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Sustainability in the Gigafactory: A Data-Driven Forecast of Non-renewable vs. Renewable Energy

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***Abstract*—The establishment of the Gigafactory is a crucial milestone in the worldwide effort to achieve a sustainable energy future. The Gigafactory employs sustainable energy sources to manufacture a battery pack. The implementation of an environmentally conscious and sustainable energy system within the gigafactory has been found to yield favorable outcomes. Non-renewable energy sources pose a significant threat to the environment due to their carbon dioxide emissions. The primary challenge is to minimize carbon dioxide emissions through the use of nonrenewable energy sources during the next ten years. To do this, it is imperative to comprehend the projected global consumption of nonrenewable energy over the next decade. Following the completion of the prediction of the level of consumption for the subsequent ten years, governments will be able to ascertain whether the consumption of renewable energy or nonrenewable energy will be increasing or declining. Predictive models are necessary to determine the anticipated energy consumption levels for future decades in areas where there is a noticeable rise in energy consumption. The study employed the Automatic ARIMA model, a predictive model commonly utilized for forecasting purposes, to anticipate the levels of nonrenewable energy consumption and the absorption of energy from renewable sources. This prediction was carried out using the R package forecast. The research demonstrates that the implementation of Auto ARIMA on historical energy consumption data enables the projection of future non-renewable energy and renewable energy consumption for ten years. Based on the forecast, the consumption level of nonrenewable energy surpasses that of sustainable energy sources.**

***Keywords*—** Gigafactory, non-renewable, renewable, energy, prediction, ARIMA model

I. Introduction

Implementation of nonrenewable energy sources and the subsequent release of carbon emissions have been identified as prominent factors in the exacerbation of global climate change. The process of burning fossil fuels, such as coal, oil, and natural gas, during the process of energy generation, results in the emission of carbon dioxide and various other greenhouse gases into the Earth's atmosphere. As to the findings of the World Economic Forum [1], the global carbon emissions resulting from the combustion of fossil fuels have attained a record-breaking peak in the year 2022, amounting to 36.6 gigatonnes of carbon dioxide (GtCO2) in Figure 1. Greenhouse gases can retain thermal energy, resulting in the elevation of the Earth's surface temperature and consequent ramifications on the environment and society.

The elevation in the concentration of carbon dioxide in the atmosphere and other greenhouse gasses is a contributing factor to the greenhouse effect, resulting in the amplification of the planet's global temperature. The phenomenon of global warming is associated with a range of negative outcomes, including the escalation of sea levels, the occurrence of severe weather events, alterations in patterns of precipitation, and transformations in ecosystems and habitats for various species of wildlife. The alterations mentioned have the potential to negatively impact biodiversity, agriculture, and water resources, hence presenting potential hazards to human well-being, livelihoods, and overall societal equilibrium. The mitigation of adverse consequences associated with non-renewable energy necessitates the imperative pursuit of sustainable and renewable energy alternatives. An encouraging endeavor in this regard is the notion of a gigafactory. A gigafactory refers to a substantial manufacturing facility that is specifically designed to produce renewable energy goods, such as batteries and solar panels, on a significant scale [2].

The presence of these factories contributes to the reduction of costs associated with renewable energy technology by capitalizing on economies of scale, hence enhancing their accessibility and affordability for widespread implementation. Gigafactories have the potential to make a substantial contribution towards mitigating the negative impacts associated with non-renewable energy sources, as they facilitate the development and adoption of clean energy technology. For example, the establishment of a gigafactory dedicated to the production of lithium-ion batteries has the potential to facilitate the extensive integration of electric vehicles, thereby leading to a substantial decrease in reliance on fossil fuels within the transportation industry. Gigafactories have a substantial impact on facilitating the widespread production of renewable energy solutions, thereby fostering the shift towards a more sustainable and ecologically conscious energy system. Consequently, the utilization of gigafactories helps mitigate the adverse consequences linked to non-renewable energy sources.

The paper is arranged as follows. The Literature Review is shown in Section II, and Section III provides a summary of the Data Collection. The Method used for this research is explained in Section IV, and the Result is highlighted in Section V. In Section VI covered the Discussion of the whole work and in the final section, Section VII, there added Conclusions about the research.

