Zagazig Veterinary Journal, ©Faculty of Veterinary Medicine,
Zagazig University, 44511, Egypt.
Volume 51, Number 1, p 27-44-March 2023
DOI: 10.21608/zvjz.2023.178561.1195

RESEARCH ARTICLE

Predicting the Monthly Average Price (LE/KG) For Egyptian Broiler Farms (2019–2022) Using Auto regressive Integrated-Moving-Average (ARIMA) Model

Sara E. Shahin[1*], Magdy Roshdy[2], and Mohamed A. Omar[1]
[1]Animal Wealth Development Department, Faculty of Veterinary Medicine, Zagazig University, 44511 Egypt
[2] Veterinarian at Faculty of Veterinary Medicine, Zagazig University, 44511, Zagazig, Egypt
*Corresponding author e-mail: saraesam2011@gmail.com

Article History: Received: 14/12/2022 Received in revised form: 04/02/2023 Accepted: 18/02/2023

Abstract

Auto regressive Integrated-Moving-Average model (ARIMA) was employed to detect the monthly average price (LE/Kg) for broiler farms in Egypt during the period from September 2019 to December 2022. On the basis of the lowest Akaike's Information Criterion AIC value, the best suitable model was carefully chosen. It consists of Moving Average Process (MAP), the-Autoregressive Process (AR), and the Dif-021ferencing Process (d). Identification model, estimation parameter, check diagnostic, and fore-casting make up the four steps of the Box: Jenkins technique for time series analysis and modeling. For last four months of 2022, the best accurate model to forecast the monthly average price (LE/Kg) for Egyptian broiler farms is the ARIMA (1, 1, 0) model. The % values were 25.25 LE/Kg (2.46) in September, 24.58 LE/Kg (4.33) in October, 24.61 LE/Kg (4.23) in November, and 25.32 LE/Kg (4.11) in December. The policy makers can consider the prices of feedstuffs and one-day-old chicks to maintain the food security margin by using the monthly average price (LE/Kg) for broiler farms in Egypt (2019–2022) that was estimated and anticipated using the ARIMA model using Univariate historical data.

Keywords: Predicting, Forecasting, Average Price, ARIMA, and Broilers.

Introduction

The majority of the animal protein is of high quality, which is essential for growth and present in broiler meat. More than any other form of animal protein, consumption of chicken meat has grown internationally. As soon as five to six weeks after hatching, modern broiler chickens can achieve the marketable weight of 2 kg [1, 2]. Significant animal-derived proteins, critical amino acids, and trace elements can all be found in chicken meat. Additionally, chicken meat makes a substantial contribution as an affordable alternative to red meat, which is badly undersupplied in Egypt. Chicken burgers, chicken fillets, chicken lunches, chicken nuggets, and chicken panne are just a few of the chicken meat items that have been produced and introduced as a result of the swift advancements in food processing and technology. Due to their unique flavor and aroma, these products stand out and entice clients, especially children [3, 4].

Broiler farming provides employment and dependable net income due to its rapid growth and condensed cycle of production. Although gross margin (net profit) is a combination of return and production costs, adequate returns can only be assured when generated at the lowest cost of production and at the youngest possible market age. Low production costs are preferred because they produce higher returns, but marketing age must be carefully considered. Increased profit in broilers requires lower production costs with a minimum market age and higher returns [5, 6].

Marketing age, weight, feed efficacy, flock size, ideal raising conditions, vaccination schedule, and total production costs are among the parameters that have an impact on net returns in the production of broilers [7].

Net profit was found to have a positive correlation with flock size and a negative correlation with mortality [8, 9]

Chickens are the most widely produced and economically successful avian livestock. Chickens are more efficient at turning a variety of feed sources into foods high in protein than other animal species. Production of broiler chicken is also advised over that of pork, beef, and fish [10, 11].

Chicken has become more popular among customers since it is so inexpensive. Processors provide a variety of goods, including chickens, chicken portions, and a wide range of commodities with added value because chicken meat is thought to be healthier than ham and beef [12].

Consumers prefer white meat—chicken parts like the breast and wings—in broiler meat by a 2-to-1 ratio over dark meat like the thighs and legs for health reasons because white meat contains more protein and less fat than other dark meat [13]. Customers benefit from the quick increases in productivity because broiler output has exceeded other meat production as well as demand for broiler, which has resulted in relatively low broiler prices.

In light of these trends in consumer demand, white meat consumption is rising while red meat consumption is falling.

Egypt's poultry industry has grown to be a significant contributor to agricultural output. In the past, keeping chickens in backyard farms was merely a customary activity that contributed to the prosperity of a particular household. It simply means that its contribution to total domestic poultry consumption has decreased. This does not necessarily imply that backyard poultry production has ceased. The development of Egypt's poultry industry has occurred under a number of conditions since the middle of the 20th century. It is well known that the socialist era was marked by lavish support and subsidies. The Egyptian poultry industry is currently largely driven by the market and has to navigate a turbulent international market [14].

The usage of data mining techniques like neural networks, classification, clustering, decision trees, and others has increased across a wide range of industries, including corporate intelligence, the sciences, finance, government, economics, and marketing. The employment of such methodologies will often have an impact on the social sciences and humanities [15]. A study by [16] analyses the behavior of month-over-month (m-o-m) inflation using an appropriate - auto-regressive moving average (ARMA) model.

Due to its positive effects on returns, production costs, and net profit, the price paid per kilogram (Kg) of chicken sold is one of the most crucial elements determining broiler production and profitability. In July 2020, the average costs /month of Egyptian chicken farm was 28.86 L.E./ Kg, or 1.84 US dollars, a little reduction from the previous month of 1.27 percent..Starting in January 2019, the average expense per kilogram ranged from 25.42 L.E. (1.62 U.S. $) to 34.44 LE. (2.20 US $) [17].

The COVID-19 curfew increased demand, which resulted in a price increase that brought the price per kilogram to 30.72 L.E (1.96 U.S. dollars) in April 2020 and to 31.19 L.E. (1.99 U.S. dollars) in May 2020. Due to the fact that both products are influenced by the same market conditions, the mean price of farm chicken generally followed the same trajectory as local chicken prices over the course of the study period, with a few minor exceptions [17].

