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Modeling and Predicting the Egyptian Pound's Exchange Rate Per the American Dollar on a Short-Term Scale by Using ARIMA – Probability Distributions

Ghareeb A. Marei [a++*], Hassan Ismail Faris Aly [b] and Mohammed Ahmed Farouk [b]

[a] *Faculty of Computers and Information System, Egyptian Chinese University, Cairo, Egypt.*
[b] *Higher Institute for Computers & Information Technology, El Shorouk, Cairo, Egypt.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

A time series is an ordered sequence of data points that are chronologically indexed. By evaluating the values in a time series both presently and retrospectively, it is possible to predict the future values of most time series with a reasonable degree of accuracy. In this paper modeling of Egyptian pound exchange rate per US dollar in the short term by using the ARIMA model and many probability distributions. The ARIMA $(0, 1, 1)$ is the best ARIMA (p, d, q) that assumed in this study in modeling the data set of the exchange rate of the pound in Egypt per US dollar and the Burr probability distribution is the best probability distribution in modeling the same data set.

++ *Lecturer of Mathematical Statistics;*
**Corresponding author: Email: ghareb.adel@sha.edu.eg, marei_89@yahoo.com;*

Keywords: Exchange rate; ARIMA model; probability distributions.

Abbreviations

ARIMA : Autoregressive Integrated Moving Average
ARMA : Autoregressive Moving Average
FX : Foreign-Exchange Rate
ACF : Autocorrelation Function
PACF : Partial Autocorrelation Function
DL : Difference Logarithm
AIC : Akaike info criterion
SC : Schwarz criterion
CDF : Cumulative Distribution Function
ADF : Augmented Dickey-Fuller

1 Introduction

Across the fields of statistical inference and econometric estimation, and specifically in the realm of time series analysis, an amalgamation of autoregressive and moving average methods, the ARIMA model provides an all-encompassing solution beyond what the ARMA model can offer. Both models are employed to investigate time series data, either to gain a deeper understanding of the data or to anticipate future values (i.e., forecasting). ARIMA models are especially useful in situations where non-stationarity is detected in the mean (but not in variance or auto-covariance), whereby an initial differencing step (in line with the "integrated" element of the model) can be implemented one or more times to elimination the non-stationarity of the mean, see Swainet al [1].

The autoregressive (AR) component of ARIMA denotes that the evolving variable of interest is regressed against its own past values. Meanwhile, the moving average (MA) element indicates that the regression error is a linear combination of error terms that occurred contemporaneously or in the past, see Box, George E. P. [2]. The integrated (I) component signifies that the data values have been transformed by taking the difference between their values and the previous ones (and this differencing process may have been repeated several times). Each of these components strives towards the ultimate objective of attaining utmost accuracy in fitting the data for the model.

Typically represented by ARIMA (p, d, q), non-seasonal ARIMA models are defined by three non-negative integers as parameters. Specifically, p corresponds to the order (i.e., number of time lags) of the AR model, d denotes the degree of differencing (i.e., the number of times past values have been subtracted from the data), and q pertains to the order of the MA model.

If two of the three numbers in the model are zero, we can just use the one that's not zero to name the model. We don't need to use all the letters in the acronym. For example, if the numbers are (1, 0, 0), we can just call it AR (1). If the numbers are (0, 1, 0), we can call it I (1), and if the numbers are (0, 0, 1), we can call it MA (1).

In the realm of finance, an exchange rate (alternatively referred to as a foreign-exchange rate, forex rate, FX rate, or Agio) is the value at which one currency can be traded for another. Essentially, it represents the relative worth of a particular country's currency vis-à-vis another nation's currency. Put simply, an exchange rate is the price that must be paid to acquire a unit of a foreign currency in exchange for one's own.

The value of money from different countries changes all the time because people are always buying and selling it. This is kind of like how the price of gold or stocks can go up or down. The amount of money you can get for a foreign currency depends on how many people want it and how much of it is available. It also depends on how well that country's economy is doing and other stuff like that.

The outcomes of this paper have the potential to contribute significantly to the understanding of short-term fluctuations in the Egyptian Pound's exchange rate. The insights gained from this study could be valuable for policymakers, financial institutions, and investors, aiding them in making informed decisions.

This paper organized as: In section 2 Modeling, Forecasting, and Modeling and Forecasting of Egyptian pound exchange rate per US dollar in the short term by using the ARIMA model, in section 3 modeling of Egyptian pound exchange rate per US dollar in the short term by using many probability distributions and in section 4 contains the conclusions of this paper.