II. Literature Review

Hakanu et al. used an [3] ARDL and Toda-Yamamoto causality analysis. This study concentrates its attention on examining the interplay among energy consumption, economic growth, and climate

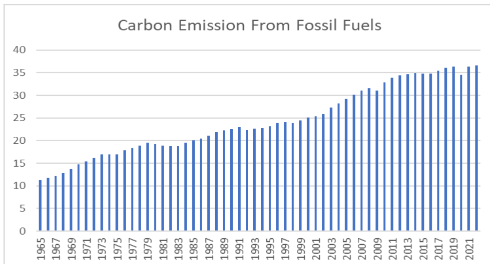

Fig. 1. Bar chart shows the global carbon emission from fossil fuels

change in Turkey, and the intent of this study, it aims to determine empirical evidence of causality and gain insight into the effects of energy use on climate change within the context of Turkey. The Dogan et al. suggest [4] that the adoption of renewable energy sources has a mitigating effect on environmental deterioration, whereas the utilization of nonrenewable resources is associated with increased emissions of CO2.

Bulut et al. found [5] results indicating a positive correlation between CO2 emissions and both nonrenewable and use of natural energy sources in Turkey. Additionally, the present study posits that, despite its capacity to provide electricity with reduced emissions, renewable energy in isolation falls short of meeting the objectives set by policymakers in terms of CO2 emission reduction. Apart from this, This study emphasizes the necessity of implementing enduring energy policies in Turkey to effectively mitigate CO2 emissions. Shang, Yunfeng, et al. implement [6] the ARDL limits test to examine the cointegration and estimate the long-term and short-term impacts of climate policy uncertainty on the demand for renewable and nonrenewable energy in the United States. However, the author's findings of this study carry significant policy implications with regard to the reduction of nonrenewable energy consumption and the promotion of renewable energy utilization in the United States, specifically through the implementation of climate policies.

Inglesi-Lotz et al. [7] applies a panel analysis methodology to estimate the factors influencing emissions of CO2 compounds in the top 10 energy-generating countries in Sub-Saharan Africa. The analysis covers the period from 1980 to 2011 and the results indicate that a higher proportion of nonrenewable energy sources in the energy composition will lead to an escalation in air pollution levels, whereas the utilization of renewable energy sources has a beneficial impact on air quality. Saudi, M. H. M. et al. have identified [8] a persistent detrimental impact of renewable energy consumption on environmental degradation in some areas, however, other has discovered a notable inverse connection between the use of sources of environmentally friendly energy and the release of carbon.

Ragazzi et al. assess [9] the environmental effects of both renewable and nonrenewable energy sources, focused on the production of heat and electricity, which is the main source of CO2 emissions in the European Union. This study investigates the practicality of implementing district heating systems that utilize thermo-chemical processes to convert various fuel sources, including wood, coal, municipal solid waste, refuse-derived fuel, biomass-derived waste, and solid recovered fuel. The quantities of municipal solid waste (MSW) and residual municipal solid waste (RMSW) produced in the chosen regions were determined using population size as a determining factor. Utilizing the lower heating values (LHVs) of the fuels under examination as well as emission factors for sulfur dioxide (SO2), carbon monoxide (CO), and carbon dioxide (CO2), environmental evaluations were carried out. One billion tons of carbon dioxide (CO2) are released during the production and use of coal-based energy in EU Member states. This amounts to around one-fourth of all CO2 emissions inside the EU.

To explore the variables affecting carbon dioxide (CO2) emissions in countries that are members of the Organization for Economic Co-operation and Development (OECD), Shafiei et al. [10] presented the STIRPAT model. Regression-based, the STIRPAT model takes into account a wide range of independent variables, including population size, GDP per capita, industrialization, GDP contribution from the service sector, population density, and urbanization. To evaluate how these factors affect CO2 emissions, these variables are employed. To accommodate for differences in the economic structure of various countries, the model also includes other factors, such as the kind of energy source used.

