# ARIMA Time Series Analysis in Forecasting Daily Stock Price of Chittagong Stock Exchange (CSE)

Tasnim Uddin Chowdhury<sup>1</sup>, Md. Shahidul Islam<sup>2</sup>

<sup>1</sup>Assistant Professor (Finance Discipline), Department of Business Administration, Premier University, Chattogram, Bangladesh, <sup>2</sup>Divisional Officer, Service Engineering Division, Bangladesh Forest Research Institute, Chattogram, Bangladesh

Abstract- The aim of the study is to examine the nature of daily share price and select a suitable ARIMA model to forecast the future daily share price from the previous daily share price of Chittagong Stock exchange (CSE). A random sampling method has been followed to collect the closing price of 60 companies for the period of January 2019 to December 2019 (241 trading days). Durbin-Watson test has been conducted to find the autocorrelation in each of the share prices. Then the Augmented Dickey-Fuller test has been applied to test the stationary of data the Autocorrelation function (ACF) and Partial and Autocorrelation function (PACF) has been calculated to determine the lag value of moving average MA(q) and autocorrelation AR(p)based on Ljung-Box Test Q, root mean square error, mean absolute error, mean absolute percent error and R-square values. After selecting ARIMA (p,d,q) model, forecasted values for each of the shares are calculated for the next 22 trading days of January 2020. Then a comparison has been made between the forecasted prices and the actual share prices by using the Goodness-of-fit Test, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) to validate the model. The result shows that the ARIMA model is applicable to forecast the daily share price of CSE.

*Keywords*-Time series analysis, Autoregressive Integrated Moving Average (ARIMA), Durbin-Watson test, Augmented Dickey-Fuller test, Goodness of fit test.

# I. BACKGROUND

C tock market analysts prefer to conduct both fundamental Danalysis and technical analysis for taking investment decision. The former one involves analyzing the fundamental factors like- the company's financial position, operating performance, dividend payment history, market competition etc. that affects the future earning capacity of the company and identifying the mispriced stocks by determining its intrinsic value. On the contrary, the latter one undertakes the analysis of historical price movements to get a forecast of future price. To conduct technical analysis different charts like- bar chart, line chart, candle stick chart etc. is used. By using the charts different patterns of price movement is identified to get a sense of price trend that may prevail in the future. Jarrett and Kyper (2005) find predictable patterns in monthly stock prices examining the daily returns for more than 50 firms from American Stock Exchanges. But, unlike technical analysis, time series analysis is a statistical tool which is applied to forecast the price for a particular period of time in the future based on the historical series of data regarding price at constant time interval.

Forecasting involves taking sense of what may happen in the future based on the available past data. For the investors who actively trade in the stock market, forecasting the price of individual stock and market behavior based on past price movement plays a significant role in their decision making. The more accurate a forecast is; the more gain an investor would have. On the contrary, if the forecast goes wrong, it may even result in a significant loss. As such, stock market forecasting has been considered as one of most difficult tasks in the area of finance due to the stochastic behaviors and complex interdependencies of stock market (Wei, 2013).

# II. LITERATURE REVIEW

A good number of researches have been done to predict the future movement patterns of stock prices in the literature of finance. Several studies find that, it is possible to forecast the stock price with high level of accuracy by applying statistical, econometric and machine learning models if the models can be formulated properly. Sen and Datta forecasted the stock price with a high level of accuracy based on time series decomposition (Sen & Datta Chaudhuri, 2018a;Sen & Datta Chaudhuri, 2017a; Sen & Datta Chaudhuri, 2017b; Sen & Datta Chaudhuri, 2017c; Sen & Datta Chaudhuri, 2017c; Sen & Datta Chaudhuri, 2017d; Sen & Datta Chaudhuri, 2016).Studies have also been done by Sohail, Kamal and Ali (2012), Kumar (2006) and Al-Zeaud (2011).

Another school of researchers support the "efficient market hypothesis" and belief that it is not possible to forecast the price of stock appropriately. Keane (1983) finds that the extent to which an emerging market would be inefficient depends on the market size, thinness of trading and quality of disclosed information. Poterba & Summers (1988), Roux & Gilberson (1978), Harvey (1994), Classens et al (1995), Khababa (1998) finds that the market is not efficient when it is in the weak form which implies that, there is possibility to predict the future stock prices and design a trading strategy which is profitable based on historical prices of stock. According to the studies of Fama and French (1988), Poterba and Summers (1988) and Ding, Granger and Engle(1993) all the time series of stock returns does not follow a random-walk process. Although, Kendall (1953), Granger & Morgenstern (1963) and Solnik (1973) finds that random walk is usually valid for the stock markets of developed countries.

Applying the ARIMA (1,0,1) for Egypt, ARIMA(1,0,2) for Ghana and ARIMA (2,0,1) for Mauritius, Simons and Laryea (2004) predicts the stock market return and generates one period forecasts for the subsequent twelve periods. Al-Shihab (2006) examines the daily index of Amman Stock Exchange (ASE) for the period starting from April, 2004 toOctober, 2004 and tried to forecast the return of the market. Jia (2016) studies the effectiveness of Long Short-Term Memory (LSTM)for the prediction of stock market and finds the model to be effective for getting a pattern in the stock market.