2 Modeling, Forecasting, and Modeling and Forecasting of Egyptian Pound Exchange Rate Per Us Dollar in the Short Term by Using the Arima Model

2.1 Using ARIMA model in modeling of Egyptian pound exchange rate

In this sub section the ARIMA model (p, d, q) was used in modeling the Egyptian pound exchange rate per US Dollar in the short term, based on 30 values of Egyptian pound exchange rate per US Dollar in the short term, the estimated ARIMA model (p, d, q) was used to predict Egyptian pound exchange rate per US Dollar.

In the realm of statistical prediction methods, the ARIMA model was conceived by Box and Jenkins during the 1970s. Comprising three components - namely, the Autoregressive model (AR), an order-indicating combination (I), and the Moving Average model (MA) - this model typically entails establishing a science-based framework for a stationary sequence.

The stationarity of a time series is typically assessed through a unit root test. If the series is found to be non-stationary, it can be transformed into a stationary series through a process distinction operation. The degree of corresponding difference required is denoted as the order of integration. The ARIMA (p, d, q) model is a powerful tool that combines the differential operator and the ARMA (p, q) model to model such non-stationary data, as evidenced by Box et al [3] and Fan et al [4].

When we look at patterns over time, we sometimes find that they change a lot. We call these patterns "non-stationary I(d) processes." But we can make them easier to understand by using a special method called "difference-stationary" or "unit root." This helps us turn the pattern into a "stationary ARMA (p, q) process" which is easier to work with. We use a special notation called "ARIMA (p, d, q)" to show that we've done this. The ARIMA (p, d, q) model looks like this:

$$\Delta^d y_t = c + \rho_1 \Delta^d y_{t-1} + \cdots + \rho_p \Delta^d y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_1 \varepsilon_{t-q}. \tag{1}$$

Where

$\Delta^d y_t$ denotes a d–th differenced series, and ε_t is an uncorrelated process with mean zero. In lag operator notation, $L^i y_t = y_{t-i}$, which means that the y_t will be lag for (i) periods, Then the ARIMA (p, d, q) model can be written as follows:

$$\rho^*(L) y_t = \rho(L)(1-L)^d y_t = c + \theta(L)\varepsilon_t \tag{2}$$

Where,

$\rho^*(L)$ is an unstable AR operator polynomial with exactly d unit roots. This polynomial can factor as $\rho(L)(1-L)^d$, where $\rho(L) = (1 - \rho_1 L - \cdots \rho_p Lp)$ is a stable degree AR (p) lag operator polynomial. Similarly, $\theta(L) = (1 - \theta_1 L - \cdots \theta_q Lq)$ is an invertible degree MA (q) lag operator polynomial.

The ARIMA model is widely recognized as an accurate short-term forecasting tool for time series data. This model operates under the premise that certain time series data are composed of stochastic variables that are time-dependent, yet the changes in the overall data series conform to specific rules, which can be represented by an appropriate mathematical model. By analyzing this mathematical model, the fundamental properties and structure of the time series can be better comprehended, ultimately leading to an optimal prediction that minimum variance, see Li [5].

2.2 ARIMA modeling forecasting

The ARIMA models leverage the process of differencing to transform non-stationary time series into stationary ones, followed by predicting future values using historical data. These models employ "auto" correlations and moving averages to capture residual errors in the data, thereby forecasting future values. Ma et al [6] presents a diagrammatic portrayal of the ARIMA analysis and prediction cycle.

ARIMA modeling is a fancy way of figuring out some important numbers called p, d, and q, see [7-10].

These numbers help us make predictions about things like the stock market or the weather. It's like a puzzle where we have to carefully put the pieces together to get the right answer. Here's how we do it:

(1) To figure out if a time series is stationary, we need to look at a bunch of graphs. These graphs show us if the sequence is staying the same over time or if it's changing. We use something called the Augmented Dickey-Fuller test to help us figure out if there are any patterns or trends in the data. This helps us see if the time series is stationary or not.
(2) To figure out the order of the single number (d), we need to make sure the time series is stationary. If it's not, we have to do some tricks like taking the difference, making the variance stationary, using logarithms, or square roots to make it stationary. The number of times we have to do these tricks is the same as the order of the single number.
(3) ARMA forecasting. Concerning the derived sequence from Step (2), So, we're trying to figure out some numbers for a math thing called ARMA. We use two special numbers called ACF and PACF to help us. These numbers help us guess what other numbers we need to use for ARMA. It's like a puzzle, and we're trying to put all the right pieces together. As shown in Table 1 at [5], a simple guideline is given for ascertaining the sequence of p and q.
(4) The identification of significant coefficients in parameter estimation requires an analysis of autocorrelation and partial autocorrelation graphs. This step enables the selection of a preliminary model for the time series.
(5) A white noise test is used to perform diagnostic testing and optimize the model through examination of the residuals. If the leftover numbers from the model don't pass the test, go back to step 4 and pick a different model. But if the leftover numbers do pass the test, keep going with step 4 and make a bunch of models. Then, use the test results to pick the best one.

