# The Path to Carbon Neutrality: A Time Series Approach

Haoran Zhang[a,b] and Yuchen Dong[b]

[a]Northeastern University, Boston, MA, USA
[b]The MathWorks Inc., Natick, MA, USA

## ABSTRACT

Achieving carbon neutrality has become the United Nation's most urgent mission, but the lack of data, evaluation criteria and associated techniques presents a challenge. Moreover, the energy crisis in 2022 has unexpectedly complicated carbon dioxide ($CO_2$) data, and existing research focuses primarily on $CO_2$ absolute emissions. Policymakers have established milestones on carbon reduction roadmap but have failed to meet them. Therefore, we adopt the new $CO_2$ emission and sink data released in November 2022. Our approach leverages Time Varying Parameter Vector Auto Regression (TVP-VAR) model and Monte-Carlo simulation to monitor the dynamics of net-zero emission roadmap. This approach provides insights into the global pathway towards The United Nations Framework Convention on Climate Change (UNFCCC).

**Keywords:** carbon neutrality, carbon emission, climate change, Time Varying Parameter Vector Auto Regression model, Monte-Carlo simulation, Long Short-term Memory model

## 1. INTRODUCTION

Achieving carbon neutrality is one of the United Nation's critical objectives. Most countries promise net-zero carbon emission by 2050. However, as of 2023, $CO_2$ emissions have resumed their increasing trend, undermining the effort to limit global temperature increases by less than 2.8 degrees Celsius.[1]

Existing research on $CO_2$ forecasting has been limited to absolute emission and selected countries, resulting in a limited understanding of global $CO_2$ emission, sink and carbon cycles. Meanwhile, the Ukraine War has unexpectedly impacted fossil fuel consumption and the transition to clean energy, disrupting the estimated roadmap in $CO_2$ reduction. To address these shortcomings in data, we enhance our analysis by incorporating the unleveraged ocean and carbon sink and carbon cycle information provided in the Global Carbon Budget report[2] released in November 2022, to understand the $CO_2$ net emission. We also introduce another data on $CO_2$ and greenhouse gas emissions[3] to picture the historical trend.

Organizations have established $CO_2$ emission milestones, such as the Net Zero Roadmap by the International Energy Agency. However, policymakers have failed to meet these targets and need adjusted prediction to close the gap. Previous studies have applied RNN models[4] and demonstrated some success; however, their weaker interpretability makes reproducing their work difficult and at times overly complex, especially when we introduce new data signals. We use TVP-VAR model and Monte-Carlo simulation as an alternative approach for predicting the net emission roadmap, more apt to quantify to what level the world must do annually to fulfill net-zero commitements.

Our approach supplies valuable insights into the global pathway towards The United Nations Framework Convention on Climate Change.[5]

Further author information: (Send correspondence to Haoran Z.)
Haoran Z.: E-mail: zhang.haoran1@northeastern.edu, Telephone: 1 508 647 7615
Yuchen D.: E-mail: yuchend@mathworks.com, Telephone: 1 508 647 3657

# 2. GLOBAL CARBON $CO_2$ EMISSION HISTORY

Carbon emissions, predominantly in the form of $CO_2$, result from various human activities such as burning fossil fuels, deforestation, and industrial processes. These emissions have significant implications for the Earth's climate system and contribute to the phenomenon of global warming and climate change. See Fig. 1.

On the other hand, carbon sinks play a crucial role in mitigating the effects of greenhouse gases. Carbon sinks are natural or artificial reservoirs that absorb and store carbon dioxide from the atmosphere, helping to regulate its concentration and reduce the impact of global warming. Three major types of carbon sinks are the ocean sink, land sink, and cement carbonation sink.

This figure below (see Fig. 2) illustrates the increasing atmospheric growth in imbalance between carbon emissions and sinks.