In this age of digital era, forecasting the stock market through the use of Artificial Intelligence (AI) and different Machine Learning (ML) methods has also become a vital issue in the field of finance and investment. Over the decade, researchers have devoted their utmost effort to come up with predictive models which is more reliable (Ariyo et al., 2014). Lots of studies have been done to forecast the stock price by using AI and ML. To improve the time series forecasting several ML methods like- Support Vector Regression (SVR), Artificial Neural Networks (ANNs), Bayesian Neural Network (BNN) etc has been applied throughout the recent years (Wei, 2013). Neural Networks (NNs) have been proved to be one of the more important methods for predicting the stock price with better accuracy (Schöneburg, 1990). It requires very large number of historical data (Kryzanowski et al., 1993; Yoon et al., 1994) and in case of complicated networks, reliability of results may be low (Yoon et al., 1994). Mostafa (2010) used neural network-based models and predicted the stock market movements in Kuwait appropriately. Oh et al. (2006), Chang and Liu (2008) and Liu et al. (2012) works on fuzzy neural networks and Cao and Tay (2003), Gavrishchaka and Banerjee (2006) and Yeh et al. (2011) works on SVR model to overcome the shortcomings that traditional time series analysis tools have.

Study to forecast the stock pricehas also been conducted based on Dhaka Stock Exchange (DSE).Kader and Rahman(2005), Islam and Khaled(2005), Ahmed (2002); Rahman and Hossain(2006) and Alam and Uddin (2007) finds that the market is inefficient. So, their study supports that historical prices of the stocks can be used to forecast the future market returns in DSE. Rahman & Hossain (2006) applies ARIMA(3,0,1) and ARIMA(1,0,1) models on the stock prices of companies from DSE and finds that the models are best fit for forecasting. Study has also been done by Mollick and Bepari (2008) using ARIMA(1,0,2). They also find applicability of the model they used in their study. Haider and Kabir (2009) applies ARIMA(3,1,1) and ARMA(3,1) to forecast the growth of the market based on the index and return series of DSE from the period of January 1993 to March 2011. Working with the monthly data of DSE general index for the period of January 2002 to July 2013, Kamruzzaman, Khudri and Rahman (2017) finds that,

application of ARIMA (2, 0, 2) is effective as a model to forecast the market return behavior of DSE.

Beside the aforementioned studies, lots of studies have also been performed to develop an appropriate model for forecasting the stock price. Most of the studies are out of the context of Bangladesh. Even, the models applied in the studies are very much difficult for the investors to understand and apply to forecast the price of stock. This study tries to examine whether time series model, a simple and convenient model for understanding, is applicable or not, to forecast the price of stock in the Chittagong Stock Exchange(Coordinate: 22.321079<sup>0</sup>N 91.811129<sup>0</sup>E), one of the two major stock exchanges of Bangladesh.

# **III. OBJECTIVES OF THE STUDY**

The major objective of the study is to examine the nature of daily share price and select a suitable ARIMA model to forecast the daily share price from the previous daily share price of Chittagong Stock exchange.

### **IV. HYPOTHESIS**

This study tests the following three hypotheses:

Hypothesis 1

Null Hypothesis,  $H_0$ : There are no autocorrelation in the share prices.

Alternative Hypothesis,  $H_1$ : There are autocorrelation in the share prices.

Hypothesis 2

Null Hypothesis, H<sub>0</sub>: Stock values have a unit root.

Alternative Hypothesis, H<sub>1</sub>: Stock values have no unit root.

Hypothesis 3

Null Hypothesis,  $H_0$ : There is no significant difference between the actual share price and the forecasted share price.

Alternative Hypothesis,  $H_1$ : There is a significant difference between the actual share price and the forecasted share price.

## V. METHODOLOGY

To examine the applicability of time series method secondary source of data has been used. A random sampling method has been followed to collect the closing price of sixty randomly selected companies (out of three hundred thirty eight listed companies)from the website of CSE (www.cse.com.bd). A total number of 241 trading days for the period of January 2019to December 2019 has been collected for each of the selected companies. Then Durbin Watson test has been conducted for each company to observe the autocorrelation in the daily share prices. The Augmented Dickey Fuller Test has been conducted to test the unit root for each company data. Then the 1<sup>st</sup> difference has been calculated from the previous data values to make the data stationary. After that, Auto-Regressive Integrated Moving Average (ARIMA) has been developed based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) of lag 16from the collected data. The Auto-regression with p lag AR(p) may be defined as equation (i):

$$y_t = \mu + \sum_{i=1}^p \gamma_i y_{t-i} + \epsilon_t \dots \dots \dots (i)$$

Where,  $y_t$  is the share price at time t,  $\mu$  is constant, $\gamma_i$  is the coefficient of lag variable,  $y_{t-i}$  is the share price at time (t - i) and  $\epsilon_t$  is the error term.

The Moving average with q lag MA(q) may be defined as equation (ii):

$$y_t = \mu + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t \dots \dots \dots (ii)$$

Where,  $y_t$  is the share price at time t,  $\mu$  is constant,  $\theta_i$  is the coefficient of lag variable,  $y_{t-i}$  is the share price at time (t - i) and  $\epsilon_t$  is the error term. Now autoregressive moving average ARMA (p,q) model combines both p autoregressive terms with q moving average which can be termed as equation (iii):

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t \dots (iii)$$

To develop the ARMA (p,q) model it requires the data to be stationary. To convert the data into stationary differencing I(d) is made. Where, d is the differencing made to make the data stationary. The model that we get then is ARIMA (p,d,q) with autoregressive p lag, differencing d to make stationary and moving average q lag. Then the selection of ARIMA (p,d,q) has been done from 241 trading days (January 2019 to December 2019) for future forecasting each share values. To test the fitness of the model Ljung-Box Test O, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and R-square value has been used. After that, by applying the selected ARIMA model, the forecasted share price ofnext22 trading days in the month of January 2020 has been calculated. Then these calculated forecasted prices have been compared with the actual prices by using the Goodness-of-fit Test, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) to validate the model. IBM SPSS Statistics 20and STATA 15 statistical package has been used to conduct the analysis.

#### VI. RESULT AND DISCUSSION

The line diagram of daily closing share price for each company is shown below in Figure 1.







