AGORA International Journal of Economical Sciences, http://univagora.ro/jour/index.php/aijes
ISSN 2067-3310, E-ISSN 2067-7669
Vol. 18, No. 1 (2024), pp. 55-64

ANALYZING AND FORECASTING CO2 EMISSIONS IN THE ALUMINUM SECTOR USING ARIMA MODEL

R. HASANOV, J. SAFAROV, A. SAFARLI

Ramil Hasanov[1], Jamil Safarov[2], Arzu Safarli[3]
[1] University of Technology of Azerbaijan, Azerbaijan
https://orcid.org/0000-0003-4267-7039, E-mail: r.hasanov@uteca.edu.az
[2] University of Technology of Azerbaijan, Azerbaijan
https://orcid.org/0009-0004-0392-3860, E-mail: jamil.safarov@Azeraluminium.com
[3] Azerbaijan Technical University, Azerbaijan
https://orcid.org/0000-0003-2670-0665, E-mail: arzu.safarli@aztu.edu.az

Abstract: *The urgent and pressing challenge posed by global climate change underscores the critical need for immediate and decisive action, particularly in the mitigation of greenhouse gas (GHG) emissions to facilitate a trajectory towards sustainability. The significance of the aluminium industry, characterized by its notable carbon footprint, accentuates the importance of conducting comprehensive and environmentally conscious analyses within this sector. Heightened environmental apprehensions surrounding aluminium production necessitate the development of effective approaches for emission forecast. The primary aim of the article is to elucidate the present situation and future predictions of carbon emissions within the global aluminium industry, particularly in the context of escalating concerns regarding global climate security. The research concluded that there will be a decrease in CO2 emissions within the aluminium industry in the future as a result. Through meticulous assessments and exhaustive forecasts of CO2 emissions across the global aluminium industrial chain system, this study employed the Autoregressive Integrated Moving Average (ARIMA) model to scrutinize data spanning from 2005 to 2030. By furnishing valuable insights into prospective emission patterns and providing guidance for the formulation of sustainable policy measures, this research assumes a pivotal role in shaping data-driven strategies aimed at mitigating the environmental impact of aluminum production. Consequently, it contributes significantly to the collective endeavor to combat climate change and foster a more resilient and sustainable future for humanity.*

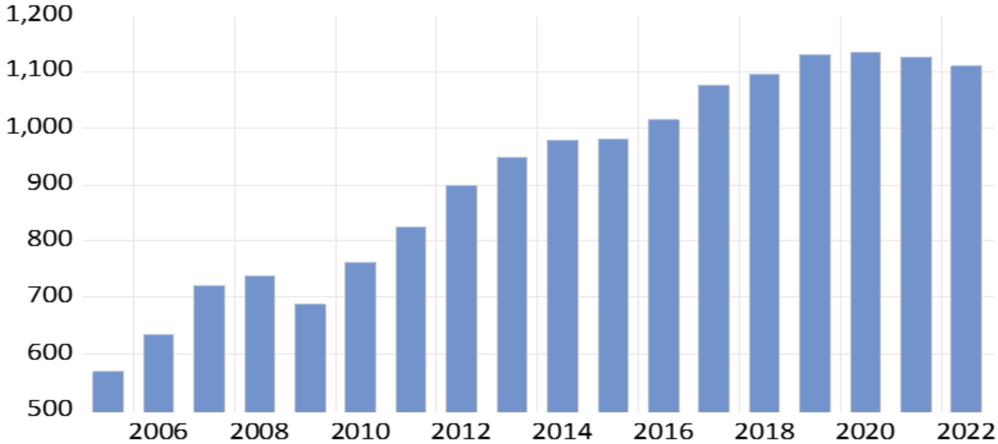
Keywords: *green economics, aluminum industry, CO2 emissions, ARIMA model, sustainability.*

INTRODUCTION

Aluminium plays a vital role in various technologies essential for the energy transition, but it also serves as a significant source of CO_2 emissions, emitting close to 270 million tonnes of direct CO_2 emissions in 2022, which corresponds to approximately 3% of the world's direct industrial CO_2 emissions (IEA, 2023). Despite being consumed in lower quantities compared to steel or cement, aluminum emerges as the most carbon-intensive material per tonne among the top three highest-emitting materials (Berker, 2022). These statistics reiterate the fundamental importance of the current sector in promoting a sustainable eco-economic system.

