Time Series Long-Term Forecasting of per Capita Electricity Consumption for Bangladesh

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Bangladesh government has announced Vision-2041 of electricity generation and distribution to uplift the socio-economic conditions of Bangladesh. It is now entering into the list of middle-income countries and now planning for energy as one key measure to sustainable development. Policymakers are trying to forecast the future per capita electricity consumption and set up a feasible way of electricity generation over longer periods for sustainable development of Bangladesh through preventing underestimation or overestimation that could cause a huge loss in the financial sector of Bangladesh. This work focuses on long-term estimation of electricity consumption for Bangladesh, time series models have been used to forecast per capita electricity consumption from fiscal year (FY) 2019/20-2040/41 (next 22 years). An actual past historical data of FY 1976/77-2018/19 (43 years) has been analysed on Minitab 17 to get the most favourable time series model for forecasting per capita electricity consumption of Bangladesh. ARIMA has appeared as the most accurate time series model over the actual historical data of 43 years with the lowest MAPE, MAD, and MSD as 4.50, 3.23, and 15.40, respectively.

Keywords: forecasting; electricity consumption; sustainable development; time series models; ARIMA

I. INTRODUCTION

Bangladesh is one of the fastest developing countries reported by the Asian Development Bank (ADB) (Bangladesh and Asian Development Bank, 2018). Bangladesh has declared energy as a main sector of the Sustainable Development Goals (SDGs) (Sustainable Development Goals of Bangladesh, 2015), of the United Nations agreement to be achieved by the year 2030 (Sustainable Development Agenda in United Nations, 2015), and planned to reach high-income country status through Vision 2041 (Bangladesh Development Update, 2019). Among the SDGs of Bangladesh, self-dependency in the energy sector is the leading one. With the rapid industrialisation and development, electricity consumption in Bangladesh has drastically increased over the last two decades (Key Energy Statistics of Bangladesh, 2018). Considering Bangladesh’s current economic growth and improved quality of living standards (World Bank Data, 2018), self-dependency and self-sustainability in electricity are essential. Therefore, good planning of electricity generation and estimation of future per capita consumption is essential to secure the SDGs.

According to the International Energy Agency (IEA), developing regions such as countries from Asia and Africa are anticipated to experience a high need for energy from the year 2017 to 2040 (World Energy Outlook, 2018). Being a developing country, the growing economy of Bangladesh needs uninterrupted electricity in the near future.

Bangladesh Power Development Board (BPDB) has reported 374.62 kWh/per capita electricity consumption in FY 2018/19, which is pretty high compared to its first
estimated quantity in FY 1976/77 (Bangladesh Power Development Board, 2019). An overall jumped of 96.69% is noticeable for the passage of FY 1976/77-2018/19 (43 years), where the source for the electricity comes from different energy sources as presented in Figure 1 (Bangladesh Power Development Board, 2019). This increasing rate would probably continue and will be accelerated due to the government policy to obtain SDGs (Sustainable Goals Tracker, 2018). To comply and support this development process, proper prediction of electricity consumption up to the year 2041 (Vision-2041) is essential to guide the proper use of resources shown in Figure 1 and reduce financial losses that may occur due to lack of proper statistical data analysis of the past consumption. Historical demand data or consumption per capita data can be a good tool, which can be arranged in a time-series manner to predict the future electricity consumption per capita in Bangladesh up to 2041.

Figure 1. Electricity production scenario of Bangladesh FY 2018/19
(Source: Bangladesh Power Development Board, 2019)

Time series analysis is a widespread technique for demand forecasting (Gooijer & Hyndman, 2006), with smoothing techniques (Maçairaa et al., 2015), trend analysis (Zahan & Kenett, 2013), decomposition and statistical analysis (Wang et al., 2012), regression-based techniques (Rahman et al., 2018) has been used in the energy as well as electricity forecasting (Tepedino et al., 2014). The major aspect of forecasting with the time series model is to identify the various energy consumption trends (Campillo et al., 2012), which will lead to policy adaptation regarding demand response. For example, Stoimenova et al. (2007), Lee et al. (2018), Jain et al. (2018), and Ostertagova et al. (2012) has used time series model with different smoothing techniques to determine and forecast future energy as well as electricity consumption for different sector and community. The statistical period (Hussain et al., 2016; Lepojevic & Andelkovic-Pesic, 2011) and smoothing techniques (Ostertagová & Ostertag, 2012; Lepojevic & Andelkovic-Pesic, 2011; Oliveira & Oliveira, 2018) of the actual data were different depending on the real situation of the cases (Stoimenova et al., 2007; Hussain et al., 2016), though time series forecasting (Razak et al., 2009) can significantly enhance the forecasting accuracy with a limited span of historical data (Jiang et al., 2020).