Figure 1: Line diagram of closing price

From the above figures, it is observed that all the shares have a trend value with constant intercept in y axis. The Durbin-Watson test result for each share price is shown in Table 1. The Durbin-Watson test statistics of the share price varies from 0.065 to 0.462. It is observed that all the test statistics values of Durbin-Watson test are nearly zero which rejects the null hypothesis 1 and provides an evidence of having autocorrelation in the daily share prices. The daily share prices of each company values are tested for unit root by using Augmented Dickey Fuller Test. The test statistic of Augmented Dickey-Fuller Test is shown in Table 1 for all the selected share prices. The test statistics Z(t) for Augmented Dickey-Fuller Test varies from 0.013 to 3.293 (with p-value 0.0152 to 0.9660). In the case of EASTERNINS and UTTARABANK the p-value of Augmented Dickey-Fuller Test are less than 0.05. Therefore, for the case of above two companies the null hypothesis 2 can be rejected which implies that the share price of EASTERNINS and UTTARABANK are considered d equal to 0 in ARIMA(p,d,q) model. For rest of all 58 companies the p-value of Augmented Dickey-Fuller Test is greater than 0.05which implies that, we can accept the null hypothesis 2. So, it may be concluded that, for the 58 companies (96.67%) the share price data are non-stationary. Now, the share values of the non-stationary 58 companies are deducted from the previous values (1<sup>st</sup> differencing) of each company to make them stationary for applying the ARIMA model. As such, Augmented Dickey-Fuller Test has been conducted again for each company to test the stationarity of the data value and the result is shown in Table I. The test

statistics for Augmented Dickey-Fuller Test for  $1^{st}$  difference varies from 12.2490 to 25.8020 (with each p-value 0.0000). In these cases, the p-values are less than 0.05. Now all the  $1^{st}$  difference values are stationary and considered d equal to 1 for the 58 companies in ARIMA(p,d,q) model.

TABLE I Durbin Watson test, Augmented Dickey-Fuller Test and Model selection result

			<b>G</b> 1	a st		1
Name of the Company	Variable Name	Durbin Watson test Statistic s	Stock Price Dickey -Fuller Z(t) Statisti c (p- value)	Differenc e Dickey- Fuller Z(t) Statistic (p-value)	Model Select ion	
AAMRA TECHNOLOGIES LTD.	AAMR ATECH	0.181	1.574 (0.496 7)	19.251 (0.0000)	ARIM A(1,1, 0)	
THE ACME LABORATORIES LTD.	ACME LAB	0.076	0.390 (0.911 8)	15.606 (0.0000)	ARIM A(1,1, 0)	
ACTIVE FINE CHEMICALS LTD.	ACTIV EFINE	0.094	0.015 (0.957 3)	14.495 (0.0000)	ARIM A(1,1, 0)	
ADVENT PHARMA LTD.	ADVE NT	0.152	1.325 (0.617 8)	14.983 (0.0000)	ARIM A(1,1, 0)	
AFTAB AUTOMOBILES LIMITED	AFTAB AUTO	0.145	0.738 (0.836 6)	16.294 (0.0000)	ARIM A(1,1, 0)	
AL-ARAFAH ISLAMI BANK LTD.	ALARA BANK	0.160	0.952 (0.770 3)	16.722 (0.0000)	ARIM A(1,1, 0)	
APEX FOOTWEAR LIMITED	APEXF OOT	0.143	1.654 (0.455 1)	17.990 (0.0000)	ARIM A(1,1, 0)	
APPOLLO ISPAT COMPLEX LTD	APOLO ISPAT	0.137	0.743 (0.835 4)	13.529 (0.0000)	ARIM A(1,1, 0)	
BARAKA POWER LIMITED	BARK APOW ER	0.193	0.350 (0.918 1)	16.243 (0.0000)	ARIM A(1,1, 0)	
BATA SHOE COMPANY (BD) LIMITED	BATAS HOE	0.087	0.143 (0.945 0)	15.671 (0.0000)	ARIM A(1,1, 0)	
BAY LEASING & INVESTMENT LTD.	BAYLE ASING	0.140	1.559 (0.503 9)	17.236 (0.0000)	ARIM A(1,1, 0)	
BEXIMCO LIMITED	BEXIM CO	0.121	0.235 (0.934 2)	14.957 (0.0000)	ARIM A(1,1, 0)	
BD INDUSTRIAL FINANCE CO. LTD	BIFC	0.123	1.062 (0.730 0)	14.021 (0.0000)	ARIM A(1,1, 0)	
BRAC BANK LIMITED	BRACB ANK	0.069	1.073 (0.725 6)	14.767 (0.0000)	ARIM A(1,1, 0)	
BD SHIPPING CORPORATION	BSC	0.071	2.286 (0.176 4)	15.023 (0.0000)	ARIM A(1,1, 0)	
BEXIMCO PHARMACEUTIC ALS LTD	BXPHA RMA	0.147	1.001 (0.752 8)	17.971 (0.0000)	ARIM A(2,1, 0)	
THE CITY BANK LIMITED	CITYB ANK	0.065	0.900 (0.788 0)	15.303 (0.0000)	ARIM A(1,1, 0)	
C & A TEXTILES	CNATE	0.126	1.136	15.361	ARIM	

