Predicting Livestock Trends: A Box-Jenkins Approach Using ARIMA (The case of Algeria 1990-2025)

التنبؤ باتجاهات الثروة الحيوانية: نهج بوكس–جينكينز باستخدام نموذج ARIMA (حالة الجزائر 1990–2025)

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Received: 01/09/2024 ***Accepted: 09/12/2024*** ***Published:01/01/2025***

Abstract:

This study aims to forecast livestock using the Box-Jenkins methodology, specifically applying it to a time series of annual livestock numbers in Algeria from 1990 to 2021.

It concluded with the estimation of a forecasting model based on the Autoregressive Integrated Moving Average (ARIMA) approach, specifically ARIMA(0,1,1), which demonstrated good accuracy with a Mean Absolute Percentage Error (MAPE) of 10.40%. The forecast indicates an increase in livestock numbers during the period from 2022 to 2025.

Keywords: Livestock; forecasting, Box-Jenkins; ARIMA; Algeria.

JELClassificationCodes:C_{18}; C_{41} ; Q_{11} ; Q_{18}

ملخص:

تهدف هذهالدراسة إلى تقدير نموذج للتنبؤ بالثروة الحيوانية منخلالاستعمالطريقةبوكس–جينكيز، وتطبيقها على سلسلة زمنية للعدد السنوي من رؤوس الثروة الحيوانية في الجزائرخلالالفترةالممتدة ما بين 1990 و 2021.

خلصت النتائج إلى تقدير نموذج للتنبؤ من خلال نموذج الانحدار الذاتي للمتوسطات المتحركة على شكل ARIMA (0,1,1)، وبتقييم جيد لدقته حسب إحصائية (MAPE=10.40%)،

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وتحصلناعلىتقدير للثروة الحيوانية في الجزائر خلالالفترة (2022-2025)، والذي كان بشكلمتزايدمنسنةإلىأخرى.

كلمات مفتاحية: الثروة الحيوانية، التنبؤ، بوكس-جينكيز، الانحدار الذاتي والمتوسط المتحرك، الجزائر.

تصنيفاتJEL : C_{18}; C_{41} ; Q_{11} ; Q_{18}

1. INTRODUCTION

Studies on livestock in Algeria are extremely rare, despite its significant importance to the economy, standard of living, and food security. This study's focus on livestock aims to illuminate the economic aspects of this field through time series forecasting methods. Additionally, it encourages further exploration and writing by researchers in this area.

In developing countries, there is considerable uncertainty for future of livestock, this sector is evolving in response to rapidly increasing demand, (Thornton, 2010, p. 2853), some countries have transitioned from being exporters to importers of livestock(Upton, 2004, p. 2), In Sudan, for example, the percentage of the livestock sector's contribution to GDP decreased from 1.3% to 0.3% during period (2001-2015)(Warrag & Al-Nadawi, 2022, p. 47).

This study aims to apply econometrics measurement in forecasting livestock in Algeria, and its future trends. This provides a clear vision for the government and private investors, helping them manage the livestock sector effectively,including nutrition, healthcare, breed improvement, pasture management, and marketing strategies. It also supports investment strategies, market development, and policy formulation to achieve sustainable and profitable livestock production systems. we will try to apply the Box-Jenkins methodology, away from the external factors affecting the production and consumption of livestock.

1.1.Research Question

From the above we can formulate the problematic:

What are the future predictions for livestock numbers in Algeria based on the Box-Jenkins model?

To deepen the understanding, the main question can be divided into the following sub-questions:

-What are the predictions for livestock in Algeria in short term?

-What is the accuracy of forecasting livestock numbers in Algeria using the Box-Jenkins methodology?

Historical data on livestock indicates an upward trend in headcount. In the context of this study, two main hypotheses will be proposed as follows:

Hypothesis 1: There are predictions of an increase in livestock numbers in Algeria in the near future.

Hypothesis 2: The forecast of livestock numbers in Algeria using the Box-Jenkins methodology will achieve a high level of accuracy.

1.2.Objectives of the Study

- Knowledge of the stages of the Box-Jenkins methodology for forecasting and its application to data;
- Estimate livestock in Algeria for four years.
- Assess the validity of the Box-Jenkins method in forecasting.
- Analyze future trends in livestock production in Algeria in the short term.

2.Literature Review:

Several studies have focused on forecasting livestock and red meat using time series analysis, the most important of which is the study of: (Qasim & al., 2019) entitled "**Forecasting buffalo population of Pakistan using autoregressive integrated moving average (ARIMA) time series models**", it aimed to determine a model for forecasting buffalo numbers during period (2018-2030), by using the most fitted ARIMA model (1,0,0) out of other models, it concluded that the buffalo production will rise approximately 30%during period of study. (Nouman, 2014) was aimed to estimate a time trend for beef, mutton, poultry meat during period (1971-2020), by using an exponential function of the form $Y_f = ce^{bt}$, it concluded that the overall explanatory power of the model was very high (R^2 = 99%), and the meat productiongrowth will be 1.6% per year. The study of (Akram, Amin, Yasin, & Aslam, 2022) entitled "**Future trends of red meat production in Pakistan: time series analysis**", it aimed to determine a model for forecasting the production of red meat in Pakistan during period (2020-2025), by using various time series models (Random Walk, Random Walk with Drift, Linear Trend, Quadratic Trend, Exponential Trend, S-Curve Trend, Moving Average (2), Simple exponential smoothing), it concluded that the best model on the basis of RMSE was " Random walk model with drift". The study of: (Paul,

Alam, & Paul, 2014) entitled "**Prospects of livestock and dairy production in India under time series framework**", It concluded to forecasting of milk production in India during period 2012-2015, by using ARIMA (1,1,0) model, it has been found a significantly increasing trend, evaluation of model was carried out with (MAPE=1.9%).