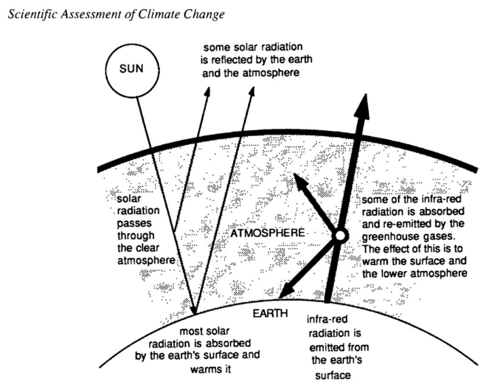



Figure 1: Assessment of Climate Change[6]

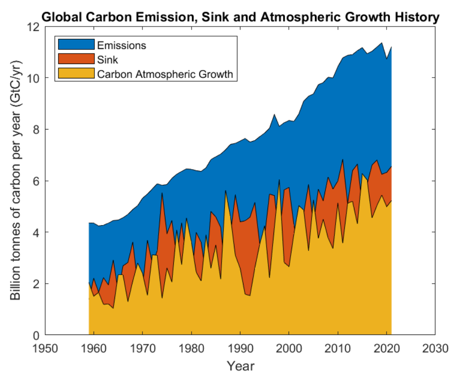



Figure 2: Global Carbon History

# 3. US, UK, JAPAN AND CHINA CARBON EMISSION STUDY

## 3.1 Data Preprocessing

The data we select are absolute value of carbon emission, carbon emission per capita, population and GDP. Considering missing values and difference in years covered, we focus on data between the year of 1905 and the year of 2020 to improve data completeness and help make comparison between countries. In particular, we study four countries: United States, United Kingdom, Japan and China. Those four countries represent a mix of developed and developing countries and major continents across the globe.

Before data modelling, we performed time series stationary test with the Augmented Dickey-Fuller (ADF) test. The ADF test is a statistical test commonly used in time series analysis to determine if a given time series is stationary or not.[7] Stationarity is important because it ensures consistent statistical properties over time.

The ADF test helps identify non-stationarity, which can affect accurate analysis and forecasting. By confirming stationarity, the ADF test provides a solid basis for applying time series models and statistical techniques.

| Country | Variable | ADF Stationary Result |
|---|---|---|
| *US* | $CO_2$ | Not Stationary |
| *US* | $\Delta CO_2$ | *Stationary* |
| *UK* | $CO_2$ | Not Stationary |
| *UK* | $\Delta CO_2$ | *Stationary* |
| *Japan* | $CO2$ | Not Stationary |
| *Japan* | $\Delta CO2$ | *Stationary* |

(a) $CO_2$

| Country | Variable | ADF Stationary Result |
|---|---|---|
| *US* | *GDP* | Not Stationary |
| *US* | $\Delta$GDP | Stationary |
| *UK* | *GDP* | Not Stationary |
| *UK* | $\Delta$GDP | Stationary |
| *Japan* | *GDP* | Not Stationary |
| *Japan* | $\Delta$GDP | Stationary |

(b) GDP

| Country | Variable | ADF Stationary Result |
|---|---|---|
| *US* | *Population* | Not Stationary |
| *US* | $\Delta$Population | Not Stationary |
| *US* | $\Delta^2$Population | *Stationary* |
| *UK* | *Population* | Not Stationary |
| *UK* | $\Delta$Population | Not Stationary |
| *UK* | $\Delta^2$Population | *Stationary* |
| *Japan* | *Population* | Not Stationary |
| *Japan* | $\Delta$Population | Not Stationary |
| *Japan* | $\Delta^2$Population | *Stationary* |

(c) Population

Figure 3: ADF test results on $CO_2$, GDP and Population variables

### 3.2 TVP-VAR model based Prediction

The TVP-VAR model is a statistical framework used to analyze and forecast time series data.[8] Traditional VAR models assume constant parameters over time, while the TVP-VAR model allows for dynamic variations in parameters to capture the changing relationships in the data. It is particularly useful when dealing with economic and financial time series data, where relationships between variables may evolve over time due to various factors. In our case, the TVP-VAR model estimates time-varying coefficients through Bayesian methods, such as Markov Chain Monte Carlo (MCMC) techniques, providing a flexible and powerful approach to modeling and forecasting complex time series data.

