International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(3), 17-22.

Primary Aluminium Production and Energy Intensity: Long-Run Dynamics Explored through the ARDL Approach

Jamil I. Safarov[1,2], Ramil I. Hasanov[2,3,4]*, Arzu Safarli[5]

[1]Azerbaijan Technological University, Ganja, Azerbaijan, [2]Azeraluminium LLC, Ganja, Azerbaijan, [3]Mingachevir State University, Mingachevir, Azerbaijan, [4]Western Caspian University, Baku, Azerbaijan, [5]Azerbaijan Technical University, Baku, Azerbaijan.
*Email: ramil.hasanov@azeraluminium.com

Received: 27 November 2024 **Accepted:** 10 March 2025 **DOI:** https://doi.org/10.32479/ijeep.18660

ABSTRACT

The escalating global demand for aluminum has highlighted various environmental challenges associated with its production, with energy consumption emerging as the predominant factor. Aluminum production is inherently energy-intensive, necessitating a thorough understanding of the relationship between energy consumption and production efficiency to enhance sustainability across both economic and environmental dimensions. It is particularly crucial as the industry faces increasing pressure to minimize its environmental impact while simultaneously meeting growing global demand. This study examines the long-term dynamics between global primary aluminum production and energy intensity from 1980 to 2023 using the Autoregressive Distributed Lag (ARDL) approach. This econometric method facilitates a detailed examination of the temporal interactions between these two pivotal variables. The analysis reveals a significant inverse relationship, where a 1-unit reduction in smelting energy intensity correlates with an approximate 10.76-unit increase in primary aluminum production. This finding underscores the critical importance of improving energy efficiency within the aluminum sector as a strategy to foster higher production while concurrently reducing energy consumption. Additionally, the study highlights the significance of technological advancements and process optimization in mitigating energy intensity, reinforcing their role in fostering sustainable production practices.

Keywords: Primary Aluminum Production, Energy Intensity, Econometrics, Time-Series, Energy Efficiency, Sustainability
JEL Classifications: Q40, O13, L69, C22

1. INTRODUCTION

The growing global demand for aluminum, often regarded as the metal of the future, has resulted in a substantial expansion of primary aluminum production. According to the International Aluminum Institute, global aluminum production reached 70.7 million metric tonnes in 2023, reflecting a considerable rise from 52.3 million metric tonnes a decade prior (IAI, 2024). China dominated the primary aluminum production market, surpassing all other producers with an output of approximately 41 million metric tonnes (SRD, 2024). Countries involved in aluminum production are actively working to enhance their annual output to meet the growing global demand.

The mechanical properties of aluminum make it highly advantageous for industrial applications. Its lightweight nature, durability, and enhanced strength and hardness through various alloys have positioned it as a leading material in the industrial sector. These characteristics have also established aluminum as a sustainable and environmentally friendly metal of the future. However, a critical challenge lies in the substantial energy required for its initial production, resulting in notable eco-economic impacts. Historically, aluminum production was exceedingly energy-intensive, consuming approximately 17,000 kWh of electricity/tonne (Claisse, 2016).Over the past decade, advancements in technology have reduced this energy requirement significantly, with modern and upgraded electrolytic aluminum production facilities consuming less than 12,750 kWh/tonne (Peng et al., 2022). Currently, the global average energy consumption for aluminum production stands at approximately 14 megawatts/tonne.

Aluminum is an essential material for various technologies integral to the energy transition, but it also constitutes a significant source of carbon dioxide emissions. According to the International Energy Agency (IEA), the aluminum industry was responsible for approximately 270 million tonnes of direct CO2 emissions in 2022, representing around 3% of global industrial CO_2 emissions (Simon and Vass, 2023). However, over the past decade, the global average direct emissions intensity of aluminum production has seen a moderate reduction, decreasing at an average annual rate of nearly 2%.This reduction highlights the industry's ongoing efforts to enhance energy efficiency and mitigate its environmental impact.

