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SEASONAL ARIMA APPROACH FOR MODELING AND FORECASTING TEMPERATURES IN BANGLADESH

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Abstract

This study tries to analyze the temperatures of Bangladesh by employing statistical techniques. The main objectives of this study are to examine temperatures over time in Bangladesh and find a suitable model for forecasting. This study utilizes temperature data from Bangladesh Meteorological Department (BMD), recorded at 6 divisional meteorological stations for the period of 1976 to 2015. This study reveals that annual average temperature of Bangladesh is 25.52°C. Initially data set was checked for whether it is stationary or not through ACF, PACF and Augmented Dickey Fuller test. Data was found non-stationary but it was transformed to stationary after taking first difference. Then seasonal ARIMA model was tried to fit using Box and Jenkins methodology. After completion of diagnostic checking, ARIMA (1,0,0) $(2,1,1)_{12}$ model was identified as an appropriate model for forecasting 60 months (January 2016-December 2020) seasonal temperatures of Bangladesh. The findings of this study expect to play significant role in many areas, since Bangladeshi economy is heavily dependent on temperature patterns.

Key words: Box-Jenkins, Ljung-Box test, normality test, stationarity, SARIMA

Introduction

Bangladesh is one of the largest deltaic countries in the world. It is a flat low-lying plain land made up of alluvial soil having small hilly area in the northeast and southeast regions. The great Himalayan Range is to the north and the vast Bay of Bengal is on the south. It is located between 20.57ºN to 26.63ºN and 88.02ºE to 92.68ºE. It is bounded on the west, north and east by India. In the southeast there is a common border with Myanmar (DEW-DROP, 2016). Bangladesh experiences different types of natural hazards or disasters almost every year which includes cyclones and associated storm surge, flood, flash flood, severe thunderstorm, tornado, heavy rainfall, heat wave, cold wave, dense fog etc. Loss of lives and properties associated with these hazards or disasters are very common. Area specifictimely and accurate forecast and early warning with sufficient lead time is one of the best ways to reduce loss of lives and properties

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which may enhance the sustainability of the economic growth of Bangladesh. Furthermore, Bangladesh is one of the most climate vulnerable countries in the world. Due to high impact of climate change, climate information is highly demandable (BMD, 2016).

Bangladesh was a subtropical monsoon climate characterized by wide seasonal variations in rainfall, moderately warm temperatures, and high humidity. Regional climatic differences in this flat country are minor. Four meteorological seasons are recognized as pre-monsoon (March, April and May), monsoon (June to September), post-monsoon (October and November) and winter (December, January and February). Generally, pre-monsoon months are hot and humid; monsoon months are humid and rainy, post-monsoon months are quiet hot and dry but the winter months are cool and dry. Southwest monsoon or monsoon is the most important feature of controlling the climate of Bangladesh. More than 71% of the annual rainfall is received during this season. Variability in the onset, withdrawal of monsoon and quantum of rainfall during the monsoon season was profound impacts on water resources, power generation, agriculture, economics, ecosystems and fisheries in Bangladesh. On the other hand, in winter season, temperature falls down sharply in the north and north-western parts of Bangladesh (DEW-DROP, 2016). Many socio-economic activities apparently depend on the weather condition of Bangladesh.

Bangladesh is mainly an agricultural country. The agricultural activities of our country are largely depends on climate. But due to unnatural behavior of atmosphere, the cultivation is often hampered. For the development of agriculture sector and agricultural production, it is very important to extensively study the weather condition of Bangladesh. Components of weather are directly related to different types of crops. On the other hand, potential increase in temperature was a significant impact on crop productivity. Every year a huge amount of rice production is lost due to its increasing temperature which eventually threatens the food security in Bangladesh. It was assessed that in the year 2020, 2030, 2040 and 2050 there were be a considerable yield reduction (1.5, 2.5, 4.4 and 5.4% respectively) which will directly affect the total rice production in the country and at the same time economy of Bangladesh (Basak *et al.,* 2010).

Increasing temperature also was an apparent negative effect on human health. Heat stress reduces labor capacity considerably and as temperature raises the frequency of heat-related conditions such as hypoxia and heat stroke increases. The higher temperatures were increased concentrations of ground level ozone, which is the reason for many respiratory conditions (Syeda *et al.,* 2012). After reviewing all available literatures, this study made an attempt to analyze the temperature data of Bangladesh by employing appropriate statistical techniques. Since agricultural production, human health, ecosystem, biodiversity and many other important factors depends on temperature; it is of immense importance to observe the pattern and variations of temperature in the air of

Bangladesh. In this study, it has been studied the long range behavior of the average temperature of Bangladesh from 1976 to 2015. The main objective of this study was to apply seasonal ARIMA (autoregressive integrated moving average) model to analyze the temperature series and other objectives were as follows: (i) to observe the present trends of temperatures in Bangladesh (1976-2015), (ii) to decompose of time series components from temperature series, (iii) to fit an appropriate seasonal ARIMA model for Bangladesh temperature, and (iv) to forecast next 60 months (2016-2020) average temperatures of Bangladesh.

