AS-Proceedings
https://alls-academy.com/index.php

3rd International Conference on Scientific and Academic Research

December 25-26, 2023 : Konya, Turkey

https://www.icsarconf.com/

A Historical Overview of Low-Carbon Energy Consumption in the USA, Russia, China, and Japan

Zeydin Pala[1*], İlyas Bozkurt[2]

[1]*Department of Software Engineering, Engineering Faculty, Muş Alparslan University, Muş, Türkiye*
[2]*Mechanical Engineering, Engineering Faculty, Muş Alparslan University, Muş, Türkiye*

**z.pala@alparslan.edu.tr*

Abstract – This article provides a comprehensive summary of the historical trajectories of low-carbon energy consumption in four major global economies the United States, Russia, China, and Japan from 1965 to 2022. Tracking the evolution of these nations' approaches to low-carbon energy is crucial for understanding their contributions to global sustainability goals and the diverse strategies employed in response to changing energy landscapes. In this study, future predictions were made regarding the low-carbon energy consumption of United States, Russia, China, and Japan between 1965-2022 with the help of R-based Auto.Arima, TBATS, ETS and THETAF 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

The change in the energy system in the world, which started with the industrial revolution, continues dramatically until today. 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.

United States: In the mid-20th century, the United States relied heavily on fossil fuels for energy, with coal dominating the mix. Over the decades, however, a significant shift occurred. The USA witnessed a gradual increase in low-carbon energy consumption, driven by the growth of nuclear power and, more recently, the rapid expansion of renewable energy sources. Government incentives, technological advancements, and environmental policies played pivotal roles in fostering this transition. By 2022, the USA had made substantial progress in reducing its carbon footprint, with renewables, including wind and solar, contributing significantly to the energy mix.

Russia: Historically, Russia has been a major player in the global energy landscape, primarily due to its vast reserves of fossil fuels, especially natural gas and oil. While Russia's energy consumption patterns have evolved, there has been a relatively slower transition to low-carbon alternatives. Nuclear power has been a notable contributor to low-carbon energy in Russia, but renewable energy sources have yet to play a significant role. The country's energy policies have been shaped by its abundant fossil fuel resources, contributing to a slower pace of adopting low-carbon alternatives compared to some other nations.

China: China's journey in low-carbon energy consumption is marked by remarkable transformation. In the 1960s and 1970s, coal dominated China's energy mix, leading to significant environmental challenges. However, recognizing the need for sustainable development, China shifted its focus towards diversifying its energy portfolio. In recent decades, the country has emerged as a global leader in renewable energy deployment. Massive investments in solar and wind power, coupled with ambitious policy initiatives, have propelled China towards a more sustainable energy future. By 2022, China had made substantial strides in reducing its reliance on coal and increasing the share of low-carbon energy in its total energy consumption.

Japan: Japan's approach to low-carbon energy consumption has been influenced by historical events, particularly the Fukushima nuclear disaster in 2011. Prior to the incident, nuclear power played a significant role in Japan's energy mix. However, in the aftermath of Fukushima, Japan underwent a shift in energy policies, emphasizing greater reliance on renewable energy and energy efficiency. By 2022, Japan had made strides in adopting cleaner energy sources, including solar and offshore wind, to diversify its energy mix and reduce carbon emissions.

II. MATERIALS AND METHOD

In this study, time series, which have a very wide application area [4], [5], [14]–[22], [6]–[13] , were used. Low-carbon consumption data of United States, Russia, China, and Japan used in the forecasting of time series, were retrieved from the website https://ourworldindata.org/energy. Low-carbon energy consumption data graphs for four countries are given in Figure 1. Low-carbon energy consumption of the world's largest economies such as Japan, China, the USA and Russia covers the years 1965-2022, 1971-2022, 1983-2022 and 1990-2002, respectively. As seen in Figure 1, Japan has adopted low-carbon energy consumption since 1965 and continued with an increasing trend until the 2000s. Then there were ups and downs from time to time. There were sharp declines after 2010. This may be due to the nuclear power plant accident in Fukushima. It then continued to increase again. China's low-carbon energy consumption has continued to increase since 1971. In addition, low-carbon energy consumption of the USA has been increasing since 1983 and Russia's since 1990.