First, consider the following special structural VAR (SVAR) model:

$$A\mathbf{y}_t = F_1\mathbf{y}_{t-1} + \cdots + F_s\mathbf{y}_{t-s} + \mathbf{u}_t, \quad t = s+1, \ldots, n \tag{1}$$

$$\mathbf{u}_t \sim N(\mathbf{0}, \Sigma^T\Sigma) \tag{2}$$

$$\Sigma = \mathrm{diag}(\sigma_1, \ldots, \sigma_k) \tag{3}$$

where $\mathbf{y}_t$ is a $k \times 1$ vector of observed variables, $A, F_1, \ldots, F_s$ are $k \times k$ coefficient matrices, and $\mathbf{u}_t$ is the disturbance term. Suppose $A$ is a lower triangular matrix with diagonal elements all equal to 1, i.e.

$$A = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ a_{k1} & \cdots & 1 \end{pmatrix} \tag{4}$$

Its $i$-th component is not affected by the contemporaneous impact of subsequent components, but may have contemporaneous impact on previous components. Noting that the inverse of $A$ must exist, the model can be rewritten as:

$$\mathbf{y}_t = B_1\mathbf{y}_{t-1} + \cdots + B_s\mathbf{y}_{t-s} + A^{-1}\Sigma\boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, I_k) \tag{5}$$

where $B_i = A^{-1}F_i$.

It can be further rewritten as:

$$\mathbf{y}_t = X_t\boldsymbol{\beta} + A^{-1}\Sigma\boldsymbol{\varepsilon}_t \tag{6}$$

where

$$X_t = I_k \otimes (\mathbf{y}_{t-1}^T, \cdots, \mathbf{y}_{t-s}^T) \tag{7}$$

The notation $\otimes$ here denotes Kronecker product.

At this time, the original SVAR model becomes a VAR model where each random disturbance term is not independent. When we consider that the impact of the endogenous variables and random disturbances in the model will change over time, we have:

$$\mathbf{y}_t = X_t\boldsymbol{\beta}_t + A_t^{-1}\Sigma_t\boldsymbol{\varepsilon}_t \tag{8}$$

Let $\mathbf{a}_t$ represent the vector formed by connecting the lower triangular elements except for the diagonal elements row by row, i.e.,

$$\mathbf{a}_t = (a_{21}, a_{31}, a_{32}, \cdots, a_{k,k-1})^T \tag{9}$$

$$\Sigma_t = \mathrm{diag}(\sigma_{1t}, \cdots, \sigma_{kt}) \tag{10}$$

$$\mathbf{h}_t = (h_{1t}, \cdots, h_{kt})^T \tag{11}$$

$$h_{jt} = \log \sigma_{jt}^2, \quad j = 1, \cdots, k \tag{12}$$

Assume that the time-varying parameters follow a random walk process, which can reduce the number of parameters to be estimated, i.e.,

$$\boldsymbol{\beta}_{t+1} = \boldsymbol{\beta}_t + \mathbf{u}_{\beta t} \tag{13}$$

$$\mathbf{a}_{t+1} = \mathbf{a}_t + \mathbf{u}_{at} \tag{14}$$

$$\mathbf{h}_{t+1} = \mathbf{h}_t + \mathbf{u}_{ht} \tag{15}$$

In the model, we assume that $\beta_{s+1} \sim N(u_{\beta 0}, \Sigma_{\beta 0})$, $a_{s+1} \sim N(u_{a0}, \Sigma_{a0})$, and $h_{s+1} \sim N(u_{h0}, \Sigma_{h0})$. For the random disturbance term, considering that in real life, time series data are subject to impact from factors with drift coefficients and random fluctuations. Using a model with time-varying coefficients but constant volatility may result in a bias in the estimated time-varying coefficients, ignoring possible changes in disturbances. To avoid this problem, we assume that the random disturbances between different parameters are independent, i.e.,

$$\begin{pmatrix} \epsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right). \tag{16}$$

In this problem, we use the first difference of $CO_2$ as the explanatory variable, the first difference of GDP as the dependent variable, and follow Primiceri's suggestion of using a normal prior distribution. The parameters of the prior distribution determined based on the parameters estimated from the VAR model established in the previous question. Based on historical data from 1905 to 2020, we estimate the model and get the following forecast expression:

$$\hat{y}_t = X_t \hat{\beta}_t \tag{17}$$

The second step is to choose the lag order, denoted as nlag in the following model. It is an essential parameter to determine in VAR models. It specifies the number of previous time points (lags) that should be included as predictors in the model.