Materials and Methods

Data and variables

The study uses data from Bangladesh Meteorological Department. This study uses temperatures from six divisional observatories (Dhaka, Chittagong, Rajshahi, Sylhet, Khulna and Barishal) only, since Rangpur and Mymensingh division was declared seventh and eighth division recently (2010 and 2015 respectively). The processed monthly temperature data from six divisional observatories during the period of 1976-2015 were collected from Bangladesh Meteorological Department archive. Keeping study objectives in mind, data were processed in several stages. The procedures are as follows:

i) firstly, monthly data of each station were processed by summing each month daily temperature data of each station,
ii) then, this study calculates each month descriptive measures such as mean, maximum, minimum etc., and
iii) finally, this study analyzes 480 months temperature. This information measured from the first month of 1976 to the last month of 2015.

The data includes two sets of variables. Such as:

i) time: The years (from 1976 to 2015),
ii) temperature: Monthly average temperature in Celsius scale.

Data processing

In regard to data processing this study extensively uses R programming language (version 3.3.2). Several packages of R programming language are used such as “ggplot2”, “t series”, “time Series”, “forecast”, “grid Extra”“TTR” and “reshape2”.

Autoregressive Integrated Moving Average (ARIMA) Model

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average or (ARMA) model. These models are fitted to time series data to predict future points in the series. The ARIMA model is applied in some cases where data show evidence of non-stationarity. The model is generally referred to as an

ARIMA (p, d, q) model where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively (Gujarati *et al.*, 2012).

Seasonal Autoregressive Integrated Moving Average (SARIMA)

Seasonal ARIMA (SARIMA) is used when the time series exhibits a seasonal variation. Natural phenomena such as temperature, rainfall etc. was strong components corresponding to seasons. Hence, the natural variability of many physical, biological and economic processes tends to match with seasonal fluctuations. Because of this, it is appropriate to introduce autoregressive and moving average polynomials that can be identified with seasonal lags (Gallop *et al.*, 2012; Brockwell *et al.*, 1996). The ARIMA notation can be extended readily to handle seasonal aspects and the general shorthand notation is as follows:

$$\text{ARIMA}\,(p, d, q)(P, D, Q)_S$$

Where,

(p, d, q) refers to the non-seasonal part of the model

(P, D, Q) refers to the seasonal part of the model

And *s* refers to the number of periods per season

Box-Jenkins Methodology

In econometrics, the Box-Jenkins methodology, named after the statisticians George Box and Gwilym Jenkins, applies autoregressive moving average ARMA or ARIMA models to find the best fit of a time series to past values of this time series, in order to make forecasting. The Box-Jenkins methodology consists of a four-step iterative procedure: tentative identification, estimation, diagnostic checking and forecasting (Gujarati *et al.*, 2012).

The first step in developing a Box-Jenkins model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modeled. Stationarity can be assessed from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay. An augmented Dickey Fuller test (ADF) is a test for a unit root in a time series sample. The augmented Dickey-Fuller (ADF) statistic, used in the test, is a negative number. At the model identification stage, the goal is to detect seasonality, if it exists, and to identify the order for the seasonal autoregressive and seasonal moving average terms. For many series, the period is known and a single seasonality term is sufficient. However, it may be helpful to apply a seasonal difference to the data and regenerate the autocorrelation and partial autocorrelation plots. This may help in the model identification of the non-seasonal component of the model.

Box-Jenkins forecasting models are based on statistical concepts and principles and are able to model a wide spectrum of time series behavior. The series also needs to be at least weakly stationary (Gujarati *et al.*, 2012).