Technological innovations play a crucial role in achieving sustainable production across various industrial sectors. Specifically, advancements in artificial intelligence, computer control, and robotics are delivering significant eco-economic benefits to a wide range of manufacturing industries (Mao et al., 2019; Safarov et al., 2024; Lee et al., 2022).Several projects aim to evaluate different path planning algorithms for automating the navigation of fluoride feeder vehicles within the aluminum industry, with the objective of developing a solution that identifies the optimal route between arbitrary starting and finishing points on a 2D map (Boscarato, 2021). Studies have also explored several technological innovations aimed at reducing energy consumption and enhancing sustainable efficiencies, which are closely aligned with the topic at hand(Gupta and Basu, 2019; Kermeli et al., 2015). Overall, technological innovations serve as a critical driver for the advancement of green manufacturing practices within the aluminum industry.

The primary aluminum production process is highly energy-intensive, and understanding the relationship between energy consumption and production efficiency is essential for enhancing sustainability within the industry. Energy efficiency serves as a fundamental factor in the eco-economic viability of primary aluminum production, particularly when aligned with green standards. The main aim of this study is to critically examine the two pivotal factors of aluminum production and energy consumption, within a sector of considerable global strategic significance. The research aims to evaluate current trends and empirical findings in relation to these factors. By examining these dynamics, the study contributes to the broader discussion on energy efficiency in manufacturing industries, with a particular focus on the aluminum sector, where technological advancements and energy optimization are pivotal for long-term sustainability. The insights derived from this research are expected to offer significant policy and operational implications for industry stakeholders, supporting efforts to achieve a balance between economic growth and environmental responsibility.

2. LITERATURE REVIEW

As the research focuses on a particular industry, the majority of scientific studies on the topic have been conducted by experts within the field. Research on this specific subject remains relatively scarce compared to more prominent areas of study. Nonetheless, several significant contributions have been made to scientific literature. Nunez and Jones (2016) identified alumina refining and electrolysis as the primary sources of greenhouse gas emissions in aluminium production, with electricity, particularly coal-based energy in China, playing a significant role. The International Aluminium Institute (IAI) stresses the importance of transparent environmental reporting and the inclusion of Chinese production data to enhance the precision of global aluminium impact assessments. The authors utilized comprehensive data from the International Aluminium Institute (IAI) to provide robust life cycle inventory (LCI) data for life cycle assessment (LCA) practitioners, thereby supporting material and design decisions with the most current environmental information. Paraskevas et al. (2016) sought to quantify and compare the environmental impact of primary aluminium production across 29 major countries, taking into account variations in technology, electricity, and heat mixes. Using Life Cycle Assessment methods, the analysis reveals substantial geographic differences in impact per unit mass, influenced by specific production technologies and energy inputs. The study provides a detailed assessment of each country's primary impact factors for the year 2012.

Abbas et al. (2024) examined the long-term and causal relationships between metallic minerals production, renewable energy consumption, GDP growth, financial development, and urbanization on CO_2 emissions in China from 1977 to 2021, utilizing the IPAT framework alongside various econometric techniques. The results indicate that metallic minerals production, GDP growth, and urbanization exert a positive impact on CO_2 emissions, whereas renewable energy consumption and financial development contribute to emissions reduction. The study recommends the adoption of metal recycling and the deployment of low-carbon technologies to alleviate environmental effects. Camara (2023) investigated the relationship between bauxite mining and economic growth in Guinea, employing both autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) models with annual data spanning from 1986 to 2020. The findings reveal that bauxite production has a positive effect on Guinea's economic performance, significantly influencing GDP and GDP per capita in the short term. However, these effects diminish in significance over the long term.

Sustainable development and the efficient utilization of energy are key research priorities worldwide. These aspects are especially critical for the aluminum industry, where advancements in energy efficiency play a vital role in enhancing sustainability (Gulaliyev et al., 2020; Rusiadi et al., 2024). Haraldsson and Johansson (2020) explored the effects of energy efficiency measures in primary aluminium production, specifically examining primary energy use, greenhouse gas (GHG) emissions, and energy and CO_2 costs. The study finds that substantial savings can be realized through measures such as vertical electrode cells, inert anodes with wettable cathodes, and direct carbothermic reduction. The most significant GHG emission reductions depend on the region's energy mix. The authors recommend combining vertical electrode cells with other energy-saving technologies for optimal GHG reduction, while achieving similar cost savings to direct carbothermic reduction, and emphasize the potential for carbon-neutral aluminium production with the appropriate technological innovations. Peng et al. (2019) assessed the energy consumption and GHG emissions from both primary and recycled aluminium production in China, comparing the findings with those from the U.S. The study reveals that China's primary aluminium production consumes approximately twice the energy and emits twice the GHGs compared to the U.S., primarily due to its reliance on coal-powered electricity. Additionally, the study underscores the environmental advantages of recycling aluminium, which consumes significantly less energy and produces far fewer GHG emissions, advocating for the promotion of the recycling sector and the use of low-carbon electricity in aluminium production. Similar outcomes have been observed in several other research studies examining the relationship between primary aluminum production and energy consumption (Lucio et al., 2013; Paraskevas et al., 2016; Pedneault et al., 2021).