Name of the Company	Variable Name	Durbin Watson test Statistic s	Stock Price Dickey -Fuller Z(t) Statisti c (p- value)	1 <sup>st</sup> Differenc e Dickey- Fuller Z(t) Statistic (p-value)	Model Select ion
LIMITED	Х		(0.700 6)	(0.0000)	A(1,1, 0)
CONFIDENCE CEMENT LIMITED	CONFI DCEM	0.189	0.650 (0.859 3)	18.752 (0.0000)	ARIM A(1,1, 0)
CVO PETROCHEMICA L REFINERY LIMITED	CVOPR L	0.123	0.160 (0.943 1)	12.249 (0.0000)	ARIM A(1,1, 0)
DHAKA ELECTRIC SUPPLY CO. LTD.	DESCO	0.217	2.155 (0.222 9)	17.945 (0.0000)	ARIM A(1,1, 0)
DESHBANDHU POLYMER LIMITED	DESHB ANDH U	0.213	2.275 (0.180 1)	25.802 (0.0000)	ARIM A(1,1, 0)
EASTERN INSURANCE COMPANY LTD	EASTE RNINS	0.091	3.262 (0.016 7)		ARIM A(1,0, 0)
EASTERN BANK LIMITED	EBL	0.327	2.462 (0.125 1)	19.061 (0.0000)	ARIM A(2,1, 0)
EASTERN CABLES LIMITED	ECABL ES	0.073	1.625 (0.469 9)	15.188 (0.0000)	ARIM A(1,1, 0)
EXPORT IMPORT BANK OF BD LTD	EXIMB ANK	0.172	1.502 (0.532 4)	17.450 (0.0000)	ARIM A(2,1, 0)
FAREAST FINANCE & INVESTMENT LIMITED	FAREA STFIN	0.160	1.165 (0.688 6)	20.050 (0.0000)	ARIM A(4,1, 0)
FIRST FINANCE LIMITED	FIRSTF IN	0.150	1.483 (0.542 1)	14.546 (0.0000)	ARIM A(1,1, 0)
FU-WANG FOODS LIMITED	FUWA NGFOO D	0.087	0.548 (0.882 3)	15.264 (0.0000)	ARIM A(1,1, 0)
GRAMEENPHON E LIMITED	GP	0.144	0.804 (0.818 0)	14.294 (0.0000)	ARIM A(1,1, 0)
HAKKANI PULP & PAPER MILLS LTD	HAKK ANIPU L	0.162	1.710 (0.425 8)	16.523 (0.0000)	ARIM A(1,1, 0)
INTECH LIMITED	INTEC H	0.105	1.342 (0.609 7)	13.973 (0.0000)	ARIM A(1,1, 0)
INFORMATION SERVICES NETWORK LTD.	ISNLT D	0.127	1.789 (0.386 0)	16.546 (0.0000)	ARIM A(1,1, 0)
JAMUNA OIL COMPANY LIMITED	JAMUN AOIL	0.119	0.553 (0.881 4)	15.186 (0.0000)	ARIM A(2,1, 0)
KHULNA PRINTING & PACKAGING LIMITED	KPPL	0.126	2.369 (0.150 8)	16.799 (0.0000)	ARIM A(1,1, 0)
MAKSONS SPINNING MILLS LIMITED	MAKS ONSPI N	0.211	1.230 (0.660 6)	15.501 (0.0000)	ARIM A(1,1, 0)
METRO SPINNING	METR OSPIN	0.167	2.070 (0.256	15.611 (0.0000)	ARIM A(1,1,

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Name of the Company	Variable Name	Durbin Watson test Statistic s	Stock Price Dickey -Fuller Z(t) Statisti c (p- value)	1 <sup>st</sup> Differenc e Dickey- Fuller Z(t) Statistic (p-value)	Model Select ion	Name of the Company	Variable Name	Durbin Watson test Statistic s	Stock Price Dickey -Fuller Z(t) Statisti c (p- value)	1 <sup>st</sup> Difference e Dickey- Fuller Z(t) Statistic (p-value)
LIMITED			9)		0)	CHEMICAL INDUSTRY LTD	CHEM		(0.825 5)	(0.0000)
MOZAFFAR HOSSAIN SPINNING MILLS LIMITED	MHSM L	0.176	1.548 (0.509 9)	16.329 (0.0000)	ARIM A(1,1, 0)	TALLU SPINNING MILLS LIMITED	TALLU SPIN	0.167	1.144 (0.697 2)	14.507 (0.0000)
MILLS LIMITED MIDAS FINANCING LIMITED MITHUN	MIDAS FIN	0.105	1.603 (0.481 9)	17.916 (0.0000)	ARIM A(1,1, 0)	TITAS GAS TRANSMISSION & DISTRIBUTION	TITAS GAS	0.085	0.013 (0.957 4)	16.175 (0.0000)
KNITTING AND DYEING (CEPZ) LTD.	MITHU NKNIT	0.093	0.585 (0.874 4)	15.459 (0.0000)	ARIM A(1,1, 0)	TUNG HAI KNITTING AND DYEING LTD.	TUNG HAI	0.133	1.622 (0.471 6)	17.318 (0.0000)
OLYMPIC ACCESSORIES LTD.	OAL	0.158	0.751 (0.833 2)	16.248 (0.0000)	ARIM A(1,1, 0)	UNION CAPITAL LIMITED	UNION CAP	0.168	0.639 (0.862 0)	16.470 (0.0000)
PADMA ISLAMI LIFE INSURANCE LIMITED	PADM ALIFE	0.151	1.256 (0.649 0)	17.236 (0.0000)	ARIM A(1,1, 0)	UNITED AIRWAYS (BD) LTD.	UNITE DAIR	0.197	1.295 (0.631 7)	18.205 (0.0000)
PRIME FINANCE & INVESTMENT LTD	PRIME FIN	0.114	1.386 (0.589 1)	17.498 (0.0000)	ARIM A(1,1, 0)	USMANIA GLASS SHEET FACTORY LIMITED	USMA NIAGL	0.067	0.099 (0.966 0)	14.823 (0.0000)
PRIME INSURANCE COMPANY LTD	PRIMEI NSUR	0.121	1.913 (0.325 8)	13.244 (0.0000)	ARIM A(1,1, 0)	UTTARA BANK LIMITED	UTTAR ABAN K	0.391	3.293 (0.015 2)	
PRIME TEXTILE SPINNING MILLS RANGPUR	PRIME TEX	0.086	0.428 (0.905 3) 1.564	15.151 (0.0000)	ARIM A(1,1, 0) ARIM	UTTARA FINANCE & INVESTMENT LIMITED	UTTAR AFIN	0.462	2.332 (0.162 0)	18.772 (0.0000)
DAIRY & FOOD PRODUCTS LTD REGENT	D	0.144	(0.501 8) 0.428	(0.0000)	A(1,1, 0) ARIM	WESTERN MARINE SHIPYARD LTD.	WMSHI PYARD	0.122	0.838 (0.807 8)	15.386 (0.0000)
TEXTILE MILLS LIMITED R. N. SPINNING	TTEX	0.084	(0.905 3) 1.243	(0.0000)	A(1,1, 0) ARIM	YEAKIN POLYMER LIMITED	YPL	0.073	1.129 (0.703 5)	13.556 (0.0000)
MILLS LIMITED SALVO	N SALVO	0.075	(0.654 9) 0.778	(0.0000)	A(1,1, 0) ARIM	ZAHEEN SPINNING LTD.	ZAHEE NSPIN	0.066	1.566 (0.500 5)	14.117 (0.0000)