Researchers of different country (Sisman, 2016; Nawaz et al., 2014) and organisation (Sen et al., 2016; Nepal et al., 2020) has used and relied on the times series for its accuracy in energy forecasting (Oliveira & Oliveira, 2018; Sisman, 2016; Shilpa & Sheshadri, 2017) as well as in other sectors (Sen et al., 2016). Oliveira et al. (2018) have rated time series forecasting as an improved method not only for developed countries but also for developing countries in case of long-term forecasting (Jain et al., 2018; Chujai et al., 2013). Rajbhandari et al. (2021) studied the effect of temperature and weekends and weekdays in short-term electricity demand forecasting in the urban area of Nepal while using a time series model with Artificial Neural Networks (ANNs).

This study used the time series forecasting model as a benchmark and the ANNs model developed as feedforward to track the effect of temperature and weekends and weekdays. It was found that the time series model with ANNs performed better in terms of Mean Absolute %age Error (MAPE) on a weekday by 0.34% and 8.04% on weekends. An Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to predict time series electricity demand in Ghana (Acakpovi et al., 2020). Data from 2003-2018 was collected and ANFIS was applied in MATLAB using various scenarios. Then the results were compared with SVR, Least Square Support Vector Machine (LS-SVM), and ARIMA and concluded that ANFIS performed prediction accurately with reliable data for training and reliable parameters setting.

Previously, the time series model (Tirkeş et al., 2017; Towards Data Science, 2019) has been applied for electricity demand or consumption forecasting for Bangladesh. Few pieces of research emphasised local demand forecasting, few
on short-run forecasting, and some for countrywide and long-run forecasting. It has been found that a local electricity demand forecasting for Rajshahi city in Bangladesh done by Sarkar et al. (2015) for the year 2012 to 2020 using Fuzzy Linear Regression model of time series. They used annual average temperature, annual consumer number, and annual electricity consumption data from the year 2001 to 2011. The lowest MAPE found was 1.24% for the years 2012 and 2013. The same approach has been used for local energy forecasting of an isolated island (Kutubdia) in Bangladesh. They forecasted the 12-month electricity demand for the island (Kutubdia) using inverse matrix calculation and linear regression analysis (Islam et al., 2013). Since the island is isolated, no past data was found and therefore, the forecasting was done based on the identification of the key driving factors for the electrical load growth of that area rather than using the historical data.

Another local electricity demand forecasting for Chattogram City in Bangladesh was addressed by Islam et al. (2020). This study applied Long Short-Term Memory Network (LSTM) and results were compared with the Support Vector Machine (SVM) and LSTM outperforms SVM with the reduction of 52.24% and 21.67% error in MAE and RMSE, respectively. For the short-run energy demand forecasting, several machine learning algorithms namely K Nearest Neighbor, Random Forest, and Long Short-Term Memory (LSTM) were applied for short-term (3 years) energy demand forecasting of Bangladesh (Mahmud et al., 2019). In particular, the time series investigation of the causal relationship between electricity consumption and real GDP for Bangladesh from the year 1971 to 2014 has done by Dey and Tareque (2019). They have broadly covered up several issues and did a long forecast focusing on electricity. Their work was a helpful tool for policy adaption on electricity generation, distribution, and management as a short-run solution for higher economic growth. On the other side, the researcher also helped to determine a long-run solution for Bangladesh by adequate investment for electricity supply relates to GDP growth.

Islam et al. (2010) also used time series models to analyse the trend of electricity generation and forecasting electricity demand in Bangladesh up to 2020. They have used the past 28 years of data (1981-2008) and forecast long-term demands for 12 years (2009-2020). Their forecasted total electricity demand for 2020 is 13916 MW. Rahman et al. (2016) did a long-term energy demand forecasting with the time series model (Gooijer & Hyndman, 2006) using an exponential smoothing method (Maçairoa et al., 2015). It has used electricity demand data from the year 1990 to 2010. The energy demand from the year 2011 to 2040 was forecasted with time series on SPSS statistics. The MAPE of this energy consumption forecast for the year only 2012 was found 5.68%, low enough to denote the accuracy of the time series model for energy demand forecasting. It can be highlighted that the available researches and reports for forecasting energy in Bangladesh mostly covered energy sources, the use of energy, and energy demand. There is no research found to be discussed particularly in the long-term per capita electricity consumption for Bangladesh which is a prime concern for the policymaker to meet the generation challenges to obtain SDGs.

In this study, actual historical demand data or consumption per capita of the past 43 years ranged from 1976/77 to 2018/19 (Bangladesh Power Development Board, 2019), has been used in different time series forecasting models (Tirkeş et al., 2017). The errors of the models are estimated to determine the best fit time series model (Towards Data Science, 2019) that coincides nearly with the actual historical data. Later, the best fit time series model has used to forecast future electricity consumption per capita for the next 22 years (FY 2019/20-FY 2040/41) to provide an energy prediction guideline to the policymaker. The accuracy of the best fit time series forecasting model has also been discussed.