3. DATA AND METHODOLOGY

This research examines the long-term association between Primary Aluminium Production and Smelting Energy Intensity. The analysis is grounded in high-quality, comprehensive datasets obtained from reputable sources, ensuring the reliability and robustness of the findings. The primary dataset is sourced from the International Aluminium Institute (IAI), renowned for its extensive and accurate industry-specific data on primary aluminium production and energy intensity. To provide a broader analytical context, supplementary data from globally recognized institutions have been incorporated, including:

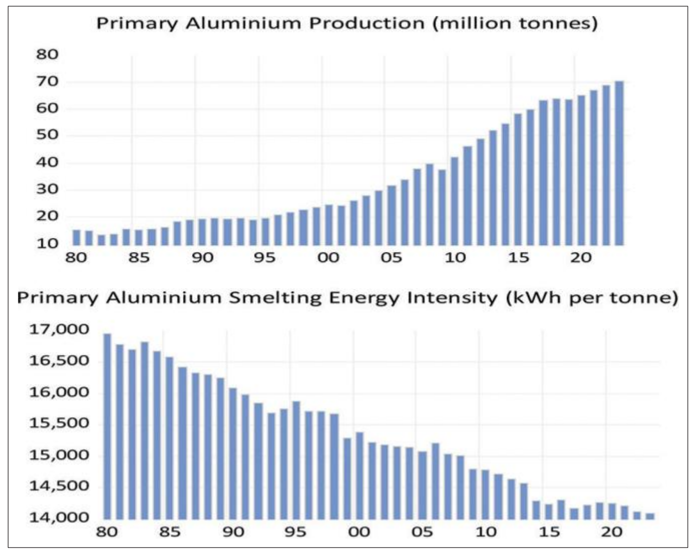
- The Aluminum Association (AA, 2021) - offering valuable insights into global aluminium industry practices and energy consumption trends.
- European Aluminium (EA, 2024) - providing detailed reports and statistical evaluations on aluminium production and energy efficiency, with a primary focus on Europe.
- International Aluminium Journal (IAJ, 2024) - contributing scholarly analyses and up-to-date information on global developments within the aluminium sector.

The variables utilized in this study are as follows: Primary Aluminium Production (PAP), quantified in metric tons, denotes the total production of primary aluminium during the study period. Smelting Energy Intensity (SEI), expressed in megawatt-hours per metric ton (KWh/ton), measures the energy consumption per unit of aluminium produced, serving as a key indicator of energy efficiency trends in the smelting process. Figure 1 depicts the trends in primary aluminum production and smelting energy intensity from 1980 to 2023. Aluminum production displays a continuous upward trajectory, indicative of rising industrial demand and activity. Meanwhile, smelting energy intensity shows a pronounced reduction, reflecting significant progress in technological innovation and energy efficiency within the production process.

Table 1 highlights the variability and skewness observed in both PAP and SEI. The higher standard deviation of PAP indicates considerable variation in production levels across regions. Both variables exhibit positive skewness, signifying that a small number of entities demonstrate substantially higher production or energy intensity levels compared to the majority. Additionally, the kurtosis values for PAP and SEI suggest moderately heavy-tailed distributions, indicating the presence of some outlier values.