Khan et al. proposed [11] a machine learning-based hybrid model approach, combining multilayer perceptron (MLP), support vector regression (SVR), and CatBoost, for power forecasting. Additionally, The hybrid technique that was developed demonstrated encouraging outcomes in the prediction of energy consumption for both renewable and nonrenewable power sources. Zaidi et al. examine [12] the respective contributions of energy consumption from environmentally friendly sources and energy consumption from sources that are not renewable to emissions of dioxide of carbon (CO2) compounds in Pakistan. The analysis employs an auto-regressive distributive lag (ARDL) model utilizing data spanning the years 1970 to 2016. They got the result which is economic growth exerts a beneficial influence on carbon dioxide (CO2) emissions within the framework of the renewable energy model, however, such a relationship is not observed in the non-renewable energy model. Al Araby et al. found [13] that a panel data estimation utilizing data from EU-15 nations from 1995 to 2010 suggests that the development of renewable energy sources may be capable of effectively reducing carbon emissions. However, A panel regression model was constructed to investigate the relationships between carbon dioxide emissions and a variety of factors. These factors include the GDP per capita, the value added by the industrial sector to the GDP, the percentage of renewable electricity output, the percentage of nuclear electricity output, and the percentage of coal electricity output. Ben Mbarek et al. proposed a method [14] that investigates the static characteristics of the variables and the causative connections among economic growth, energy utilization, the release of carbon dioxide pollution, and the utilization of energy from renewable sources in Tunisia. This approach also highlights the importance of strategy in Tunisia's effective utilization of green energy enablers, a lesson that can be applied to other developing nations seeking to preserve their natural resources and develop an eco-friendly economy.

III. Data Collection

To make a forecast based on the data regarding the use of various sources of energy, both renewable and nonrenewable, we utilized the auto-arima model. The information that was used for this study was obtained from the website known as Our World in Data [15]. This website has information on World Wide Non-Renewable Energy, which is based on global fossil fuels consumption statistics, as well as information on Renewable Energy, which is based on total per capita energy consumption data from 1965 to 2022 for solar, wind, and hydro consumption.

A. Data Preprocessing and Visualization

It's open sources of data, Renewable energy data have four features which are Entity, Code, Year, and Renewables Per Capita(kWh-equivalent). The data have several country individual year energy consumption values. Create another subset to take just a particular year and sum all the country's energy consumption values. After that, We drop the Entity and Code column. In this way, preprocessing Renewable Energy data and similarly, preprocessing nonrenewable energy fossil fuel consumption data both are shown in Table I. Figure 2 visualizes both energy consumption data.

TABLE I
GLOBAL NON-RENEWABLE ENERGY AND RENEWABLE ENERGY CONSUMPTION DATA (1965 TO 2022)

Year	Renewable Energy (kWh - equivalent)	Non-Renewable Energy (Twh-equivalent)
1965	168123.4	40440.53
1966	173869.9	42545.57
..	..	..
2021	623017.2	136585.13
2022	628970.1	137236.67

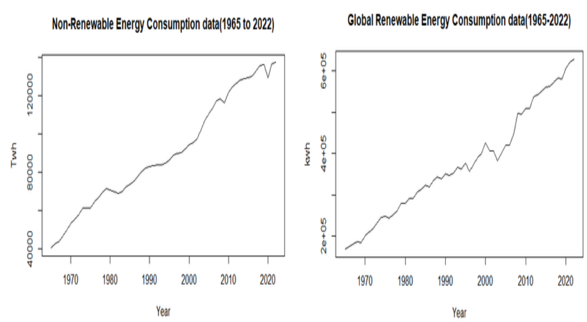

Fig. 2. Visualization of non-renewable energy and renewable energy consumption data (1965 to 2022) by plot chart

IV. METHOD

ARIMA is a part of a Machine Learning algorithm. Theoretically, the most popular models for predicting future values of time series data are ARIMA models. The ARIMA model gained prominence through the work of Box and Jenkins [16]. The three order parameters that make up the ARIMA model are p, d, and q. Parameters d for differencing order, q for average shifting terms, and p for the number of autoregressive terms that make up the model. p represents the order of the autoregressive (AR) component, d the order of the differencing (D) component, and q the order of the moving average (MA) component. An autoregressive (AR) model compares the current value of the variable of interest to its previous values. It can be phrased as follows if y_t is modeled using the AR process:

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \quad (1)$$

Another type of linear model is the MA. In MA, the output or variable of interest is modeled using its own erroneously predicted values for both the present and the past. When expressed in terms of errors, it can be written as follows:

$$y_t = \mu + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

So, mathematical equation of ARIMA(p,q) is as follows:

$$y_t = \delta + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (3)$$

Apart from this, The process of choosing the best parameters for an ARIMA (AutoRegressive Integrated Moving Average) model can be complicated and is typically time-consuming. AutoARIMA is an automated and data-driven approach to time series forecasting [17]. When utilizing ARIMA models for time series forecasting, it is necessary to specify several parameters, including the number of moving average terms (q), the order of differencing (d), and the number of autoregressive terms (p). Manually identifying these factors can be difficult and time-consuming, frequently requiring trial and error. Implemented the AutoARIMA model in R package forecast [18] [19] and used RStudio Software.

V. RESULT

To identify the best possible ARIMA model fit for univariate time series, this package is used. It does this by returning the best ARIMA model as determined by the Akaike Information Criterion (AIC), its small-sample equivalent (AICc), or the Bayesian Information Criterion (BIC) value [20], [21]. The model specifications and relevant AIC values are listed in Table II. Based on AIC, the best models of Non-Renewable energy and Renewable energy are marked.

TABLE II
BEST MODEL SELECTION USING AUTO.ARIMA FOR NON-RENEWABLE ENERGY AND RENEWABLE ENERGY

Non-Renewable Energy		Renewable Energy	
Model	AIC	Model	AIC
ARIMA(2,1,2)	Inf	ARIMA(2,1,2)	Inf
ARIMA(0,1,0)	1030.767	ARIMA(0,1,0)	1235.744
ARIMA(1,1,0)	1032.748	ARIMA(1,1,0)	1236.5
ARIMA(0,1,1)	1032.745	ARIMA(0,1,1)	1236.588
ARIMA(0,1,0)	1060.342	ARIMA(0,1,0)	1255.322
ARIMA(1,1,1)	Inf	ARIMA(1,1,1)	1238.38
Best Model	ARIMA (0,1,0)	Best Model	ARIMA (0,1,0)

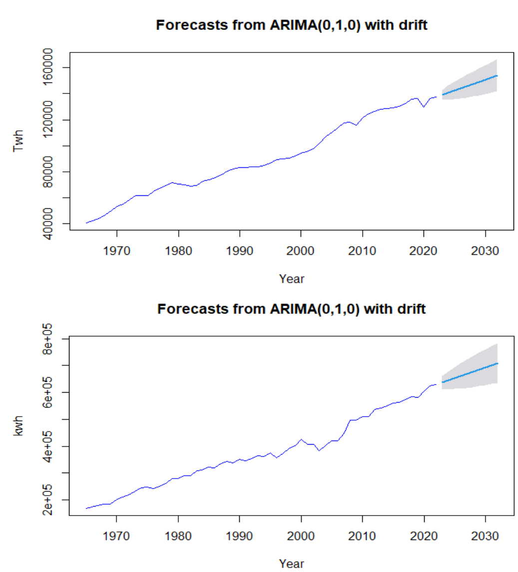

Fig. 3. Decadal forecast of non-renewable energy(Top) and renewable Energy (below) consumption value

TABLE III
FORECAST OF NON-RENEWABLE AND RENEWABLE ENERGY CONSUMPTION

Non-Renewable Energy				Renewable Energy			
Years	Forecast (TWh)	Lo 95	Hi 95	Years	Forecast (KWh)	Lo 95	Hi 95
2023	138934.8	135031.6	142838.1	2023	637055.1	613488.0	660622.2
2024	140633.0	135113.0	146153.1	2024	645140.2	611811.3	678469.1
2025	142331.2	135570.6	149091.8	2025	653225.2	611811.3	694044.6
2026	144029.4	136222.9	151835.9	2026	661310.2	614176.0	708444.4
2027	145727.6	136999.6	154455.5	2027	669395.2	616697.6	722092.9
2028	147425.7	137864.7	156986.7	2028	677480.3	619752.9	735207.6
2029	149123.9	138796.9	159451.0	2029	685565.3	623212.6	747918.0
2030	150822.1	139782.0	161862.2	2030	693650.3	626992.5	760308.2
2031	152520.3	140810.5	164230.0	2031	701735.4	631034.1	772436.7
2032	154218.4	141875.3	166561.6	2032	709820.4	635294.7	784346.1