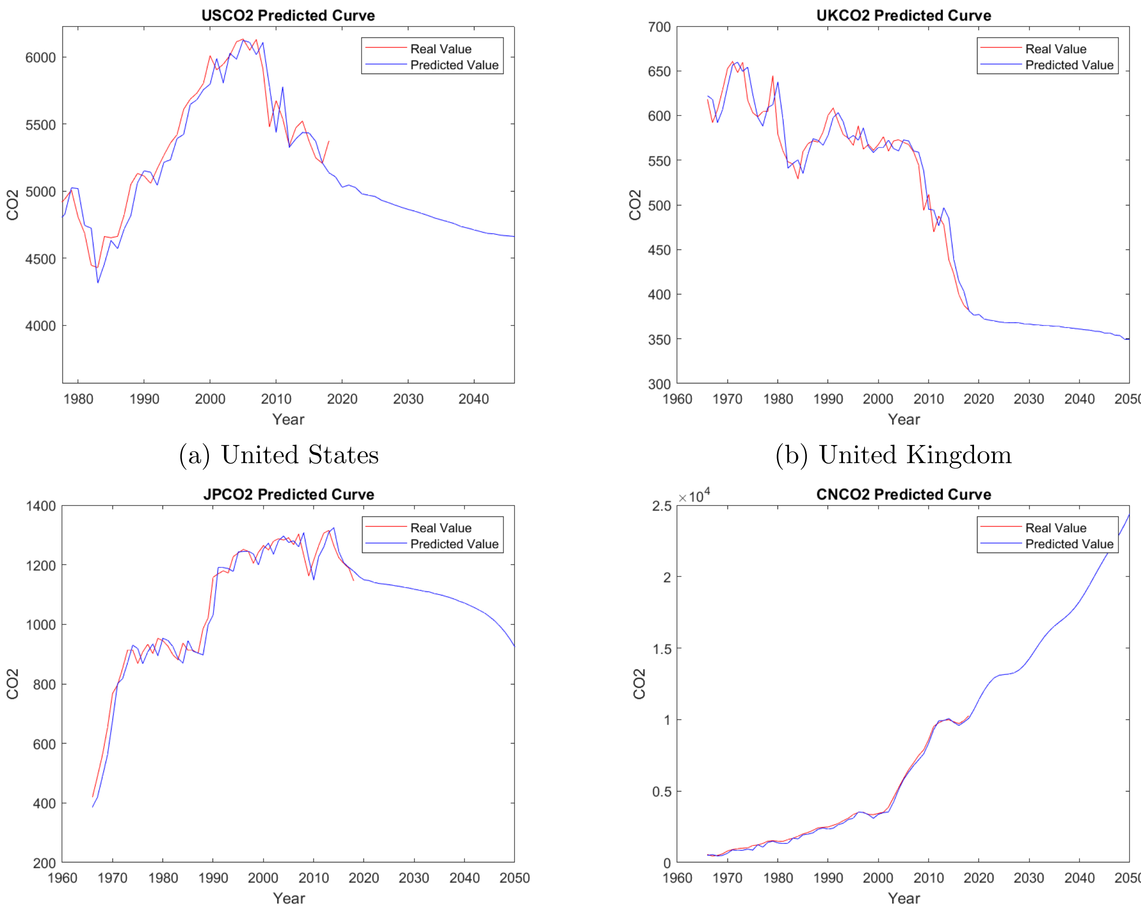
We use Akaike Information Criterion (AIC) to select the appropriate lag length, considering that AIC provides a balance between fit and complexity, and it optimizes predictive performance.[9] Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, it provides an approach for model selection.