The ARIMA model is a useful tool for predicting future values of a time series, and the EViews software offers a powerful solution for modeling and forecasting with ARIMA. EViews provides two methods for forecasting: Static and Dynamic. The procedure for using EViews to forecast with ARIMA is as follows:

(1) If the time series is non-stationary, it must first be transformed into a stationary series using appropriate techniques. Next, the best model parameters are chosen and a (p, d, q) ARIMA model is applied.
(2) If you're using EViews and you want to make a forecast, here's what you go to do. First, go to the Equation window. Then, click on the Forecast menu. You'll see two options: Static and Dynamic. Choose the one that fits what you need. Next, you can give your forecast a name if you want, or just stick with the default name. Finally, click ok and you're done.

2.3 Modeling and forecasting of Egyptian pound exchange rate

In this subsection the data description, Stationarity test, Model Identification, Model establishment and inspection and Data forecasting for Egyptian Pound Exchange Rate per US Dollar in the short term will be shown as follows:

2.3.1 Data description

Egyptian Pound Exchange Rate per US Dollar is one of the indicators of national economic, where the Movements in the exchange rate influence the decisions of individuals, businesses and the government. Collectively, this affects economic activity, inflation and the balance of payments. The Central Bank of Egypt publishes the exchange rate of the Egyptian pound against the US dollar daily. The values of the Egyptian Pound Exchange Rate per US Dollar during the period from 15-8-2022 to 25-9-2022 are illustrated in Table 1 as follows:

Table 1. The Egyptian Pound Exchange Rate per US D. form 15-8-2022 to 25-9-2022

Date	Buy	Sell	Mean	Date	Buy	Sell	Mean
15-08-2022	19.0997	19.1783	19.139	05-09-2022	19.1814	19.2583	19.21985
16-08-2022	19.1003	19.1783	19.1393	06-09-2022	19.1914	19.2683	19.22985
17-08-2022	19.1003	19.1783	19.1393	07-09-2022	19.2222	19.2983	19.26025
18-08-2022	19.1008	19.1783	19.13955	08-09-2022	19.2622	19.3383	19.30025
21-08-2022	19.1008	19.1783	19.13955	11-09-2022	19.2922	19.3683	19.33025
22-08-2022	19.1008	19.1783	19.13955	12-09-2022	19.3117	19.3883	19.35
23-08-2022	19.1197	19.1983	19.159	13-09-2022	19.3122	19.3883	19.35025
24-08-2022	19.1308	19.2083	19.16955	14-09-2022	19.3414	19.4183	19.37985
25-08-2022	19.1417	19.2183	19.18	15-09-2022	19.3719	19.4483	19.4101
28-08-2022	19.1408	19.2183	19.17955	18-09-2022	19.3719	19.4483	19.4101
29-08-2022	19.1603	19.2383	19.1993	19-09-2022	19.3719	19.4483	19.4101
30-08-2022	19.1803	19.2583	19.2193	20-09-2022	19.3928	19.4683	19.43055
31-08-2022	19.1808	19.2583	19.21955	21-09-2022	19.4419	19.5183	19.4801
01-09-2022	19.1808	19.2583	19.21955	22-09-2022	19.4422	19.5183	19.48025
04-09-2022	19.1808	19.2583	19.21955	25-09-2022	19.4422	19.5183	19.48025

Source: *Central Bank of Egypt*

2.3.2 Stationarity test

Fig. 1 displays the plotted data series for the Egyptian Pound Exchange Rate per US Dollar from 15-8-2022 to 25-9-2022.