II. METHODOLOGY

In this anticipated work, the time series forecasting model has been used to analyse the historical data collected from the Bangladesh government authenticated annual report of FY 2018/19 published by BPDB (Bangladesh Power Development Board, 2019). The data set contains electricity consumption per capita from the FY 1976/77 to FY 2018/19 as of the latest presented in Table 1. Electricity consumption was found to be increasing each year with an upward trend for most of the years except for some years with a little downward trend. For the collected data in Table 1, different time series models were applied namely as Moving Average
(MA) model, Single Exponential Smoothing (SES) model, Double Exponential Smoothing (DES) model, Winter’s Multiplicative and Additive model, Decomposition Multiplicative and Additive model, Linear Trend model, Quadratic Trend model, Exponential Trend model, S Curve Trend Analysis model, and Autoregressive Integrated Moving Average (ARIMA) model.

The forecasting errors of each time series model were evaluated and compare the performance of the models for electricity consumption per capita from the year 1976/77 to 2018/19 for Bangladesh. This model evaluation gave the best fit model with a lower forecasting error of the actual historical data. Using the best fit time series model, possible electricity consumption per capita was forecasted for the FY 2019/20 to FY 2040/41 that is the anticipated timeline to achieve the Vision-2041 (Bangladesh Development Update, 2019) of Bangladesh. The model is expected to provide more conclusive results than the other estimation done partially for different parts of Bangladesh.

### Table 1. Electricity consumption per capita for FY 1976/77 to FY 2018/19 (Bangladesh Power Development Board, 2019)

| Fiscal Year (FY) | 1976/77 | 1977/78 | 1978/79 | 1979/80 | 1980/81 | 1981/82 | 1982/83 |
|-----------------|---------|---------|---------|---------|---------|---------|---------|
| Consumption per capita (kWh) | 12.39 | 14.39 | 16.13 | 16.04 | 19.43 | 22.07 | 25.49 |
| Fiscal Year (FY) | 1983/84 | 1984/85 | 1985/86 | 1986/87 | 1987/88 | 1988/89 | 1989/90 |
| Consumption per capita (kWh) | 28.12 | 28.96 | 33.07 | 33.81 | 35.77 | 43.49 | 42.6 |
| Fiscal Year (FY) | 1990/91 | 1991/92 | 1992/93 | 1993/94 | 1994/95 | 1995/96 | 1996/97 |
| Consumption per capita (kWh) | 44.04 | 53.7 | 60.02 | 64.08 | 71.32 | 75.88 | 78.9 |
| Fiscal Year (FY) | 1997/98 | 1998/99 | 1999/00 | 2000/01 | 2001/02 | 2002/03 | 2003/04 |
| Consumption per capita (kWh) | 80.44 | 88.69 | 95.85 | 106.08 | 113.8 | 122.43 | 133.11 |
| Fiscal Year (FY) | 2004/05 | 2005/06 | 2006/07 | 2007/08 | 2008/09 | 2009/10 | 2010/11 |
| Consumption per capita (kWh) | 139.68 | 150.22 | 149.97 | 158.2 | 165.32 | 170.27 | 180.08 |
| Fiscal Year (FY) | 2011/12 | 2012/13 | 2013/14 | 2014/15 | 2015/16 | 2016/17 | 2017/18 |
| Consumption per capita (kWh) | 197.72 | 213.15 | 232.56 | 249.16 | 281.36 | 308.22 | 335.99 |
| Fiscal Year (FY) | 2018/19 | | | | | | |
| Consumption per capita (kWh) | 374.62 | | | | | | |

### III. DATA ANALYSIS AND RESULTS

Time series forecasting of the collected historical selected data found from the Government source of Bangladesh was placed in the Minitab 17 to determine the best method. The best fit time series model was decided based on the accuracy parameter of the historical data. The error provided by the different approaches of the time series model for the actual historical data has been compared. To be mentioned that, forecasting accuracy refers to the least forecasting deviation between the actual and forecasted value, which also means least forecasting error. In this anticipated forecasting, we have used three forecasting error determinants namely Mean Absolute % Error (MAPE), Mean Absolute Deviation (MAD), Mean Squared Error (MSE).

They were calculated by the following relations as presented below:

\[
\text{MAPE} = \frac{\sum (\text{Actual}_t - \text{Forecast}_t)}{\text{Actual}_t}
\]

\[
\text{MAD} = \frac{\sum |\text{Actual}_t - \text{Forecast}_t|}{n}
\]

\[
\text{MSD} = \frac{\sum (\text{Actual}_t - \text{Forecast}_t)^2}{n-1}
\]

where, \(\text{Actual}_t\) = Actual value at time period \(t\), \(\text{Forecast}_t\) = Forecasted value at time period \(t\), \(n\) = Specific number of time periods. However, MAD and MSD are selected based on the lowest MAPE.