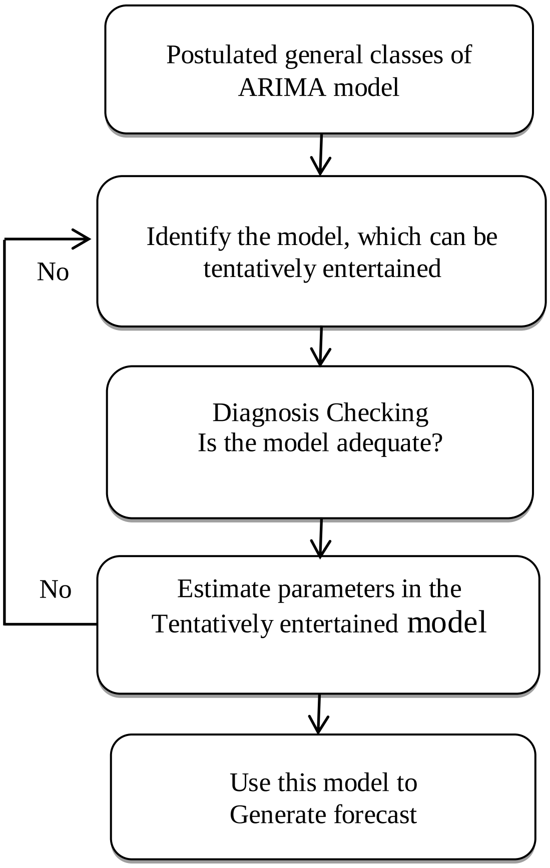

Fig. 1. Box-Jenkins methodology for optimal model selection

Results and Discussion

Statistical analysis: Descriptive statistics

The results of this study reveal that the annual average temperature is 25.52°C. Maximum monthly average temperature was found in the month of June (35.7°C) and minimum was found in January (10°C). During this period (1976-2015), Monthly average temperature was found highest in Khulna (26.04°C) and minimum was found in Sylhet division (24.66°C) (Islam, 2014). The following tables present some descriptive statistics on temperatures of Bangladesh.

Table 1. Descriptive statistics of temperatures according to division

Division	Mean	Maximum	Minimum
Dhaka	25.87968365	34.4	10.4
Chittagong	25.87009878	32.5	13.9
Khulna	26.04306715	33.8	11.8
Rajshahi	25.24537888	35.7	10
Barisal	25.99534547	33.6	13.7
Sylhet	24.6645303	32.4	10.6

Table 2. Monthly descriptive statistics of temperatures

Month	Mean	Maximum	Minimum
January	18.22272	29.2	10
February	21.36453	28.8	13.6
March	25.67649	32.3	17.3
April	28.04174	35	19
May	28.64398	35	19.6
June	28.64968	35.7	22.7
July	28.37034	32.8	23.5
August	28.49501	32.6	23.5
September	28.2836554	32.4	21.5
October	27.1594919	31.6	18.3
November	23.7235266	29.2	16.5
December	19.62576658	26.6	11.7

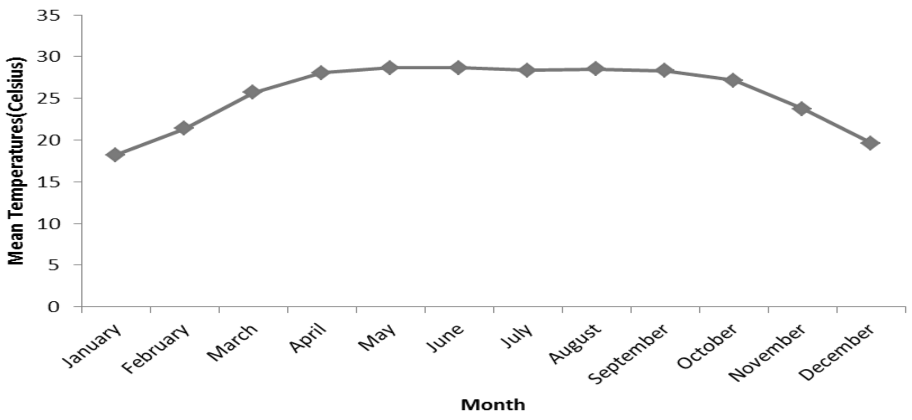

Fig. 2. Mean monthly temperatures of Bangladesh

Identification of a Seasonal ARIMA Model

Variance stability: A visual plot of monthly average temperature is plotted in Figure 3. From the plot we can say that, there is no prominent trend is present in our data. Moreover it seems that the data are non-stationary in the mean only. So that does not need any transformation of the data to obtain stability in variance (Gujarati *et al.*, 2012).