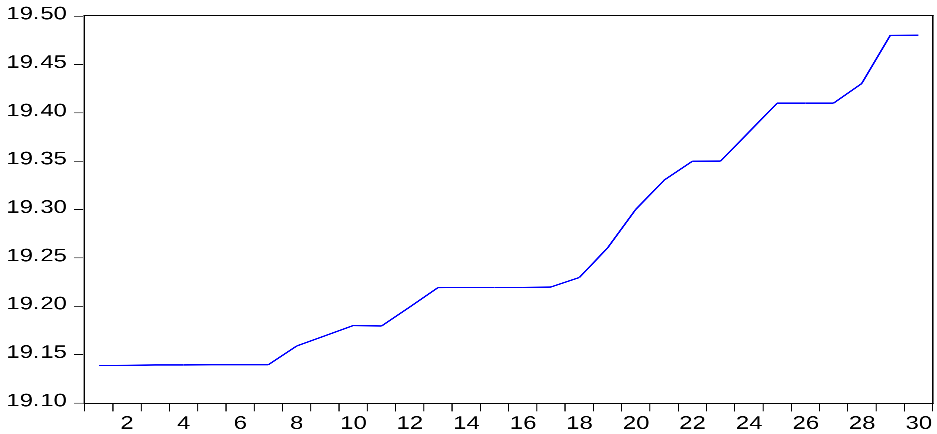


Fig. 1. The Egyptian Pound Exchange Rate per US Dollar data during 15-8-2022 to 25-9-2022

Fig. 1 shows that The Egyptian Pound Exchange Rate per US Dollar data during 15-8-2022 to 25-9-2022 takes an ascending trend over time

Table 2. Exploring the Augmented Dickey-Fuller unit root test conducted on The Egyptian Pound Exchange Rate per USD

	t-statistic	Prob.*
Augmented Dickey-Fuller test statistic	1.842684	0.9996
Test critical values:	1% level	-3.679322
	5% level	-2.967767
	10% level	-2.622989

**Mackinnon (1996) one-sided p-values*

Table 2 shows that ADF is bigger than the important numbers for 0.01, 0.05, and 0.1. This means that the Egyptian Pound Exchange Rate per US Dollar sequence isn't steady.

Table 3. ADF conducting a test for unit roots on DL (Egyptian Pound Exchange Rate per US Dollar)

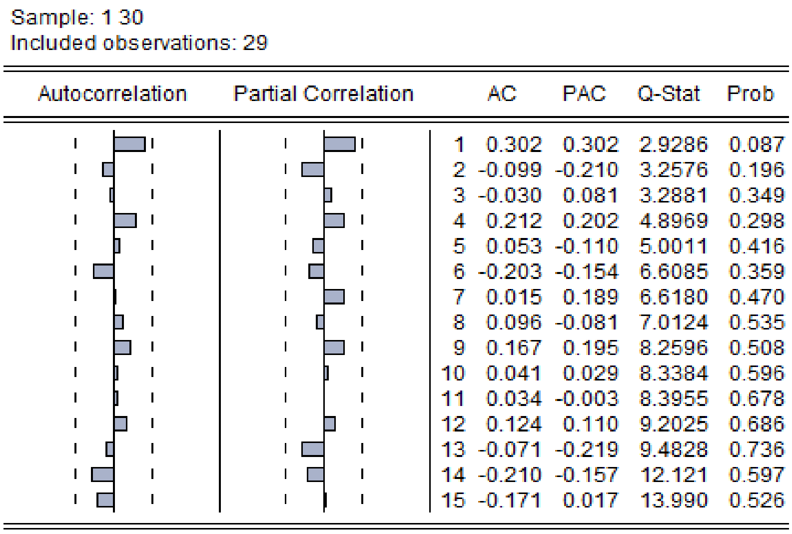
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.906197	0.0061
Test critical values:	1% level	-3.699871	
	5% level	-2.976263	
	10% level	-2.627420	

**Mackinnon (1996) one–sided p-values*

Table 3 shows that ADF = -3.906197 is smaller than the three important values of the test level. This means that the DL (Egyptian Pound Exchange Rate per US Dollar) sequence is now stationary after we changed it using logarithms and first-order difference. We did a test to check if it's stationary and it passed! This means that the original Egyptian Pound Exchange Rate per US Dollar sequence is now a first-order integrated sequence, which is written as Egyptian Pound Exchange Rate per US Dollar ~ I (1).

2.3.3 Model identification

The autocorrelation and partial autocorrelation function graphs of the DL (Egyptian Pound Exchange Rate per US Dollar) Plot points for a range of sequences can be found in Fig. 2.