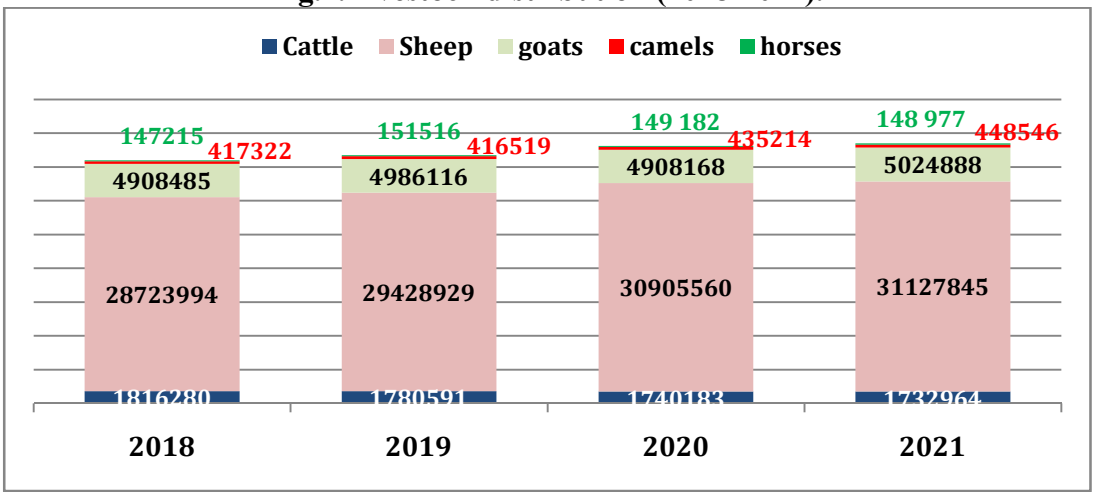
2.1. Livestock and economics:

Livestock and economics are closely interconnected, it provides employment opportunities, global food security, and economic value (Herrero, et al., 2013, p. 3). The term "livestock" refers to all domestic animals that produce consumer goods and as the main source of animal protein such as meat, milk and hides, including poultry that provides white meat and eggs (FAO, 2023), The growth of livestock in Near East and North Africa was 2.1% per year, and FAO expects that the net added value of animal production will reach about 42% at the beginning of 2032 (FAO, 2023, p. 106). The supply of livestock is affected by animal diseases (Pritchett, Thilmany, & Johnson, 2005, p. 23), nutrition and feed, research and development (Herrero, et al., 2013, p. 3), May be population growth, income per capita, and urbanization factors that affect livestock demand, as well as natural factors (land and water) (Thornton, 2010, p. 2853).

2.2. Livestock in Algeria

Since ancient history, the livestock trade has made Algeria famous, as evidenced by ancient writings and wall inscriptions discovered in historical sites such as Timgad and Cirta.(صندوق، 2015، صفحة 21), It is mainly characterized by the predominance of five breeds: cattle, sheep, goats, camels and horses (ONS, 2021, p. 40).

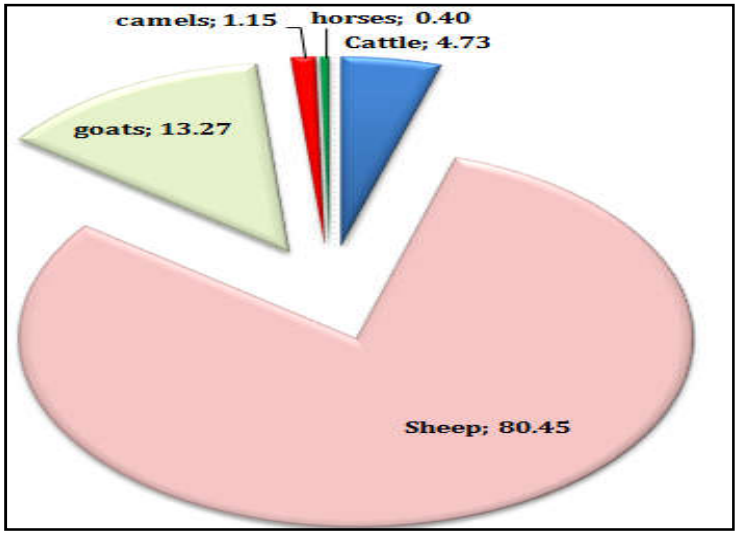
Fig.1.Livestock distribution (2018-2021).



Source:by researchers from:(ONS, 2021, p. 41)&(ONS, 2020-2021, p. 11)

The average annual number of livestock during the period 2018-2021 is estimated at more than 37.30 million heads, against 27.71 million heads during (1990-2021), with an increase of 41.65%.

Fig.2.Livestock structure (2018-2021 average).



Source: by researchers from:(ONS, 2021, p. 41)&(ONS, 2020-2021, p. 11)

The predominance of the livestock is for the sheep breed which represents 80.45%, or 30.04 million heads. Goats come in second place with a rate of 13.27% followed by cattle with 4.73%.