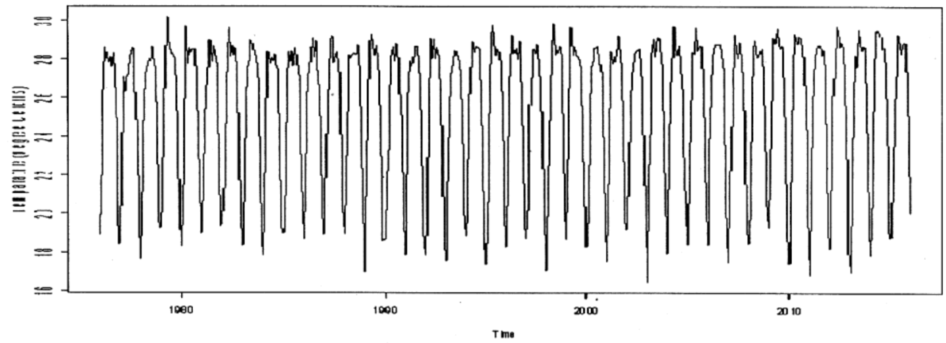

Fig. 3. Observed time plot of the temperatures of Bangladesh

Decomposition of time series components

The factors that are responsible to bring about changes in a time series, also called the components of time series. Figure 4 shows the decomposition of the temperature data (Gujarati *et al.*, 2012).

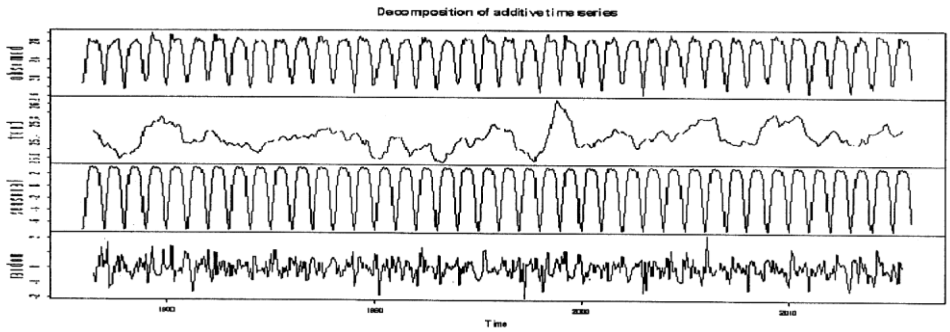

Fig. 4. Decomposed time plot of the temperatures of Bangladesh

Checking the Stationarity

ACF and PACF plot: To obtain the ACF and PACF plot of monthly average temperature data at Figure 5. To achieve Stationarity the figure suggests that non-seasonal difference parameter $(d=0)$. Noting the peaks at seasonal lags in figure 6, $h=1s, 2s, 3s, 4s$ where $s=12$ $(i.e., h=12, 24, 36, 48)$ with relatively slow decay suggests that a seasonal difference (D) is needed. Figure 7 shows the ACF and PACF plot after taking seasonal difference of the data. First concentrating on the seasonal $s=12$ lags, the characteristics of the ACF and PACF of this series tend to show a strong peak at $h = 1s, 2s$ in the autocorrelation function and the peaks at $h = 1s, 2s, 3s, 4s$ in the partial autocorrelation function.