Graph 1 depicts the CO_2 emissions of the global aluminum industry over the past 18 years, revealing a notable shift from an upward trend to a decrease since 2020. Concurrently, there has been observed growth in global aluminum production, indicating a positive trend towards green integration in recent years.

Graph 1. CO_2 Emissions In Aluminum Sector (In Million Tons).



Source: International Aluminum Institution (IAI). https://international-aluminium.org/statistics/greenhouse-gas-emissions-aluminium-sector/ (25.01.2023)

The global aluminum industry holds considerable economic significance, yet its manufacturing activities contribute significantly to greenhouse gas emissions, particularly carbon dioxide (CO_2). Therefore, understanding the emission patterns within this sector is crucial for implementing effective mitigation strategies. Utilizing some techniques in time series analysis and forecasting, this research aims to examine CO_2 emission data in the global aluminum industry to identify prevailing trends and forecast future emission patterns. By conducting thorough analysis and forecasting modeling, the findings of this study aim to provide insights that can guide strategic decision-making processes geared towards promoting sustainability in the aluminum sector.

LITERATURE REVIEW

Time series forecasting is indispensable across multiple fields, including finance, economics, engineering, and social sciences. ARIMA (Autoregressive Integrated Moving Average) models serve as a cornerstone in statistical time series analysis, offering a flexible and powerful framework for forecasting future values based on past observations. ARIMA models have become a well-established tool within the field of economics for forecasting key macroeconomic indicators. These indicators, such as Gross Domestic Product (GDP), inflation rates, and unemployment levels, provide crucial insights into the health and trajectory of a nation's economy. Vafin (2020) utilized the Automatic ARIMA forecasting method to anticipate significant macroeconomic indicators across seven notable economies, uncovering anticipated reductions in employment and inflation within the United States, alongside diminishing rates of labor force participation in Russia, alongside other forecasted patterns.

Moreover, this model is extensively employed in financial analysis and forecasting. Numerous scientific articles exist that explore this area (Li, Han, & Song, 2020; Ariyo, Adewumi, & Ayo, 2014; Cheng et al, 2020).

In addition to these instances, the ARIMA forecasting model is employed in a multitude of scholarly investigations centered on sustainable economic development and resilience. Using annual time series data from 1960 to 2017 on CO_2 emissions in China, employs Nyoni, & Mutongi (2019) the Box-Jenkins ARIMA approach to model and forecast CO_2 levels, revealing an anticipated increase in emissions and suggesting four key policy recommendations for the Chinese government. Dritsaki, M., & Dritsaki, C. (2020) investigate the most effective model for forecasting CO_2 emissions in the EU-28, utilizing an ARIMA(1,1,1)-ARCH(1) model with parameter optimization via maximum likelihood estimation, employing both static and dynamic methods for forecasting, with the static approach demonstrating superior accuracy in forecasting.

The thorough scientific analysis of carbon dioxide emissions within the global aluminum industry, renowned for its expansive industrial network, holds considerable importance on a global scale. Ciacci et al. (2014) employs Standard Material Flow Analysis (MFA) and Life Cycle Assessment (LCA) models to study the historical greenhouse gas emissions from Italian aluminum production (1960-2009), aiming to guide future industrial and environmental policies. It calculates annual emissions and cradle-to-gate factors, revealing the carbon footprint and highlighting emissions transfers between production and use locations. The study suggests potential emissions reductions through aluminum recycling and underscores the value of integrating MFA and LCA for comprehensive environmental analysis. Liu & Muller (2012) conducted an extensive analysis of aluminum life cycle assessments, taking into account sustainability principles from a wide-ranging perspective.

