Prediction of the Growth of Renewable Energies in the European Union using Time Series Analysis

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Abstract: - The whole world is affected by climate change and renewable energy plays an important role in combating climate change. To add to the existing precarious situation, the current political events such as the war in Ukraine mean that fossil raw materials such as oil and gas are becoming more and more expensive in the raw material markets. This paper presents the current state of renewable energies in Germany and Europe. Using data from the past 56 years, the predictive models ARIMA and Prophet are used to find out if the conversion to renewable energies and the elimination of fossil raw materials in the energy sector can be achieved in the EU. The results are compared with the target of the EU in 2030 and a long-term outlook until 2050 will be provided.

Key-Words: - Renewable energy, climate change, fossil fuels, wind energy, hydropower, solar energy, bioenergy, Logistic Regression, time series forecasting, ARIMA, Prophet.

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1 Introduction

Climate change is the long-term changes in climate patterns of the Earth, which has wide-ranging and potentially catastrophic impacts on the environment. We can observe shifts in weather patterns, rising global temperatures, the increase in extreme weather events rising sea levels, melting ice caps and glaciers, more frequent and severe heatwaves, droughts, floods, and disruptions to ecosystems. It also poses risks to human health, food security, and economies. The primary driver of contemporary climate change is the increase in greenhouse gas emissions, primarily carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O), from human activities, such as burning fossil fuels (coal, oil, and natural gas), deforestation, and industrial processes, [1], [2], [3], [4].

Climate change is a huge challenge of the 21st Century and the most important action item is to reduce greenhouse gas emissions from the energy sector. A transition from conventional energy sources like oil, gas, and coal to renewable energies like solar-, hydro-, bio-, or wind energy is required. Renewable energy is energy that is derived from sources that are naturally replenished and are considered environmentally sustainable. These sources include solar energy, wind energy, hydropower, geothermal energy, and biomass. These sources produce little to no greenhouse gas emissions during electricity generation, making them a crucial part of efforts to combat climate change. They also reduce air and water pollution, decrease dependence on fossil fuels, and create jobs in the renewable energy industry. Renewable energy technologies include solar panels (photovoltaic), wind turbines, hydroelectric dams, geothermal power plants, and bioenergy facilities, [5], [6], [7], [8].

Integrating renewable energy into the energy mix involves building infrastructure, such as solar and wind farms, and developing energy storage solutions to address intermittency issues (i.e., the variability of renewable energy sources). The United Nations knows that and therefore declared the seventh sustainable development goal: affordable and clean energy, [9].

The European Union (EU) also recognized the necessity and set goals to increase the share of renewable energy in total energy consumption. According to the EU, the energy sector is responsible for more than 75% of the emissions in the EU and therefore it is the most important field to take action. For 2020 the EU target was to a share of renewable energy consumption of at least 20%. With 22% according to Eurostat's renewable energy statistics that goal was reached, [10]. Now for 2030, the target is to increase the share of renewable energy consumption to at least 32%, [11]. This target will be compared with the prediction models in this paper. The EU's long-term strategy for 2050 is an economy with net-zero greenhouse gas emissions, [12]. There is no renewable energy target for 2050 but a huge growth in renewable energy production is necessary to reach the long-term goal. The historical data can be analyzed and predict how the renewable energy share could develop in the long term.

This paper is arranged by adhering to the standard structure. The following section focuses on the related work done by different authors; section 3 provides information about the dataset and algorithms used in this research; the experimental results are presented in section 4 and section 5 covers the conclusions. Finally, the references are mentioned in the last section.

2 Review of Related Literature

The journey from fossil fuels to renewable energy is a long and costly process that cannot happen overnight. Nevertheless, it is becoming more and more important with increasingly dwindling resources. Renewable also called regenerative energies are collective terms. They can, as the name reflects, regenerate themselves independently and within a human time scale, [13]. This property represents an irreplaceable security for the sustainable energy supply. There are different forms of renewable energy sources such as solar and wind energy, hydropower, geothermal energy, and biomass, [2], [14].

According to a study by the Federal Statistical Office, in Q1 2022, 47.1% of the total energy requirement in Germany could already be fed into the power grid from renewable energies, [15]. At 30.1%, wind power is now one of the most important renewable energies, [15]. Wind power achieved its breakthrough in 1973 after government subsidies made it economically attractive, [16]. A distinction is made between onshore and offshore wind energy. Onshore refers to the wind turbines on land, offshore to those that are off the coast at sea. Wind turbines are used exclusively for electricity production and use the so-called lift principle for this purpose, which means that the wind flowing past sets the rotor blades in lift and thus in rotation. This rotating motion then generates electricity.