Prices of chicken are affected by the cost of rearing them, which includes both fixed and variable costs. The profitability of a commercial broiler business would increase if management were not a constraining issue because production costs are the primary determinant of pricing per kilogram of poultry sold. Concrete sheds, clean broiler barns, and good management all resulted in cheaper production costs, but poor management will increase expenses [5]. The cost of production is divided into three categories: fixed costs, variable costs, and total cost of production [18].

For the purposes of this study, we used time-series simple data of monthly average prices (LE/Kg) for broiler farms, which were then analysed using the standard ARIMA methodology. To predict the monthly average price (LE/K g) for broiler farms in Egypt, the best ARIMA model among those that were observed was selected.

Materials and Methods

Data Set Collection

The average monthly price (LE/Kg) for broiler farms in Egypt from September 2019 to December 2022 is the data used in this study. An ARIMA model's ability to analyze and forecast the monthly average price (LE/Kg) for broiler farms will be evaluated in the next months for year 2022by applying ARIM A model [19] using E-views 10. It is made up of the Moving Average Process (MAP), Auto-Regressive Process (AR), and Differencing Process (dp) [20].

Model description

The three components of ARIMA model are separated based on the type of data. An auto-regressive moving average (ARMA) model is an extension of the ARIMA model.

Both of these models are fitted to time series data in order to enhance understanding of the records or to forecast upcoming series points (forecasting). ARIMA models may be used when data demonstrate mean non-stationarity (but not variance or autocovariance). In these cases, the mean function's non-stationarity (i.e., the trend) may be eliminated by applying a primary differencing step (matching to the "integrated" section of model) once or more times [19, 21, 22].

When time series data are evaluated, relationships in the -short term and long term typically coexist. Error correction mechanisms (ECMs) can be added to describe the dynamics of the long run and short run term impacts, allowing for the examination of both processes at once [23, 24]. However, a test for the sequence of integration should come first [25]. The basic approach is to do a simple linear regression of values at time t versus values of the exact same variables at time t1. Given that the variable is being regressed on its former value, this is unquestionably an autoregression. If the coefficient of the variable at time t1 is less than 1, the variable at time t is said to be integrated of order zero in the regression.

Based on the sum of the variable's actual value at time t1 and the autoregressive coefficient, it is likely that the variables anticipated value at time t will deviate from its actual value. There may be a relationship between these error terms over time or the error process may show autocorrelation.

.

Instead of using a simple regression that includes extra components to capture changes in the variable's earlier values for particular delays, [26] propose utilizing a multiple regression to overcome this problem. To maintain certain degrees of freedom, these lags must be as short as feasible. Unit root tests are the analogous tests, often known as: Dickey Fuller tests (ADF).

In the absence of order zero integration of the underlying variable, the same steps are taken to generate a new model; however, the change in the variable's value from time t1 to time t is regressed against the change in the variable from t2 to t1. First differencing is the term for this. Order 1 integration is used when the autoregressive coefficient is less than 1. If more stages are required to check for higher degrees of integration, the same procedure is repeated. The approach first or second discriminates the raw data until stationarity is attained if the raw data are not stationary [27].

1. The Autoregressive (AR) Model The following is an AR(p).

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} +, \ldots, B_p Y_{t-p} + u_t$$

Where ut: indicates a white –noise- error- term.

The dependent variable (the variable of concern) is projected using an autoregressive (AR) time series model, which is the first part.

2. Moving Average (MA) Model

Using previous data from the white noise process in the second part, moving average (MA) models forecast future records of the dependent variable (i.e., historical forecast errors).

The following image represents the first-order MA model (MA) (1).

The MA (q) model, which is a weighted or moving average of the present and past white noise error components, is another technique for simulating Yt.

$$Y_t = C_0 + C_1 u_t + C_2 u_{t-1} +, \ldots, C_j u_{t-q}$$

3. The ARMA (p,q) model combines both AR and MA

The 2 stationary MA and AR models are combined to form the stationary

ARMA model. If the inputted data are non-stationary, a third component is used to convert them into stationarity by diffencing integrating original series [28, 29].

$$y'_t = y_t - y_{t-1}$$

Where (yt) is an original series and yt1 is a lagged original series, and yt is the anticipated consumption When the three first-order models are integrated, estimate models are produced.

Stages of building ARIMA model

These four steps make up the model identification, parameter estimations, diagnostic validation, and forecasting processes of the Box-Jenkins technique of time series analysis and modeling [19].

Identification Model

Time series models should be built with stationary data. A model's conclusions could indicate an incorrect link if it uses non-stationary data. [22] Therefore, Time series data must be examined for stationary patterns before choosing the model.

Static statistical properties describe data that do not change over time [29]. Formally, a time series is regarded as stationary when its mean, variance, and auto-covariance are all constant during the course of the data [20]. If any of these requirements is not met, the data are considered non-stationary.

The data were exposed to the autocorrelation function in order to determine this problem (ACF). If the ACF plot is positive and has a very slow linear reduction trend, the data are non-stationary. Proper data differencing can be used to remedy this non-stationarity issue, whether the variance, mean, or model modification caused it [20, 29, and 30]. Choosing the initial values for the seasonality and non-seasonality orders is the next stage (p and q).

The two main analytical techniques used at this stage are the ACF and partial ACF (PACF). We compute correlation between Yt and Yt-k over the n-k-pairings in the data set in order to determine the auto-correlation of lag k, which is one hallmark of stationary data.

$$ACF(k) = \frac{\sum(Y_t - \mu)(Y_{t-k} - \mu)}{\sum(Y_t - \mu)^2} = \frac{Cov(Y_t, Y_{t-k},)}{Var(Y_t)}$$

Yt-k is a lag-affected variant of the original series, and is the mean, relative to the original set, where Yt stands. The PACF, which accounts for any potential impacts of linear relationships between values at intermediate lag, is the linear correlation between Yt -and Yt-k.