The line diagram of 1<sup>st</sup> difference for each company is shown in Figure 2.



Model

Select

ion

A(1,1, 0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM A(2,0, 0) ARIM

A(3,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0) ARIM

A(1,1,

0)





Figure 2: Line diagram of 1<sup>st</sup> difference

The diagram for autocorrelation function (ACF)oflag 16 foreach share is created to select MA lag value in ARIMA model and result is shown in Figure 3.









From the above figure it is seen that, the autocorrelation factors decreases gradually and all the values are higher than the confidence interval for all cases. So, no moving average slag value is convenient for the model development. It is convenient to consider MA(0) for the model of each company daily share price. Now the diagram for partial autocorrelation function (PACF) of lag 16 foreach share is created to select AR lag value in ARIMA model and result is shown in Figure 4.







Figure 4: PACF diagram of share price

From the above figures the number of partial autocorrelation values that higher than the confidence interval has been selected for AR(p) model. Then, based on the January 2019 to December 2019 stock prices (241 trading days) data with AR, I and MA values of 52 companies (86.67%) are selected for ARIMA (1,1,0), 4 companies (6.67%) are selected for TABLE HARMA

ARIMA (2,1,0), 1 company (1.67%) selected for ARIMA (3,1,0), 1 company (1.67%) is selected for ARIMA (4,1,0), 1 company (1.67%) is selected for ARIMA (1,0,0) and 1 company (1.67%) is selected for ARIMA (2,1,0) model. The result is shown in Table 1.The coefficient of each selected ARIMA model is calculated and shown in Table II.

Variable Name	ARIMA model	Ljung-Box Test O (p-value)	RMSE	MAE	MAPE	R-Square value
AAMRATECH	$Y_t = -0.028 - 0.217 Y_{(t-1)}$ Difference 1	16.049(0.520)	0.508	0.369	1.479	0.965
ACMELAB	$Y_t = -0.103 - 0.014 Y_{(t-1)}$ Difference 1	15.267(0.576)	1.075	0.718	0.973	0.989
ACTIVEFINE	$Y_t = -0.060 + 0.062 Y_{(t-1)}$ Difference 1	19.743(0.288)	0.552	0.388	1.653	0.985
ADVENT	$Y_t = -0.074 + 0.026Y_{(t-1)}$ Difference 1	12.070(0.796)	0.776	0.577	1.870	0.971
AFTABAUTO	$Y_t = -0.090 - 0.052 Y_{(t-1)}$ Difference 1	12.645(0.760)	0.637	0.455	1.311	0.992
ALARABANK	$Y_t = -0.013 - 0.080 Y_{(t-1)}$ Difference 1	9.595(0.920)	0.294	0.192	0.992	0.973
APEXFOOT	$Y_t = -0.302 - 0.158 Y_{(t-1)}$ Difference 1	12.949(0.740)	7.645	3.561	1.327	0.931
APOLOISPAT	$Y_t = -0.019 + 0.128Y_{(t-1)}$ Difference 1	13.417(0.708)	0.191	0.139	2.294	0.985
BARKAPOWER	$Y_t = -0.027 - 0.046Y_{(t-1)}$ Difference 1	12.931(0.741)	0.410	0.313	1.133	0.975
BATASHOE	$Y_t = -1.558 - 0.018 Y_{(t-1)}$ Difference 1	18.942(0.332)	2.285	12.435	1.260	0.981
BAYLEASING	$Y_t = -0.027 - 0.112 Y_{(t-1)}$ Difference 1	23.566(0.132)	0.507	0.293	1.727	0.965
BEXIMCO	$Y_t = -0.049 + 0.029 Y_{(t-1)}$ Difference 1	16.133(0.514)	0.371	0.263	1.319	0.989
BIFC	$Y_t = -0.014 + 0.093 Y_{(t-1)}$ Difference 1	8.795(0.946)	0.221	0.130	3.023	0.982
BRACBANK	$Y_t = -0.076 + 0.041 Y_{(t-1)}$ Difference 1	13.228(0.721)	1.331	0.894	1.351	0.980
BSC	$Y_t = 0.010 + 0.025 Y_{(t-1)}$ Difference 1	18.968(0.330)	1.034	0.742	1.512	0.932
BXPHARMA	$\begin{array}{c} Y_t = -\ 0.053 - 0.176 Y_{(t-1)} - \\ 0.111 \ Y_{(t-2)} \\ \text{Difference 1} \end{array}$	11.566(0.773)	1.126	0.842	1.033	0.926
CITYBANK	$Y_t = -0.040 + 0.006Y_{(t-1)}$ Difference 1	15.099(0.588)	0.452	0.334	1.265	0.982
CNATEX	$Y_t = -0.010 + 0.027 Y_{(t-1)}$ Difference 1	12.581(0.764)	0.122	0.090	3.081	0.982
CONFIDCEM	$Y_t = -0.335 - 0.193Y_{(t-1)}$ Difference 1	8.797(0.946)	3.252	2.281	1.585	0.977
CVOPRL	$Y_t = -0.275 + 0.241 Y_{(t-1)}$ Difference 1	10.768(0.868)	3.943	2.892	1.990	0.988
DESCO	$Y_t = -0.012 - 0.150Y_{(t-1)}$ Difference 1	18.789(0.341)	0.898	0.568	1.301	0.900
DESHBANDHU	$Y_t = -0.010 - 0.125Y_{(t-1)}$ Difference 1	18.948(0.332)	0.362	0.255	1.992	0.901
EASTERNINS	$Y_t = -42.662 - 0.968 Y_{(t-1)}$ Difference 0	12.917(0.742)	2.177	1.321	2.929	0.883