To enhance the efficiency and interpretability of the econometric analysis, the data variables are subjected to logarithmic transformation. Figure 2 presents the trends of the logarithmically transformed data in two graphs. The LPAP graph exhibits an upward trajectory, reflecting a consistent increase in primary

Figure 1: Trends in primary aluminum production and smelting energy intensity (1980–2023)



Data Source: International Aluminium Institute (IAI)

Figure 2: Logarithmic trends in data variables

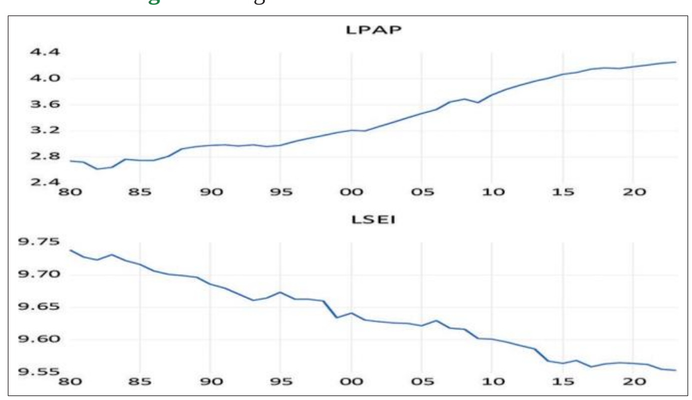


Table 1: Descriptive statistics of data variables

Statistic	PAP	SEI
Mean	34.237	15351.2
Median	25.406	15213.5
Maximum	70.581	16951
Minimum	13.544	14091
Std. Dev.	18.833	880.531
Skewness	0.676	0.178
Kurtosis	1.947	1.840

aluminum production over time. In contrast, the LSEI graph displays a downward trajectory, signifying a reduction in energy intensity during the smelting process. The logarithmic transformation compresses the data range and linearizes exponential patterns, facilitating a clearer visualization of the rates of change in production and energy efficiency.

The ARDL (Autoregressive Distributed Lag) model is particularly well-suited for this analysis due to its ability to accommodate variables with mixed integration orders (i.e., I(0) and I(1)) without the need for prior differencing. Additionally, it facilitates the simultaneous estimation of both long-run and short-run dynamics, thereby providing a holistic view of the interrelationship between the variables. The ARDL model is specified as follows to capture the relationship among the selected data variables:

$$\Delta PAP_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta PAP_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta SEI_{t-j} + \varphi_1 PAP_{t-1} + \varphi_2 SEI_{t-1} + \varepsilon_t \quad (1)$$

To verify the stationarity of the variables and determine their integration order, unit root tests such as the Augmented Dickey and Fuller (1979) and Phillips and Perron (1988)tests are performed. ADF and PP unit test procedures ensure that the variables are integrated of order I(0) or I(1), as the ARDL approach is not applicable to variables integrated of order I(2).

The long-run coefficients are obtained directly from the ARDL model estimation. Following this, the error correction model (ECM) is developed to investigate the short-run dynamics, as outlined by:

$$\Delta PAP_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta PAP_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta SEI_{t-j} + \lambda ECM_{t-1} + \varepsilon_t \quad (2)$$

To ensure the reliability and robustness of the ARDL model, several diagnostic tests are conducted. The Breusch-Godfrey LM test is utilized to identify autocorrelation in the residuals (Breusch, 1978; Godfrey, 1978). Heteroskedasticity is assessed through the Breusch-Pagan test or White test (Breusch and Pagan, 1979). Furthermore, the CUSUM and CUSUMSQ tests are performed to evaluate the model's stability over time. Collectively, these diagnostic tests validate the accuracy and consistency of the ARDL model.

The ARDL econometric approach offers a comprehensive framework for investigating the complex interplay between aluminium production and energy efficiency, addressing both short-term fluctuations and long-term equilibrium relationships.

4. EMPIRICAL RESULTS

Table 2 presents the findings of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for the variables LPAP and LSEI. The results indicate that LPAP is stationary at levels, as reflected in the statistical significance of both ADF and PP tests. In contrast, LSEI is non-stationary at levels but achieves stationarity after first differencing, signifying that it is integrated of order one, I(1). These findings are fundamental for selecting the appropriate lag structure and validating the cointegration assumption in the ARDL model applied to these variables.

Table 3 displays the coefficient covariance matrix, which highlights the relationships between the estimated coefficients for LPAP(−1), LSEI, and the constant term in the model. The diagonal elements represent the variances of the individual coefficients, while the off-diagonal elements show the covariances between pairs of coefficients. This matrix is a critical tool for statistical inference, as it aids in assessing the uncertainty and precision of the model's parameter estimates.