Despite the fact that the second order can be calculated as shown below, the first order partial is equivalent to the first order autocorrelation.

$$PACF = \frac{Cov(Y_t, Y_{t-2} \backslash Y_{t-1})}{\sqrt{(VarY_t \backslash Y_{t-1})(VarY_{t-2} \backslash Y_{t-1})}}$$

While the PACF issues the order of MA (q), the ACF issues the order of AR (p)

Estimating parameters

After selecting an appropriate order for ARIMA, we attempt to find accurate estimation of the models parameters using least squares, as termed by Box & Jenkins (p, d, q).

The variables are computed using maximum likelihood, which is a symptotically accurate for time series.

Diagnostic verification

It produces diagnostic results to determine whether the model is appropriate. By evaluating the importance of the parameters, determine whether some model parameters may be eliminated. If there is more data in the residual series that may be used to test a different model, repeat the estimation and diagnostic testing stages. If this were not the case, using tests to determine fit model test residuals would simply follow the white noise.

Forecasting

We predict the future values of the time series addition using the final model and compute confidence intervals for these estimates. How well an ARIMA model predicts both inside and outside the sample period serves as its main performance metric.

Results and discussion

The First Stage: Identification Model

One cause of non-stationarity is unit roots; the mean, variance, and covariance are fundamental distributional characteristics that remain constant over time.

Figures (1) and (2) demonstrate that the monthly average price (LE/Kg) for broiler farms has not been constant throughout this period of time in accordance with the time charts in the introductory material. It's common to refer to a unit root stochastic trend in a time series—also called a unit root process or a difference stationary process—as a "random walk with drift." A time series will have an unpredictable systematic pattern if it has a unit root. Unit root tests look at the stationarity of a time series.

These tests typically have relatively poor statistical power. Numerous tests are available because none stand out as having the maximum power. One of the tests is the Augmented Dickey-Fuller (ADF) test, which is based on linear regression [31].

Using of linear regression as revealed in Table 1, when serial correlation is troublesome, the Augmented Dickey-Fuller (ADF) test can be applied. Models with greater complexity are handled by the ADF. Its high percentage of Type I errors is one drawback. The Augmented Dickey Fuller Test is a method of stationarity unit root evaluation (ADF). Time series analysis using unit roots sometimes yields unexpected outcomes. Lag variations are included in these models.

- No constant, no trend: $\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant, no trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant and trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

Figures 1, 2, and 3 show the data's non-stationarity in terms of variance or mean. A logarithmic expression further illustrates the data's non-stationary behavior. To deal with variance instability, mathematical corrections can be made using natural logarithm figures. Also discussed are the null and alternatives for the Augmented Dickey-Fuller (ADF) [31] unit root test.

If the p-value from the ADF is greater than 0.05, H0 is accepted as the time series have a unit root (are non-stationary) (Table 1). The time series in Table 1 does not appear to be stationary at the data level, according to ADF, and stationarity must be achieved through differencing, which is used to build ARIMA models. Time series are not unit root-following, ha! (Stationary). Hence, using the series is stable because of the first-order difference in monthly average price (LE/Kg) (Table 2).

Table 1: Unit root test by The Augmented Dickey-Fuller test statistic (ADF) Test

1. The test — The Augmented Dickey-Fuller test statistic (ADF) in Levels-intercept

Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-3.59)	Non-stationary
		5% level (-2.93)	Non-stationary
Monthly average price (LE/Kg)	-2.48 (0.12)	10% level (-2,60)	Non-stationary

2. The test — The Augmented Dickey-Fuller test statistic (ADF) in Levels-Trend and intercept

Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-4.18)	Non-stationary
		5% level (-3.51)	Non-stationary
Monthly average price (LE/Kg)	- 2.47(0.33)	10% level (-3.18)	Non- stationary

3. The test — The Augmented Dickey-Fuller test statistic (ADF) Non Levels- trend and intercept

Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-2.61)	Non- stationary
		5% level (-1.94)	Non- stationary
Monthly average price (LE/Kg)	-0.25 (0.58)	10% level (-1.61)	Non- stationary

Table 2: Unit Root test at the first difference by The Augmented Dickey-Fuller statistic (ADF) Test

1. The test — The Augmented Dickey-Fuller test statistic (ADF) in Levels-intercept

Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-3.59)	Stationary
		5% level (-2.93)	Stationary
Monthly average price (LE/Kg)	-6.33 (0.000)	10% level (-2,60)	Stationary

2. The test — The Augmented Dickey-Fuller test statistic (ADF) in Levels- trend and intercept

Variable	ADF Statistic and probability	Critical Values	Conclusion

		1% level (-4.19)	Stationary
		5% level (-3.52)	Stationary
Monthly average price (LE/Kg)	-6.28 (0.000)	10% level (-3.19)	Stationary

3.The test The Augmented Dickey-Fuller test statistic (ADF) in Non Levels-trend and intercept

Variable	ADF Statistic and probability	Critical Values	conclusion
		1% level (-2.62)	Stationary
		5% level (-1.94)	Stationary
Monthly average price (LE/Kg)	-6.41 (0.000)	10 %Level (-1.16)	Stationary

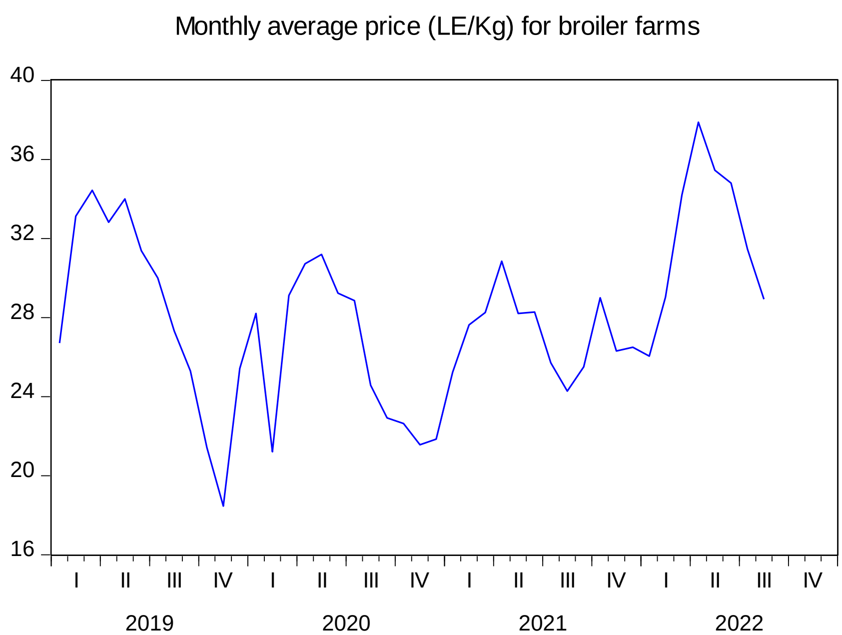


Figure (1): The time plots of the initial data indicate that monthly average price (LE/Kg) for broiler farms is not a stationary for this series.