As for camels, they represent only 1.15% of the average annual population. Horses are very unrepresentative, i.e. 0.4%. During the period 2010-2019, the evolution of the number of livestock is marked by an upward

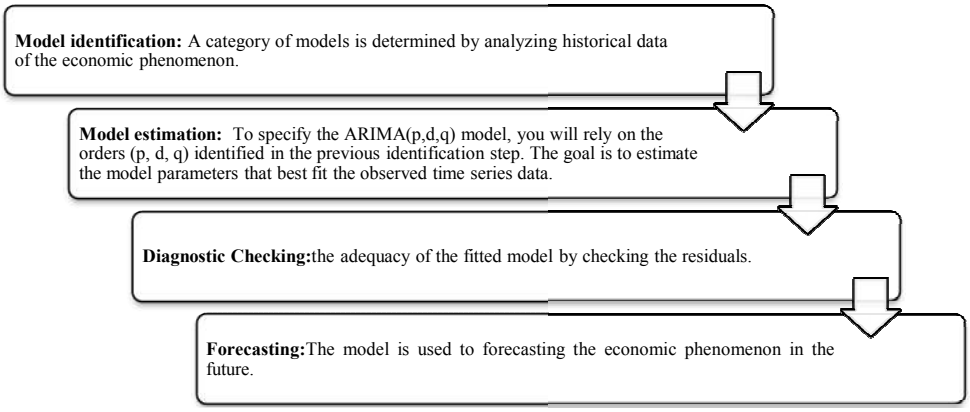
trend. Indeed, in 2021 the overall workforce stood at 38.319.684 heads against 36.013.296 heads in 2018, an increase of more than 6% (2.306.388 more heads).

3. Research Methodology

3.1. The Box-Jenkins method

The Box-Jenkins method is a purely quantitative approach for forecasting, used to construct a model that best captures the behavior of a time series (Adala, 2011, p. 136), it follows a three phases procedure as shown in Figure 3.

Fig.3. Box-Jenkins methodology steps



Source: By the researchers from(Aldjandali, 2017, p. 59)

3.2. Data Collection:

The data of this study was the annual number of livestock in Algeria during period 1990-2021 (unit: head), obtained from Algerian National Statistics Office.

Table 1: the annual number of livestock in Algeria during 1990-2021.(unit: head)

Years	livestock	Years	livestock	Years	livestock	Years	livestock
1990	22164000	1998	22955000	2006	25505000	2014	35548810
1991	21283000	1999	23736000	2007	26155000	2015	35822922
1992	22392000	2000	22736000	2008	25863000	2016	35708907
1993	23197000	2001	22553000	2009	27586000	2017	35839768
1994	22144000	2002	22360000	2010	29437805	2018	36013296
1995	21842000	2003	22905000	2011	30734530	2019	36763671
1996	22170000	2004	23877000	2012	32191105	2020	38138307
1997	22235000	2005	24598000	2013	33947240	2021	38319684

Source: (ONS, 1962 - 2020, p. 201)**&**(ONS, 2020-2021, p. 11)

3.3. Application of method

3.3.1. Estimation of mixed ARMA

The role of ARMA (p,q) model (**A**uto**re**gressive **M**oving **A**verage) is to modeling and forecasting in the times series as demonstrated by the statistician WOLD in 1954, it characterized by high flexibility, it is capable to producing a variety of autocorrelation, structures (Paolella, 2019, p. 31)**.**

ARMA model is defined by linear difference equations with constant coefficients (Brockwell & Davis, 2016, p. 47).

AR is a model that uses the dependent relationship between an observation and some number of lagged observations (Brownlee, 2019, p. 32), The model is given by the following equation (a P^{th}-order autoregressive, noted **AR(p)**)(Chunling, Chunlin, Youlong, & Sujie, 2014, p. 2085):

$$Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t$$

Or:

$$Y_t = c + \sum_{i=1}^{p} \emptyset_i \, Y_{t-i} + \varepsilon_t$$

Where: $\emptyset_1, \emptyset_2, \ldots, \emptyset_p$ are coefficients express the strength of the linear connection between two successive values;

c is a constant;

ε_t is white noise.

The **MA** model is used to determine the dependency between the observations and the residual errors applied to lagged observations (Brownlee, 2019, p. 32), were q: order of moving averages, the model **MA (q)** is written as(Brockwell & Davis, 2016, pp. 43-47):

$$Y_t = \mu + \varepsilon_t + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \cdots + \omega_q \varepsilon_{t-q}$$

Or:

$$Y_t = \mu + \sum_{i=0}^{q} \omega_i \, \varepsilon_{t-i}$$

Where the $\omega_1, \ldots, \omega_q$ are the parameters of the model;

μ is the expectation of Y_t (often assumed to equal 0);

$\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ are white noise error terms.