At 5.4%, biogas is one of the third most important renewable energies, [15]. A biogas plant has the primary purpose of generating electricity. For this purpose, biogas is produced in the biogas plant, which drives a motor to generate electricity. The biogas produced is a mixture of biomethane and carbon dioxide in particular. Strictly speaking, the designation bioenergy plant or bioelectricity plant is therefore more appropriate. Nevertheless, the production process is generally associated with the term biogas plant, [17]. It is generated in three overarching steps. First, the biological raw materials are stored then the raw materials are fed into the fermentation tanks, in which the fermentation process that releases the biogas takes place. Finally, the gas is converted into electricity or fed directly into it. In particular, the decomposition process and the generation of biogas is a natural process that also takes place in bogs, liquid manure pits, or, in particular, in the rumen of ruminants, [17].

In contrast to the two previously presented technologies, photovoltaics can not only be used to generate electricity. Solar energy can be used, for example, by means of solar collectors to generate heat. With the help of water vapor, it generates electricity within solar thermal power plants, or it is used to generate direct current through photovoltaic systems. However, solar radiation is subject to daily, seasonal, and regional fluctuations, [18]. This puts solar energy in second place with 6.3%, [15].

3 Material and Method

This section highlights the dataset used and the algorithms used to build various models in the present research work.

3.1 Materials Used

The data used for the underlying analysis is Renewable Energy dataset available as open data at "Our World in Data", [19]. There are a total of 17 tables in this dataset, and in most cases, data are available for the years 1965 to 2021. Occasionally, tables also contain only smaller time periods and show different data on the expansion and use of renewable energies around the world. For example, the generation of energy from wind, solar, hydro, geothermal, or biofuel energy is shown. The data is grouped by country or continent and by year. Also, data from the whole world can be retrieved because data are also grouped under the attribute world.

The tables "modern-renewable-prod.csv", "modern-renewable-energy-consumption" and "renewable-share-energy.csv" are used for the analysis. The table "modern-renewable-prod.csv" contains the energy produced in terawatt hours, divided among the different countries or continents per year. The single record here contains the energy production of the different types of renewable energy in terawatt-hours. The table “modern-renewable- energy-consumption” includes the consumed renewable energy in terawatt hours by energy type and by country/continent. The table "renewable-share-energy.csv" shows the share of renewable energies in the total energy consumption of the country. Here, too, a grouping per year and country or continent takes place.

3.2 Methods Used

To master the data processing, Python is used. Python is a programming language that has diverse application areas, [1], [2], [20]. With Python, machine learning, automation, or even web design can be realized. The project was realized in Google Colaboratory using the jupyter notebook for doing Python programming. All the necessary libraries like numpy, pandas, matplotlib, etc. were imported and necessary datasets were input for carrying out the exploratory analysis using line charts, pie charts, bar charts and scatter plots.

Several algorithms for conducting the predictive analytics were applied to data. These include, for example, Linear Regression, ARIMA, Exponential Smoothing, or LSTM. In this paper, the Autoregressive Integrated Moving Average (ARIMA) algorithm and the automatic forecasting procedure Prophet by Facebook are used, [21]. A detailed explanation of ARIMA and Prophet follows in the rest of the paper.

The Python modules that have been used to build the model are pandas, numpy, matplotlib, os, sklearn, statsmodel, pmdarima, math, pystan, and fbprophet.

4 Experiments and Results

There are four different categories and degrees of complexity for analytics as shown in Figure 1. The first one is descriptive analytics which can be used to analyze the data of the past and tell what happened. The second one is diagnostic analytics which goes deeper to find out why something happened. A further step is predictive analytics which uses various models to find out trends and patterns to predict what will happen in the future. The last stage is prescriptive analytics. It is the most complex one and here the tool would tell based on the results of predictive analytics what someone should do in the future to reach a goal, [22], [23].

In this paper, the focus lies on descriptive and predictive analytics. To discover the chosen dataset some descriptive analyses will be done first. The dataset was prepared for analysis and to help derive various insights. The original data file was downloaded to a database (Microsoft SQL Server 2017 Database) which made it easier to work as the original data was converted to a simple text file.