TABLE IV
BOX-LJUNG TEST RESULTS FOR RESIDUALS

Non-Renewable Energy		Renewable Energy	
lag	p-value	lag	p-value
5	0.9877	5	0.7487
10	0.9317	10	0.3695
20	0.7114	20	0.3952
30	0.9023	30	0.6264

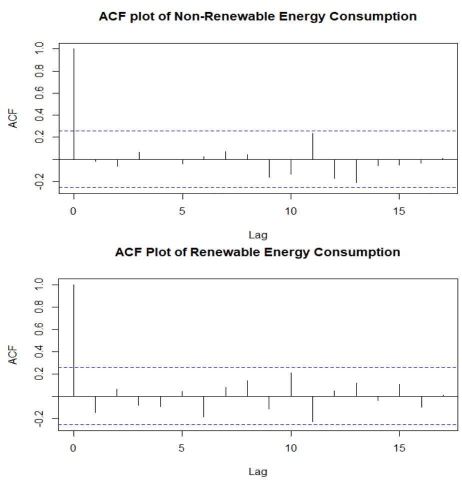

Fig. 4. ACF plots of non-renewable energy and renewable energy consumption

Following the Selection of the Best Model, the best-fit model is used to forecast the consumption of Non-Renewable and Renewable energy globally. Based on nonrenewable and renewable energy consumption data, predictions for the next ten years are made. Table III displays the projected values for the upcoming decade, taking into account a 95% confidence interval (CI). The table also includes the lowest and highest values for both confidence intervals. Apart from this, Figure 3 shows plot charts of the forecast, where the blue line indicates the forecast value and dark gray shows the 95% confidence interval. For example, it is anticipated that nonrenewable energy will be a trend that will increase the number of consumption values during the next ten years. In the case of nonrenewable energy, the confidence interval of 95% indicates that an increase in the number of watt-hours consumed would range from a minimum of 135031.6 (Twh) to a high of 142838.1 (Twh). For the same reason, the lower bound for renewable energy would be

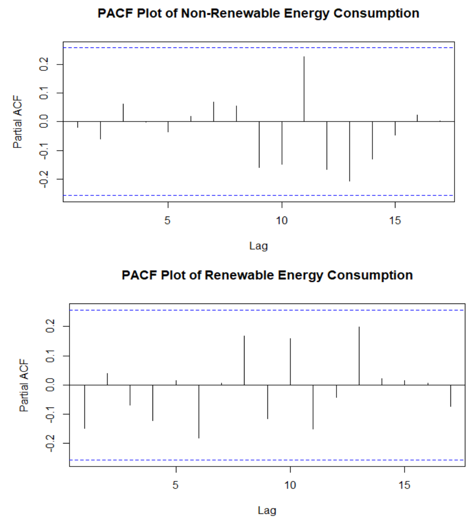

Fig. 5. PACF plots of non-renewable energy and renewable energy consumption

613488.0 kilowatt hours, while the upper bound would be 660622.2 kilowatt hours. The ACF and PACF plots in Figure 4 and Figure 5 demonstrate the absence of notable autocorrelations, suggesting that the residuals exhibit characteristics similar to white noise. To evaluate the adequacy of the fitted ARIMA models, the Box-Ljung examination was performed on the residuals to assess the presence of any significant autocorrelation. The test was applied for lags up to 30, and the results are summarized in Table 4 for both energies. Table 4 demonstrates that the p-values for both models at all lags were higher than the significance parameters of 0.05. This assertion is supported by the data. This suggests that the ARIMA models can appropriately reflect the underlying patterns in the data, as it demonstrates that we are unable to reject the null hypothesis that there is no autocorrelation in the residuals by a significant margin.