DATA AND METHODOLOGY

The present study employs data concerning Aluminum Life Cycle Emissions (ALCE), offering insights into carbon CO_2 emissions associated with the worldwide aluminum sector. Spanning from 2005 to 2022, this dataset provides a holistic perspective on emission patterns throughout the specified timeframe. Sourced primarily from the International Aluminium Institute (IAI, 2023) and derived through Total-Cradle to Gate calculations, this dataset serves as a pivotal resource for comprehending the environmental ramifications of aluminum production processes, serving as the cornerstone for subsequent analyses and interpretations within the study.

Table 1 presents the descriptive statistical analysis of CO_2 emissions in the aluminum sector spanning from 2005 to 2022, providing essential insights for environmental and industrial evaluation. The mean annual emission is documented at 913.00 million tons, with a median emission of 964.00 million tons, signifying the central tendency of the data. Additionally, the dataset highlights a range of emissions, with a minimum of 569.00 million tons and a maximum of 1133.00 million tons, alongside a moderate level of variability (SD = 189.25), a slight left skew (skewness = -0.35), and a moderately peaked distribution (kurtosis = 1.74). These findings are instrumental for researchers and policymakers to discern trends and devise sustainable strategies within the aluminum industry.

Table 1. Descriptive Statistical View (ALCE In Level).

Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
913.00	964.00	1133.00	569.00	189.25	-0.35	1.74

Unit root tests are statistical techniques employed to ascertain the stationarity of a time series variable. A stationary time series variable is characterized by consistent attributes, including a constant mean, variance, and autocorrelation, which remain unchanged over time. The Augmented Dickey-Fuller (ADF) test (1979) evaluates the presence of a unit root, implying non-stationarity, in a time series variable, whereas the Phillips-Perron (PP) test (1988), a comparable unit root examination, incorporates modifications to account for serial correlation and heteroscedasticity. ADF and PP tests are implemented to evaluate the stationarity of the ALCE series. In instances where the data exhibits non-stationarity, indicating alterations in statistical properties over time, differencing techniques are employed to attain stationarity. The correlogram provides a visual representation of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the ALCE series. This visualization facilitates the identification of serial dependence patterns, indicating correlations between past and present values within the dataset.

The Autoregressive Integrated Moving Average (ARIMA) model serves as a widely employed approach for time series forecasting. This model was established through the pioneering contributions of Box and Jenkins (1970). Their incorporation of differencing into the ARMA framework transformed the ARIMA model, enabling the handling of non-stationary time series data via observation differencing. ARIMA model is defined by three parameters, represented as (p, d, q), where p signifies the count of autoregressive terms integrating preceding values, d indicates the degree of differencing essential for achieving stationarity, and q denotes the number of moving average terms accounting for past forecast errors.

In this research endeavor, we examine the utilization of this methodology for forecasting emissions, as articulated by the equation:

$$ALCE_t = \alpha_1 \; ALCE_t^{1} + \varepsilon_t \qquad (1)$$

here:

- $ALCE_t$ is the CO_2 emissions in aluminum sector in period t.
- $ALCE_t^{1}$ is CO_2 emissions in the aluminum sector during the preceding period.
- ε_t represents the error term, assumed to be white noise, characterized by being independent and identically distributed with a mean of zero.

The selection of the most suitable ARIMA model relies on statistical metrics such as p-values, R-squared, Akaike Information Criterion (AIC), and Schwarz Bayesian Criterion (SBC), which penalize excessive model complexity in favor of simpler alternatives demonstrating enhanced forecasting precision.

For a more dependable forecasting analysis of the model, it is imperative to obtain the AR and MA roots results. These outcomes offer critical information about the stability and characteristics of the autoregressive (AR) and moving average (MA) components, thereby augmenting the accuracy and reliability of the forecasting process.