Table 4 reports an F-statistic value of 10.33852, which surpasses the upper critical bounds value (I(1)) at the 1% significance level (5.58), confirming the presence of a long-run cointegrating relationship between LPAP and LSEI. The coefficient of LSEI in the levels equation is −10.7635, indicating that a 1-unit decrease in LSEI is associated with an approximate 10.76-unit increase in LPAP, assuming other factors remain constant. This negative relationship implies that reductions in energy intensity correspond to higher aluminium production, potentially due to advancements in energy efficiency or smelting technology. The t-statistic for LSEI is −6.8572, with a P-value of 0.0000, demonstrating that the coefficient is highly statistically significant. These findings provide strong evidence for a long-term relationship where decreasing energy intensity is linked to increased aluminium production.

Table 2: Unit root test

The Augmented Dickey-Fuller (ADF)		
Variable	**Level**	**1st Difference**
LPAP	−2.716 (0.235)	−5.447 (0.000***)
LSEI	−3.301 (0.079)	−8.372 (0.000***)
Phillips-Perron (PP)		
Variable	**Level**	**1st Difference**
LPAP	−2.725 (0.232)	−5.433 (0.000***)
LSEI	−1.093 (0.709)	−8.436 (0.000***)

***Significant at 1% level

Table 3: Coefficient covariance matrix

Variables	LPAP(-1)	LSEI	C
LPAP(−1)	0.00349682.	0.03237302.	−0.3236954.
LSEI	0.03237302.	0.31508592.	−3.1449233.
C	−0.3236954.	−3.1449233.	31.3919699.

Table 4: ARDL model (1,0) long run and bounds test

F-Bounds Test				
K	**Value**	**Significance**	**Lower Bound**	**Upper Bound**
1	10.338	10%	3.02	3.51
	1	5%	3.62	4.16
		1%	4.94	5.58
Levels Equation				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**P-value**
LSEI	−10.763	1.569	−6.857	0
C	107.4396	15.254	7.043	0

In Table 5, the error correction term (LPAP(−1)) in the conditional error correction regression has a coefficient of −0.0973. This coefficient reflects the speed at which deviations from the long-run equilibrium are corrected following a short-term disturbance. The negative sign, combined with a borderline P-value of 0.1078, suggests that the coefficient is marginally significant. It implies that approximately 9.73% of the deviation from the long-run equilibrium is corrected in each period, indicating a relatively slow adjustment process toward equilibrium.

Table 6 presents the results of the Breusch-Godfrey Serial Correlation LM Test and the Breusch-Pagan-Godfrey Heteroskedasticity Test. The Breusch-Godfrey test checks for serial correlation in the model's residuals, with results showing no significant evidence of correlation based on the F-statistic, ObsR-squared, and their respective probabilities. The Breusch-Pagan-Godfrey test assesses homoscedasticity, and the results suggest that the assumption of constant variance in the errors is not rejected at conventional significance levels. In conclusion, the diagnostic tests indicate that the model's residuals exhibit no significant serial correlation or heteroskedasticity.

Table 5: Error correction regression

ECM Regression				
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**P**
CointEq(-1)*	−0.097266	0.017044	−5.706692	0
Statistics				
R-squared	**Log likelihood**	**Akaike info criterion**	**Schwarz criterion**	**S.E. of regression**
0.092	74.109	−3.400	−3.359	0.043

Table 6: Diagnostic test results

Test	Statistic	Value	Probability
Breusch-Godfrey Serial Correlation LM Test	F-statistic	1.738167	0.1895
	Obs*R-squared	3.60404	0.165
Heteroskedasticity Test: Breusch-Pagan-Godfrey	F-statistic	2.216278	0.1222
	Obs*R-squared	4.289646	0.1171
	Scaled explained SS	5.699702	0.0579