		Linne Den Test				DC
Variable Name	ARIMA model	Q (p-value)	RMSE	MAE	MAPE	R-Square value
EBL	$Y_t = -0.014 - 0.232 Y_{(t-1)} - 0.101 Y_{(t-2)}$ Difference 1	22.820(0.119)	0.798	0.555	1.500	0.883
ECABLES	$Y_t = -0.117 - 0.013 Y_{(t-1)}$ Difference 1	18.416(0.363)	9.626	6.898	2.382	0.936
EXIMBANK	$\begin{array}{c} Y_t = -\ 0.009 - 0.135 Y_{(t-1)} - \\ 0.090 \ Y_{(t-2)} \\ \text{Difference 1} \end{array}$	19.538(0.242)	0.185	0.123	1.085	0.965
FAREASTFIN	$\begin{array}{l} Y_t = -\ 0.010 + \ 0.257 Y_{(t-1)} - \\ 0.003 Y_{(t-2)} + \ 0.044 Y_{(t-3)} + \\ 0.064 \ Y_{(t-4)} \\ Difference \ 1 \end{array}$	23.602(0.051)	0.208	0.155	3.591	0.980
FIRSTFIN	$Y_t = -0.007 + 0.036Y_{(t-1)}$ Difference 1	15.609(0.552)	0.230	0.105	2.109	0.964
FUWANGFOOD	$Y_t = -0.023 + 0.011 Y_{(t-1)}$ Difference 1	21.457(0.206)	0.318	0.229	1.770	0.987
GP	$Y_t = -0.346 + 0.075 Y_{(t-1)}$ Difference 1	12.312(0.781)	5.839	4.054	1.171	0.971
HAKKANIPUL	$Y_t = -0.103 - 0.074 Y_{(t-1)}$ Difference 1	11.668(0.820)	2.049	1.483	2.575	0.963
INTECH	$Y_t = -0.185 + 0.097 Y_{(t-1)}$ Difference 1	22.665(0.160)	1.200	0.808	2.798	0.991
ISNLTD	$Y_t = 0.065 - 0.065 Y_{(t-1)}$ Difference 1	15.249(0.578)	1.312	0.859	2.734	0.912
JAMUNAOIL	$Y_t = -0.160+0.015Y_{(t-1)}-$ 0.137 Y <sub>(t-2)</sub> Difference 1	11.850(0.754)	2.517	1.702	0.991	0.968
KPPL	$Y_t = -0.026 - 0.089 Y_{(t-1)}$ Difference 1	17.684(0.409)	0.531	0.315	2.051	0.943
MAKSONSPIN	$Y_t = -0.015 - 0.004 Y_{(t-1)}$ Difference 1	23.132(0.145)	0.167	0.123	2.105	0.979
METROSPIN	$Y_t = -0.007 - 0.013Y_{(t-1)}$ Difference 1	16.090(0.517)	0.244	0.187	2.552	0.925
MHSML	$Y_t = -0.015 - 0.059 Y_{(t-1)}$ Difference 1	14.296(0.646)	0.494	0.360	3.285	0.956
MIDASFIN	$Y_t = -0.047 - 0.145 Y_{(t-1)}$ Difference 1	10.308(0.890)	0.765	0.551	3.029	0.973
MITHUNKNIT	$Y_t = -0.046 - 0.004 Y_{(t-1)}$ Difference 1	14.501(0.631)	0.455	0.286	2.344	0.987
OAL	$Y_t = -0.029 - 0.053 Y_{(t-1)}$ Difference 1	13.735(0.686)	0.268	0.201	2.163	0.986
PADMALIFE	$Y_t = -0.037 - 0.109 Y_{(t-1)}$ Difference 1	19.532(0.299)	0.701	0.394	1.902	0.975
PRIMEFIN	$Y_t = -0.007 - 0.133 Y_{(t-1)}$ Difference 1	12.134(0.792)	0.288	0.182	2.109	0.966
PRIMEINSUR	$Y_t= 0.064+0.149 Y_{(t-1)}$ Difference 1	17.798(0.402)	0.807	0.491	2.315	0.948
PRIMETEX	$Y_t = -0.059 - 0.093 Y_{(t-1)}$ Difference 1	19.347(0.309)	0.814	0.590	2.155	0.968
RDFOOD	$Y_t = -0.013 - 0.022 Y_{(t-1)}$ Difference 1	26.320(0.069)	0.269	0.193	1.442	0.974
REGENTTEX	$Y_t = -0.028 + 0.016Y_{(t-1)}$ Difference 1	13.054(0.733)	0.391	0.294	2.205	0.980
RNSPIN	$Y_t = -0.021 + 0.0145 Y_{(t-1)}$ Difference 1	11.213(0.845)	0.201	0.149	2.735	0.990
SALVOCHEM	$Y_t = -0.035 - 0.065 Y_{(t-1)}$ Difference 1	11.557(0.826)	0.494	0.318	2.382	0.970
TALLUSPIN	$Y_t = -0.014 + 0.083 Y_{(t-1)}$ Difference 1	11.213(0.845)	0.198	0.127	2.623	0.975
TITASGAS	$Y_t = -0.024 - 0.047 Y_{(t-1)}$ Difference 1	19.936(0.277)	0.434	0.301	0.804	0.964
TUNGHAI	$Y_t = -0.015 - 0.117 Y_{(t-1)}$ Difference 1	15.249(0.578)	0.149	0.106	3.087	0.981
UNIONCAP	$Y_t = -0.026 - 0.062 Y_{(t-1)}$ Difference 1	19.934(0.278)	0.345	0.237	2.378	0.987
UNITEDAIR	$Y_t = -0.007 - 0.163 Y_{(t-1)}$ Difference 1	7.264(0.980)	0.089	0.064	3.014	0.978

