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Evolution of Low-Carbon Energy Consumption in Türkiye, United Kingdom, and France: A Historical Perspective

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Abstract – This article provides a comprehensive summary of the historical development of low-carbon energy consumption in Türkiye, United Kingdom, and France, spanning from the past to the present. The transition to low-carbon energy sources is a crucial aspect of global efforts to mitigate climate change, and understanding the trajectories of these three nations offers valuable insights into regional variations and policy influences. In this study, future predictions were made regarding the low-carbon energy consumption of Türkiye, United Kingdom and France between 1965-2022 with the help of R-based Auto.Arima, TBATS, ETS and HOLT statistical models. Prediction results were evaluated with the Mean Absolute Percentage Error (MAPE) metric.

Keywords – Low-Carbon Energy, Time Series, R-Based Models

I. INTRODUCTION

Low carbon energy [1], [2] consumption refers to the utilization of energy sources and technologies that produce minimal greenhouse [3] gas (GHG) emissions, contributing to efforts to mitigate climate change and reduce environmental impact. The impact of low carbon energy consumption on the environment can be substantial and is generally positive.

Low-carbon energy is generally defined as the sum of nuclear and renewable resources. Renewable sources include hydropower, solar, wind, geothermal, wave and tidal, and bioenergy. This does not include traditional biofuels.

Türkiye: In the past, Türkiye heavily relied on fossil fuels, particularly coal, for its energy needs. However, in recent years, the country has shown a commitment to diversifying its energy mix and reducing carbon emissions. Türkiye has significantly increased its investment in renewable energy sources, such as wind and solar power. Government initiatives and incentives have played a pivotal role in fostering the growth of renewable energy projects. As a result, Türkiye has witnessed a notable rise in low-carbon energy consumption, with a focus on decreasing its dependence on traditional fossil fuels.

United Kingdom: UK has a long history of industrialization and fossil fuel use, particularly coal during the 19th and early 20th centuries. However, in the latter half of the 20th century, United Kingdom began a gradual shift toward cleaner energy sources [4]. The decline of the coal industry, coupled with concerns about air quality and climate change, led to increased investments in nuclear power and later, renewable energy. UK has made substantial progress in reducing carbon emissions by expanding its renewable energy capacity, including wind farms and solar installations. The government's commitment to phasing out coal and promoting cleaner technologies has been pivotal in shaping United Kingdom's low-carbon energy landscape.

France: France stands out as a pioneer in low-carbon energy consumption, largely due to its extensive use of nuclear power. In the 1970s, France made a strategic decision to invest heavily in nuclear energy as a means of reducing dependence on fossil fuels and achieving energy security. Nuclear power has since become a dominant force in France's energy portfolio, contributing significantly to low-carbon electricity generation. The country has also invested in renewable energy sources, such as hydroelectric power and wind energy, to further diversify its energy mix. France's proactive approach to nuclear energy has positioned it as a leader in low-carbon electricity production.

II. Materials and Method

In this study, time series, which have a very wide application area [5]–[22] , were used. Low-carbon consumption data of Türkiye, France and United Kingdom, used in the forecasting of time series, were retrieved from the website https://ourworldindata.org/energy. Low-carbon energy consumption data graphs for three countries are given in Figure 1. As seen in the graph, United Kingdom's low-carbon energy consumption is higher than Türkiye and France. United Kingdom continued to increase its low-carbon energy consumption until the 2000s, continued to progress steadily with ups and downs between 2000 and 2015, and then entered a downward trend. On the other hand, the low-carbon energy consumption of Türkiye and France continued with an upward trend, with partial ups and downs over time.

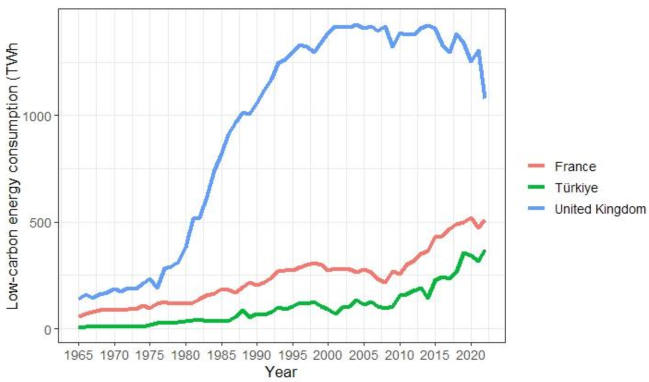

Fig. 1 Low-carbon energy consumption of Türkiye, United Kingdom and France between 1965 and 2022

Data covering 58 years between 1965 and 2022 were first converted to annual time series format. Auto.arima[23], [24], TBATS[25], ETS [10] and HOLT [26], [27] statistical models were used using Rstudio. Due to the limitations of time series, each consisting of 58 records, the use of statistical models was preferred instead of deep learning models. In the prediction analyses, the first 49 records of each dataset were used for training and the remaining 9 records were used for testing. In other words, 85% of the data was used for training and the remaining 15% for testing. In this case, future 9-year predictions were made. The Mean absolute percentage error (MAPE) [28] metric was used to evaluate the prediction results. The MAPE is a commonly used metric for evaluating the accuracy of predictions in forecasting models. It expresses the average absolute percentage difference between actual and predicted values. MAPE is easy to understand and interpret. It provides a straightforward measure of the average percentage difference between predicted and actual values, making it accessible to both technical and non-technical audiences. However, MAPE has a critical limitation when dealing with zero or near-zero actual values. In such cases, the percentage error becomes undefined, leading to challenges in applying MAPE to datasets with a significant number of zero values.