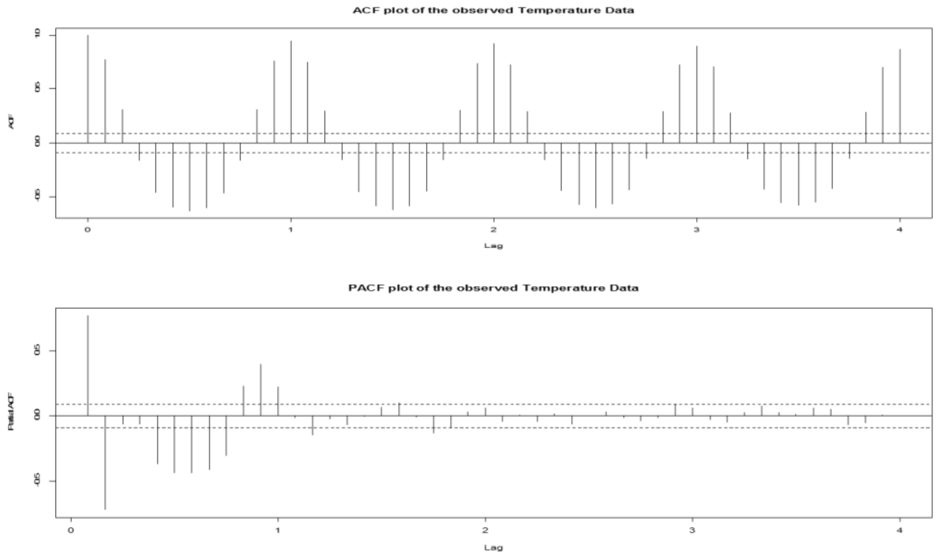

Fig. 5. ACF and PACF plot of the observed temperature data

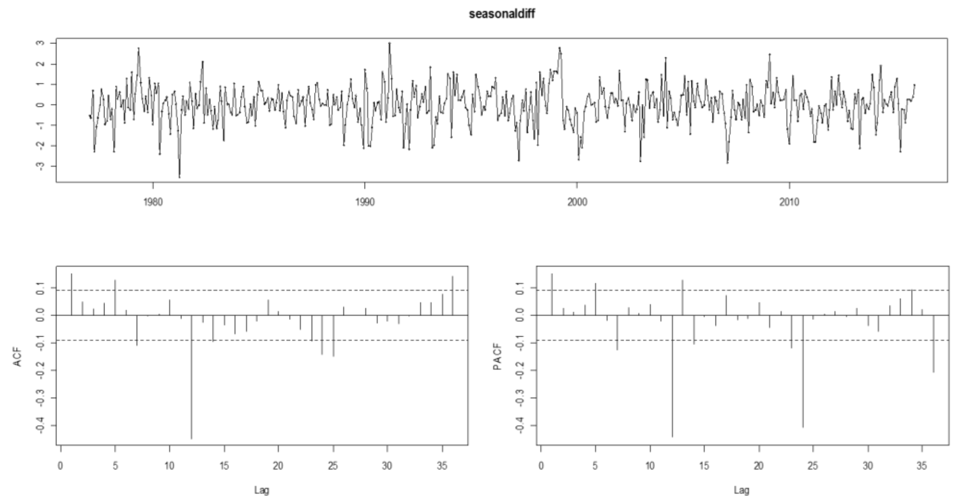

Fig. 6. ACF and PACF Plot of the first seasonal difference data

Augment Dickey-Fuller (ADF) test about stationarity

To test the Stationarity the null and alternative hypotheses are

H_0: Data is non-stationary

H_a : Data is stationary

To test the Stationarity (Non-seasonality parameter) Augmented Dickey-Fuller test is used. The value of the Augmented Dickey-Fuller test statistic has been found -26.248 with lag order 7. The p-value is 0.01. It indicates that the data set is stationary in mean. So differencing or transformation is not necessary to achieve stationarity. To test the stationarity of the seasonal differenced model, again Augmented Dickey-Fuller test was used. The value of the test statistic has been found -7.2376 with lag order 7. The p-value is 0.01 which indicates that the data is stationary in mean. Finally it can be concluded that non-seasonality difference parameter is $(d=0)$ and seasonality difference parameter $(D=1)$.

Model selection

To determine an appropriate seasonal ARIMA model it is necessary to choose parameters such as order of non-seasonal (*p*, *q*) and seasonal (*P*, *Q*) parameters. Following table shows the AIC and BIC values for different combinations of non-seasonal (*p*, *q*) and seasonal (*P*, *Q*) parameters, that is, for different ARIMA (*p*, 0, *q*) (*P*, 1, *Q*)$_{12}$ models.

Table 3. AIC and BIC values of the fitted models

Models	AIC	BIC
ARIMA(1,0,1)(0,1,1)$_{12}$	974.17	990.76
ARIMA(0,0,1)(1,1,1)$_{12}$	976.21	992.81
ARIMA(1,0,0)(0,1,1)$_{12}$	972.94	985.38
ARIMA(1,0,0)(1,1,0)$_{12}$	1143.68	1156.13
ARIMA(1,0,0)(1,1,1)$_{12}$	974.02	990.61
ARIMA(1,0,0)(2,1,0)$_{12}$	1052.83	10.69.43
ARIMA(1,0,0)(2,1,1)$_{12}$	**969.80**	990.54
ARIMA(1,0,0)(2,1,2)$_{12}$	**970.10**	994.99
ARIMA(1,0,1)(0,1,1)$_{12}$	974.17	990.70
ARIMA(1,0,1)(1,1,0)$_{12}$	1145.66	1162.26
ARIMA(1,0,1)(1,1,1)$_{12}$	975.29	996.03
ARIMA(1,0,1)(2,1,1)$_{12}$	**970.77**	995.66
ARIMA(1,0,1)(0,1,2)$_{12}$	975.02	995.76
ARIMA(1,0,2)(0,1,1)$_{12}$	975.95	996.69
ARIMA(1,0,2)(1,1,0)$_{12}$	1147.11	1167.86
ARIMA(1,0,2)(0,1,1)$_{12}$	975.95	996.69
ARIMA(1,0,2)(0,1,2)$_{12}$	976.72	1001.61
ARIMA(1,0,2)(2,1,1)$_{12}$	972.41	1001.45
ARIMA(1,0,0)(1,0,0)$_{12}$	1315.04	1331.74

ARIMA (1,0,0) $(2,1,1)_{12}$ model shows least AIC values than the other model. Now this study checked the diagnosis checking of the ARIMA (1,0,0) $(2,1,1)_{12}$ model.