Sample: 1 30
Included observations: 29

	AC	PAC	Q-Stat	Prob
1	0.302	0.302	2.9286	0.087
2	-0.099	-0.210	3.2576	0.196
3	-0.030	0.081	3.2881	0.349
4	0.212	0.202	4.8969	0.298
5	0.053	-0.110	5.0011	0.416
6	-0.203	-0.154	6.6085	0.359
7	0.015	0.189	6.6180	0.470
8	0.096	-0.081	7.0124	0.535
9	0.167	0.195	8.2596	0.508
10	0.041	0.029	8.3384	0.596
11	0.034	-0.003	8.3955	0.678
12	0.124	0.110	9.2025	0.686
13	-0.071	-0.219	9.4828	0.736
14	-0.210	-0.157	12.121	0.597
15	-0.171	0.017	13.990	0.526

Fig. 2. Evaluation of the ACF and ACF graphs for the DL (Egyptian Pound Exchange Rate per US Dollar)

Observing Fig. 2, we note that the autocorrelation coefficient for the DL (Egyptian Pound Exchange Rate per US Dollar) significant non-zero sequence can be seen at a lag order of 1, while for orders greater than 1, it largely falls within the confidence band. As such, we can safely set q to 1. Similarly, the first order partial autocorrelation coefficient is significantly non-negligible, while the second order coefficient shows significant deviation from 0, suggesting that we should consider p=1 or p=2. Given that such assessments can be subjective, we adopt a more rigorous approach by establishing multiple ARMA (p, q) models, while suitably relaxing the range of p and q values. We then perform autoregressive moving average pre-estimation with orders of 0, 1, and 2 on the processed sample data for the DL (Egyptian Pound Exchange Rate per US Dollar).

In Table 4, we present the test outcomes for ARMA (p, q) across various parameters. Selecting an appropriate model is crucial, and we evaluate this based on multiple criteria, including the Adjusted R-squared, AIC value, SC value, and S.E. of regression. While the AIC and SC criteria are widely employed for ranking, these alone do not guarantee optimal model selection. Typically, larger coefficient of determination values corresponds with lower AIC and SC values and residual variance, indicating the superiority of the equivalent ARMA model with parameters p and q.

Table 4. Results of ARMA (p, q) for DL (egyptian pound exchange rate per US dollar)

Sample Size Elements of Results	ARMA (1,0)	ARMA (1,1)	ARMA (1,2)	ARMA (2,0)	ARMA (2,1)	ARMA (2,2)	ARMA (0,1)	ARMA (0,2)
C	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
Prob.	0.0292	0.0211	0.0109	0.0012	0.0068	0.0019	0.0192	0.0017
AR(p)	0.3062	-0.2346	0.4418	-0.1299	-0.1941	-0.9871		
Prob.	0.0961	0.6305	0.0323	0.5831	0.5075	0.0000		
MA(q)		0.6876	-0.3077		0.4272	0.9147	0.4764	-0.0877
Prob.		0.1336	0.2697		0.0393	0.0781	0.0199	0.7251
SIGMASQ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob.	0.0079	0.0135	0.0097	0.0218	0.0130	0.0154	0.0044	0.0209
R-squared	0.0957	0.1574	0.1594	0.0141	0.1733	0.1608	0.1498	0.0091
Adjusted R-squared	0.0262	0.0563	0.0585	-0.0618	0.0741	0.0601	0.0844	-0.0671
S.E. of regression	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007	0.0007	0.0008
Sum squared resid	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log likelihood	169.318	170.219	170.280	168.096	170.493	169.679	170.133	168.03
F-statistic	1.3761	1.5567	1.5804	0.1856	1.7467	1.5970	2.2913	0.1197
Prob(F-statistic)	0.2703	0.2247	0.2190	0.8317	0.1832	0.2151	0.1212	0.8877
Mean dependent var	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
S.D. dependent var	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
Akaike info criterion	-11.470	-11.463	-11.468	-11.386	-11.482	-11.426	-11.526	-11.382
Schwarz criterion	-11.329	-11.275	-11.279	-11.245	-11.294	-11.238	-11.385	-11.240
Hannan-Quinn criter.	-11.426	-11.404	-11.409	-11.342	-11.423	-11.367	-11.482	-11.337
Durbin-Watson stat	1.7289	1.8497	1.8172	1.2451	1.7898	1.1735	1.8811	1.2813

It is essential to note that while the AIC and SC values are commonly used to select an appropriate ARMA model, to find the best model, we can't just rely on one thing. We have to do a bunch of tests to make sure it's really the best. First, we pick the model with the lowest AIC and SC values. Then, we check if the model's parts are important and if there are any random errors. If everything looks good, we found the best model! But if not, we try again with the next lowest AIC and SC values and do more tests. This process is repeated until an appropriate model is selected. Based on our analysis, we recommend utilizing the ARMA (0,1) model to estimate the DL (Egyptian Pound Exchange Rate per US Dollar).