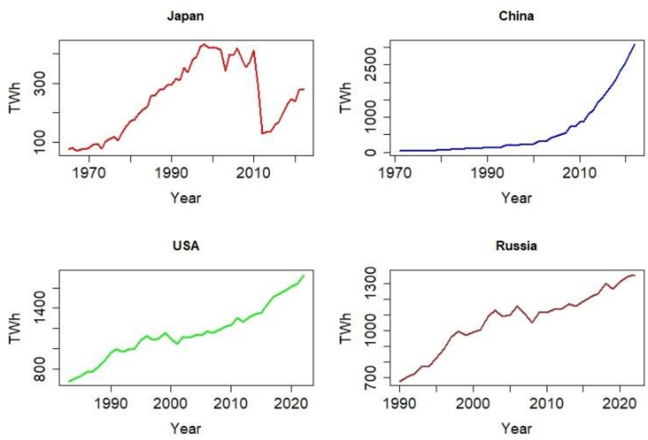

Fig. 1 Low-carbon energy consumption of Japan, China, USA and Russia between 1965 and 2022

The data used varies by country. Data for Japan, China, USA and Russia cover the years 1965-2022, 1971-2022, 1983-2022 and 1990-2002, respectively. The lengths of data for Japan, China, USA and Russia consist of 58, 52, 40 and 33 records, respectively.

Auto.arima [23], [24], TBATS[25], ETS [17] and THETAF [17] statistical models were used using Rstudio. Since time series, each of different lengths, have a limited number of records, statistical models were preferred instead of deep learning models. In prediction analyses, 90% of the data was used for training and the remaining 10% for testing. In this case, future predictions of 6, 5, 4 and 3 years were made for Japan, China, USA and Russia, respectively. The Mean absolute percentage error (MAPE) [26] 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 Japan (JPN), United States (USA), China (CHN) and Russia (RUS) MAPE test values of the future forecast results for years are given in Table 1.

Table 1. MAPE test values obtained from forecasts for Japan, USA, China, and Russia with the help of R-based models

R-Models	MAPE Test (JPN)	MAPE Test (USA)	MAPE Test (CHN)	MAPE Test (RUS)
Auto.Arima	29.57	2.14	5.70	2.52
ETS	29.65	1.94	7.33	1.57
TBATS	29.12	0.99	3.62	4.40
THETAF	25.88	4.37	23.36	4.14

The graphs of the predictions of the R-based models used for the predictions of the four countries are given in Figures 2, 3, 4 and 5 for Japan, USA, China, and Russia, respectively.

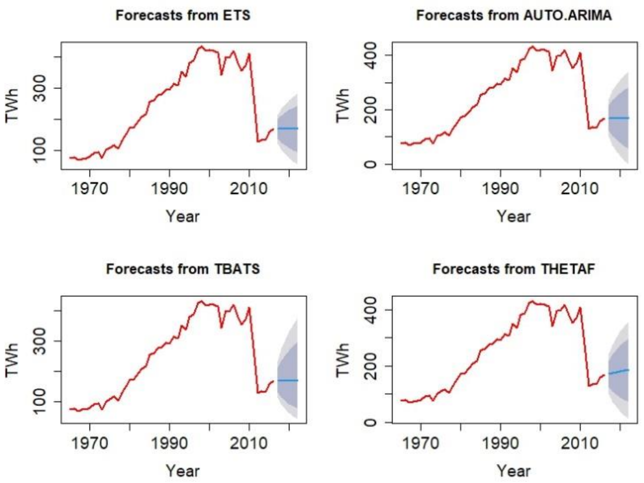

Fig. 2 Model graphics used for Japan's low-carbon energy consumption forecast results

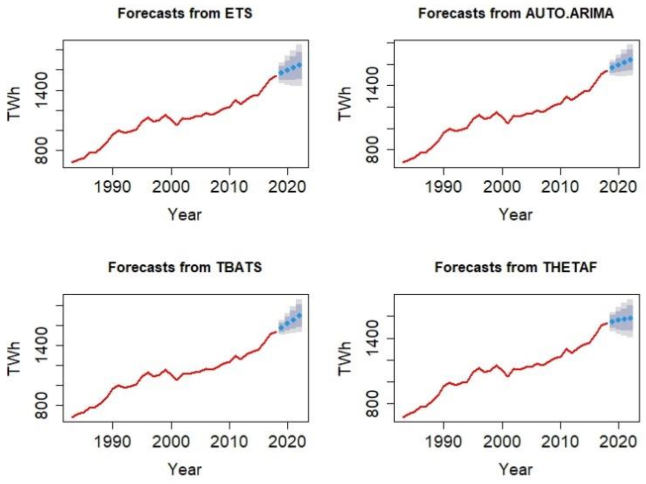

Fig. 3 Model graphics used for United Sates's low-carbon energy consumption forecast results