Estimation and diagnostic checking

ARIMA (1,0,0) $(2,1,1)_{12}$, includes a non-seasonal AR (autoregressive) and a seasonal MA (moving average). To test the significance of the parameters, the coefficient of their estimated value and corresponding *p* values are given in the following table.

Table 4. The significance test of the parameter

Parameter	Estimate	Std. Error	P-Values	Decision
ar1	0.1873	0.0464	0.00	highly significant
sar1	-0.0807	0.0521	0.01	highly significant
sar2	-0.1309	0.0520	0.00	highly significant
sma1	-0.8927	0.0317	0.00	highly significant

Note: The above table shows that all the parameters are significant.

Shapiro-Wilk test for checking normality assumption of residuals

In order to check the residuals are normally distributed or not, Shapiro-Wilk test is conducted. Here, the null and alternative hypotheses are

H_0 : The residuals are normally distributed

H_a : The residuals are not normally distributed

Here, after conducting the test, the p- value founded is 0.06. Thus, the null hypothesis cannot be rejected. Hence, the residuals can be concluded as normally distributed. This test can be interpreted using normal *q-q* plot is the following.

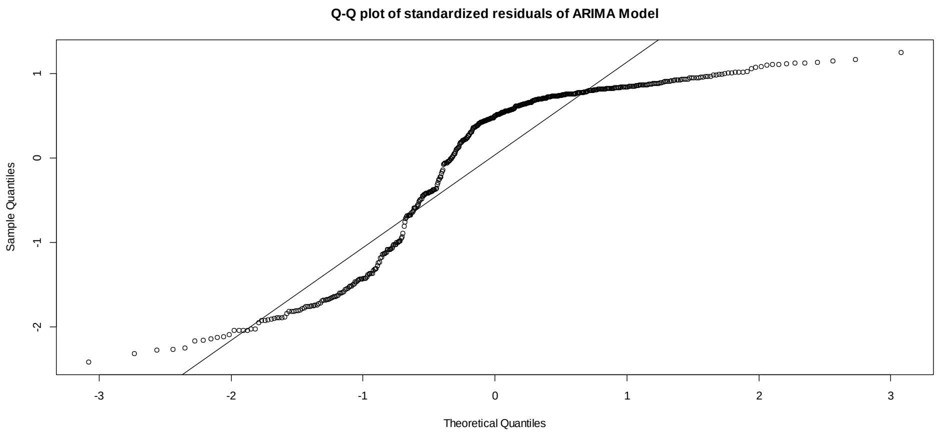

Fig. 7. Q-Q Plot of standardized residuals of ARIMA (l,0,0)$(2,l,1)_{12}$ model

Diagnostic checking

Figure 8 shows the behavior of the residuals left over after fitting the ARIMA (1,0,0) $(2,1,1)_{12}$ model. The plot of the standardized residuals shows that most of the standardized residuals are within 95% limit. The plot of ACF of residuals is shown in figure 8. In both cases, all the spikes are in 95% limit and near to zero. In order to check the residuals are white noise or not, Ljung-Box test has been conducted to check the normality test of the residuals. Here, the null and alternative hypotheses are:

H_0 : The residuals are white noise,

H_a : The residuals are not white noise.

The p value of Ljung-box test is found 0.5975 indicates that the residuals are white noise.