2.3.4 Model establishment and inspection

According to the previous subsections it is preferable to prefer the ARIMA $(0, 1, 1)$ model for estimated the data set of DL (Egyptian Pound Exchange Rate per US Dollar) during the period from 15-8-2022 to 25-9-2022, and the ARIMA (0,1,1) model has generated the following estimated outcomes:

Table 5. Estimating the ARIMA (0, 1, 1) model has produced results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000581	0.000233	2.497428	0.0192
MA(1)	0.476353	0.192009	2.480890	0.0199
SIGMASQ	4.66E-07	1.49E-07	3.123024	0.0044
R-squared	0.149842	Mean dependent var		0.000610
Adjusted R-squared	0.084445	S.D. dependent var		0.000753
S.E. of regression	0.000721	Akaike info criterion		-11.52641
Sum squared resid	1.35E-05	Schwarz criterion		-11.38497
Log likelihood	170.1330	Hannan-Quinn criter.		-11.48211
F-statistic	2.291276	Durbin-Watson stat		1.881118
Prob(F-statistic)	0.121198			

The last version of the DL (Egyptian Pound Exchange Rate per US Dollar) sequence is called ARIMA (0, 1, 1). You can see what it looks like in Equation (3). The numbers in the parentheses under the equation are called T-test statistics. They help us figure out how accurate our estimates are.

$$DL(Egyptian\ Pound\ Exchange\ Rate\ per\ US\ Dollar) = 0.000581 + 0.476353\ \varepsilon_{t-1} \quad (3)$$
$$(2.497428)(2.48089)$$

The variance of the error term for the ARIMA model is estimated to be 0.000721. The model coefficients are statistically significant at the 0.05 level, as evidenced by the t-statistic and P-value.

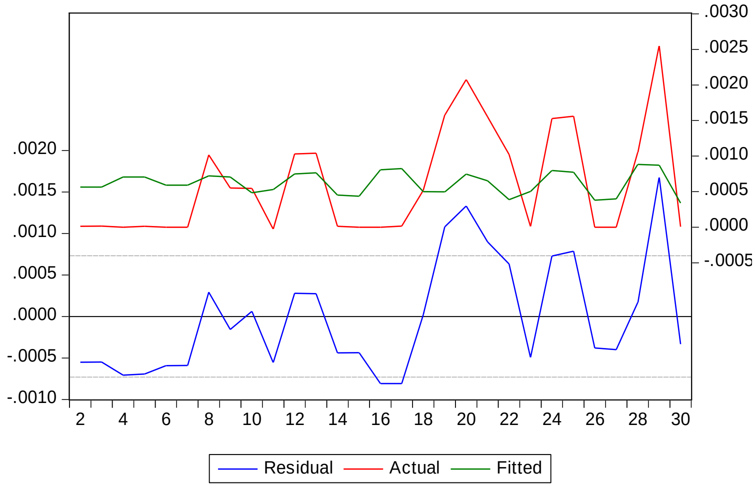
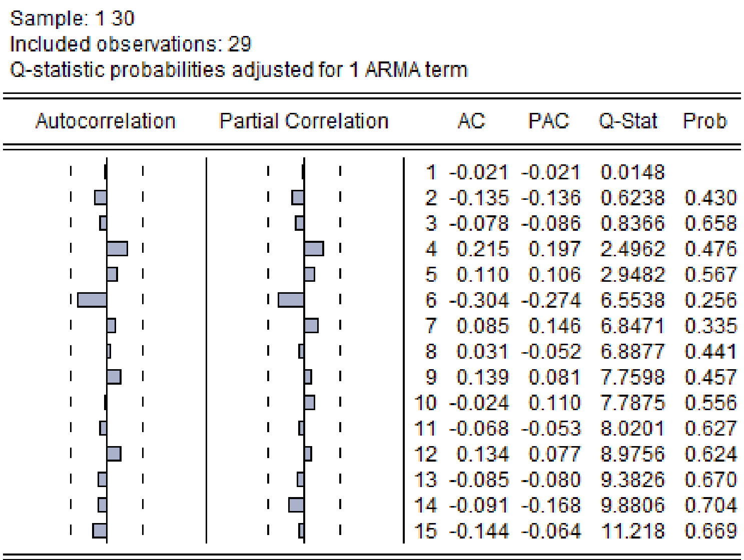


Fig. 3. Actual series, fitted series and residual series of the DL (Egyptian Pound Exchange Rate per US Dollar) sequence

The DL (Egyptian Pound Exchange Rate per US Dollar) data is fitted using this model, and the results are presented in Fig. 3. Your eye should follow the red line for actual data and the blue and green lines for fitted values and residuals respectively as they are displayed on the following graph.