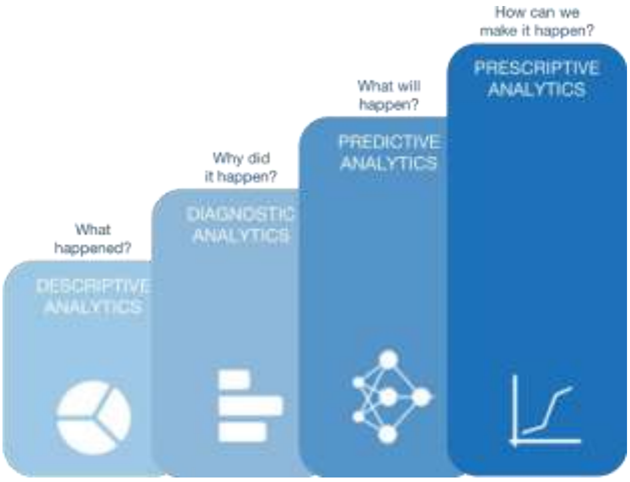

Fig. 1: Different analytics categories

4.1 Descriptive Analytics

First, the dataset is explored and different analyses with the German and EU data are carried out. It must be considered that the data of the EU contains the data of Germany.

Figure 2 shows the TWh generated within Germany. The years are shown on the X-axis and it ranges from the year 1965 to the year 2021. The Y-axis shows the generated energy in TWh. Over the years, the generated energy from water energy was mostly around 20 TWh. Sometimes it was less than 20 TWh, but sometimes even more than 20 TWh. Wind energy was the most promoted in Germany. Here, slightly less than 120 TWh was produced in 2021. In comparison, solar and other renewables produced only about 50 TWh. Wind power is very strongly developed in Germany. The reason for this is that Germany has a very large wind power area due to its proximity to the Alps in the south and the North Sea and Baltic Sea in the north, [24], [25].

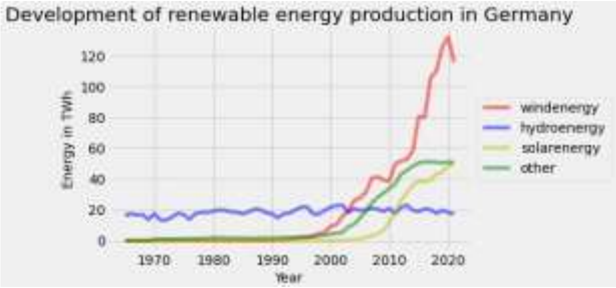

Fig. 2: Line chart of the German development

Within the EU, the picture is different for hydro energy as depicted in Figure 3. The production of renewable energies has increased here. Whereas in 1965 this was just over 200 TWh, in 2021 the amount is just under 350 TWh. Wind, solar, and other renewable energies show a similar picture as in the EU. Wind energy accounts for the largest share of renewables here, at just under 400 TWh. The solar and other renewable energies are, as in Germany, similarly high. When looking at the graph, it must of course also be noted that Germany has an influence on the graph on the development within the EU, as Germany is also part of the EU.

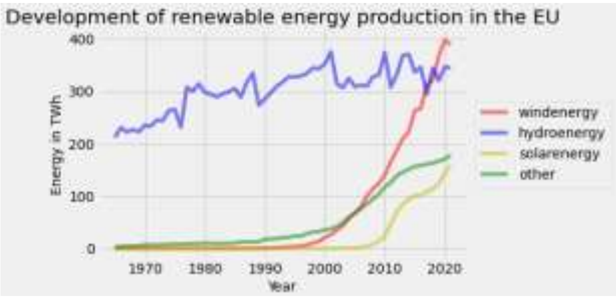

Fig. 3: Line chart of the development in the EU

Furthermore, Germany and Europe can be compared based on the produced renewable energy categories in the last year as presented in Figure 4. Germany produced 233.21 TWh of renewable energy in 2021. Half of that was produced by wind energy. The other half comes from solar energy (21%), hydro energy (7%), and other energy categories including bioenergy (22%).