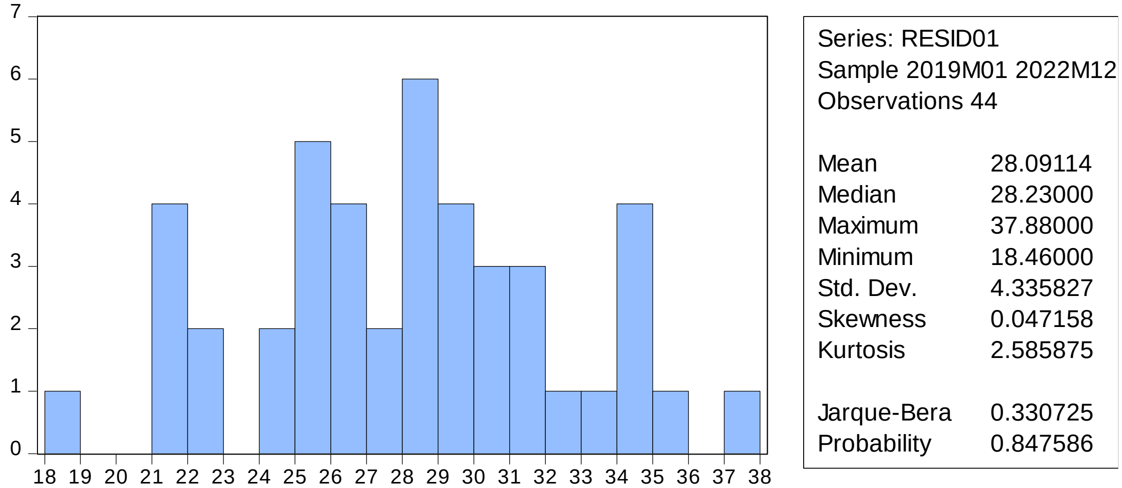


Figure (2): Histogram and Stats of the initial data indicate that monthly average price (LE/Kg) for broiler farms is not a stationary for this series.

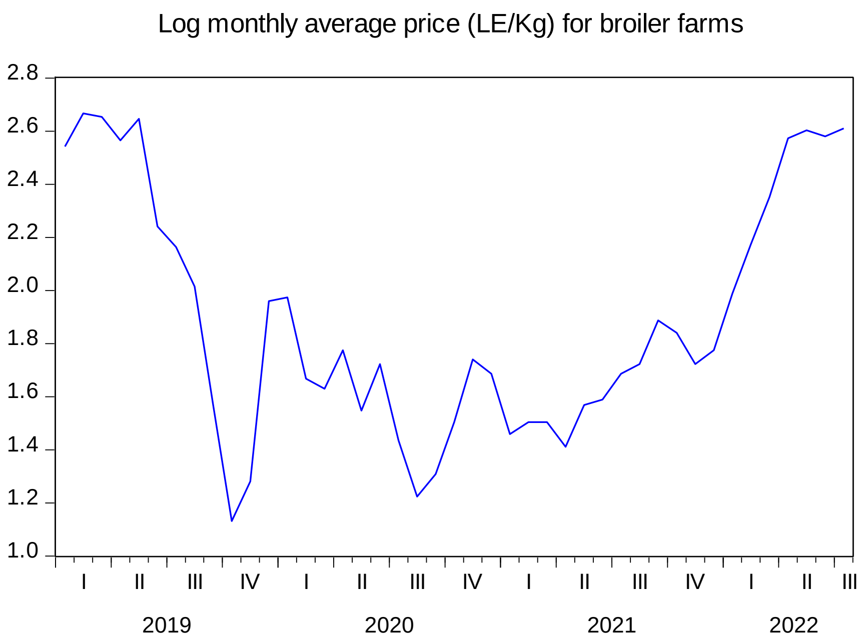


Figure (3) A logarithmic expression also show Non- stationary behavior of the data.

The Second Stage: Estimation Model

The values of the other two parameters of the ARIMA models p and q, are calculated from the PACF and ACF values. The Correlogram (at 1" Differences) in Figure 4 directs us in selecting a test lag length.

Figures 5, 6, and 7 were evaluated using a variety of models, which demonstrate that statistically significant and providing a workable model, the first lag value of PACF. The autoregressive (AR) time series model uses historical data to forecast the dependent variable (i.e., the variable of interest) [32].

For the Monthly Average Price (LE/Kg) for a Series of Egyptian Broiler Farms, the data are best fit by the ARIMA model (1, 1, 0). Although none of the subsequent lag values are statistically significant, the first lag value of PACF is b in Figure 5. This proposes a potential model for the AR (1) series. The suggested moving average is MA (0) since only the initial lag of the ACF is statistically relevant and all other subsequent autocorrelations are not.

The model that best fits the Egyptian monthly average price (LE/Kg) series comes after the first order, and that model is ARIMA (1, 1, 0). Figure 5 demonstrated that all of output's values are significant, as expected. As a result, this method is used in forecasting. It is essential to verify assumptions first before forecasting [33].