We calculate AIC and its optimal point for single countries (US, UK, Japan and China) as well as 4 countries' combinations.

Table 1: Use AIC to determine lag order

| **Country(ies)** | **nlag value where AIC minimizes** |
|---|---|
| United States | 3 |
| United Kingdom | 1 |
| Japan | 1 |
| China | 2 |
| US-UK-JP-CN combination | 1 |

In our model, we choose **nlag=4**, larger than current optimal point nlag=3 for two reasons: the optimal point for single and multiple countries requires AIC to be 3 at most; in practice we need a larger nlag to represent the dynamic behaviour.




(a) United States (b) United Kingdom

(c) Japan (d) China

Figure 4: $CO_2$ emission prediction

The forecasted and actual values of $CO_2$ emissions for the United States, United Kingdom, and Japan from 1960 to 2020 are basically in alignment with the Figure. 4. In addition, based on the real-world circumstances, it is known that the United States peaked in carbon emissions in 2005, the United Kingdom in 1971, and Japan in 2013. Carbon emissions were at a high level in the 20th century and have seen a significant decrease in recent years. These research results are also perfectly in line with the graphics drawn by this model. Moreover, with the improvements in technology in developed countries, energy transitions, and policy incentives, the reduction of $CO_2$ emissions from 2020 to 2050 is inevitable. In summary, this stationary time series model can more accurately predict $CO_2$ emissions.

### 3.3 Monte-Carlo based Carbon Neutrality Path Simulation

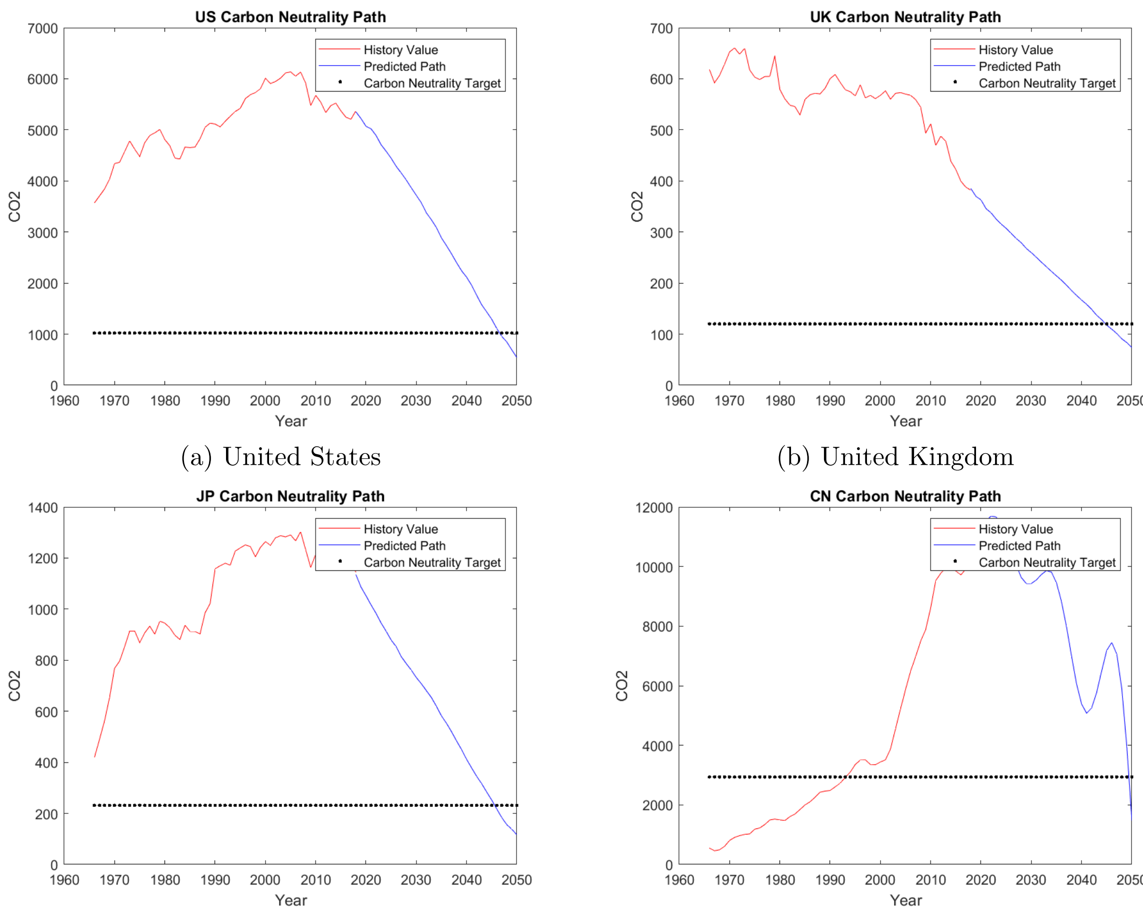
Carbon Emission Reduction is an essential part to achieve carbon neutrality. Policymakers have set the carbon emission reduction commitment at United Nations Climate Change Conference (UNCCC). According to the target and existing research,[10] we set expectations for different countries by 2050 to achieve carbon neutrality in 2050.