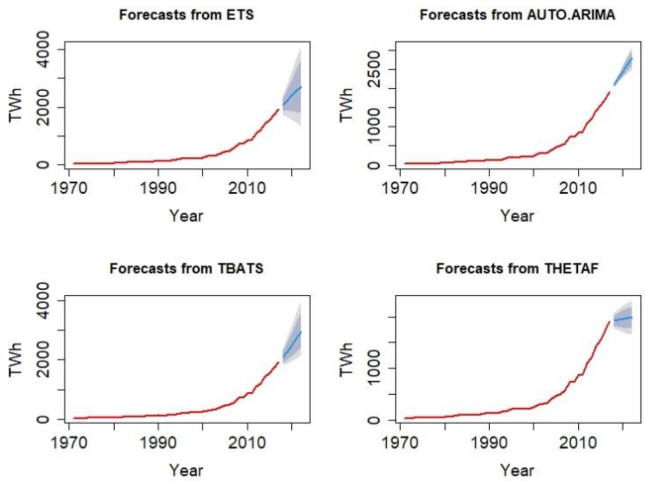

Fig. 4 Model graphics used for China's low-carbon energy consumption forecast results

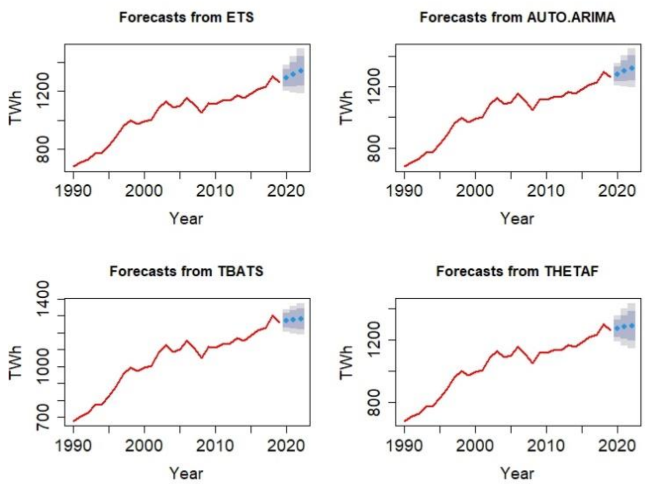

Fig. 5 Model graphics used for Russia's low-carbon energy consumption forecast results

DISCUSSION

As seen in Table 1, the best MAPE prediction results for Japan, USA, China and Russia Kingdom are THETAF (25.88%), TBATS (0.99%), TBATS (3.62%), ETS (1.57%) respectively.

Since a smaller MAPE value means a better prediction, among the three countries, the best prediction was made by the TBATS model with an error of 0.99%, in other words, an accuracy of 99.01%.

IV. CONCLUSION

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

The historical trajectories of low-carbon energy consumption in the USA, Russia, China, and Japan from 1965 to 2022 reflect diverse approaches shaped by geopolitical, economic, and environmental factors. While the USA and China have made significant progress in transitioning to low-carbon energy, Russia's reliance on abundant fossil fuel resources has slowed its pace. Japan, facing unique challenges, has adjusted its energy policies to prioritize safety and sustainability. Understanding these national narratives is essential for global efforts to address climate change and transition towards a more sustainable and low-carbon energy future.

REFERENCES

[1] Z. Xin-gang and Z. Ying, “Can China’s renewable energy industry policy support the low-carbon energy transition effectively?,” *Environ. Sci. Pollut. Res.*, vol. 30, no. 11, pp. 29525–29549, 2023.

[2] F. J. J. S. Bai, “A Machine Learning Approach for Carbon Di Oxide and Other Emissions Characteristics Prediction in a Low Carbon Biofuel-Hydrogen Dual Fuel Engine,” *FUEL*, vol. 341, no. January, p. 127578, 2023.

[3] M. Crippa *et al.*, *Fossil CO2 and GHG emissions of all world countries*, vol. 105, no. D2. 2019.

[4] R. Niu, C. Guo, Y. Zhang, L. He, and Y. Mao, “Study of ionospheric TEC short-term forecast model based on combination method,” *Int. Conf. Signal Process. Proceedings, ICSP*, vol. 2015-Janua, no. October, pp. 2426–2430, 2014.

[5] I. Bozkurt, Z. Pala, and T. Etem, “Measurement and evaluation of low frequency electromagnetic field in camera observation rooms,” in *2017 13th International Conference Perspective Technologies and Methods in MEMS Design, MEMSTECH 2017 - Proceedings*, 2017.