RESULTS

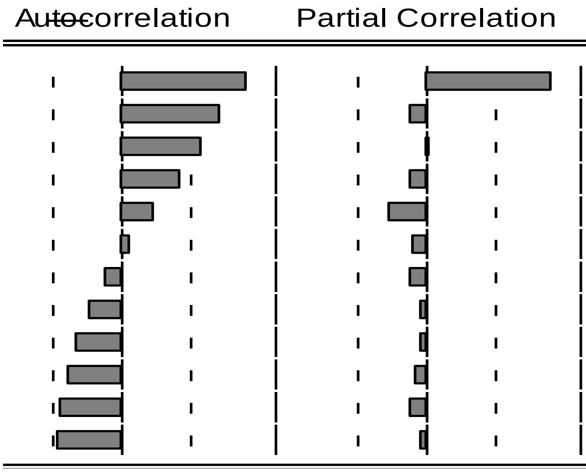
Table 2 displays the results from two unit root examinations, specifically ADF and PP tests, which are conducted assuming the presence of both trend and intercept in the data. The p-values presented in the table serve the purpose of determining whether the null hypothesis of a unit root can be rejected. Upon the first difference operation, where the data undergoes differencing once, the test statistic yields a value of -3.262 with a corresponding p-value of 0.107. Despite this p-value being lower compared to the initial level, it does not attain sufficient significance to reject the null hypothesis at the conventional 5% significance level. However, its proximity to the threshold suggests the consideration of either a test with improved power or a decreased significance level. Conversely, at the second difference, the test statistic stands at -4.718 with a p-value of 0.010, denoting statistical significance. This finding implies the potential attainment of stationarity in ALCE subsequent to two difference operations. The outcomes of the Phillips-Perron test closely mirror those of the ADF test, displaying insignificance at the initial level and first difference, but significance at the second difference, hinting at the likelihood of achieving stationarity after two differences.

Table 1. Unit Root Test: ALCE.

Augmented Dickey-Fuller		**Level**	**1st Difference**	**2nd Difference**
Trend and Intercept	**t-statistic**	-1.075	-3.262	-4.718
	p-value	0.903	0.107	0.010
Phillips-Perron		**Level**	**1st Difference**	**2nd Difference**
Trend and Intercept	t-statistic	-1.308	-3.284	-6.586
	p-value	0.849	0.104	0.000

The correlogram provided in Graph 2 illustrates the autocorrelation coefficients for ALCE across various lag intervals, spanning up to 12 lags, where the vertical axis denotes these coefficients and the horizontal axis represents lag duration. Additionally, the correlogram incorporates partial autocorrelation coefficients (PAC), which reveal correlation patterns after adjusting for intervening lags. Notably, the prominently elevated and positive first lag autocorrelation coefficient indicates a persistent influence of CO_2 emissions, while diminishing coefficients suggest decreasing correlations with extended lag durations. Multiple coefficients, demonstrating statistical significance, suggest the presence of serial dependence, while other observed patterns hint at potential non-stationarity. Leveraging the correlogram facilitates the identification of appropriate ARIMA models for diagnostic purposes.

Graph 2. The Correlogram Of ALCE.



	AC	PAC	Q-Stat	Prob
1	0.837	0.837	14.840	0.000
2	0.671	-0.100	24.969	0.000
3	0.537	0.009	31.888	0.000
4	0.397	-0.112	35.937	0.000
5	0.210	-0.252	37.153	0.000
6	0.042	-0.085	37.206	0.000
7	-0.101	-0.099	37.539	0.000
8	-0.212	-0.032	39.150	0.000
9	-0.297	-0.030	42.688	0.000
10	-0.363	-0.067	48.608	0.000
11	-0.417	-0.104	57.572	0.000
12	-0.437	-0.037	69.033	0.000

**Derived through the utilization of the Eviews software application*

Several scholars (Ning, Pei, & Li, 2021; Sharma et al., 2023; Lotfalipour, Falahi, & Bastam, 2013) have applied the ARIMA forecasting model to analyze carbon dioxide (CO_2) emissions, as evidenced by a body of research in the field. Based on the findings presented in Table 4, we examine the suitability of employing AR(1)MA(1) models for the analysis and forecasting of time series data. The AR(1) model characterizes a time series wherein the current value exhibits a linear dependence on the previous value (lag 1), while the MA(1) model captures the relationship between the current value and the preceding error term (lag 1). In contrast, AR(1) employs lagged outcome values for forecasting, while MA(1) utilizes unobserved error terms as inputs, leading to distinct methodologies and estimation outcomes. Through comparison and diagnostic evaluation, encompassing measures such as R-squared and Hannan-Quinn criteria, it is evident that the AR(1)MA(1) model proves to be more suitable.