Monte Carlo simulation is a powerful technique used to model and simulate possible outcomes of a system,[11,12] such as the carbon emission ecosystem we study. Specifically, in path simulation with historical data and a future

Table 2: Countries' Carbon Emission Reduction Targets

| **Country** | **2020 Target at UNCCC** | **2050 Global Neutrality Target** |
|---|---|---|
| China | 45% less than 2005 | 50% less than 2005 |
| United States | 4% less than 1990 | 80% less than 1990 |
| European Union (including UK) | 30% less than 1990 | 80% less than 1990 |
| Japan | 25% less than 1990 | 80% less than 1990 |

target goal, Monte Carlo simulation generates multiple random scenarios (in our parameter settings, 10,000 times) to assess the likelihood of achieving the goal based on historical data. By incorporating randomness and variability, it provides insights into potential carbon emission paths, probabilities, and helps make informed decisions on carbon emission reduction.



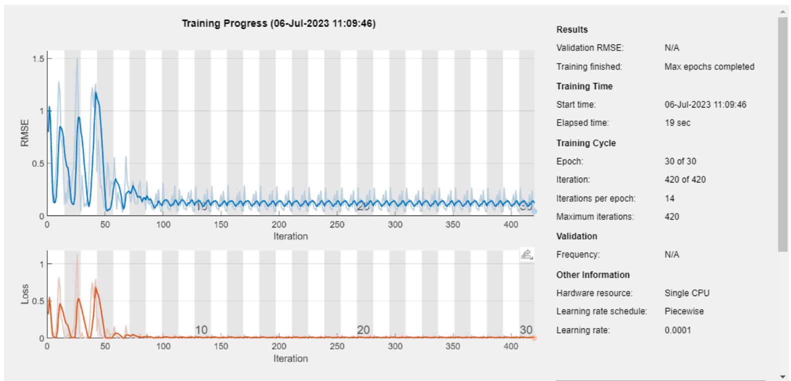

(a) United States (b) United Kingdom (c) Japan (d) China

Figure 5: $CO_2$ neutrality path simulation

If all countries maintain the current situation, then the United States, the United Kingdom, Japan, and China have a certain probability of achieving their respective carbon neutrality goals by 2050, with **less than 5% success rate**. Among them, United States' and United Kingdom's probability to achieve neutrality goal are 2.76% and 4.15%, respectively, while Japan's and China's probability to achieve neutrality goal are 3.26% and 0.26%, respectively.

### 3.4 LSTM model based Simulation

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is widely used in time series analysis and prediction tasks.[13] Unlike traditional feedforward neural networks, LSTM networks have the ability to retain information over longer sequences, making them well-suited for modeling and predicting time-dependent data. Besides, LSTM works better if we are dealing with data with nonlinear patterns. The classic statistical method, such as Autoregressive integrated moving average (ARIMA), are generally better-suited for capturing linear patterns in the data.