Below, forecasting errors were presented that were obtained by the set of time series models for the actual historical data (FY 1976/77 - FY 2019/20) to determine the best fit time series model with better accuracy.
**A. Moving Average**

In this moving average method, eleven moving average value was computed using a different value of the forecasting period (n). Error determinants of eleven sets (n = 2, 3…, 12) were calculated and the lowest values of MAPE, MAD, and MSD are found when the forecasting period is 2 (n = 2). The values of MAPE, MAD, and MSD are ranged between 11.06-35.76, 12.73-51.71, and 313.69-3781.95, respectively. The deviation between actual consumption data and forecasted data for the forecasting period (n = 2) of the moving average method is shown in Figure 2.

**B. Single Exponential Smoothing**

It is suggested that if time series varies in the base level, single exponential smoothing is one of the best options for the estimation of the upcoming time series value. In this method, the exponential smoothing constant (α) is an important consideration. MAPE, MAD, and MSD were calculated using nine values of α within the range (0 < α < 1) to find the optimum value of the α. The least forecasting errors were obtained for the highest value of α = 0.9. The values obtained for MAPE, MAD, and MSD are ranged between 8.99-37.71, 9.34-46.83, and 178.30-3925.04, respectively.

The variation between the actual and predicted data for smoothing constant α = 0.9 has presented in Figure 3.

**C. Double Exponential Smoothing**

There are two smoothing constants in the double exponential smoothing model namely level (α) and trend (γ). Forecasting error sets were calculated by using the value of α and γ ranged between 0.1-0.3 for both. Nine trials were taken, and errors were ranged for MAPE, MAD, and MSD between 30.75-46.80, 12.40-26.16, and 278.40-1169.34, respectively. The lowest errors were obtained for MAPE at α = 0.3 and γ = 0.1, for MAD and MSE at α = 0.3 and γ = 0.3. To obtain the main selection parameter MAPE, we have selected the MAPE, MAD, and MSD for α = 0.3 and γ = 0.1. The graphical illustration of Figure 4 reveals that actual data and forecasted data coincide for some periods.

The equation is shown in Figure 4 is the equation for double exponential smoothing. So, forecasting equation, \( F_{t+h} = l_t + hb_t \) where the Level equation is \( l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}) \) and Trend equation is \( b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \).
$F_{t+h}$ is the forecast for period $h$, $l_t$ is the estimated time of level at time $t$, $y_t$ is the forecast at time $t$, $l_{t-1}$ is the previous estimate level time, $b_t$ is the estimated time of trend at time $t$, $h_{t-1}$ is the previous estimate time trend, $\alpha$ is the smoothing constant for level ($0 < \alpha < 1$), $\gamma$ is the smoothing constant for trend ($0 < \gamma < 1$).

**D. Winter Model**

Winter’s model consists of two types of models namely multiplicative and additive, and they were used to find out the error set. Winter time series model considers an additional smoothing constant seasonality ($\delta$) with the regular smoothing constant of level ($\alpha$) and trend ($\gamma$) in respect to the double exponential smoothing model. For all of the smoothing constants $\alpha$, $\gamma$, and $\delta$ in the Winter time series model, the values of the constants ranged between 0.1-0.3. A total of 27 trials were considered. The values of MAPE, MAD, and MSD in the Winter Multiplicative model were ranged between 11.12-16.43, 9.35-18.78, and 154.37-678.08, respectively. The lowest value of trial for MAPE in Winter multiplicative was 11.12, for MAD was 9.35 and for MSD was 154.37 at $\alpha = 0.3$, $\gamma = 0.2$, $\delta = 0.3$.

On the other hand, the values of MAPE, MAD, and MSD in the Winter additive model were ranged between 19.51-25.86, 12.57-23.54, and 224.25-975.91 respectively. The lowest value for Winter-additive MAPE was 19.51 at $\alpha = 0.3$, $\gamma = 0.2$, $\delta = 0.3$; for MAD was 12.57 at $\alpha = 0.3$, $\gamma = 0.3$, $\delta = 0.3$; and for MSD was 224.25 at $\alpha = 0.3$, $\gamma = 0.3$, $\delta = 0.3$. Figure 5(a) and 5(b) presents the comparison of actual data and forecasted data of multiplicative and additive models respectively based on MAPE’s lowest value for the smoothing constant $\alpha = 0.3$, $\gamma = 0.2$, $\delta = 0.3$, where Winter multiplicative model was shown better accuracy than the additive model.