We conduct estimation for the equation below to identify a prospective model suitable for forecasting, ultimately culminating in the generation of forecasts:

$$ALCE = C(1) + AR(1) * C(2) + MA(1) * C(3) + UNCOND \quad (2)$$

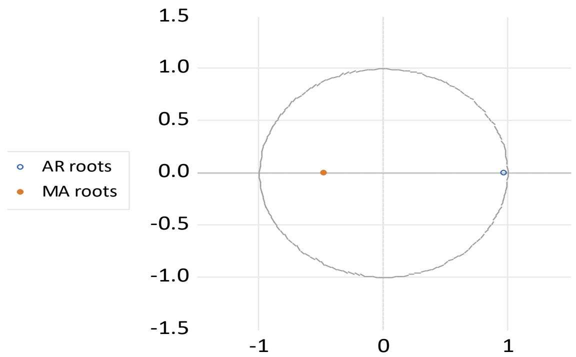
ALCE refers to carbon emissions in the aluminum sector, with C(1), C(2), and C(3) denoting the coefficients associated with the constant, autoregressive (AR), and moving average (MA) components, respectively. UNCOND signifies unconditional estimation.

Table 3. ARMA Maximum Likelihood Method Results.

	AR(1)MA(1)	AR(1)MA(2)	AR(2)MA(1)
R-squared	0.948	0.933	0.930
F-statistic	85.232	65.107	62.826
Akaike criter.	10.965	11.198	11.226
Schwarz criter.	11.163	11.396	11.424
Hannan-Quinn criter.	10.992	11.226	11.253

Graph 3 illustrates the roots of the AR and MA polynomials within the ARIMA model framework. The positioning of AR roots is crucial for determining the stability of the AR component, which is confirmed when all roots lie within the unit circle. Similarly, the placement of MA roots plays a significant role in model stability, with invertibility being essential for precise estimation and interpretation. The stability of the ARIMA model is essential for analyzing ALCE data, emphasizing the importance of thorough validation of model assumptions and meticulous interpretation of results to support informed decision-making in environmental science and policy domains.

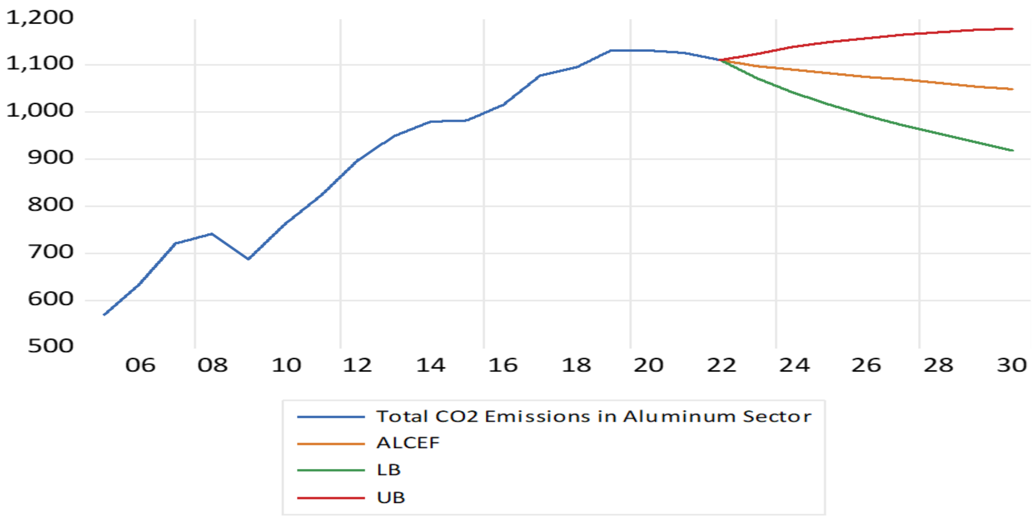
Graph 3. ALCE: Inverse Roots of AR/MA Polynomial(s).