(a) Training Progress Monitor


(b) Performance and Result

Figure 6: LSTM Model

We deployed LSTM model onto US dataset and achieved 199.2431 and 227.8825 in train set's and test set's Root of Mean Squared Error (RMSE) value.[14] The RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{18}$$

To better compare RMSE between models, we take the normalization of RMSE in the training set and test set, 0.06 and 0.04, respectively.

$$\text{normalized\_RMSE\_training\_set} = \frac{\text{RMSE\_training\_set}}{\text{mean(training set)}} \tag{19}$$

$$\text{normalized\_RMSE\_test\_set} = \frac{\text{RMSE\_test\_set}}{\text{mean(test set)}} \tag{20}$$

By dividing the RMSE by the mean of the actual set values, the formula (19) aims to provide a relative measure of the model's performance. It helps in comparing the RMSE across different datasets or models with varying scales or magnitudes of the target variable. Normalizing the RMSE by the mean is useful because here the target variable has a wide range of values. It allows for a more standardized comparison of model performance, as it takes into account the average magnitude of the target variable.

A lower normalized RMSE, such as 0.06 and 0.04 in the above model, indicates better performance, as it means the model's average prediction error is relatively smaller compared to the average value of the target variable.

## 4. CONCLUSION

Our research undertakes the task of assessing the potential achievement of carbon neutrality goals by 2050 for four major countries: the United States, the United Kingdom, Japan, and China. We also consider their interaction in the model. By utilizing advanced statistical and deep learning methodologies, our research has revealed substantial findings which have significant implications for policy and future research.

Utilizing TVP-VAR model coupled with Monte Carlo simulations, our results indicate a less than 5% success rate for all four nations in achieving their carbon neutrality goals by 2050 under current conditions. This sobering result underscores the magnitude of the challenge that lies ahead for these countries. The current rate of progress is not sufficient to meet the desired carbon neutrality targets, thus necessitating significant changes and additional efforts in policy and practice.

Moreover, our application of LSTM deep learning model reinforces these findings, adding a dimension of robustness to our results. Not only did this model corroborate the TVP-VAR model's results, but it also provided an efficient and accurate method of prediction with a normalized RMSE as small as 0.06 in the training set. The use of the LSTM model represents a promising step forward in the domain of carbon emissions forecasting, demonstrating the potential on deep learning techniques in environmental modeling and prediction.

In conclusion, this research underscores the need for heightened urgency and action to mitigate carbon emissions in the US, UK, Japan, and China. Despite the sobering results, our findings should serve as a wake-up call to prompt more significant commitment and innovative strategies to achieve the ambitious goal of carbon neutrality by 2050. Our research illustrates the utility of advanced statistical and deep learning models in forecasting carbon emissions, paving the way for their further application in environmental research and policy planning. Future work should focus on exploring potential interventions and strategies that can alter the current trajectory and increase the probability of achieving the carbon neutrality targets.

## 5. REFLECTION AND FUTURE WORK

Reflecting upon the methodology and results of this research, it is evident that both the TVP-VAR model and LSTM neural networks proved proficient in fitting the data and providing reliable predictions. Despite the strengths of both methods, we observed that the TVP-VAR model demonstrated superior interpretability. This highlights the continued relevance and utility of traditional statistical models, especially in areas where the interpretability of results is critical for decision-making and policy planning.

The extension of the LSTM neural networks, such as Bidirectional LSTM (BiLSTM), convolution LSTM, etc, provides an intriguing glimpse into the future of carbon emissions modeling, underscoring the potential of deep learning techniques in generating accurate predictions. This affirms the increasing importance of leveraging advanced machine learning methodologies in environmental research, particularly in areas where data is complex and nonlinear.

Looking forward, there is a significant opportunity for further research and improvements. While exploration of new models remains an exciting avenue, a potentially more impactful approach would be to augment our dataset with new variables and dimensions of analysis. Incorporating data on different carbon emission sources and sinks in the ecosystem, as well as emission data from different industries, could significantly enrich our model and provide a more nuanced and comprehensive understanding of carbon emissions dynamics.