The equation is shown in Figures 5(a) and 5(b) are the equation for the Winter Multiplicative and Additive model. The forecasting equation for the Winter Multiplicative model is $F_t = (L_{t-1} + T_{t-1})S_{t-p}$ where the Level equation is $L_t = \alpha \left( \frac{y_t}{S_{t-p}} \right) + (1 - \alpha)(L_{t-1} + T_{t-1})$. Trend equation is $T_t = \gamma (L_t - L_{t-1}) + (1 - \gamma)T_{t-1}$. The Seasonal equation is expressed as $S_t = \delta \left( \frac{y_t}{L_t} \right) + (1 - \delta)S_{t-p}$.

The forecasting equation for the Winter additive model is, $F_t = L_{t-1} + T_{t-1} + S_{t-p}$, where the Level equation is $L_t = \alpha(y_t - S_{t-p}) + (1 - \alpha)(L_{t-1} + ,Trend equation, T_t = \gamma (L_t - L_{t-1}) + (1 - \gamma)T_{t-1}$ Seasonal equation is $S_t = \delta (y_t - L_t) + (1 - \delta)S_{t-p}$, where, $F_t= forecast of one period advanced at time $t$, $L_t$ is the estimated time of level at time $t$, $T_t$ is the estimated time of trend at time $t$, $S_t$ is the estimated time of seasonal at time $t$, $y_t$ is data value at time $t$, $p$ is season period, $\alpha$ is the smoothing constant for level ($0 < \alpha < 1$), $\gamma$ is the smoothing constant for trend ($0 < \gamma < 1$), $\delta$ is the smoothing constant for seasonality ($0 < \alpha < 1$).

**E. Decomposition Model**

The decomposition model also consists of two models namely multiplicative and additive. The MAPE, MAD, and MSD for the multiplicative model are 49.653, 25.323, 970.679, respectively and for the additive model are 50.230, 25.850, 1039.580. The analysis result for the multiplicative and additive model is shown in Figures 6(a) and 6(b), respectively. Each figure represents that actual and
forecasted values are almost same for the most of the period whereas trend value follows different from the actual and forecasted values.

\[
F_t = T_t \times C_t \times S_t \times I_t
\]

The equation is shown in Figures 6(a) and 6(b) are the equation of decomposition multiplicative and additive model respectively. So, the equation for the decomposition multiplicative model is, \( F_t = T_t C_t S_t I_t \) and additive model is, \( F_t = T_t + C_t + S_t + I_t \) where, \( F_t \) is the forecasting series, \( T_t \) is the long-term trend, \( C_t \) is the cycle, \( S_t \) and \( I_t \) are expressed in terms of trend \( T_t \) and cycle \( C_t \) in the Multiplicative model, Whereas \( S_t \) is seasonality and \( I_t \) is Irregularity in the additive model.

**F. Trend Analysis**

Four types of trends were analysed namely linear, quadratic, exponential growth, and S curve. Below the analysis, the results were shown for all types of trend analysis in Figures 7, 8, 9, and 10. Over the past 43 years (FY 1976/77-2018/19) of electricity consumption, the linear trend was found to be like Equation (1). In Figure 7, the actual and forecasted electricity consumption for linear trend analysis is shown. Quadratic trend analysis presented in Figure 8 shows a better result than linear trend analysis. The Equation (2) shows the quadratic trend mathematical form over the 43 years of data (FY 1976/77-2018/19).

\[
F_t = -42.1 + 7.058 \times t \quad (1)
\]

\[
F_t = 29.72 - 2.518 \times t + 0.2176 \times t^2 \quad (2)
\]

However, Exponential growth depicts a better result than the linear and quadratic trend. The MAPE, MAD, and MSD are found to be 8.36, 8.32, and 128.21, respectively. The Equation (3) was found for exponential growth trend analysis. A comparison of forecasting error sets of Exponential growth trends of actual data and forecast data is shown in Figure 9.

\[
F_t = 14.5268 \times (1.07852^t) \quad (3)
\]
\[ F_t = \beta_0 (\beta_1^t) \]

\[ F_t = \frac{10^a}{\beta_0 + \beta_1 \beta_2} \]

\[ \theta_q a_{t-q} \] where, \( \theta^d \) represents the difference in time series, \( z_t = \) times series data at time period \( t \), \( \varphi_1 \ldots \varphi_p \) are autoregressive parameters ((\( p \neq 0 \) and \( p \leq 5 \)), \( \Theta_1 \ldots \Theta_q \) are moving average parameters ((\( q \neq 0 \) and \( q \leq 5 \)), \( a_t \) is a series of unknown random errors or residuals assumed by the normal distribution, \( z_{t-1} \ldots z_{t-p} \) is the \( p \) past function used for the predicts of the current value \( z_t \), \( a_{t-1} \ldots a_{t-q} \) is the \( q \) past function used for the predicts of the current value \( a_t \). MAPE, MAD, and MSD were measured by the ARIMA time series model and the value obtained is 4.50, 3.23, and 15.40, respectively. In ARIMA, we have taken 30 trials for various combinations of \( (p, q, d) \) and the lowest MAPE, MAD, and MSD has been found at \( (5, 0, 5) \). Forecasting error under ARIMA and Chi-Square statistic is shown in Table 2 and 3, respectively. Figure 11 shows the residual plot for the electricity consumption per capita of the ARIMA model. Figure 11(a) represents that no other pattern is observed in residual values and normally distributed, Figure 11(b) depicts fitted value that means the forecasted value is aligned with the residual values, Figure 11(c) shows the occurrence of residuals, and Figure 11(d) presents the observational order of residuals.