Figure 3: Results of CUSUM and CUSUM of squares tests for model stability

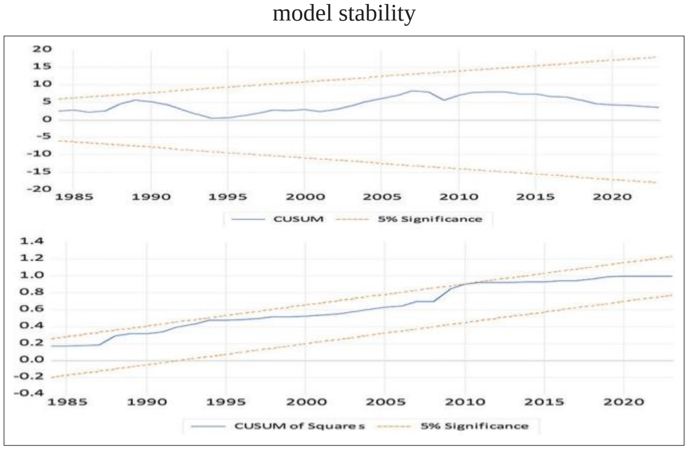


Figure 3 illustrates the results of two diagnostic CUSUM tests: one assessing parameter stability and the other evaluating variance stability. The CUSUM test monitors the cumulative sum of recursive residuals to detect potential structural breaks or shifts in the model's parameters over time. In a similar vein, the CUSUM of Squares test examines the cumulative sum of squared recursive residuals to assess the stability of the model's error variance. Should either test exceed the 5% significance boundaries, it would suggest the presence of parameter instability or variations in error variance. However, the results indicate that neither test statistic surpasses the significance thresholds, thereby confirming the overall stability of the model.

Recent scholarly investigations have examined analogous methodological approaches and industry-specific contexts. For example, Hasanov et al. (2024) utilized the ARDL model to analyze the relationship, uncovering a significant long-term association wherein a 1% increase in global aluminum production corresponds to a 0.843% reduction in accident rates.

The findings from our research demonstrate a significant inverse relationship between energy intensity and production levels, indicating that greater energy efficiency is connected to higher aluminum production. This relationship can be attributed to technological advancements, where innovations in smelting processes reduce the energy required per ton of aluminum, facilitating more cost-effective and increased production. Additionally, economic and sustainability initiatives may contribute by enabling production growth while simultaneously mitigating environmental impacts. It is essential for governments and industry stakeholders to encourage investments in energy-efficient technologies, as these investments can yield both environmental benefits and economic advantages by fostering increased production.

5. CONCLUSION

This research offers valuable insights into the long-term relationship between primary aluminium production (PAP) and smelting energy intensity (SEI) through the application of the ARDL econometric model. The findings reveal a notable inverse correlation, highlighting that reductions in energy intensity are correlated to increased aluminium production. Specifically, a 1-unit decrease in SEI corresponds to an approximate 10.76-unit increase in PAP. Furthermore, the long-run correlation is supported by the F-bounds test, which further corroborates the existence of a significant relationship between the variables. Diagnostic tests, including unit root, cointegration, and the error correction model (ECM), confirm the robustness and validity of the results. Moreover, the negative and statistically significant coefficient for SEI emphasizes the potential for technological advancements to enhance energy efficiency while simultaneously boosting production.

These findings carry significant implications for policymakers and industry stakeholders, stressing the importance of continued investment in energy-efficient technologies to foster sustainable aluminium production. Such investments not only stimulate economic growth but also contribute to environmental sustainability by reducing energy consumption and mitigating carbon emissions.

Future research could examine the dynamic interactions between additional key factors influencing aluminium production, such as technological developments and regulatory frameworks, to refine these conclusions and provide further guidance for industry strategies.

REFERENCES

AA. (2021), Data & Resources. Aluminum Association. Available from: https://www.aluminum.org/data-resources

Abbas, Q., Hongxing, Y., Shahbaz, M., Ramzan, M., Fatima, S. (2024), Metallic minerals production and environmental sustainability in China: Insights using ARDL bounds testing and wavelet coherence approaches. Resources Policy, 92, 105037.

Boscarato, M. (2021), Development of Path Planning Algorithms for AGVs in the Primary Aluminium Industry [UNIVERSITÀ DEGLI STUDI DI PADOVA]. Available from: https://thesis.unipd.it/handle/20.500.12608/22991

Breusch, T.S. (1978), Testing for autocorrelation in dynamic linear models. Australian Economic Papers, 17(31), 334-355.

Breusch, T.S., Pagan, A.R. (1979), A simple test for heteroscedasticity and random coefficient variation. Econometrica, 47(5), 1287.