Variable Name	ARIMA model	Ljung-Box Test Q (p-value)	RMSE	MAE	MAPE	R-Square value
USMANIAGL	$Y_t = -0.232 + 0.041 Y_{(t-1)}$ Difference 1	19.192(0.318)	2.740	1.740	2.006	0.983
UTTARABANK	$\begin{array}{rrr} Y_{t} = & 28.411 + \ 0.907 \ Y_{(t-1)} - \\ & 0.001 \ Y_{(t-2)} \\ & \text{Difference } 0 \end{array}$	16.691(0.406)	0.482	0.332	1.154	0.823
UTTARAFIN	$\begin{array}{l} Y_t = -\ 0.049 - 0.261 Y_{(t-1)} - \\ 0.246 Y_{(t-2)} - \ 0.126 Y_{(t-3)} \\ \text{Difference 1} \end{array}$	14.613(0.480)	1.619	1.043	1.696	0.907
WMSHIPYARD	$Y_t = -0.040 - 0.002 Y_{(t-1)}$ Difference 1	14.940(0.600)	0.357	0.260	1.726	0.988
YPL	$Y_t = -0.005 + 0.112Y_{(t-1)}$ Difference 1	14.609(0.624)	0.321	0.230	2.105	0.982
ZAHEENSPIN	$Y_t = -0.010 + 0.081 Y_{(t-1)}$ Difference 1	20.265(0.261)	0.296	0.222	2.533	0.972

The Ljung-Box Test Q-statistics value varies from 7.264 to 26.320 (p-value 0.980 to 0.051). For every ARIMA model Ljung-Box Testp-values are greater than 0.05. The root mean square error (RMSE) values of the ARIMA model varies from 0.089 to 0.626. The mean absolute error value of the model also varies from 0.064 to 6.989. The mean absolute percentage error (MAPE) of each model varies from

0.804% to 3.591% (<5%), which shows as excellent fit. On the other hand, the R-Square values of the models are 0.823 to 0.992. So, 82.3% to 99.2% data are fit in the developed ARIMA model. By using the above ARIMA models the forecasted share values with confidence interval of January 2020 (22 trading days) for each company are calculated and result is shown in the following Figure 5.





Figure 5. Forecasted value of ARIMA model

After calculating the predicted values, the actual share values of January 2020 (22 trading days) are compared with goodness fit test and result is shown in Table III.

Variable Name	Chi-Square of Goodness fit test statistic value (p-value)	RMSE	MAPE	MSE
AAMRATECH	6.065(0.999)	2.639	9.817	6.963
ACMELAB	2.771(1.000)	2.799	3.672	7.833
ACTIVEFINE	0.830(1.000)	0.712	4.619	0.506
ADVENT	1.558(1.000)	1.234	4.699	1.523
AFTABAUTO	1.211(1.000)	1.158	3.760	1.340
ALARABANK	0.391(1.000)	0.534	2.759	0.285

Variable Name	Chi-Square of Goodness fit test statistic value (p-value)	RMSE	MAPE	MSE
APEXFOOT	25.751(0.216)	6.492	6.394	27.974
APOLOISPAT	0.454(1.000)	0.265	6.283	0.070
BARKAPOWER	1.045(1.000)	1.036	3.775	1.073
BATASHOE	97.943(0.000)	57.968	5.872	3360.283
BAYLEASING	0.000(1.000)	0.380	2.307	0.144
BEXIMCO	1.647(1.000)	1.036	6.150	1.072