Date: 09/22/22 Time: 14:29
Sample: 2019M01 2022M12
Included observations: 44

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.737	0.737	25.599	0.000
		2	0.462	-0.180	35.883	0.000
		3	0.229	-0.090	38.483	0.000
		4	-0.041	-0.281	38.566	0.000
		5	-0.243	-0.103	41.629	0.000
		6	-0.292	0.083	46.156	0.000
		7	-0.297	-0.052	50.983	0.000
		8	-0.219	0.082	53.684	0.000
		9	-0.050	0.122	53.830	0.000
		10	0.147	0.165	55.110	0.000
		11	0.218	-0.130	58.024	0.000
		12	0.269	0.053	62.601	0.000
		13	0.283	0.039	67.844	0.000
		14	0.125	-0.227	68.902	0.000
		15	-0.049	-0.049	69.073	0.000
		16	-0.244	-0.252	73.392	0.000
		17	-0.360	0.139	83.088	0.000
		18	-0.413	-0.099	96.343	0.000
		19	-0.384	-0.033	108.28	0.000
		20	-0.284	-0.005	115.07	0.000

Figure (4): A lag length for PACF and ACF of the first order of Augmented Dickey-Fuller (ADF).

Dependent Variable: Log monthly average price (LE/Kg) for broiler farms
Method: ARMA Maximum Likelihood (BFGS)
Date: 09/22/22 Time: 13:03
Sample: 2019M01 2022M08
Included observations: 44
Failure to improve objective (non-zero gradients) after 92 iterations
Coefficient covariance computed using outer product of gradients

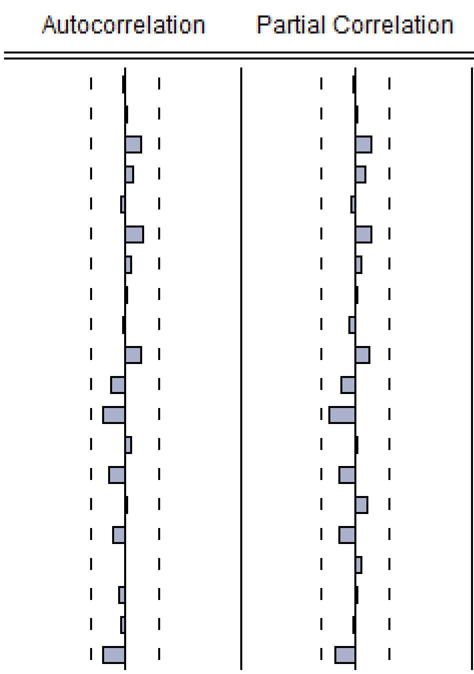
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.308716	0.029545	111.9900	0.0000
AR(1)	1.732529	0.027476	63.05695	0.0000
AR(2)	-0.992333	0.026175	-37.91194	0.0000
MA(1)	-1.208491	233.0954	-0.005185	0.9959
MA(2)	0.210295	25.48085	0.008253	0.9935
MA(3)	0.470377	362.8709	0.001296	0.9990
SIGMASQ	0.007699	1.371534	0.005613	0.9956

R-squared	0.683636	Mean dependent var	3.323502
Adjusted R-squared	0.632333	S.D. dependent var	$\boxed{0.157801}$
S.E. of regression	0.095683	Akaike info criterion	-1.566578
Sum squared resid	0.338746	Schwarz criterion	-1.282729
Log likelihood	41.46471	Hannan-Quinn criter.	-1.461313
F-statistic	13.32563	Durbin-Watson stat	2.019875
Prob(F-statistic)	0.000000		

Inverted AR Roots	.87+.49i	.87-.49i	
Inverted MA Roots	.84-.54i	.84+.54i	-.47

Figure (5): TheAutoamtic equations for ARIMA model out put for the log monthly average price (LE/Kg) for broiler farms data for Egypt 2019-2022.

Date: 09/22/22 Time: 14:25
Sample: 2019M01 2022M08
Included observations: 44
Q-statistic probabilities adjusted for 5 ARMA terms



	AC	PAC	Q-Stat	Prob
1	-0.015	-0.015	0.0111	
2	0.024	0.024	0.0386	
3	0.150	0.151	1.1501	
4	0.081	0.087	1.4786	
5	-0.026	-0.030	1.5140	
6	0.158	0.133	2.8399	0.092
7	0.056	0.042	3.0089	0.222
8	0.011	0.009	3.0161	0.389
9	-0.023	-0.064	3.0455	0.550
10	0.156	0.122	4.4864	0.482
11	-0.128	-0.130	5.4905	0.483
12	-0.196	-0.234	7.9282	0.339
13	0.065	0.018	8.2050	0.414
14	-0.148	-0.147	9.6900	0.376
15	0.015	0.105	9.7064	0.467
16	-0.105	-0.143	10.500	0.486
17	-0.004	0.058	10.501	0.572
18	-0.057	0.024	10.756	0.631
19	-0.049	-0.015	10.947	0.690
20	-0.193	-0.181	14.097	0.518

Figure (6): The Autoregressives (AR)(p) and the Moving Average (MA)(q) for ARIMA models out put for the monthly average price (LE/Kg) for broiler farms.

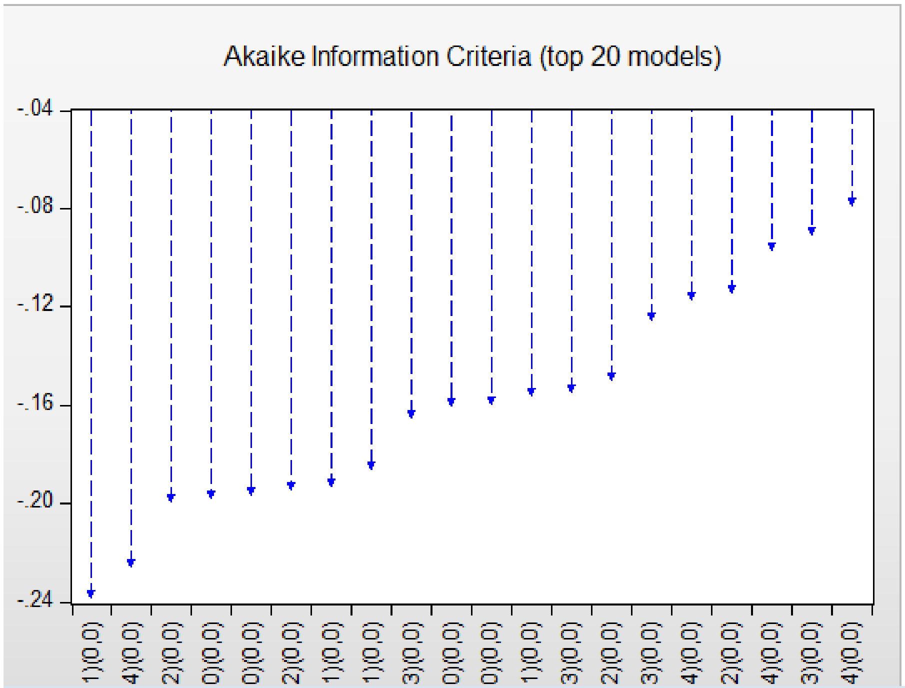


Figure (7): Akaike's information criterion (AIC) compares the quality of a set of statistical models (20) to each other.