**G. ARIMA**

ARIMA is a powerful model that explains not only stationary time series but also non-stationary time series is named as an autoregressive integrated moving average (ARIMA) process. An ARIMA process order of \( (p,q,d) \) is defined by the following  

\[ \theta^d z_t = \varphi_1 z_{t-1} + \cdots + \varphi_p z_{t-p} + a_t - \Theta_1 a_{t-1} - \cdots - \]
Based on the residual plot and accuracy, it can be concluded that ARIMA (5, 0, 5) model is suitable for forecasting per capita electricity consumption. To overview the MAPE, MAD, and MSD values obtained by the different forecasting methods, we have summarised all the forecasting errors computed using the time series model in Table 4. The comparison shows that MAPE, MAD, MSD obtained by ARIMA among the time-series forecasting model is the lowest error set that complies with our actual historical data. Therefore, the ARIMA (5,0,5) model can be applied for forecasting the electricity consumption per capita for the next 22 years’ data (Up to 2041) with the highest accuracy.

Table 4. Forecasting accuracy over 43 periods (FY 1976/77-2018/19) (descending order of MAPE)

| Forecasting methods         | MAPE  | MAD  | MSD   |
|-----------------------------|-------|------|-------|
| Trend analysis linear       | 51.33 | 26.43| 1093.73|
| Decomposition-additive model| 50.23 | 25.85| 1039.58|
| Decomposition-multiplicative model | 49.65 | 25.32| 970.68|
| Double exponential smoothing| 30.76 | 13.97| 399.61 |
| Winter additive            | 19.51 | 12.60| 241.03 |
| Trend analysis quadratic   | 15.39 | 10.01| 196.44 |
| Winter multiplicative      | 11.13 | 9.36 | 154.38 |
| Moving average             | 11.06 | 12.73| 313.69 |
| Single exponential smoothing| 8.99  | 9.35 | 178.31 |
| Trend analysis exponential growth | 8.36  | 8.32 | 128.21 |
| Trend analysis S curve      | 5.84  | 9.65 | 457.34 |
| ARIMA                      | 4.50  | 3.23 | 15.40 |

H. Forecasting for Vision-2041

To make the forecasting data resourceful to the Bangladesh Government as well as to the other energy-related institutions, the maximum forecasting year was set FY 2040/41, in which the Bangladesh Government planned to reach high-income country status. It will help in forecasting electricity to meet the SDGs goals also. However, per capita electricity consumption was forecasted with all the time series models to broaden the acceptability of the resource and to facilitate a comparison among the other time series model and our suggested best fit time series model determined through the actual historical data. The forecasting data obtained by using the time series model is shown in Table 5 for the next 22 periods of electricity consumption per capita with all the model equations described above. The first forecasting period has started at 44 (FY 2019/20) and ends at period 65 (FY 2040/41) though a wider forecast period is also possible.
| Year   | Forecast Period | Double exponential smoothing | Winters Model | Decomposition | Trend Analysis | ARIMA |
|--------|----------------|-----------------------------|--------------|---------------|---------------|-------|
|        |                |                             |              |               |               |       |
|        |                |                             | Multiplicative | Additive       | Linear         |        |
|        |                |                             |              |               | Quadratic      |        |
|        |                |                             | Exponential growth | S Curve |         |       |
| 2019/20| 44             | 284.98                      | 324.40       | 340.18        | 276.90        | 270.32 |
| 2020/21| 45             | 295.43                      | 331.23       | 349.31        | 271.09        | 274.72 |
| 2021/22| 46             | 305.88                      | 342.09       | 358.02        | 265.05        | 276.74 |
| 2022/23| 47             | 316.33                      | 361.07       | 369.90        | 277.07        | 285.41 |
| 2023/24| 48             | 326.78                      | 390.63       | 384.66        | 280.58        | 292.72 |
| 2024/25| 49             | 337.23                      | 402.20       | 408.56        | 303.18        | 303.75 |
| 2025/26| 50             | 347.68                      | 416.07       | 424.43        | 300.05        | 310.81 |
| 2026/27| 51             | 358.13                      | 433.66       | 439.49        | 316.02        | 317.86 |
| 2027/28| 52             | 368.58                      | 475.23       | 461.00        | 331.25        | 324.92 |
| 2028/29| 53             | 379.03                      | 516.27       | 478.93        | 334.07        | 335.13 |
| 2029/30| 54             | 389.48                      | 559.89       | 497.22        | 350.96        | 339.04 |
| 2030/31| 55             | 399.92                      | 611.99       | 516.59        | 356.95        | 347.24 |
| 2031/32| 56             | 410.37                      | 521.16       | 506.40        | 364.01        | 354.94 |
| 2032/33| 57             | 420.82                      | 522.47       | 515.53        | 354.19        | 359.34 |
| 2033/34| 58             | 431.27                      | 530.52       | 524.25        | 344.28        | 361.36 |
| 2034/35| 59             | 441.72                      | 551.24       | 536.13        | 357.88        | 370.03 |
| 2035/36| 60             | 452.17                      | 587.71       | 550.88        | 360.47        | 377.33 |
| 2036/37| 61             | 462.62                      | 596.93       | 574.78        | 387.50        | 387.75 |
| 2037/38| 62             | 473.07                      | 609.71       | 590.65        | 381.61        | 394.10 |
| 2038/39| 63             | 483.52                      | 627.95       | 605.71        | 382.13        | 400.64 |
| 2039/40| 64             | 493.97                      | 680.49       | 627.22        | 417.39        | 412.16 |
| 2040/41| 65             | 504.42                      | 731.50       | 645.15        | 430.40        | 419.74 |