Camara, M. (2023), Bauxite mining and economic growth in Guinea over the period 1986–2020: Empirical evidence from ARDL and NARDL approaches. Mineral Economics, 36(1), 157-179.

Claisse, P. A. (2016). Alloys and nonferrous metals. ICivil Engineering Materials, 2016, 361–368.

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.

EA. (2024), About Aluminium. European Aluminium. Available from: https://european-aluminium.eu/about-aluminium

Godfrey, L.G. (1978), Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. Econometrica, 46(6), 1293.

Gulaliyev, M.G., Mustafayev, E.R., Mehdiyeva, G.Y. (2020), Assessment of Solar Energy Potential and Its Ecological-Economic Efficiency: Azerbaijan Case. Sustainability, 12(3), 1116.

Gupta, A., Basu, B. (2019), Sustainable primary aluminium production: Technology status and future opportunities. Transactions of the Indian Institute of Metals, 72(8), 2135-2150.

Haraldsson, J., Johansson, M.T. (2020), Effects on primary energy use, greenhouse gas emissions and related costs from improving energy end-use efficiency in the electrolysis in primary aluminium production. Energy Efficiency, 13(7), 1299-1314.

Hasanov, R.I., Giyasova, Z., Musayeva, R., Zemri, B.E., Kazimova, A. (2024), Examining the relationship between primary aluminium production and accident rates. International Journal of Safety and Security Engineering, 14(5), 1403-1408.

IAI. (2024), Primary Aluminium Production. International Aluminium Institute. Available from: https://international-aluminium.org/statistics/primary-aluminium-production

IAJ. (2024), Energy efficiency. International Aluminium Journal. Available from: https://www.aluminium-journal.com/topic/energy-efficiency

Kermeli, K., Ter Weer, P.H., Crijns-Graus, W., Worrell, E. (2015), Energy efficiency improvement and GHG abatement in the global production of primary aluminium. Energy Efficiency, 8(4), 629-666.

Lee, C.C., Qin, S., Li, Y. (2022), Does industrial robot application promote green technology innovation in the manufacturing industry? Technological Forecasting and Social Change, 183, 121893.

Lucio, N.R., Lamas, W.Q., de Camargo, J.R. (2013), Strategic energy management in the primary aluminium industry: Self-generation as a competitive factor. Energy Policy, 59, 182-188.

Mao, S., Wang, B., Tang, Y., Qian, F. (2019), Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. Engineering, 5(6), 995-1002.

Nunez, P., Jones, S. (2016), Cradle to gate: life cycle impact of primary aluminium production. The International Journal of Life Cycle Assessment, 21(11), 1594-1604.

Paraskevas, D., Kellens, K., Van de Voorde, A., Dewulf, W., Duflou, J.R. (2016), Environmental impact analysis of primary aluminium production at country level. Procedia CIRP, 40, 209-213.

Paraskevas, D., Van de Voorde, A., Kellens, K., Dewulf, W., Duflou, J.R. (2016), Current status, future expectations and mitigation potential scenarios for China's primary aluminium industry. Procedia CIRP, 48, 295-300.

Pedneault, J., Majeau-Bettez, G., Krey, V., Margni, M. (2021), What future for primary aluminium production in a decarbonizing economy? Global Environmental Change, 69, 102316.

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.

Peng, T., Ren, L., Du, E., Ou, X., Yan, X. (2022), Life cycle energy consumption and greenhouse gas emissions analysis of primary and recycled aluminum in China. Processes, 10(11), 2299.

Phillips, P.C.B., Perron, P. (1988), Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Rusiadi, R., Hidayat, M., Rangkuty, D.M., Ferine, K.F., Saputra, J. (2024), The influence of natural resources, energy consumption, and renewable energy on economic growth in ASEAN region countries. International Journal of Energy Economics and Policy, 14(3), 332-338.

Safarov, J., Tistsov, E., Jatsun, S. (2024), Robotic Device for Active-Passive Mechanotherapy of the Ankle Joint. In: 2024 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM). p818-823.

Simon, R., and Vass, T. (2023), Energy System, Industry, Aluminium. IEA. Available from: https://www.iea.org/energy-system/industry/aluminium

SRD. (2024), Major Smelter Producers of Primary Aluminum in 2023. Statista Research Department. Available from: https://www.statista.com/statistics/215986/major-aluminum-producers