Furthermore, the integration of these additional data streams could facilitate the development of sector-specific or ecosystem-specific models that could offer more targeted and actionable insights for policymakers and stakeholders. With an increasing availability of detailed environmental and industry data, this represents a feasible and promising direction for future research.

In summary, this research journey has highlighted the strengths and limitations of both traditional statistical and advanced deep learning methodologies in the context of carbon emissions modeling. It emphasizes the criticality of continuous methodological innovation and the importance of diverse, detailed datasets in advancing our understanding of carbon emissions and informing effective policy responses. As we move forward, the integration of rich data and innovative models will remain central to our ongoing efforts to understand and address the urgent challenge of carbon neutrality.

## 6. ACKNOWLEDGMENTS

I express my sincere gratitude to The MathWorks Inc. for their funding support. A special acknowledgment is extended to Jason Jumper and David Willingham, for their insightful review of both the paper and poster, and for their support in enabling my conference presentation. I also thank Professor Karl Ni at Northeastern University for his exceptional academic writing guidance. This work has been greatly enhanced by your contributions.

MATLAB® R2023a is used for all code work, primarily with add-on Econometrics Toolbox™ and Deep Learning Toolbox™. Please find the related code work at https://github.com/hrcheung/carbon-neutrality-paper.

## REFERENCES

[1] "Statement on the 'climate change 2023: Synthesis report'," *States News Service* (2023).

[2] Friedlingstein, P., O'sullivan, M., Jones, M. W., Anew, R. M., Gregor, L., Hauck, J., Quéré, C. L., and Peters, W., "Global carbon budget 2022," *Earth system science data* **14**(11), 4811–4900 (2022).

[3] Ritchie, H., Roser, M., and Rosado, P., "$Co_2$ and greenhouse gas emissions," *Our World in Data* (2020). https://ourworldindata.org/co2-and-greenhouse-gas-emissions.

[4] Ameyaw, B., Li, Y., Annan, A., and Agyeman, J. K., "West africa's co2 emissions: investigating the economic indicators, forecasting, and proposing pathways to reduce carbon emission levels," *Environmental science and pollution research international* **27**(12), 13276–13300 (2020).

[5] [*United Nations Framework Convention on Climate Change message from the President of the United States transmitting the United Nations Framework Convention on Climate Change, adopted May 9, 1992, by the resumed fifth session of the intergovernmental negotiating committee for a Framework Convention on Climate Change ("convention"), and signed on behalf of the United States, at the United Nations Conference on Environment and Development (UNCED) in Rio De Janeiro on June 12, 1992*], U.S. G.P.O, Washington (1992).

[6] [*Climate change : the 1990 and 1992 IPCC assessments : IPCC first assessment report, overview and policymaker summaries and 1992 IPPC supplement*], Intergovernmental Panel on Climate Change, Geneva (1992).

[7] Kulaksizoglu, T., "Lag order and critical values of the augmented dickey-fuller test: A replication," *Journal of applied econometrics (Chichester, England); J.Appl.Econ* **30**(6), 1010 (2015).

[8] Primiceri, G. E., "Time varying structural vector autoregressions and monetary policy," *The Review of economic studies; The Review of Economic Studies* **72**(3), 821–852 (2005).

[9] Ingram, T., Mahler, D. L., and Hansen, T., "Surface: detecting convergent evolution from comparative data by fitting ornstein-uhlenbeck models with stepwise akaike information criterion," *Methods in ecology and evolution* **4**(5), 416–425 (2013).

[10] Leggett, J. A., [*A U.S.-centric chronology of the United Nations Framework Convention on Climate Change*], Congressional Research Service, Washington, D.C (2018).

[11] Nakajima, J., "Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications," (2011).

[12] Zio, E., [*The Monte Carlo simulation method for system reliability and risk analysis*], Springer, London (2012).

[13] Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M., "Rainfall–runoff modelling using long short-term memory (lstm) networks," *Hydrology and earth system sciences* **22**(11), 6005–6022 (2018).

[14] Mujeeb, S. and Javaid, N., "Deep learning based carbon emissions forecasting and renewable energy's impact quantification," *IET renewable power generation* **17**(4), 873–884 (2023).