The Third Stage: Diagnostic Checking

Akaike's information criterion (AIC) is used to evaluate the quality of a collection of statistical models [34]. The AIC will rank each model from best to worst. The "best" model will be neither too small nor too large (Figures 8 and 9).

Furthermore, the Correlogram-Q-Statistics in Figure 8 show that there is no lag with a p-value less than 0.05. As a result, the residual is said to be devoid of autocorrelation [22].

Model	LogL	AIC*	BIC	HQ
(1,1)(0,0)	9.086010	-0.236559	-0.072726	-0.176142
(2,4)(0,0)	12.820888	-0.224227	0.103438	-0.103395
(4,2)(0,0)	12.249437	-0.197648	0.130017	-0.076815
(3,0)(0,0)	9.228503	-0.196675	0.008116	-0.121154
(2,0)(0,0)	8.189555	-0.194863	-0.031030	-0.134447
(1,2)(0,0)	9.152122	-0.193122	0.011669	-0.117601
(2,1)(0,0)	9.125336	-0.191876	0.012915	-0.116356
(4,1)(0,0)	10.963939	-0.184369	0.102338	-0.078641
(2,3)(0,0)	10.520495	-0.163744	0.122963	-0.058015
(1,0)(0,0)	6.420237	-0.159081	-0.036206	-0.113769
(4,0)(0,0)	9.395355	-0.157923	0.087825	-0.067299
(3,1)(0,0)	9.331026	-0.154931	0.090817	-0.064307
(1,3)(0,0)	9.294389	-0.153227	0.092521	-0.062603
(2,2)(0,0)	9.187367	-0.148250	0.097499	-0.057625
(3,3)(0,0)	10.663318	-0.123875	0.203790	-0.003042
(1,4)(0,0)	9.487177	-0.115683	0.171024	-0.009954
(3,2)(0,0)	9.428947	-0.112974	0.173733	-0.007246
(3,4)(0,0)	11.053534	-0.095513	0.273110	0.040424
(4,3)(0,0)	10.921358	-0.089366	0.279258	0.046571
(0,4)(0,0)	7.655077	-0.076980	0.168769	0.013644
(4,4)(0,0)	11.132649	-0.052681	0.356900	0.098360
(0,3)(0,0)	5.233009	-0.010838	0.193953	0.064683
(0,2)(0,0)	2.735442	0.058817	0.222649	0.119233
(0,1)(0,0)	-6.231848	0.429388	0.552263	0.474701
(0,0)(0,0)	-26.619861	1.331156	1.413073	1.361365

Figure (8): ***Correlogram-Q-Statistics*** **based on the correlogram above, it can be seen that there is no lag that has a probability value of <0.05. So it can be concluded that the residual does not contain autocorrelation.**

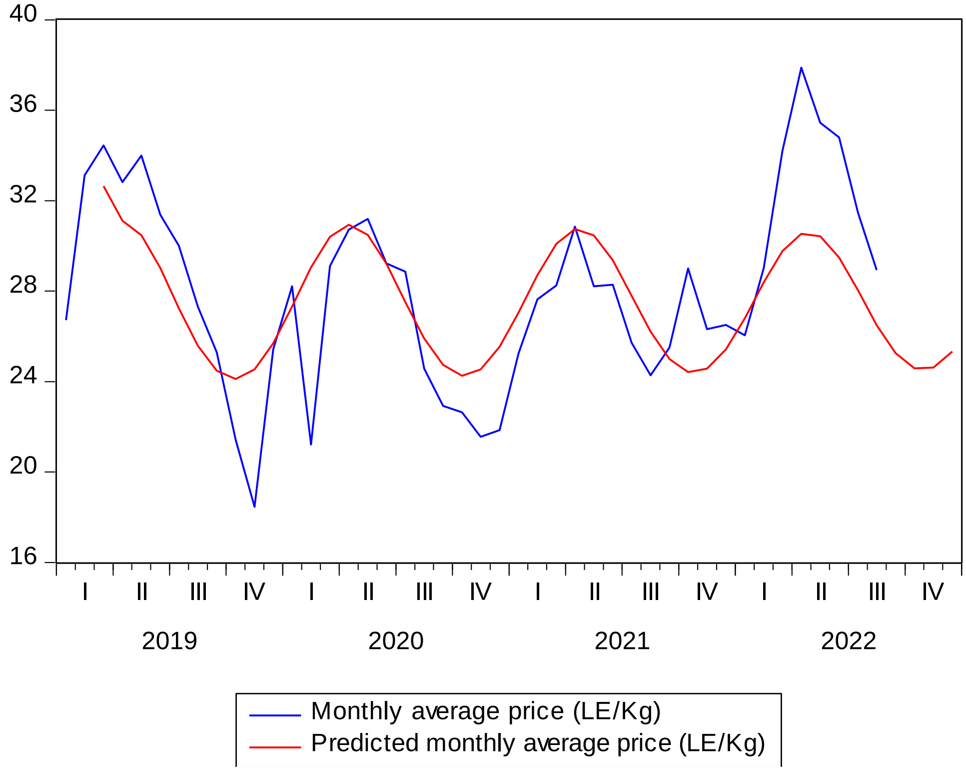


Figure (9): The Forecasting results of the monthly average price (LE/Kg) for broiler farms for the next four months (September till December) of 2022.