Table 5. Forecasting for next 22 periods (FY 2019/20 to FY 2040/41)
After forecasted the data for the next 22 periods (FY 2019/20 to FY 2040/41), the total periods for the data is 65 (FY 1976/77 to FY 2040/41) consists of 43 periods for actual historical data (FY 1976/77 to 2018/19) and 22 periods for forecasted data (FY 2019/20 to FY 2040/41). The forecasting accuracy for the data of a total of 65 periods (FY 1976/77 to FY 2040/41) has been calculated for all the time series models except the moving average and single exponential smoothing. The forecasting accuracy for 65 periods (FY 1976/77 to FY 2040/41) is shown in Table 6 for comparison. Since ARIMA has appeared as the best fit time series forecasting method, it can be used for forecasting long-term electricity consumption per capita in Bangladesh in the future.

### IV. DISCUSSION

Based on the actual historical demand data or consumption per capita over the past 43 years ranged FY 1976/77 to FY 2018/19 (Bangladesh Power Development Board, 2019), demand or consumption per capita for a long period of time has been successfully done in this work for Bangladesh. The forecasted time period is 22 years (FY 2019/20 to FY 2040/41) to link the forecasting data with the Vision-2041 goals of Bangladesh. ARIMA time series model was applied to forecast the consumption per capita for its accuracy with the actual historical data. For the above forecasting analysis and trials, the following points can be concluded:

(a) The actual historical data for Bangladesh has always been increasing trend except for some FY with a little downward trend. Over the FY 1976/77 to FY 2018/19 tenure an overall jumped of 96.69 % electricity consumption is noticeable (Table 1). The consumption is mostly satisfied by the natural gas source and furnace oil (Figure 1). The clean or alternative source of energy has no significant contribution to the energy demand.

(b) No real forecasting for future electricity consumption per capita is available. A few cases are reported for forecasting local energy consumption or short-term forecasting using the time series forecasting model.

(c) After evaluation and comparison of the different time series models, it has been verified that ARIMA is the most appropriate model among other time series models for 43 years of consumption data with MAPE, MAD, and MSD of 4.502, 3.226, and 15.396, respectively. ARIMA time series forecasting model has the lowest forecasting errors for actual historical data of 43 years (FY 1976/77 to FY 2018/19). It has appeared as the best fit model with higher forecasting accuracy.

(d) The forecasted electricity consumption per capita using ARIMA (5, 0, 5) model in the first forecasted year is 411.28 kWh (FY 2019/20) and for the last forecasted year (FY 2040/41) is 2011.47 kWh (Table 5). Forecasting indicates a jump of 81.38 % electricity consumption for the next 22 years period.

(e) The forecasting accuracy or forecasting error in ARIMA is MAPE = 2.96, MAD = 2.67, MSD = 11.75 provided in Table 6 for 65 years periods with 95 per cent confidence level (Figures 12, 13, and 14). Both the 43 years accuracy (Table 4) and 65 years accuracy (Table 6) are close. Therefore, the forecasted electricity consumption per capita will be a true resource for the Bangladesh Government.