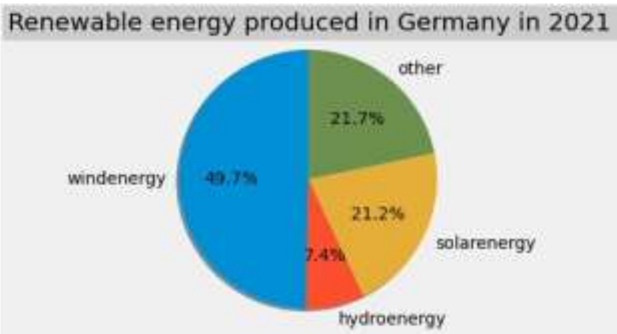

Fig. 4: Pie chart of the German production in 2021

Figure 5 shows that the EU with all 27 member states produced 1069 TWh of renewable energy in 2021. 36% of the produced energy came from wind. Compared to Germany a much larger amount originates from hydro energy. It has a share of 32% or 343.88 TWh in total. Solar energy is 15% and other sources are responsible for 17%.

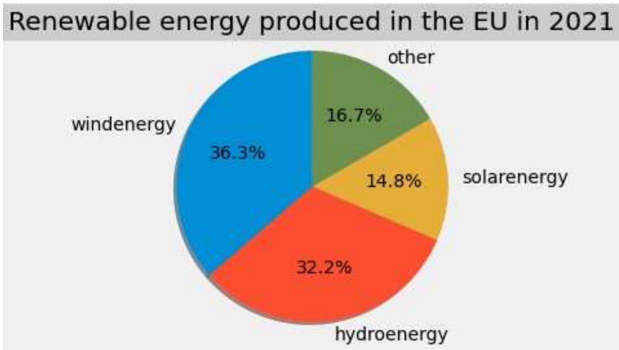

Fig. 5: Pie chart of the EU production in 2021

Figure 6 presents that Germany was the biggest producer of renewable energy in the EU in 2021 with 233.21 TWh. 21.82% of the total renewable energy production is provided by Germany. The next largest producers are Spain (124.2 TWh), France (120.46 TWh), Italy (115.85 TWh) and Sweden (115.19 TWh).

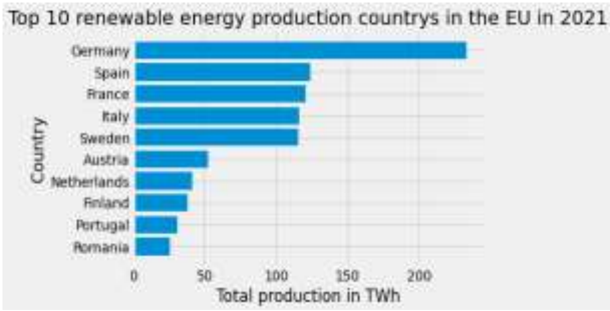

Fig. 6: Horizontal bar chart with the top 10 producers in the EU

Until now, only the production of renewable energy has been analyzed. The “Our World in Data” dataset also has data about renewable energy consumption. The production can be compared with the consumption in all 27 EU states. The most recent data are available for the year 2020. Figure 7 shows that all states consume almost exactly the amount of renewable energy they produce. As figured out earlier, Germany will be the biggest producer and consumer of renewable energy in 2020.

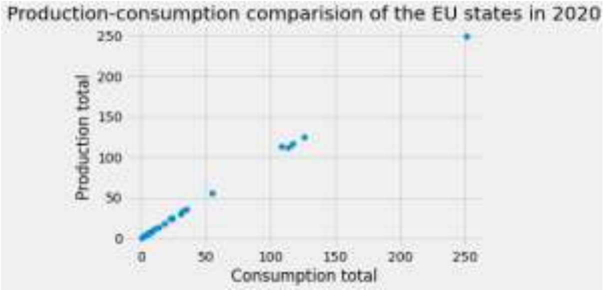

Fig. 7: Scatter Plot of the production and consumption of renewable energy

After a closer look at the different types of energy production and the producing countries, the share of renewable energy in total energy consumption can be considered. More precisely, the development of the share in the last decades from 1965 to 2020 in the EU will be analyzed. As shown in Figure 8, the data shows that the share started with a value of 6.4% in 1965 and dropped in the years afterward. It moved sideways until 2004. Since 2004 the percentage of renewable energy increased a lot and rose to almost 18% in 2020 according to the dataset.