A diagnostic test for white noise is conducted on the residuals of the ARIMA (0, 1, 1) model fit. In Fig. 4, the residual series autocorrelation and partial autocorrelation function plots are displayed, Confirmation of the white noise process compatibility in residuals validates the model.



Sample: 1 30
Included observations: 29
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.021	-0.021	0.0148	
		2	-0.135	-0.136	0.6238	0.430
		3	-0.078	-0.086	0.8366	0.658
		4	0.215	0.197	2.4962	0.476
		5	0.110	0.106	2.9482	0.567
		6	-0.304	-0.274	6.5538	0.256
		7	0.085	0.146	6.8471	0.335
		8	0.031	-0.052	6.8877	0.441
		9	0.139	0.081	7.7598	0.457
		10	-0.024	0.110	7.7875	0.556
		11	-0.068	-0.053	8.0201	0.627
		12	0.134	0.077	8.9756	0.624
		13	-0.085	-0.080	9.3826	0.670
		14	-0.091	-0.168	9.8806	0.704
		15	-0.144	-0.064	11.218	0.669

Fig. 4. AC and PAC graphs of the residual series

2.3.5 Anticipated data trend

We used a fancy model to see how well the Egyptian Pound and US Dollar exchange rate would match up from August 15th to September 25th in 2022. The model predicted that one US dollar would be worth 19.53274 Egyptian Pounds on September 25th, but in reality, it was worth 19.48025 Egyptian Pounds. That means the model was pretty close It was only off by -0.269%. So, the model did a good job of predicting the exchange rate.

3 Using Probability Distributions in Modeling of Egyptian Pound Exchange Rate Per Us Dollar in the Short Term

Normal distribution is the most important and commonly used probability distribution in statistics. It has special properties; that is, its parameters denote its mean and variance directly and its probability density function is symmetrical and bell-shaped [11,12]. However, it is only suitable for analyzing the symmetrical data. In fact, real data obtained commonly are not always symmetrical.

Normal distribution is not recommended for analyzing asymmetrical data because it can result in an inaccurate analysis. Examples of the probability distributions which are suitable for analyzing the asymmetrical data are gamma and skew-normal distributions. Gamma distribution is suitable for analyzing right-skewed data [12]. The selection of the suitable distribution for analyzing data not only considers its skewness, but also its tail behavior. A distribution which can be an alternative for analyzing the right-skewed and heavy tailed data is Burr distribution [13]. Burr distribution was first introduced in 1942 by Irving Wingate Burr. Burr distribution in the probability density function which can be either decreasing or unimodal. In addition, its hazard rate function can be either decreasing or upside-down bathtub-shaped.

The Cumulative distribution function of Burr random variable X is defined by:

$$F(x) = 1 - (1 + x^c)^{-k}, \; x \geq 0$$

If X denotes the failure time of an item, the value $F(x)$ denotes the probability that item fails before or at time x. Otherwise, the probability that item fails after time x is denoted by:

$$S(x) = P(X > x).$$

The survival function of X defined by:

$$S(x) = (1 + x^c)^{-k}, \; x \geq 0$$

The probability density function of Burr random variable X is defined as,

$$f(x) = kcx^{c-1}(1 + x^c)^{-(k+1)}, x \geq 0$$

Hence, it has an important role in survival analysis. It is widely used especially for modeling survival time in medical, economic, and engineering fields.

The application of probability distributions in survival analysis is common as it enables the modeling of data and facilitates an understanding of the underlying parameters and functions. This approach was motivated by the need to enhance the flexibility of the model in describing intricate real-world scenarios [14-18].