Consider the ARMA (p,q) of the time series $\{Y_1, Y_2, \ldots, Y_{t-1}, Y_t\}$process (Pesaran, 2015, p. 317):

$$Y_t = c + \varepsilon_t \sum_{i=1}^{p} \emptyset_i \, Y_{t-i} + \sum_{i=0}^{q} \omega_i \, \varepsilon_{t-i}$$

Or: $Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t \mu + \varepsilon_t + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \cdots + \omega_q \varepsilon_{t-q}$

3.3.2. Autoregressive Integrated-Moving Average Models ARIMA (p,d,q)

If the time series is not stationed in the mean, we use Autoregressive Integrated-Moving Average Models ARIMA (p,d,q), where p is the number of autoregressive; d is degree of differencing; q is the number of moving average terms, this model is defined as (Brockwell & Davis, 2016, p. 158):

"If d is a nonnegative integer, then $\{X_t\}$ time series, is an ARIMA (p,d,q) process if $Y_t = (1-B)^d X_t$ is a causal ARMA(p, q) process"

The ARIMA (p,d,q) is given by the formula:(Mouffok & Souar, 2018, p. 123):

$$\Delta^a Y_t = Y_t - Y_{t-1} - Y_{t-2} - \cdots - Y_{t-d}$$

3.3.3. Stationary of time series

A stochastic process X or $\{X_t\}$ is stationary if (Dor, 2009, p. 151):

- x_i is constant (it is unchanged over time): $E(X_t) = \mu x \ \forall t$;
- The variance is constant over time: $VAR(X_t) = \sigma_X^2 \ \forall t$;
- The covariance between X_t and $X_{t-\theta}$ depends only on the time: $COV(X_t, X_{t-\theta} = v(\theta) \ \forall t, \forall \theta$.

4. Analysis, results and discussion

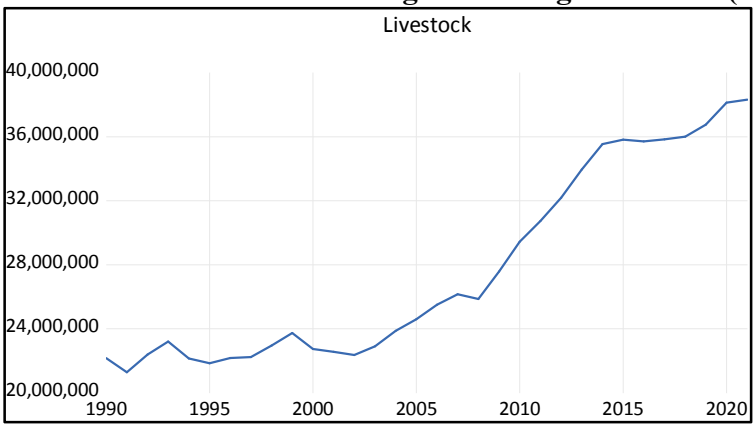
In this study, EViews 10 software was used for data entry and to obtain the results (software outputs).

4.1. Identification

To determine if a time series is stationary, the following techniques can be applied:

4.1.1.Visual Inspection: From the plot of the time series data (**Fig.4**), noticeable trends or irregular patterns indicate non-stationarity.

Fig.4.The annual Livestock data in Algeria during 1990-2021 (unit: head)

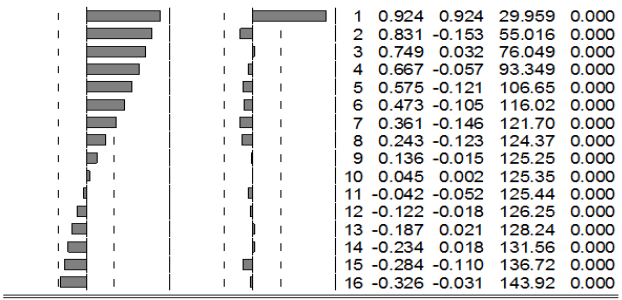


Source: researchers' own calculation using Eviews10 software.

4.1.2.ACF/ PACF correlogram: The tools that we required for identification process was correlogram, autocorrelation function (ACF), and partial autocorrelation function (PACF), each term that comes out of this interval is therefore significantly different from 0 at the 5% level (Bourbonnais, 2015, p. 253).

Fig.5. Correlogram ACF and PACF of the time series "Livestock data".

Sample: 1990 2021
Included observations: 32



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.924	0.924	29.959	0.000
		2	0.831	-0.153	55.016	0.000
		3	0.749	0.032	76.049	0.000
		4	0.667	-0.057	93.349	0.000
		5	0.575	-0.121	106.65	0.000
		6	0.473	-0.105	116.02	0.000
		7	0.361	-0.146	121.70	0.000
		8	0.243	-0.123	124.37	0.000
		9	0.136	-0.015	125.25	0.000
		10	0.045	0.002	125.35	0.000
		11	-0.042	-0.052	125.44	0.000
		12	-0.122	-0.018	126.25	0.000
		13	-0.187	0.021	128.24	0.000
		14	-0.234	0.018	131.56	0.000
		15	-0.284	-0.110	136.72	0.000
		16	-0.326	-0.031	143.92	0.000

Source:researchers' own calculation using Eviews10 software.

From the correlogram in Figure 3, the autocorrelation (ACF) is observed to be outside the standard error bounds, and it declines to zero and (-1). In the PACF correlogram, the first lag is significant, while every other one is not, indicating that the time series is non-stationary.

4.1.3.Parametric tests:

In this study, parametric tests were used to analyze the stationarity of the time series, specifically the Augmented Dickey-Fuller test, the Phillips-Perron test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

So in the table 2, the Augmented Dickey-Fuller test results (see Appendix 01).

To testing hypothesis H_0 and H_1 where:

- H_0 "Livestock" time series has a unit root, and the "Livestock" is non-stationary, if Prob.<5%;
- H_1 "Livestock" time series hasn't a unit root, and the "Livestock" is stationary, if Prob.>5%.

It is observed that:

In the 1st case (without intercept and without trend) t-Statistic>0;

In the 2nd and 3rd cases we have |t-Statistic|>|critical values| at the level of significant 5%;

In all cases Critical probs are greater than the level of significant (α=5%), so the statistical results are opposite then the null hypothesis H_0 is accepted.