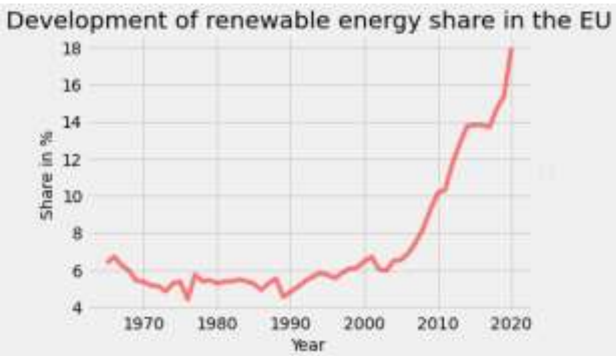

Fig. 8: Line chart of the renewable energy share in the EU

It must be mentioned that the dataset from "Our World in Data" doesn't match completely with the data cited in the Introduction, where it is said, that the EU has reached a share of 22% of renewable energy in 2020. It cannot be clearly stated which data are correct but the predictions will be done with the "Our World in Data" dataset.

4.2 Linear Regression Model

To get a first impression of how the future values could look a simple linear regression can be done. A linear regression 'is used to predict the value of a variable based on the value of another variable, [1], [2]. Figure 9 shows that the results of the linear regression are not very useful because the expected share in 2050 is still lower than the share in 2020 already was. The linear regression is too simple and not suitable for that case. More sophisticated models need to be implemented.

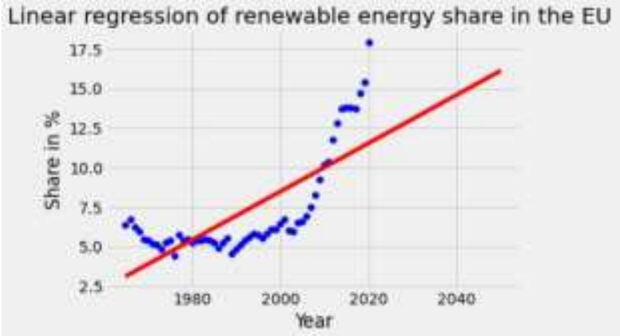

Fig. 9: Linear regression of the renewable energy share EU

4.3 ARIMA Model

One model for time series forecasting is ARIMA. It is a statistical model for time series forecasting (cf. Alam, 2022). It can be used for non-stationary time series, which means data with a steadily rising line like the renewable energy development of the EU.

ARIMA stands for Autoregressive Integrated Moving Average and firstly uses 'differencing to convert a non-stationary time series into a stationary one' (Alam, 2022). Then the future values are predicted with correlations and moving averages from the historical data. The model has three parameters: p, d, q

- p is the order of the autoregressive model (AR).
- d is the degree of differencing. It shows the number of differencing that is necessary to get a stationary time series.
- q is the order of the moving average model (MA)

To find out the best parameters for the model, the auto_arima function from the module prima is used. It calculates the best model for the present data.

```
Performing stepwise search to minimize aic
 ARIMA(2,2,2)(0,0,0)[0]             : AIC=98.012, Time=0.14 sec
 ARIMA(0,2,0)(0,0,0)[0]             : AIC=113.831, Time=0.02 sec
 ARIMA(1,2,0)(0,0,0)[0]             : AIC=99.955, Time=0.03 sec
 ARIMA(0,2,1)(0,0,0)[0]             : AIC=92.560, Time=0.04 sec
 ARIMA(1,2,1)(0,0,0)[0]             : AIC=94.448, Time=0.06 sec
 ARIMA(0,2,2)(0,0,0)[0]             : AIC=94.466, Time=0.05 sec
 ARIMA(1,2,2)(0,0,0)[0]             : AIC=96.067, Time=0.11 sec
 ARIMA(0,2,1)(0,0,0)[0] intercept   : AIC=inf, Time=0.14 sec

Best model:  ARIMA(0,2,1)(0,0,0)[0]
Total fit time: 0.620 seconds
```

Fig. 10: Calculation of the best ARIMA model parameters

The calculation of the best ARIMA model parameters is presented in Figure 10. Similarly, the best model has the parameters: ARIMA (0, 2, 1)

- p: 0. The order for the autoregressive model is 0.
- d: 2. Second-order differencing is required for this dataset.
- q: 1. The order of the moving average is 1.

In this paper, the model is used to predict the share of renewable energy in the EU until 2050. Figure 11 shows the result. The finished model predicts a value of 26.91% in 2030, 35.87% in 2040, and 44.83% in 2050. Compared with the EU target of at least 32% in 2030 the ARIMA model predicts that the goal won't be reached with the recent development. Net-zero greenhouse gas emissions in 2050 will neither be achieved with this development.