**Derived through the utilization of the Eviews software application.*

The graphical depiction in Graph 4 presents historical ALCE data and projections from 2006 to 2030, with actual emissions depicted by the blue line and forecasted emissions by the orange line (ALCEF), alongside uncertainty boundaries indicated by the green (LB) and red (UP) lines. Historically, ALCE demonstrated a consistent upward trajectory until around 2022, indicative of industrial influences. However, post-2022 forecasts anticipate a decline in ALCE, potentially influenced by environmental regulations and technological advancements. It is forecasted that if the trajectory persists according to the present trend, by 2030, notwithstanding the augmentation in yearly production and consumption, there will be a 6% decrease in CO_2 emissions compared to the levels observed in 2022.

Graph 4. ALCE: Forecasting.



*Derived through the utilization of the Eviews software application.

The presence of uncertainty bounds emphasizes the need for cautious policymaking and adaptive measures within the industry. These projections have implications for environmental sustainability, policy development, and industrial strategies, underscoring the importance of vigilance and adaptation in achieving emission reduction goals within the aluminum sector.

DISCUSSION

Mathematical forecasting offers a means to approximate future outcomes based on current trends, although exact figures may not always be attainable within this approach. Furthermore, various factors beyond mathematical models can significantly impact the socio-economic landscape. Based on the CRU report, there is a forecasted surge in demand for aluminum, projected to rise by 40% by the year 2030 (Alfed, 2022).

In the absence of significant technological advancements, the anticipated surge in aluminum demand is expected to necessitate a substantial boost in production, consequently leading to a parallel rise in carbon emissions. The majority of carbon emissions are typically released during the energy production phase. The life-cycle greenhouse gas emissions linked to one metric ton of primary aluminum are estimated to be approximately 14.7 tons of CO_2-equivalent (Peng, Ou, Yan, & Wang, 2019). Transitioning to renewable energy sources such as solar, wind, and hydroelectric power is essential for curtailing CO_2 emissions in the global aluminum industry. This change not only lessens the carbon footprint associated with energy-intensive processes but also fosters sustainability and environmental stewardship within the sector. By investing in renewable energy technologies and embracing eco-friendly practices, aluminum producers can make significant strides in combatting climate change and promoting a greener future for the planet.

Another potential scenario to consider is the implementation of inert anode technology during the aluminum production process. The adoption of inert anode technology represents a substantial stride in mitigating carbon waste during the electrolysis phase, consequently elevating the sustainability credentials of aluminum manufacturing. This breakthrough not only reduces environmental footprint but also enhances resource utilization and operational efficiency across the sector (Hasanov, 2023). The future sustainability of the aluminum industry hinges on two key elements: the evolution of the renewable energy sector and the integration of innovative technologies. These factors are instrumental in guiding the industry toward greater environmental responsibility, facilitating reductions in carbon emissions, and fostering a more sustainable approach to aluminum production.

CONCLUSIONS

This research utilized ARIMA models to examine and forecast CO2 emissions within the aluminum sector. Through unit root tests, it was determined that two differencing operations were necessary to achieve data stationarity. Analysis of the correlogram helped identify appropriate ARIMA models, with the AR(1)MA(1) model selected based on diagnostic evaluation criteria. The estimated ARIMA model effectively captured historical CO2 emission trends and projected emissions up to 2030, revealing an anticipated decrease in emissions after 2022, likely driven by environmental regulations and advancements in technology. Following a thorough diagnostic process, the AR(1)MA(1) model emerged as the most suitable for forecasting CO2 emissions. This model attained an R-squared value of 0.948, indicating its capability to explain nearly 95% of the variability in the CO2 emission data. Additionally, the Hannan-Quinn criterion, a metric assessing model simplicity, favored the AR(1)MA(1) model over alternative specifications. The forecast analysis results indicate that if the current trend persists, there will be a 6% reduction in the volume of CO2 emitted from the global aluminum sector by the year 2030.