III. Results

Time series forecast analysis was made separately and under the same conditions for Türkiye (TR), France (FR) and United Kingdom (UK), and the MAPE test values of the future forecast results for 9 years are given in Table 1.

Table 1. MAPE test values obtained from forecasts for Türkiye, United Kingdom and France with the help of R-based models

R-Models	MAPE Test (TR)	MAPE Test (FR)	MAPE Test (UK)
Auto.Arima	26.41	10.92	17.76
ETS	29.83	11.47	18.34
TBATS	11.31	11.63	16.54
HOLT	26.78	18.10	18.05

The graphs of the predictions of the R-based models used for the predictions of the three countries are given in Figures 2, 3 and 4 for Türkiye, United Kingdom and France, respectively.

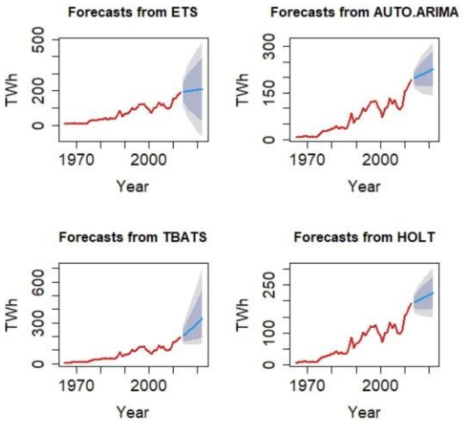

Fig. 2 Model graphics used for Türkiye's low-carbon energy consumption forecast results

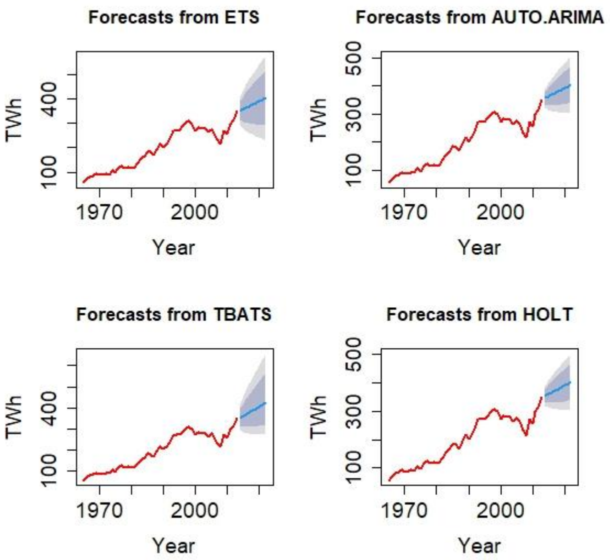

Fig. 3 Model graphics used for United Kingdom's low-carbon energy consumption forecast results

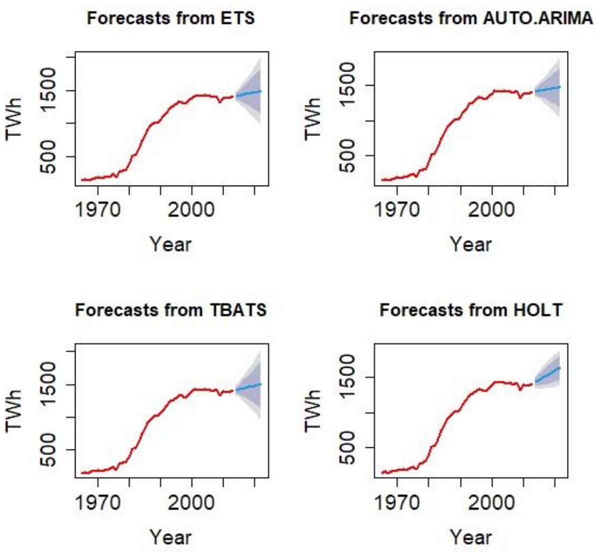

Fig. 4 Model graphics used for France's low-carbon energy consumption forecast results

DISCUSSION

As seen in Table 1, the best MAPE prediction results for Türkiye, France and United Kingdom are TBATS (11.31%), Auto.Arima (10.92%), TBATS (16.54%), respectively.

Since a smaller MAPE value means a better prediction, among the three countries, the best prediction was made by the Auto.Arima model with an error of 10.92%, in other words, an accuracy of 89.08%.

IV. CONCLUSION

In the low-carbon energy consumption estimates made here, the Auto.Arima model came to the fore with better performance.

The evolution of low-carbon energy consumption in Türkiye, United Kingdom, and France reflects the diverse paths countries can take in response to the challenges of climate change and energy sustainability. While Türkiye is making strides in transitioning from fossil fuels to renewables, United Kingdom is navigating a complex history of industrialization, and France has successfully integrated nuclear power into its energy landscape. Understanding the unique contexts and policy decisions of each nation provides valuable lessons for other countries seeking to embark on a similar journey toward a low-carbon future.

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