting enrollments based on high-order fuzzy time series. Cybernetics and Systems. 2002;33(1):1-6.
DOI:10.1080/019697202753306479

[7] Box GE. Jenkins GM. Time series analysis: Forecasting and Control San Francisco. Calif: Holden-Day; 1976.

[8]   Brockwell PJ. Davis RA. Introduction to time series and forecasting springer-verlaged. New York. 1996;1-422.

[9]   Chatfield C. Calculating interval forecasts. Journal of Business & Economic Statistics. 1993;11(2):121-35.

[10]   Gujarati DN. Basic Econometrics. Tata McGraw-Hill Education; 2009.

[11]   Chiu CW, Mumtaz H, Pinter G. Forecasting with VAR Models: Fat Tails and Stochastic Volatility. International Journal of Forecasting. 2017;33(4):1124-43.
        DOI: 10.1016/J.IJFORECAST.2017.03.001

[12]   Lütkepohl H. Vector autoregressive models. In Handbook of Research Methods and Applications in Empirical Macroeconomics 2013 Jul 30. Edward Elgar Publishing; 2013.
        DOI: https://doi.org/10.4337/9780857931023

[13]   Lee TH, Long X. Copula-based multivariate GARCH Model with uncorrelated dependent errors. Journal of Econometrics. 2009;150(2):207-18.
        DOI: https://doi.org/10.1016/j.jeconom.2008.12.008

[14]   Kling JL, Bessler DA. A Comparison of multivariate forecasting procedures for economic time series. International Journal of Forecasting. 1985;1(1):5-24.
        DOI: 10.1016/S0169-2070(85)80067-4

[15]   Breymann W, Dias A, Embrechts P. Dependence structures for multivariate high-frequency data in Finance; 1985.
        DOI: 10.1080/713666155

[16]   Evans MK. Practical Business Forecasting. Blackwell (Malden); 2003.

[17]   Crabtree BF, Ray SC, Schmidt PM, O'Connor PT, Schmidt DD. The individual over time: time series applications in health care research. Journal of Clinical Epidemiology. 1990; 43(3):241-60.
        DOI: 10.1016/0895-4356(90)90005-A

[18]   De Vries W, Wu S. Evaluation of process control effectiveness and diagnosis of variation in paper basis weight via multivariate time-series analysis. IEEE Transactions on Automatic Control. 1978;23(4):702-8.
        DOI: 10.1109/TAC.1978.1101828

[19]   Caillault ÉP, Bigand A. Comparative Study on univariate forecasting methods for meteorological time series. In 2018 26th European Signal Processing Conference (EUSIPCO). 2018;3:2380-238. IEEE.
        DOI: 10.23919/EUSIPCO.2018.8553576

[20]   Islam A. Foreign aid and economic growth: an econometric study of Bangladesh. Applied Economics. 1992;24(5):541-4.
        DOI: 10.1080/00036849200000067

[21] Sothan S. Foreign aid and economic growth: evidence from cambodia. The Journal of International Trade & Economic Development. 2018;27(2):168-83.
DOI:10.1080/09638199.2017.1349167

[22] Khan MMH, Kraemer A. Socio-economic factors explain differences in public health-related variables among women in Bangladesh: A Cross-Sectional Study. BMC Public Health. 2008;8:254.
Available:https://doi.org/10.1186/1471-2458-8-254

[23] Awal MA, Siddique MA. Rice production in bangladesh employing by ARIMA Model. Bangladesh Journal of Agricultural Research. 2011;36(1):51-62.
Available:https://doi.org/10.3329/bjar.v36i1.9229

[24] Ihsan H, Ahmad E, Sadia H. Relationship of economic and financial variables with behavior of stock returns. Journal of Economic Cooperation among Islamic Countries. 2007;28(2).

[25] Runkle DE. Vector autoregressions and reality. Journal of Business & Economic Statistics. 1987;5(4):437-42.
DOI: 10.1080/07350015.1987.10509609

[26] Sampson M. Time series analysis. Log-Linear Publications, Canada; 2001.

[27] Diebold FX. Elements of forecasting. South-Western College Pub; 1998.

[28] Diebold Francis X. Elements of forecasting. Cincinnati, Thomson South Western;2007.

[29] Bank B. Bangladesh Bank Bulletin, Money and Banking.
Available: https://books.google.ki/books?id=wrIvpGpF5wsC&source=gbs_navlinks_s

[30] Ministry of Finance. Bangladesh Economic Review; 2009.
Available:https://www.google.ki/search?tbm=bks&hl=en&q=Bangladesh+economic+review

[31] Bank B. Monthly economic trends, December, 2012. Statistics Department, Bangladesh Bank, Head Office, Dhaka, Bangladesh; 2012.

[32] Available:https://www.google.ki/search?tbm=bks&hl=en&q=Monthly+economic+trends+of+Bangladesh+bank

[33] Statistics BB. Statistical year book of Bangladesh. Statistics Division, Ministry of Planning, Dhaka. Government of the people's republic of Bangladesh; 2011.
Available:http://www.bbs.gov.bd/site/page/29855dc1-f2b4-4dc0-9073-f692361112da/Statistical-Yearbook

[34] Hayashi M. Forecasting welfare caseloads: The case of the japanese public assistance program. Socio-Economic Planning Sciences. 2014;48(2):105-14.
Available:https://doi.org/10.1016/j.seps.2013.10.002

[35] Lazariu V, Yu C, Gundersen C. Forecasting women, infants, and children caseloads: A comparison of vector autoregression and autoregressive integrated moving average approaches. Contemporary Economic Policy. 2011;29(1):46-55.
Available:https://doi.org/10.1111/j.1465-7287.2010.00203.x

[36] Khashei M, Bijari M. An Artificial neural network (P, D, Q) model for time series forecasting. Expert Systems with Applications. 2010;37(1):479-89.
Available:https://doi.org/10.1016/j.eswa.2009.05.044

[37] Joo Chang H. Explaining welfare caseload reduction in New York State: The Effect of Policy or Economy? International Review of Public Administration. 2007;12(1):105-17.
Available:https://doi.org/10.1080/12294659.2007.10805095

[38] Bagliano FC, Favero CA. Measuring monetary policy with var models: An Evaluation. European Economic Review. 1998;42(6):1069-112.
Available:https://doi.org/10.1016/S0014-2921(98)00005-1