VI. DISCUSSION

Furthermore, it is time to devote more attention to the concept of the gigafactory, as well as limit environmental pollution and refrain from using energy sources that are not renewable. The objective of this study was to predict the future values of energy consumption around the world. Now more than ever, it is essential for every industry sector, whether it be high-tech or non-high-tech, to make use of renewable energy. As a result of the projections for the next ten years, governments will be able to determine whether the consumption of renewable energy or nonrenewable energy will be increasing or decreasing. This is why it is necessary to do this study. On top of that, they can adjust their strategies accordingly. The ARIMA model was utilized to forecast the energy consumption level for the following 10 years, drawing on historical data from previous years. Based on the ARIMA model, it can be observed that there is an upward trend in nonrenewable energy consumption levels, which are also shown to be higher than the levels of renewable energy consumption. The ARIMA model is being employed to forecast the nonrenewable energy consumption levels for the years 2022 to 2031. The current consumption level stands at 137236.67 Twh, while the projected consumption level for 2031 is estimated to be 154218.4 Twh. There is a significant likelihood that carbon emissions will increase over the next decade, posing substantial harm to the environment. Contrary to this, it is observed that the consumption level of renewable energy is lower than that of nonrenewable energy. Specifically, in the year 2022, the consumption level of renewable energy is recorded as 628970.1 Kwh, and it is projected to increase to 709820.4 Kwh during the next decade. As a result, the fact that the residuals do not exhibit any substantial autocorrelation, which was verified by the Box-Ljung test, provides additional evidence that the ARIMA models are effective for forecasting the consumption of energy sources. Due to the absence of autocorrelation, it appears that the models have successfully captured the essential patterns and relationships that are present within the time series data. Having a more precise estimation of the amount of energy that will be required can result in improved procurement strategies and possibly lower overall energy expenses. It is because of this cost-effectiveness that key performance indicators (KPIs) connected to financial performance are directly contributed to, which in turn makes the operations of the Gigafactory more sustainable and economically viable. Because it makes it simpler to use energy more efficiently and promotes the use of renewable sources, the Auto ARIMA forecast model is in line with the objectives of sustainability. The Gigafactory's commitment to environmentally friendly procedures and lowering its carbon footprint is highlighted by this alignment, which has a positive influence on key performance indicators (KPIs) relating to environmental impact.

VII. Conclusions

In the Global world, the majority of the Industry sector needs electricity to run the factories. The majority of electricity produced by non-renewable energy like fossil fuels which creates a negative impact on the environment and also be isn't sustainable. Apart from that, Renewable energy is sustainable and also environmentally friendly. Unfortunately, the ARIMA model predicts next 10 years will be a chance for a massive increase in nonrenewable energy consumption compared to renewable energy. On the other hand, Gigafactory utilizes renewable energy to produce electricity which is much more environmentally friendly and sustainable. So, if the industry as a whole can use the gigafactory idea to make electricity from renewable sources, there is a very good chance that greater amounts of renewable energy will be used than nonrenewable energy. In conclusion, our study set out to examine how sustainability is evaluated closely in the context of a gigafactory. To do so, we utilized a data-driven strategy to forecast the equilibrium between non-renewable and renewable energy sources. The contribution that this study makes to the ongoing conversation about environmentally responsible practices in large-scale industrial settings, in particular those that are at the forefront of technological innovation like Gigafactories, is the driving force behind the significance of this research. Furthermore, our findings highlight the significance of data-driven forecasting in informing decision-making processes that are informed by relevant information. By making use of data that is both accurate and up-to-date, gigafactories can proactively adjust their energy portfolios so that they are in line with the objectives of global sustainability. This research contributes to the ongoing conversation on environmentally responsible manufacturing techniques, thereby setting the way for a future in which gigafactories will serve as models of environmental responsibility, energy efficiency, and innovation. In the future, every energy field will need to use Gigafactories or the idea of Gigafactories to cut down on carbon emissions and nonrenewable energy use.