The information consists of the mean of 30 observations of Egyptian Pound Exchange Rate per US Dollar during the period from 15-8-2022 to 25-9-2022: 19.139, 19.1393, 19.1393, 19.13955, 19.13955, 19.13955, 19.159, 19.16955, 19.18, 19.17955, 19.1993, 19.2193, 19.21955, 19.21955, 19.21955, 19.21985, 19.22985, 19.26025, 19.30025, 19.33025, 19.35, 19.35025, 19.37985, 19.4101, 19.4101, 19.4101, 19.43055, 19.4801, 19.48025 and 19.48025

We compare fitted models by using Kolmogorov-Smirnov test, and Anderson Darling test. Table 6 displays the values of statistics and p - values for the models being considered as well as the trade share data set. Our primary statistical goal is to use a fitting approach model to examine this data set. In this respect, we compare the fit of the proposed Burr distribution [12] with Wakeby distribution [19], Genalized pareto distribution [20], and Inverse Gaussian distribution [21].

Table 6. Different measures of goodness of fit

Distribution		Kolmogorov Smirnov		Anderson Darling
		Statistics	**P-value**	**Statistics**
1	**Burr (3 p.)**	0.1027	0.87794	0.5979
2	**Wakeby**	0.12667	0.67501	0.6074
3	**Gene. Pareto**	0.12666	0.67500	0.6072
4	**Inv. Gaussian (3 p.)**	0.14746	0.48641	1.1027

The P-P, and Q-Q plots of the data set, and the fitted Burr CDF plots with empirical CDF. These graphical goodness-of-fit methods in Fig.5 and Fig.6.

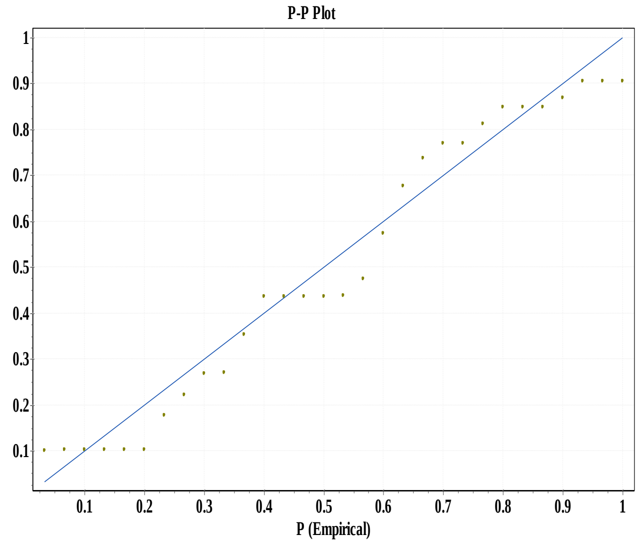


Fig. 5. P-P plot for data set, and the fitted Burr CDF plots with empirical CDF

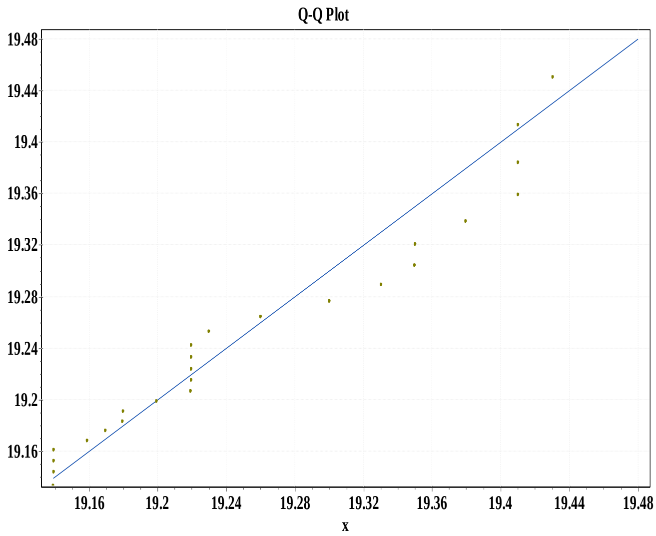


Fig. 6. Q-Q plot for data set, and the fitted Burr CDF plots with empirical CDF

4 Conclusions

Significant deviations may arise when the forecasting horizon extends over a prolonged period. Utilizing the ARIMA model, this research utilizes modeling and prediction techniques, utilizing the EViews software. However, for complex time series affected by several factors, there might be a certain degree of divergence between actual observations and model forecasts that rely only on past and present data.

After analysis we can deduce that the ARIMA (0, 1, 1) is the best ARIMA (p, d, q) that assumed in this study and the Burr probability distribution is best distribution in modeling Egyptian Pound Exchange Rate per US Dollar in the short term in our data set.

Competing Interests

Authors have declared that no competing interests exist.

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