Table 2: the Augmented Dickey-Fuller (ADF) test result for the time series "Livestock" in the level.

Hypothesis H_0: Livestock has a unit root				
Lag Length: 3 (Automatic - based on SIC, maxlag=5)				
ADF test	**t - statistic**	**critical values**	**Prob.**	**Hypothesis**
without intercept and without trend	2.3898	-1.9524	0.9947	H_0 is accepted
with intercept and without trend	0.2733	-2.9639	0.9728	H_0 is accepted
with intercept and with trend	-1.5272	-2.6210	0.7972	H_0 is accepted

Source:researchers' own calculation using Eviews10 software.

To remove the instability, differences are made to get a new time series. After finding that the time series is stationary in the 1st difference, the same tests (ADF), Phillips-Perron test (PP), and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) are used, where "D(Livestock)" is the new time series (the time series "Livestock" transformed by the 1st difference) (see Appendix 02, 03, and 4).

Table3: (ADF),(PP),(KPSS), tests for the new time series "D(Livestock)".

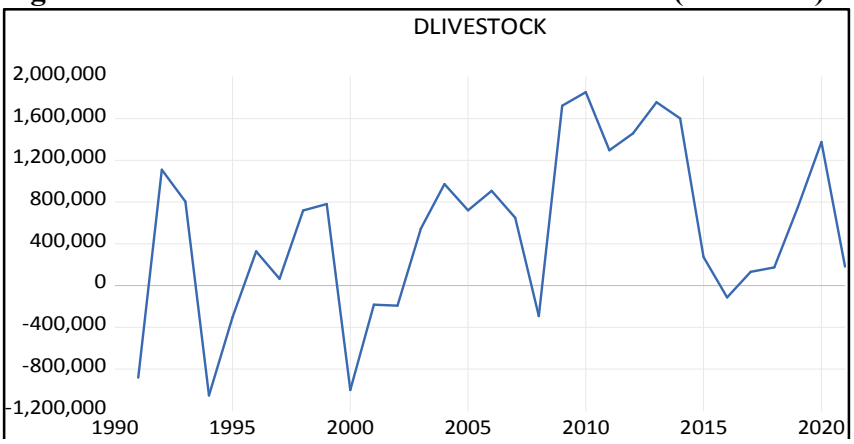
Hypothesis H_0: D(Livestock) has a unit root				
Lag Length: 3 (Automatic - based on SIC, maxlag=5)				
ADF test	**t - statistic**	**critical valuesin the level of significant 5%**	**Prob.**	**Hypothesis**
without intercept and without trend	-2.8876	-1.9524	0.0054	H_1 is accepted
with intercept and without trend	-3.9173	-2.9639	0.0055	H_1 is accepted
with intercept and with trend	-3.9416	-2.6210	0.0225	H_1 is accepted
PP test	Adj t - statistic	critical values in the level of significant 5%	Prob.	Hypothesis
without intercept and without trend	-2.8712	-1.9524	0.0056	H_1 is accepted
with intercept and without trend	-3.9793	-2.9639	0.0047	H_1 is accepted
with intercept and with trend	-3.9416	-2.6210	0.0225	H_1 is accepted
KPSS test	LM-Stat.	Asymptotic critical values	***	Hypothesis
with intercept and without trend	0.3621	0.4630	***	H_0 is accepted
with intercept and with trend	0.1080	0.1460	***	H_0 is accepted

Source: researchers' own calculation using Eviews10 software.

From the table 3, the result of the (ADF), and (PP) tests approve that:

- $|t - Statistic| > |criticalvalues|$at the level of significant 5%, where the prob is lower than 5%, so we reject the null hypothesis H_0, and we accept the H_1 hypothesis, this means that:"D(Livestock)"hasn't a unit root, the time series is stationary in the 1st difference, the (KPSS) test approve the same result because ($LM - stat < asymptoticcriticalvalues$) at the level 5%.

Fig.6. The new time series in the 1st difference "D(Livestock)"



Source:researchers' own calculation using Eviews10 software.

The figure 6 indicate that the new time series "D(Livestock)" is stationary, because the upwards is reverting to his main.

4.2. Estimation

Autocorrelation function, andPartial Autocorrelation functionwere used to estimate ARIMA model (the figure 7), from the ACF we see that q=1 , and from PACF p=1, where d=1, there are three possibilities of ARIMA model: (1,1,0), (1,1,1), (0,1,1).

Fig.7. ACF&PACF of 1st Difference.

Sample: 1990 2021
Included observations: 31

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.345	0.345	4.0482	0.044
		2	0.062	-0.064	4.1841	0.123
		3	0.199	0.226	5.6347	0.131
		4	0.016	-0.155	5.6441	0.227
		5	0.050	0.139	5.7408	0.332
		6	0.203	0.111	7.4277	0.283
		7	0.068	-0.024	7.6271	0.367
		8	0.012	-0.009	7.6335	0.470
		9	-0.075	-0.171	7.8940	0.545
		10	-0.099	0.011	8.3750	0.592
		11	-0.067	-0.073	8.6066	0.658
		12	-0.259	-0.267	12.205	0.429
		13	-0.136	0.078	13.259	0.428
		14	-0.035	-0.058	13.333	0.500
		15	-0.129	0.037	14.403	0.495
		16	-0.095	-0.062	15.017	0.523

Source: researchers' own calculation using Eviews10 software.