### Table 6. Forecasting accuracy for 65 periods (FY 1976/77 to FY 2040/41) (descending order of MAPE)

| Forecasting methods                      | MAPE  | MAD  | MSD  |
|------------------------------------------|-------|------|------|
| Double exponential smoothing              | 41.16 | 19.63| 955.43|
| Trend analysis linear multiplicative model| 33.08 | 17.69| 628.04|
| Decomposition additive model             | 33.04 | 17.26| 674.96|
| Winter additive                          | 12.81 | 9.25 | 187.19|
| Trend analysis quadratic growth          | 10.17 | 6.62 | 129.95|
| Winter multiplicative                    | 6.62  | 11.69| 305.59|
| Trend analysis S curve                   | 3.89  | 6.59 | 311.97|
| ARIMA                                    | 2.96  | 2.665| 11.745|
This forecasting effort for the per capita electricity consumption of Bangladesh has been successfully done by a selected time series forecasting model called ARIMA. The other time series model is also evaluated and ARIMA has been determined as the best fit time series model that coincides nearly with the actual historical data. Later, the best fit ARIMA time series model has used to forecast future electricity consumption per capita for the next 22 years (FY 2019/20 to FY 2040/41) to provide an energy prediction guideline to the policymaker. Considering the coming years of electricity consumption, we selected the most accurate forecasting methodology and forecasted electricity consumption for the next 22 years using Minitab 17. In this electricity forecasting, the highest electricity consumption has found 2011.47 kWh or 2.011 MWh/capita for the year of vision-2041 in the ARIMA model which is selected as more accurate. The electricity generation must meet up the demands as forecasted since Bangladesh Government has declared to turn Bangladesh into a middle-income country by the year 2021 and a high-income country by the year 2041 (Vison-2041) from the current status of the lower-middle-income country. Compared to some other high-income countries electricity consumption per capita in 2017 like Uruguay 3.0 MWh/capita (Electricity Consumption Per Capita of Uruguay, 2017), Panama 2.3 MWh/capita (Electricity Consumption Per Capita of Panama, 2017), and in 2018 Chile 4.1 MWh/capita (Electricity Consumption Per Capita of Chile, 2018), our forecasted highest consumption per capita for the year of 2041 is aligned and consistent with present conditions. Finally, accuracy measurement was also identified for all-time series except for moving average and single exponential smoothing over the 65 years data i.e., combined data of previous 43 years and forecasted 22 years electricity consumption data. This computed result also shows that ARIMA is the best option for the forecasting of electricity consumption per capita with MAPE, MAD, and MSD of 2.958, 2.665, and 11.745, respectively. This study will help the power sector of Bangladesh to electricity generation and facility expansion for future development. Also, future research direction could integrate total power generation based on various energy source's contributions and different sector energy consumption to forecast electricity

V. CONCLUSIONS

Figure 12. Forecast in ARIMA for 22 periods (FY 2019/20 to 2040/41) with 95% confidence limits

Figure 13. Partial Auto Correlation Function (PACF) residuals for consumption per capita with 5% significance limits. Red lines represent significance limits.

Figure 14. Auto Correlation Function (ACF) residuals for consumption per capita with 5% significance limits. Red lines represent significance limits.

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consumption per capita. However, the electricity consumptions rate is increasing at an exponential rate and this research has considered the linear regression model for simplicity. Thus, forecasted data may face misalignment in some cases for long periods. Again recently, a lot of alternative non-electrical energy sources are being used that may not come under this estimation.

This forecasting effort for the per capita electricity consumption of Bangladesh has been successfully done by a. this study will help the power sector of Bangladesh to electricity generation and facility expansion for future development. Also, future research direction could integrate total power generation based on various energy sources’ contributions and different sector energy consumption to forecast electricity consumptions rate is increasing at an exponential rate and this research has considered the linear regression model for simplicity. Thus, forecasted data may face misalignment in some cases for long periods. Again recently, a lot of alternative non-electrical energy sources are being used that may not come under this estimation.

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 VII. NOMENCLATURE

**F**<sub>t</sub> Forecast at time period *t*

**MA** Moving average

**A**<sub>i</sub> Actual consumption in time period *i*

**n** Number of periods (data points) in moving average

**i** The index corresponds to periods
\( F_{t-1} \) Forecast of the previous period
\( \alpha \) Smoothing constant \((0 < \alpha < 1)\)
\( A_{t-1} \) Actual value of the previous period
\( F_{t+h} \) Forecast for period \( h \)
\( l_t \) Estimated time of level at time period \( t \)
\( h \) Forecast period
\( b_t \) Estimated time of trend at time period \( t \)
\( L_{t-1} \) Previously estimated time of level
\( T_{t-1} \) Previously estimated time of trend
\( S_{t-p} \) Previously estimated time of seasonal
\( T_t \) Long-term trend
\( C_t \) Cycle
\( S_t \) Expressed in terms of trend \( T_t \) in the Multiplicative model
\( l_t \) Expressed in terms of cycle \( C_t \) in the Multiplicative model
\( S_t \) Seasonality in the Additive model
\( l_t \) Irregularity in the Additive model
\( \beta_0 \) Trend line intercept
\( \beta_1 \) The slope of the trend line
\( \beta_2 \) Rate of change in slope
\( t \) Time period