TABLE III ARIMA Model validate of share price

Variable Name	Chi-Square of Goodness fit test statistic value (p-value)	RMSE	MAPE	MSE
BIFC	0.370(1.000)	0.195	6.847	0.038
BRACBANK	19.523(0.552)	6.512	12.267	42.402
BSC	3.736(1.000)	2.837	4.590	8.051
BXPHARMA	13.479(0.891)	6.157	8.482	37.904
CITYBANK	8.374(0.993)	2.585	12.955	6.680
CNATEX	0.000(1.000)	0.094	4.238	0.009
CONFIDCEM	19.285(0.567)	9.242	8.056	85.411
CVOPRL	2.760(1.000)	3.270	2.999	10.693
DESCO	0.848(1.000)	1.186	2.690	1.406
DESHBANDHU	0.672(1.000)	0.559	4.848	0.313
EASTERNINS	10.736(0.968)	4.094	9.213	16.764
EBL	0.862(1.000)	1.109	2.458	1.230
ECABLES	6.860(0.998)	7.754	2.642	60.126
EXIMBANK	0.000(1.000)	0.266	2.267	0.071
FAREASTFIN	0.000(1.000)	0.167	4.075	0.028
FIRSTFIN	2.337(1.000)	0.727	3.254	0.528
FUWANGFOOD	2.516(1.000)	1.157	6.696	1.340
GP	58.831(0.000)	25.509	8.157	650.730
HAKKANIPUL	9.319(0.986)	4.322	8.314	18.681
INTECH	8.644(0.992)	2.271	5.247	5.160
ISNLTD	9.317(0.986)	4.010	9.192	16.080
JAMUNAOIL	1.596(1.000)	3.154	1.865	9.947
KPPL	0.815(1.000)	0.738	3.864	0.544
MAKSONSPIN	0.644(1.000)	0.373	5.890	0.139
METROSPIN	1.353(1.000)	0.589	8.726	0.347
MHSML	3.403(1.000)	1.299	10.364	1.687
MIDASFIN	1.452(1.000)	0.907	5.862	0.823
MITHUNKNIT	8.536(0.992)	1.836	9.599	3.373
OAL	0.559(1.000)	0.399	5.964	0.159
PADMALIFE	1.053(1.000)	0.890	3.854	0.792
PRIMEFIN	1.371(1.000)	0.646	8.251	0.417
PRIMEINSUR	1.424(1.000)	1.371	3.887	1.879
PRIMETEX	1.350(1.000)	1.127	4.337	1.269

Variable Name	Chi-Square of Goodness fit test statistic value (p-value)	RMSE	MAPE	MSE
RDFOOD	1.230(1.000)	0.879	5.219	0.772
REGENTTEX	0.420(1.000)	0.396	3.485	0.157
RNSPIN	0.454(1.000)	0.257	4.978	0.066
SALVOCHEM	3.067(1.000)	1.179	10.234	1.390
TALLUSPIN	0.436(1.000)	0.252	7.006	0.063
TITASGAS	0.492(1.000)	0.828	2.291	0.686
TUNGHAI	0.759(1.000)	0.278	10.442	0.077
UNIONCAP	2.266(1.000)	0.739	12.092	0.546
UNITEDAIR	1.046(1.000)	0.292	12.365	0.085
USMANIAGL	2.214(1.000)	2.102	4.217	4.418
UTTARABANK	2.588(1.000)	1.732	5.734	2.999
UTTARAFIN	2.159(1.000)	2.244	3.937	5.034
WMSHIPYARD	2.978(1.000)	1.287	10.032	1.657
YPL	2.539(1.000)	1.106	9.406	1.224
ZAHEENSPIN	3.127(1.000)	1.038	11.804	1.077

In the Chi-Square values of goodness fit test for BATASHOE and GP are 97.943 and 58.831 respectively with p-value 0.000.For these two companies(3.33%), null hypothesis 3 can be rejected, which implies that there is a significant difference between the actual share price and forecasted share price. For the rest of the 58 companies the goodness of fit tests the Chi-Square values are 0.000 to 25.751 with p-value 1.000 to 0.216. As a result, for these 58 companies, the null hypothesis 3 can be accepted. This implies that, there is no significant difference between the actual share price and forecasted share price for these 58 companies (96.67%). The root mean square error (RMSE) values, the mean absolute percentage error values and mean absolute error values of these 58 companies are varies from 0.094 to 9,242, 1.865 to 12.955 and 0.009 to 85.411 respectively. Finally, it can be seen that, out of these 58 companies 50 companies (83.33%) follow ARIMA(1,1,0) model, 4 companies (6.67%) follow ARIMA(2,1,0) model, 1 company (1.67%) follow ARIMA(3,1,0)model, 1 company (1.67%) follow ARIMA(4,1,0)model, 1 company (1.67%) follows ARIMA(1,0,0) model and 1 company (1.67%) follows ARIMA (2,0,0) model.

Moreover, the significance level values of Chi-Square of goodness fit test are greater than 0.05 implies that, there is no significant difference between the predicted stock values and actual stock values. Therefore, it may be concluded saying that ARIMA (1,1,0) model is the most suitable model that can

be applied to predict the forecast of daily share price in Chittagong Stock Exchange (CSE).

# VII. CONCLUSION

It is observed from the Durbin-Watson test result that there is autocorrelation in the daily current share prices with their previous share prices. The Augmented Dickey-Fuller Test result shows, the daily share prices of 58 (96.67%) selected company data have unit roots. Now, these 58 company's share values are differencing from the previous values (1<sup>st</sup> differencing) of respective company. The autocorrelation function (ACF) of each share shows that it is convenient to consider MA(0) for the respective ARIMA model. The partial autocorrelation function (PACF) of each share shows that autocorrelation AR(1), AR(2), AR(3) and AR(4) has been considered for the ARIMA model. Now, from the data of January 2019 to December 2019 daily stock prices (241 trading days)ARIMA(1,1,0), ARIMA(2,1,0), ARIMA(3,1,0), ARIMA(4,1,0), ARIMA(1,0,0) and ARIMA(2,0,0) model are selected based on Ljung-Box Test Q, root mean square error, mean absolute error, mean absolute percent error and Rsquare values. By using the above ARIMA models January 2020 (22 trading day) forecasted share values with confidence interval are calculated. These predicted share values are compared with the actual share price of January 2020 (22 trading day) of the respective company and validate with Chi-Square of Goodness fit test, root mean square error, mean absolute percent error, mean square error values. The result shows that 50 companies (83.33%) follow ARIMA(1,1,0) model, 4 companies (6.67%) follow ARIMA(2,1,0) model, 1 company (1.67%) follow ARIMA(3,1,0)model, 1 company (1.67%) follows ARIMA(4,1,0)model, 1 company (1.67%) follows ARIMA(1.0.0) model and 1 company (1.67%) follows ARIMA (2,0,0) model. Finally, it may be concluded that the above ARIMA model may be applied to predict the forecast the daily share prices of Chittagong Stock Exchange (CSE).

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