After comparing the results obtained without a constant by the Least Squares Method, the most fitted model is found to be (0,1,1) out of the other models, because it has the lower Akaike information criterion (AIC), Schwarz criterion (SC), and Hannan-Quinn value (HQV). The model also has

significant parameters (see Appendix 05),($prob_{MA(1)}$=0.0059), $prob_{(c)}$=0.0321, $prob_{(SIGMA^2)}$=0.0006, and R-squared=0.203991, as shown in Table 4.

Table 4: Least Squares Method test of ARIMA (p,d,q)

	ARIMA(1,1,0)	ARIMA(1,1,1)	ARIMA(0,1,1)
$SIGMA^2$	5.40	4.93	4.96
AIC	30.05045	30.03238	29.97515
SC	30.18922	30.21742	30.11392
HQV	30.09568	30.09270	30.02039
R^2	0.134246	0.209248	0.203991

Source: researchers' own calculation using Eviews10 software.

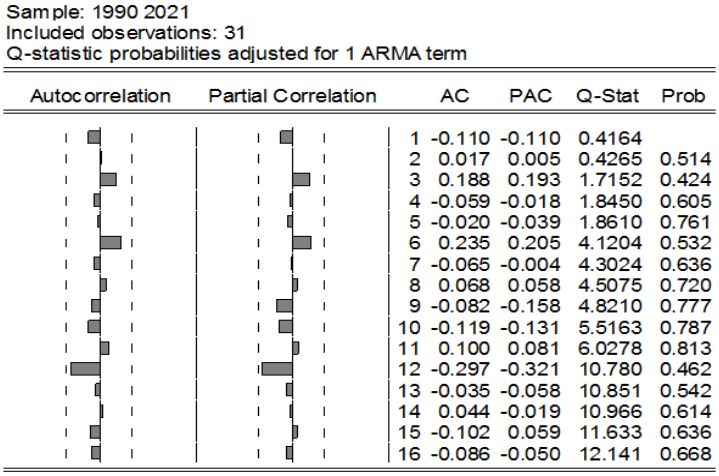
The estimated model is given by :

$$D(Livestock)_t = 480889.9 + [MA(1) = 0.598239, UNCOND, ESTSMPL = "1991\ 2021"]$$

4.3. Diagnostic Checking

For verification, the Ljung-Box test is used. the correlogram of residuals (Figure 8), indicates that there are no significant estimated residual autocorrelations in the ARIMA (0,1,1) model. All boundaries fall within the area of confidence, hence the residuals follow the white noise distribution.

Fig.8. Correlogram of residuals.



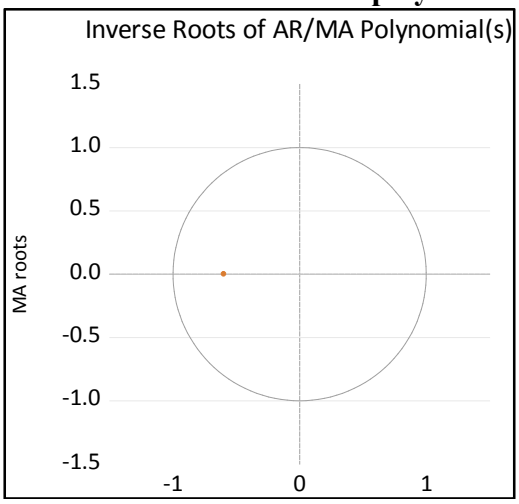
Source:researchers' own calculation using Eviews10 software.

From the correlogram of residuals (Figure 8), the following is observed:

Q-stat=12.141, lag=16, $x^2_{0.05,16} = 26{,}2962$

$x^2_{0.05,16} = 26{,}2962 >$ LB =2.4347, hence the residues follow the white error distribution.

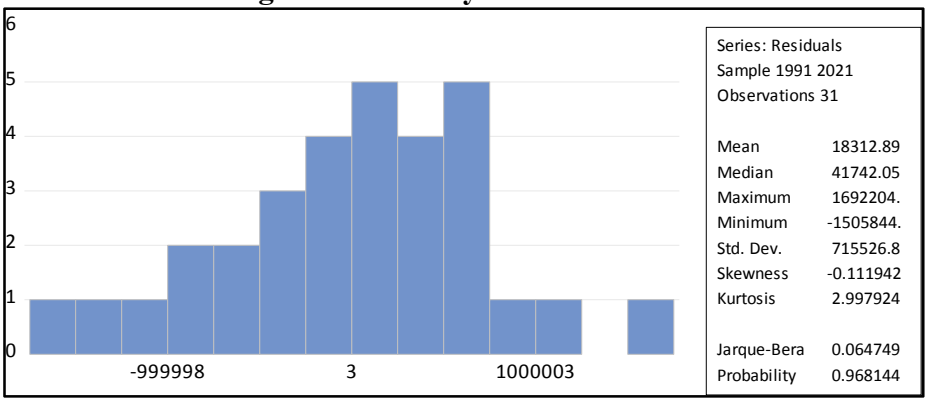
Fig.9. inverse roots of ARIMA polynomial (s).



Source: researchers' own calculation using Eviews10 software.

The figure 9 indicates that inverse roots of the characteristic polynomial lie in the circle, it proves that the ARIMA (0,1,1) model is stable.

Fig.10. Normality test of residues.



Source:researchers' own calculation using Eviews10 software.

By using Jarque-Bera test and the histogram in figure 10, for studying the normality distribution of residues, JB is less than probability (0.064749 < 0.968144), the test result and the histogram approve that these residues follow the normal distribution.