REFERENCES

1. Alfed (2022). CRU report expects aluminium demand to rise 40% by 2030. https://alfed.org.uk/wp-content/uploads/2023/10/CRU-SummaryReport-for-IAI.pdf
2. Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In 2014 UKSim-AMSS 16th international conference on computer modelling and simulation (pp. 106-112). IEEE. DOI: 10.1109/UKSim.2014.67
3. Berker A. (2022). Understand your aluminum emissions. https://www.carbonchain.com/blog/understand-your-aluminum-emissions
4. Box, G. E. P., & Jenkins, G. M. (1970). Time Series Analysis: Forecasting and Control. San Francisco, CA: Holden-Day.
5. Cheng, J., Deng, H., Sun, G., Guo, P., & Zhang, J. (2020). Application of ARIMA model in financial time series in stocks. In Artificial Intelligence and Security: 6th International Conference, ICAIS 2020, Hohhot, China, July 17–20, 2020, Proceedings, Part I 6 (pp. 232-243). Springer International Publishing. https://doi.org/10.1007/97
6. Ciacci, L., Eckelman, M. J., Passarini, F., Chen, W. Q., Vassura, I., & Morselli, L. (2014). Historical evolution of greenhouse gas emissions from aluminum production at a country level. Journal of Cleaner Production, 84, 540-549. https://doi.org/10.1016/j.jclepro.2014.03.062
7. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.
8. Dritsaki, M., & Dritsaki, C. (2020). Forecasting European Union CO2 emissions using autoregressive integrated moving average-autoregressive conditional heteroscedasticity models. International Journal of Energy Economics and Policy, 10(4), 411-423.
9. Hasanov, R. I. (2023). Towards a sustainable future in aluminium production: environmental and economic benefits of revolutionary inert anode technology. Journal of Sustainability Science and Management, 18(10), 176-186. http://doi.org/10.46754/jssm.2023.10.012
10. IAI (2023). Greenhouse Gas Emissions – Aluminium Sector. https://international-aluminium.org/statistics/greenhouse-gas-emissions-aluminium-sector/
11. IEA (2023). Tracking Aluminium. https://www.iea.org/energy-system/industry/aluminium
12. Li, Z., Han, J., & Song, Y. (2020). On the forecasting of high-frequency financial time series based on ARIMA model improved by deep learning. Journal of Forecasting, 39(7), 1081-1097. https://doi.org/10.1002/for.2677
13. Liu, G., & Müller, D. B. (2012). Addressing sustainability in the aluminum industry: a critical review of life cycle assessments. Journal of Cleaner Production, 35, 108-117. https://doi.org/10.1016/j.jclepro.2012.05.030
14. Lotfalipour, M. R., Falahi, M. A., & Bastam, M. (2013). Prediction of CO2 emissions in

Iran using grey and ARIMA models. International Journal of Energy Economics and Policy, 3(3), 229-237.

15. Ning, L., Pei, L., & Li, F. (2021). Forecast of China's carbon emissions based on Arima method. Discrete Dynamics in Nature and Society, 2021, 1-12.
16. Nyoni, T., & Mutongi, C. (2019). Modeling and forecasting carbon dioxide emissions in China using Autoregressive Integrated Moving Average (ARIMA) models.
17. Pao, H. T., Fu, H. C., & Tseng, C. L. (2012). Forecasting of CO2 emissions, energy consumption and economic growth in China using an improved grey model. Energy, 40(1), 400-409.
18. Peng, T., Ou, X., Yan, X., & Wang, G. (2019). Life-cycle analysis of energy consumption and GHG emissions of aluminium production in China. Energy Procedia, 158, 3937-3943.
19. Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.
20. Sharma, S., Mittal, A., Bansal, M., Joshi, B. P., & Rayal, A. (2023). Forecasting of carbon emissions in India using (ARIMA) time series predicting approach. In International Conference on Renewable Power (pp. 799-811). Singapore: Springer Nature Singapore.
21. Vafin, A. (2020). Forecasting macroeconomic indicators for seven major economies using the ARIMA model. Sage Science Economic Reviews, 3(1), 1-16. https://doi.org/10.17613/j3b4-h115