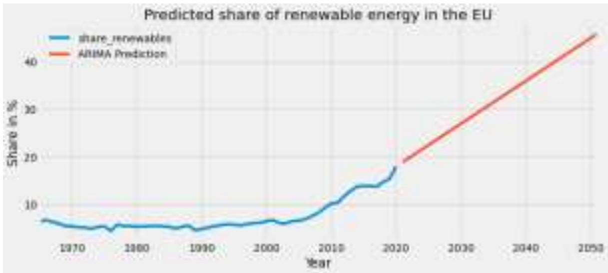

Fig. 11: Predicted development with ARIMA model

4.4 Prophet Model

Prophet is a forecasting procedure by Facebook. It can handle trends in the data as well as seasonality and holiday effects. The module is fast, fully automatic, and available in Python and R, [1]. The ARIMA model is used to forecast the development of renewable energy share in the total consumption until 2050. With the Prophet.make_future_dataframe function the prediction can be done.

The following percentages of the renewable energy share are predicted with Prophet:

- 2030: 23.10%
- 2040: 29.71%
- 2050: 36.21%

The lower and upper bound of the forecast is also drawn in the diagram. For example, for 2050, the lower bound of the forecast is 30.95% and the upper bound is 41.39%. This is the range in which the model estimates the value. The following line chart in Figure 12 shows the prediction.

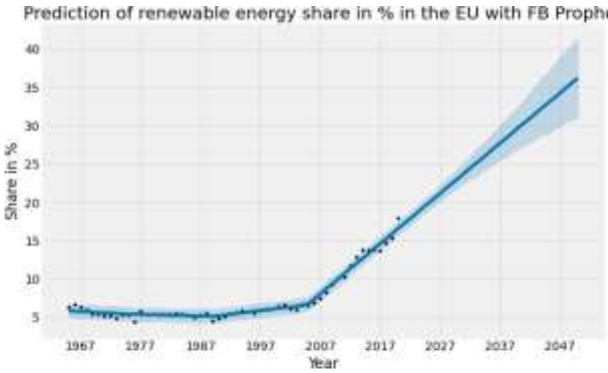

Fig. 12: Predicted development with FB Prophet

The Prophet model predicts lower values than the ARIMA model. The EU target of 32% is not reached and the forecast for 2050 is also lower.

5 Conclusion

Climate change and renewable energy are intimately connected topics that play a crucial role in addressing one of the most pressing global challenges of our time: mitigating climate change and reducing greenhouse gas emissions. Climate change is the biggest threat to the planet Earth as it has major impacts on humans and the environment. Emissions from the burning of fossil fuels play an important role in driving climate change which should give everyone a clear goal to expand renewable energy. Therefore, the main focus of the study is on the time series forecast and the analysis of the development of renewable energies in Europe. As the forecasts show, the political goals and target of a 32% share of renewables in total energy consumption by 2030 are tolerable. The ARIMA model predicts 26.91% coverage by 2030 with equal efforts. This value is 5.09% below the target value. Unfortunately, the analysis using the Prophet is not better, but even worse. A coverage of only 23.10% is predicted by 2030.

From the study, it can be summarized that the current investments and efforts to expand renewable energies are far from sufficient to achieve the short-term goal of 2030. But the even worse consequence is that if these goals are not achieved, the actual long-term goal of climate neutrality will be pushed further and further into the background.

The future work areas and research directions would be policy and regulatory analysis and technology assessment. The idea is to examine the existing policies, regulations, and international agreements related to renewable energy adoption and fossil fuel phase-out, as well as evaluate their effectiveness and identify potential barriers and opportunities for alignment with the UN timeline. In the future, there is a need to assess the state of renewable energy technologies, their scalability, and the potential for innovations in areas like solar, wind, hydropower, and energy storage, and investigate the technological challenges and opportunities in achieving a complete transition.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Neha Sharma and Jürgen Seitz, have contemplated the problem statement, as well as guided and monitored the research through out its journey
- Holger Kraenzle, Maximilian Rampp and Daniel Werner have together carried out the following tasks:
  1. Searching for the dataset
  2. Carring out the preprocessing task
  3. Did the exploratory data analysis
  4. Build the models

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Conflict of Interest

The authors have no conflicts of interest to declare.