The fourth stage: Forecasting

We use the final model to forecast future time series addition values and then generate confidence intervals (CI) or standard errors (SE) for these projections. The primary performance metric of the ARIMA model is how well it forecasts during and outside of the sample period. Table (3) and Figure 1 show the monthly average price (LE/Kg) % for the following five months of 2022. [9, 29]

.

ARIMA (1, 1, 0) model, which is steady, will be the best accurate model for predicting Egypt's monthly average price (LE/Kg) during the following five months. That holds true for the initial difference when *P* = 1 and q = 0. The monthly average price (LE/Kg), expressed as a percentage, and was 25.25 LE/Kg in September, 24.58 LE/Kg in October, 24.61 LE/Kg in November, and 25.32 LE/Kg in December.

Conclusion

The most reliable and acceptable model for forecasting is the ARIMA (1, 1, 0) model. The correlation-Q-statistics show that there is no lag with a *P*-value less than 0.05. The residual is therefore said to be free of autocorrelation. With the application of the model, the monthly average price (LE/Kg) for Egyptian broiler farms for the next four months was calculated. The percentage values were 25.25 ± 2.46 LE/Kg in September, 24.58

± 4.33LE/Kg in October, 24.61± 4.23LE/Kg in November, and 25.32 ± 4.11 LE/Kg in December. And from the predicting values, the policy makers can take into account the prices of feedstuffs and one day old chicks to keep the food security margin.

Conflict of interest: The authors declare no conflict of interest.

References

[1] Devatkal, S.; Naveen, B. and Kotaiah, T. (2019): Quality, composition, and consumer evaluation of meat from slow-growing broilers relative to commercial broilers. Poult. Sci., 98: 6177-6186.

[2] Wu, S.B.; Swick, R. A.; Noblet, J. ; Rodgers, N. ; Cadogan, D. and Choct, M. (2019): Net energy prediction and energy efficiency of feed for broiler chickens. Poult. Sci., 98: 1222-1234.

[3] Morshdy, A.E.M.A; Darwish, W.S.; Salah El-Dien, W.M. and Khalifa,S.M. (2019): Prevalence of multidrug-resistant *Staphylococcus aureus* and *Salmonella enteritidis* in meat products retailed in Zagazig City, Egypt. Slov. Vet. Res., 55: 295-301.

[4] El Bayomi, R.M. ; Darwish, W.S.; Elshahat, S.S. and Hafez, A.E. (2018): Human health risk assessment of heavy metals and trace elements residues in poultry meat retailed in Sharkia Governorate, Egypt. Slov. Vet. Res., 55: 211-9.

[5] Asghar, A.; Farooq, M.; Mian, M. A.; Pervez and Khurshid, A. (2000): Economics of broiler production in Mardan Division. J. Rural Develop. & Adminis. 32:56-64.

[6] Zahir-ud-Din, M.; Farooq, F.R.; Durrani, N.; Chand and J. Ahmad. (2001): Status of broilers produced in Swat, Pakistan Livest. Res. Rural. Dev. 13: 67-71.

[7] Khan, S.; Farooq, M.; F.R. Durrani, (2004): Economic analysis of broiler farms in the arid zone (Pakistan). Sarhad J. Agric., 20: 337-341.

[8] Farooq, M.; Mian, M.A.; and Asghar, A.(2001): Factors affecting cost of production and net profit per broiler in the subtropics. *Livestock research for rural development*, 13: 1-5.

[9] Kitsopanidis, J.P.; and Manos, H.(1991): Evaluation of the degree of variation in profitability of poultry meat production according to certain factors. Epitheorese Zootenhnikes Epistemes, 14: 59-71.

[10] González-García, S.; Gomez-Fernández, Z.; Dias, A. C., Feijoo, G.; Moreira, M. T.; and Arroja, L. (2014): Life Cycle Assessment of broiler chicken production: a Portuguese case study. Journal of Cleaner Production, 74: 125-134.

[11] Nkukwana, T.T. (2018): Global poultry production: Current impact and future outlook on the South African poultry industry. South African Journal of Animal Science, 48: 869-884.

[12] Davis, C.G.; Harvey, D.; Zahniser, S. ; Gale, F. and Liefert, W. M. (2018): Assessing the Growth of U.S. Broiler and Poultry Meat Export. Technical Report Livestock, Dairy, and Poultry Outlook, Economic Research Service, U.S.

[13] Arumugam, N.(2011): The Dark Side of the Bird. Technical report, The Slate Group, the Graham Holdings Company.

[14] El Nagar, A. and Ibrahim, A. (2021): Case study of the Egyptian poultry sector. Ministry of Agricultural and Land Reclamation, Economic Affairs Sector. University of Zagazig, Department of Agricultural Economics.

[15] Cagas,U.O.; Delima, A.J.P. and Toledo,T. L.(2019): Predictability of Faculty Instructional Performance through Hybrid Prediction Model. Int. J. Innov. Technol. Explor. Eng., 8: 22-25.

[16] Kitchin, R., (2014): Big Data, new epistemologies and paradigm shifts. Big Data Soc., 1(1): 1—12.

[17] Hafez, H. M. and Attia, Y. (2020): Challenges to the Poultry Industry: Current Perspectives and Strategic Future After the COVID-19 Outbreak. Frontiers in veterinary science, 7: 516

[18] Muhammad, D. F. (2002): Production performance and economic appraisal of commercial layers in District Chakwal. Doctoral dissertation, NWFP Agricultural University, Peshawar-Pakistan).

[19] Box, G. E. P. ; Jenkins, G. M. and Reinsel G. C.(1994): Time series analysis; Forecasting and control. 3rd edition. Prentice Hall, Englewood Cliff, New Jersey.

[20] Adubisi, O. D.; David, 1. J.; James, F. E.; Awa, U. E.and Terna, A. J. (2018): A predictive Autoregressive Integrated Moving Average (ARI M A) Model for Forecasting Inflation Rates. Res. J. Bus. Econ. Manag. , 1:1—8.

[21] Urrutia, J. D. F.; Mingo, L. T. and Balmaceda, C. N. M. (1992): Forecasting Income Tax Revenue of the Philippines Using Autoregressive Integrated Moving Average (Arima) Modeling : a Time Series Analysis," Am. Res. Thoughts, 1:1938-2015.