4.4. Forecasting

After identification, estimation and verification, the last phase is to use the model ARIMA (0,1,1) for forecasting Livestock in Algeria. (Number of heads of livestock).

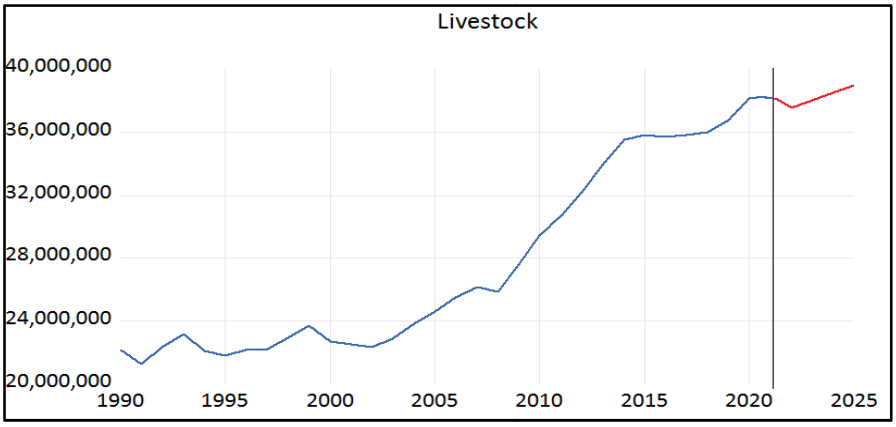
Table 5: Livestock forecast results for Algeria (2022-2025)

Years	Livestock (Unit: head)
2022	37552477
2023	38033367
2024	38514257
2025	38995147

Source:researchers' own calculation using Eviews10 software.

The table 5 displays an forecast of Livestock in Algeria from 2022-2025, according to the choosing model ARIMA(0,1,1), the results of forecasted Livestock for 4 years indicates an upward trend, hence the number of Livestock in Algeria may reach approximately 39 million heads in 2025 (figure 11).

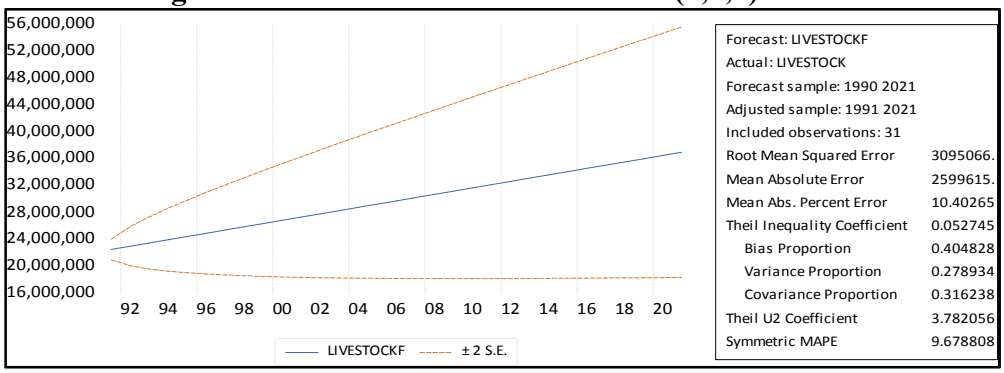
Fig.11. Livestock during period 1990-2021, forecast (2022-2025)



Source: researchers' own calculation using Eviews10 software.

To evaluate ARIMA model, the following measures were used: Mean Absolute Percentage Error, and Theil Inequality Coefficient.

Fig.12. tests for evaluation of ARIMA (0,1,1) model.



Source:researchers' own calculation using Eviews10 software.

From Fig.12 the performance evaluation measures are found to be:

- Mean Absolute Percentage Error (MAPE) value of 10.40265% is relatively high, indicating the model's predictions have, on average, a 10.4% error relative to the actual values. A MAPE below 10% is generally considered a good model fit (Lewis, 1982) from (H. Rangika Iroshani, 2016, p. 103) (see Appendix 06).

- Henri Theil introduced the Theil Inequality Coefficient as a measure of forecast accuracy. The coefficient ranges from 0 to 1, and a value closer to 0 indicates a better model fit (Theil, Beerens, Tilanus, & De Leeuw, 1966). In this case, the Theil Inequality Coefficient of 0.052745 is a normalized measure of overall model error. This relatively low Theil Coefficient value suggests the model is performing reasonably well, despite the high RMSE and MAE values.

5. Conclusion

This study analyzed the annual data on livestock numbers in Algeria from 1990 to 2021. The results from the (ADF), (PP), (KPSS) tests indicated that the time series is stationary at the first difference.

By applying the Box-Jenkins methodology, the analysis of livestock data over 31 years resulted in an ARIMA (0, 1, 1) model, which assists in predicting future values. The ARIMA (0, 1, 1) model was selected from among three other model parameters because it has the lowest Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Value (HQV). Additionally, the model features significant parameters. Therefore, the following results were obtained:

- The best model is ARIMA (0,1,1), and the estimated model is:

$$D(Livestock)_t = 480889.9 + [MA(1) = 0.598239, UNCOND, ESTSMPL = "1991\ 2021"]$$

- An estimate of the numbers of livestock in Algeria during the period 2022-2025 was obtained, which shows an increasing trend from year to year, potentially reaching approximately 39 million heads in 2025, this serves as conclusive evidence supporting the validity of the first hypothesis of the study. These results may help decision-makers develop strategies and correct deviations between the real and estimated results in a timely manner.