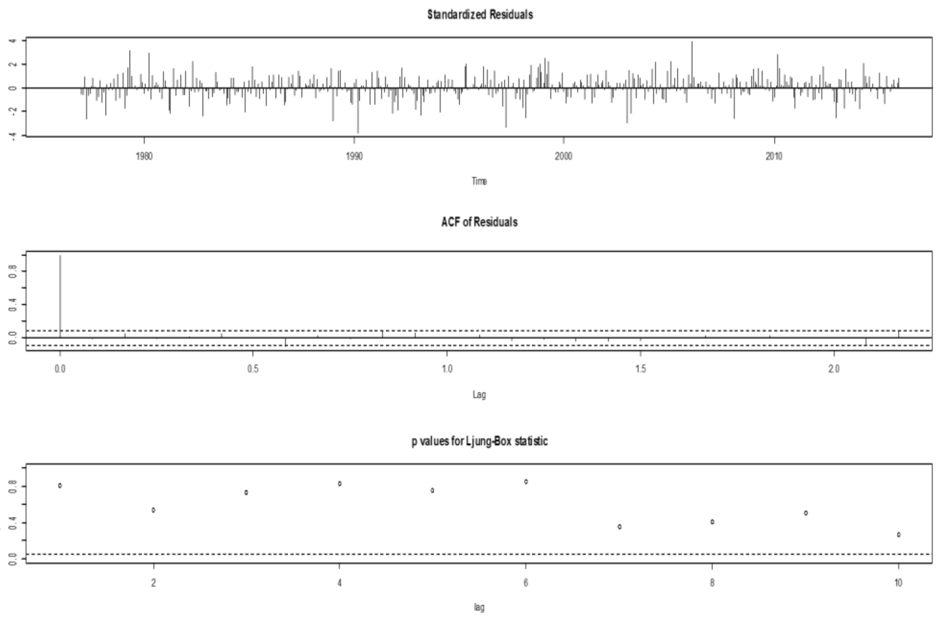

Fig. 8. Diagnostic plot of AR1MA(1,0,0)$(2,1,1)_{12}$ model

Actual and Fitted Plot

A plot of the actual values and the fitted values using the model is given in figure 9. In figure 9, the red line denotes the fitted values and the blue line denotes the actual values. From the plot, it is seen that the model was a much close fit. It can be concluded that the actual and fitted values are very close to each other.

All diagnostic check support that our selected model not only was the smallest AIC but also satisfies all assumptions of model. Now, this model has been used to forecast temperatures of Bangladesh.

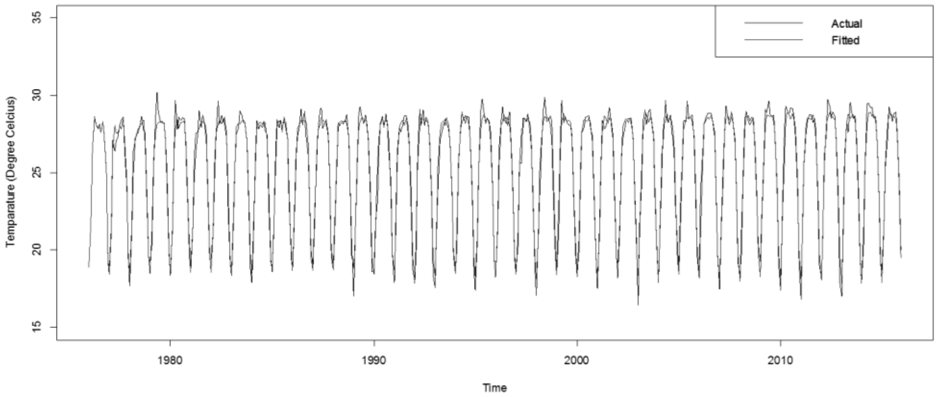

Fig. 9. Comparison between observed and fitted plot

Forecasting

The point forecast with 95% confidence interval on average temperatures of Bangladesh for the month January, 2016 to December, 2020 by using the selected model is given in Table 5 and Table 6.

Table 5. Forecasts of temperature for next 60 months (2016-2020)

Time Period	Point Forecasts	95% Confidence Intervals
January-2016	18.03401	(16.74449, 19.32353)
February-2016	21.54746	(20.23553, 22.85940)
March-2016	25.76801	(24.45530, 27.08073)
April-2016	28.01685	(26.70411, 29.32960)
May-2016	28.64210	(27.32935, 29.95484)
June-2016	28.84900	(27.53626, 30.16175)
July-2016	28.55109	(27.23835, 29.86384)
August-2016	28.64566	(27.33291, 29.95840)
September-2016	28.44590	(27.13316, 29.75865)
October-2016	27.18507	(25.87233, 28.49782)
November-2016	23.54688	(22.23413, 24.85962)
December-2016	19.45853	(18.14579, 20.77128)
January-2017	17.87585	(16.56266, 19.18904)
February-2017	21.36330	(20.05009, 22.67650)
March-2017	25.72466	(24.41145, 27.03786)
April-2017	28.24640	(26.93320, 29.55961)
May-2017	28.72214	(27.40893, 30.03534)
June-2017	28.88910	(27.57590, 30.20231)
July-2017	28.64817	(27.33496, 29.96137)
August-2017	28.62365	(27.31044, 29.93685)