[22] Chua, K.C.(2015):The effect of U.S.Inflation on the Philippiness. South East Asia J.Contemp.Business, Econ. Law, 7:16-22.

[23] Banerjee, A. ; Dolado, J.J. ; Hendry, D.F. ;Smith, G.W. (1986): Exploring equilibrium relationships in econometrics through static models: some Monte Carlo evidence. Oxford Bull. Econ. Stat. 48: 253277.

[24]Engle, R.F. and Granger, C.W.J. (1987): Co-integration and error correction: representation, estimation and testing. Econometrica, 55: 251-276.

[25] Dickey, D. A., and Fuller, W. A. (1979): Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association, 74:427-431.

[26] Dickey, D.A. and Fuller, W.A., (1981): Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49:1057-1072.

[27] Dickey, D.A. ; Jansen, D.W. and Thornton, D.L. (1991): A primer on cointegration with an application to money and income. Fed. Reserve Bank St. Louis Rev. 73: 58-78.

[28] Rohrbach, D.D. and Kiriwaggulu, J.A.B., 2001. Commercialization Prospects for Sorghum and Pearl Millet in Tanzania.. Journal of SAT Agricultural Research, 3:1-28.

[29] Nau, R.(2018): ARIMA models for time series forecasting " Retrieved: https://people.duke.edu/~rnau/ mDep. Evon.Res., 411arim.htm.

[30] Mgaya, J. F. (2019). Application of ARIMA models in forecasting livestock products consumption in Tanzania. Cogent Food & Agriculture, *5*: 1607430.

[31] Fuller, W. A. (1976): Introduction to statistical time series, new york: Johnwiley. FullerIntroduction to Statistical Time Series1976.

[32] Anderson, D. R. ; Burnham, K. P. ; Lubow, B. C. ; Thomas, L. E. N. ; Corn, P. S. ; Medica, P. A. and Marlow, R. W. (2001): Field trials of line transect methods applied to estimation of desert

tortoise abundance. J.Wildl Manag, 65: 583-597.

[33] Omar, M. A., Shahin, S. E., & Roshdy, M. (2022): Forecasting Inflation in Egypt (2019-2022) by using AutoRegressive Integrated Moving Average (ARIMA) Models. J. Adv. Vet. Res.~~,~~ 12, 670-676.

[34] Akaike, H., (1998): Information theory and an extension of the maximum likelihood principle. In Selected papers of hirotugu akaike 199-213. Springer, New York, NY.

الملخص العربي

وقع متوسط السعر الشهري (جنيه / كجم) لمزارع الدواجن المصرية (2019-2022) باستخدام نموذج المتوسط المتحرك الانحداري المتكامل (ARIMA)

سارة عصام شاهين1, مجدي رشدى2 , محمد احمد السيد عمر1
قسم تنمية الثروة الحيوانية ، كلية الطب البيطري ، جامعة الزقازيق ، 44511 مصر1
طبيب بيطري ، كلية الطب البيطري ، جامعة الزقازيق ، 44511 ، الزقازيق ، مصر2

تم إستخدام نموذج ARIMA للتنبؤ بمتوسط السعر الشهري (جنيه / كجم) لمزارع الدجاج اللاحم في مصر (2019-2022) للفترة من سبتمبر حتى ديسمبر من عام 2022 ، وتم إختيار النموذج الأنسب بعناية بناءً على الحد الأدنى من قيمة AIC. تم تطبيق نموذج ARIMA باستخدام EViews10. وهي تتكون من ثلاث عمليات: عملية الإنحدار الذاتي (AR) ، وعملية الإختلاف (د) ، وعملية المتوسط المتحرك (MA). تتميز منهجية Box-Jenkins لتحليل ونمذجة السلاسل الزمنية بأربع خطوات: تحديد النموذج ، تقدير المعلمات ، الفحص التشخيصي والتنبؤ. استخدمت هذه الدراسة نموذج الانحدار الذاتي المتحرك المتكامل (ARIMA) لتقدير وتوقع متوسط السعر الشهري (جنيه / كجم) لمزارع الدجاج اللاحم في مصر (2019-2022) باستخدام البيانات التاريخية أحادية المتغير لمتوسط السعر الشهري (جنيه / كجم). 1 ، 1 ، 0) نموذج مستقر والأنسب للتنبؤ بمتوسط السعر الشهري (جنيه / كجم) لمزارع الدجاج اللاحم في مصر للأشهر الأربعة القادمة. النسبة المئوية في سبتمبر (25.25 جنيه / كجم ± 2.46) ؛ أكتوبر (24.58 جنيه / كجم ± 4.33) ؛ نوفمبر (24.61 جنيه / كجم ± 4.23) وديسمبر (25.32 جنيه / كجم ± 4.11). النموذج الأكثر موثوقية وقبولًا للتنبؤ هو نموذج ARIMA (1، 1، 0). أنه مع قيمة p أقل من 0.05 ، يوضح Correlogram-Q-Statistics أنه لا يوجد تأخير. لذلك يُقال أن المتبقي خالٍ من الإرتباط الذاتي. مع تطبيق النموذج تم حساب متوسط السعر الشهري (جنيه / كجم) لمزارع الدجاج اللاحم المصرية للأشهر الأربعة القادمة. بينما كانت النسب المئوية 25.25 ± 2.46 جنيه / كجم فى سبتمبر ، 24.58 ± 4.33 جنيه / كجم فى أكتوبر ، 24.61 ± 4.23 جنيه / كجم فى نوفمبر ، و 25.32 ± 4.11 جنيه / كجم فى ديسمبر. ومن خلال النتائج يتبين أنه يمكن لواضعي السياسات النظر في أسعار الأعلاف والصيصان التي يبلغ عمرها يوم واحد للحفاظ على هامش الأمن الغذائي بإستخدام متوسط السعر الشهري (جنيه / كجم) لمزارع الدجاج اللاحم في مصر (2019-2022) الذي تم تقديره وتوقعه بإستخدام نموذج ARIMA بإستخدام البيانات التاريخية أحادية المتغير.