- To assess the model's accuracy, performance evaluation measures, including the Mean Absolute Percentage Error (MAPE) and the Theil Inequality Coefficient, were employed. The MAPE of 10.40% indicates a relatively low average error in predictions, while the Theil Inequality Coefficient of 0.05 reflects a good model fit. These results support the validity of the second hypothesis of the study. The low MAPE suggests that the model offers reliable predictions, which is crucial for stakeholders in the agriculture and livestock sectors. Additionally, the Theil Inequality Coefficient reinforces the model's robustness, indicating a close alignment between predicted values and actual observations.

The findings from the ARIMA (0, 1, 1) model highlight a significant upward trend in livestock numbers, which is critical for policy formulation and resource allocation. The increasing livestock population could reflect improvements in livestock management practices, government support, and investment in the sector, particularly in light of state policies that promote animal husbandry.

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7. Appendices

Appendix 01: (ADF) test result for the time series "Livestock" in the level.

Null Hypothesis: LIVESTOCK has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.389825	0.9947
Test critical values:	1% level	-2.644302	
	5% level	-1.952473	
	10% level	-1.610211	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIVESTOCK has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.273339	0.9728
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIVESTOCK has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.527299	0.7972
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

*MacKinnon (1996) one-sided p-values.

Source:researchers' own calculation using Eviews10 software.

Appendix 02: (ADF) test for the new time series "D(Livestock)".

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.887692	0.0054
Test critical values:	1% level	-2.644302	
	5% level	-1.952473	
	10% level	-1.610211	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.917397	0.0055
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.941680	0.0225
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

*MacKinnon (1996) one-sided p-values.

Source:researchers' own calculation using Eviews10 software.

Appendix 03: (PP test for the new time series "D(Livestock)".

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: None
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.871270	0.0056
Test critical values:	1% level	-2.644302	
	5% level	-1.952473	
	10% level	-1.610211	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.979357	0.0047
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIVESTOCK) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.941680	0.0225
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

*MacKinnon (1996) one-sided p-values.

Source:researchers' own calculation using Eviews10 software.

Appendix 04: (KPSS) test for the new time series "D(Livestock)".

Null Hypothesis: D(LIVESTOCK) is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.362161
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Null Hypothesis: D(LIVESTOCK) is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.108029
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Source:researchers' own calculation using Eviews10 software.

Appendix 05: Least Squares Method test of ARIMA (p,d,q)

Dependent Variable: D(LIVESTOCK)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 07/13/23 Time: 23:00
Sample: 1991 2021
Included observations: 31
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	488756.4	209055.3	2.337928	0.0268
AR(1)	0.374523	0.196621	1.904798	0.0671
SIGMASQ	5.40E+11	1.56E+11	3.463998	0.0017

R-squared	0.133622	Mean dependent var	521151.1
Adjusted R-squared	0.071738	S.D. dependent var	802257.4
S.E. of regression	772945.7	Akaike info criterion	30.05045
Sum squared resid	1.67E+13	Schwarz criterion	30.18922
Log likelihood	-462.7819	Hannan-Quinn criter.	30.09568
F-statistic	2.159234	Durbin-Watson stat	1.859405
Prob(F-statistic)	0.134246		

Inverted AR Roots .37

Dependent Variable: D(LIVESTOCK)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 07/13/23 Time: 23:06
Sample: 1991 2021
Included observations: 31
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	489905.8	196212.6	2.496811	0.0189
AR(1)	-0.133637	0.379154	-0.352462	0.7272
MA(1)	0.668305	0.274613	2.433627	0.0218
SIGMASQ	4.93E+11	1.39E+11	3.544775	0.0015

R-squared	0.209248	Mean dependent var	521151.1
Adjusted R-squared	0.121386	S.D. dependent var	802257.4
S.E. of regression	751991.2	Akaike info criterion	30.03238
Sum squared resid	1.53E+13	Schwarz criterion	30.21742
Log likelihood	-461.5020	Hannan-Quinn criter.	30.09270
F-statistic	2.381564	Durbin-Watson stat	1.968197
Prob(F-statistic)	0.091570		

Inverted AR Roots -.13
Inverted MA Roots -.67

Dependent Variable: D(LIVESTOCK)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 07/13/23 Time: 23:07
Sample: 1991 2021
Included observations: 31
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	480889.9	213188.5	2.255703	0.0321
MA(1)	0.598239	0.200816	2.979038	0.0059
SIGMASQ	4.96E+11	1.28E+11	3.883878	0.0006

R-squared	0.203991	Mean dependent var	521151.1
Adjusted R-squared	0.147133	S.D. dependent var	802257.4
S.E. of regression	740891.3	Akaike info criterion	29.97515
Sum squared resid	1.54E+13	Schwarz criterion	30.11392
Log likelihood	-461.6148	Hannan-Quinn criter.	30.02039
F-statistic	3.587732	Durbin-Watson stat	2.094570
Prob(F-statistic)	0.041007		

Inverted MA Roots -.60

Source: researchers' own calculation using Eviews10 software.

Appendix 06: MAPE value for model selection.

MAPE (%)	EVALUATION
MAPE ≤10%	High accuracy forecasting
10%<MAPE≤20%	Good forecasting
20%<MAPE≤50%	Reasonable forecasting
MAPE>50%	Inaccurate forecasting

(Lewis, 1982) **from** (H. Rangika Iroshani, 2016, p. 103)