References

[1] "Global co2 emissions from fossil fuels hit a record in 2022." https://www.weforum.org/agenda/2022/11/global-co2-emissions-fossil-fuels-hit-record-2022/, Accessed 2023-10-29.

[2] "Inside tesla's 100

[3] A. Hakanu and G. Mustafa, "Climate change caused by renewable and non-renewable energy consumption and economic growth: A time series ardl analysis for turkey," *Renewable Energy*, 2022.

[4] E. Dogan and I. Ozturk, "The influence of renewable and non-renewable energy consumption and real income on co2 emissions in the usa: Evidence from structural break tests," *Environmental Science and Pollution Research*, vol. 24, pp. 10846–10854, 2017.

[5] U. Bulut, "The impacts of non-renewable and renewable energy on co2 emissions in turkey," *Environmental Science and Pollution Research*, vol. 24, pp. 15416–15426, 2017.

[6] G. G. M. K. M. Y. Shang, D. Han and B. K. Sahoo, "The impact of climate policy uncertainty on renewable and non-renewable energy demand in the united states," *Renewable Energy*, vol. 197, pp. 654–667, 2022.

[7] R. Inglesi-Lotz and E. Dogan, "The role of renewable versus non-renewable energy in the level of co2 emissions: A panel analysis of sub-saharan africa's big 10 electricity generators," *Renewable Energy*, vol. 123, pp. 36–43, 2018.

[8] O. S. Mohammad H. M. Saudi and N. H. Jabarullah, "The role of renewable, non-renewable energy consumption, and technology innovation in testing environmental kuznets curve in malaysia," *International Journal of Energy Economics and Policy*, vol. 9, no. 1, pp. 299–307, 2019.

[9] G. I. M. Ragazzi and S. I. Cioranu, "Assessment of environmental impact from renewable and non-renewable energy sources," *International Journal of Energy Production and Management*, vol. 2, no. 1, pp. 8–16, 2017.

[10] S. Shafiei and R. A. Salim, "Non-renewable and renewable energy consumption and co2 emissions in oecd countries: A comparative analysis," *Energy Policy*, vol. 66, pp. 547–556, 2014.

[11] S. J. L. D. H. K. J. Y. K. P. W. Khan, Y. C. Byun and H. S. Park, "Machine learning-based approach to predict energy consumption of renewable and nonrenewable power sources," *Energies*, vol. 13, no. 18, p. 4870, 2020.

[12] H. H. S. A. H. Zaidi, F. Danish and F. M. Mirza, "The role of renewable and non-renewable energy consumption in co2 emissions: A disaggregate analysis of pakistan," *Environmental Science and Pollution Research*, vol. 25, pp. 31616–31629, 2018.

[13] N. S. L. Al Araby and D. M. Ibrahiem, "The impact of renewable and non-renewable energy on carbon dioxide emission: An empirical analysis for euro mediterranean countries," *International Journal of Energy Economics and Policy*, vol. 9, no. 6, pp. 103–108, 2019.

[14] K. S. M. Ben Mbarek and M. M. Rahman, "Renewable and non-renewable energy consumption, environmental degradation, and economic growth in tunisia," *Quality Quantity*, vol. 52, pp. 1105–1119, 2018.

[15] "Our world in data." https://ourworldindata.org/, Accessed 2023-10-29.

[16] G. P. E. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*. San Francisco: Holden Day, 1970.

[17] R. J. Hyndman and Y. Khandakar, "Automatic time series forecasting: The forecast package for r," *Journal of Statistical Software*, vol. 27, no. 3, pp. 1–22, 2008.

[18] *Package 'forecast'*. Available from: https://cran.r-project.org/web/packages/forecast/index.html.

[19] X. Wang, K. Smith, and R. Hyndman, "Characteristic-based clustering for time series data," *Data Mining and Knowledge Discovery*, vol. 13, pp. 335–364, 2006.

[20] G. Jain and B. Mallick, "A study of time series models arima and ets," 2017. Available at SSRN 2898968.

[21] "Using the r-package to forecast time series: Arima models and application," in *INTERNATIONAL CONFERENCE Economic Social Challenges and Problems 2010 Facing Impact of Global Crisis*, 2010.