September-2017	28.44642	(27.13322, 29.75963)
October-2017	27.17898	(25.86577, 28.49218)
November-2017	23.52982	(22.21662, 24.84303)
December-2017	19.37430	(18.06109, 20.68750)
January-2018	17.98179	(16.66817, 19.29541)
February-2018	21.38458	(20.07094, 22.69821)
March-2018	25.67979	(24.36615, 26.99343)
April-2018	28.11500	(26.80136, 29.42863)
May-2018	28.80019	(27.48655, 30.11383)
June-2018	28.89523	(27.58159, 30.20886)
July-2018	28.61126	(27.29762, 29.92489)
August-2018	28.64551	(27.33187, 29.95915)
September-2018	28.50365	(27.19002, 29.81729)
October-2018	27.20833	(25.89470, 28.52197)
November-2018	23.58242	(22.26879, 24.89606)
December-2018	19.45285	(18.13922, 20.76649)
January-2019	17.99395	(16.67323, 19.31466)
February-2019	21.40697	(20.08601, 22.72793)
March-2019	25.68909	(24.36812, 27.01006)
April-2019	28.09555	(26.77458, 29.41652)
May-2019	28.78341	(27.46244, 30.10438)
June-2019	28.88948	(27.56851, 30.21045)
July-2019	28.60152	(17.28056, 29.92249)
August-2019	28.64663	(27.32566, 29.96760)
September-2019	28.49897	(27.17800, 29.81994)
October-2019	27.20676	(25.88579, 28.52773)
November-2019	23.58041	(22.25944, 24.90138)
December-2019	19.45754	(18.13657, 20.77851)
January-2020	17.97909	(16.65158, 19.30661)
February-2020	21.40238	(20.07464, 22.73012)
March-2020	25.69421	(24.36646, 27.02196)
April-2020	28.11432	(26.78657, 29.44207)
May-2020	28.77455	(27.44680, 30.10229)
June-2020	28.88914	(27.56139, 30.21689)
July-2020	28.60714	(27.27939, 29.93489)
August-2020	28.64367	(27.31593, 29.97142)
September-2020	28.49185	(27.16410, 29.81960)
October-2020	27.20304	(25.87530, 28.53079)
November-2020	23.57369	(22.24594, 24.90144)
December-2020	19.44688	(18.11913, 20.77463)

Actual and Fitted Forecasting Plot

The forecast values with the 95% confidence intervals are shown in figure 10, where the two lines indicate the forecast values for next sixty months and the green lines indicate the 95% confidence intervals for those forecasts.

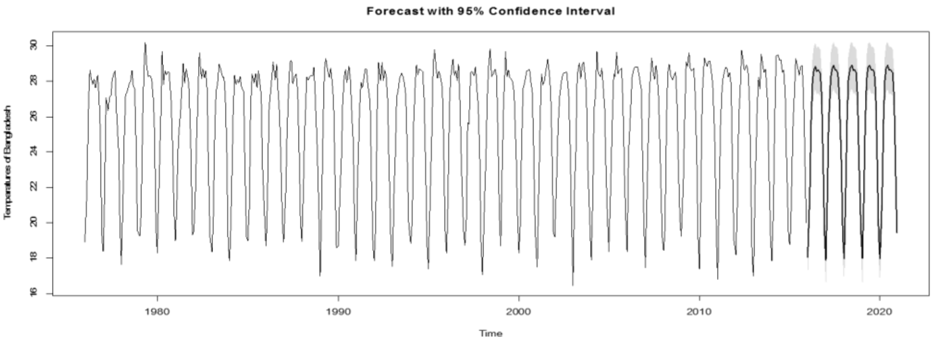

Fig. 10. Forecasts with 95% confidence interval using ARIMA (1,0,0) $(2,1,1)_{12}$ model

Conclusion

This study only considered 6 divisional meteorological stations of Bangladesh. The main objective of this study was to modeling and forecasting monthly temperatures using SARIMA model. To apply SARIMA model, this study estimate 6 parameters. Initially stationarity was checked and get an idea about non-seasonal and seasonal parameters of seasonal ARIMA model using ACF, PACF and Augmented Dickey-Fuller test. Since the observed data does not follow any trend, this study only takes the seasonal difference. Using the model selection criterion, AIC, ARIMA (1,0,0) $(2,1,1)_{12}$ model is found to be the best model for temperatures data set. The parameters of this model were estimated using the maximum likelihood method and found to be significant. The assumption on normality and independence of the residuals was checked using different plots and test. The plot comparing actual values and fitted values using the model shows much close fit. Then the model was used for forecasting temperatures from January 2016 to December 2020. The findings of this study expect that it may help the policy makers to a great extent in environmental issues and also can help to set up a fruitful policy for maintaining the ecological balance of Bangladesh.

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