[6] T. Etem, Z. Pala, and I. Bozkurt, “Electromagnetic pollution measurement in the system rooms of a university,” in *2017 13th International Conference Perspective Technologies and Methods in MEMS Design, MEMSTECH 2017 - Proceedings*, 2017.

[7] Z. Pala, “Using Decomposition-based Approaches to Time Series Forecasting in R Environment,” *Int. Conf. Data Sci. Mach. Learn. Stat. - 2019*, vol. 1, no. 1, pp. 231–233, 2019.

[8] Z. Pala and R. Atici, “Forecasting Sunspot Time Series Using Deep Learning Methods,” *Sol. Phys.*, vol. 294, no. 5, 2019.

[9] Z. Pala, “Comparative study on monthly natural gas vehicle fuel consumption and industrial consumption using multi-hybrid forecast models.”

[10] Z. Pala and İ. H. Ünlük, “Comparison of hybrid and non-hybrid models in short-term predictions on time series in the R development environment,” *DÜMF Mühendislik Derg.*, vol. 2, pp. 199–204, 2022.

[11] Z. Pala, İ. H. Ünlük, and E. Yaldız, “Forecasting of electromagnetic radiation time series: An empirical comparative approach,” *Appl. Comput. Electromagn. Soc. J.*, vol. 34, no. 8, pp. 1238–1241, 2019.

[12] Z. Pala, “Using forecastHybrid Package to Ensemble Forecast Functions in the R,” *Int. Conf. Data Sci. Mach. Learn. Stat. - 2019*, vol. 1, no. 1, pp. 45–47, 2019.

[13] Z. Pala, V. Yamli, and I. H. Ünlük, “Deep Learning researches in Turkey: An academic approach,” in *2017 13th International Conference Perspective Technologies and Methods in MEMS Design, MEMSTECH 2017 - Proceedings*, 2017.

[14] Z. Pala, I. Bozkurt, and T. Etem, “Estimation of low frequency electromagnetic values using machine learning,” in *2017 13th International Conference Perspective Technologies and Methods in MEMS Design, MEMSTECH 2017 - Proceedings*, 2017.

[15] Z. Pala, “Examining EMF Time Series Using Prediction Algorithms With R,” vol. 44, no. 2, pp. 223–227, 2021.

[16] E. Yaldız and Z. Pala, “Time Series Analysis of Radiological Data of Outpatients and Inpatients in Emergency Department of Mus State Hospital,” *Int. Conf. Data Sci. Mach. Learn. Stat. - 2019*, pp. 234–236, 2019.

[17] Z. Pala, R. Atıcı, and E. Yaldız, “Forecasting Future Monthly Patient Volume using Deep Learning and Statistical Models,” *Wirel. Pers. Commun.*, vol. 130, no. 2, pp. 1479–1502, 2023.

[18] H. Abbasimehr and R. Paki, “Prediction of COVID-19 confirmed cases combining deep learning methods and Bayesian optimization,” *Chaos, Solitons and Fractals*, vol. 142, Jan. 2021.

[19] M. Akpinar and N. Yumusak, “Estimating household natural gas consumption with multiple regression: Effect of cycle,” *2013 Int. Conf. Electron. Comput. Comput. ICECCO 2013*, pp. 188–191, 2013.

[20] E. Özgüner, O. B. Tör, and A. N. Güven, “Probabilistic day-ahead system marginal price forecasting with ANN for the Turkish electricity market,” *Turkish J. Electr. Eng. Comput. Sci.*, vol. 25, no. 6, pp. 4923–4935, 2017.

[21] P. G. Zhang, “Time series forecasting using a hybrid

ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, 2003.
[22] Z. Pala, "Prediction of Electricity Consumption in Turkey with Time Series," *MAUN J. Fac. Eng. Archit.*, vol. 4, no. 1, pp. 32–40, 2023.
[23] Z. Ceylan, "Estimation of COVID-19 prevalence in Italy, Spain, and France," *Sci. Total Environ.*, 2020.
[24] T. Chakraborty and I. Ghosh, "Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis," *Chaos, Solitons and Fractals*, vol. 135, 2020.
[25] M. Abotaleb *et al.*, "State of the art in wind speed in England using BATS , TBATS , Holt ' s Linear and ARIMA model," vol. 1, no. January, pp. 129–138, 2022.
[26] S. Kim and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," *Int. J. Forecast.*, vol. 32, no. 3, pp. 669–679, 2016.