The Prediction of Carbon Dioxide Emissions from Past Data Based on Algorithms

Linkai Jin[1,*], You Wu[2] and Enzo Zhang[2]

[1]Raffles Institution, Singapore, Singapore

[2]East Sussex College, Lewes, the United Kingdom

[3]Department of Physics, Northeastern University, Paris, France

*Corresponding author: 22YJINL139T@alumni.ri.edu.sg

Abstract. Carbon dioxide is one of the most notorious greenhouse gases, which has been largely emitted especially in recent years. Therefore, it is crucial to predict the emission trends in order to propose corresponding measures to reduce it. Thanks to the invention and development of machine learning schemes, it is feasible to predict the trends accurately. With this in mind, this study explores the crucial task of predicting carbon dioxide (CO_2) emissions based on past data. Leading authorities and organizations have relied on predictive models to anticipate future emission levels. As the implementation of models and algorithms becomes increasingly common, this project seeks to explore different approaches to this topic and summarizes their common discoveries, as well as discussions on possible variations. According to the analysis, the pros and cons of the different models are clarified. Overall, these results shed light on guiding further exploration of carbon dioxide (CO_2) emissions predictions.

Keywords: Carbon dioxide (CO_2) emissions; greenhouse gases; Machine learning.

1. Introduction

Energy transformation is an inevitable trend in the development of human society today. It is in the common interest of the mankind to accelerate the development of energy production and consumption from fossil energy to clean and low carbon. The construction of global energy Internet advocated by China has provided practical new ideas for people to promot the world's energy transformation and address climate change. Reducing carbon dioxide emissions and controlling global warming are important goals and driving forces for energy transition. Accurately predicting the process and development trend of global carbon emissions such as the construction plan of global energy Internet plays an important role in rationally formulating the strategic measures of energy transformation. Carbon dioxide is believed to be one of the most important among all greenhouse gases (EPA) [1].

It is widely known that the concept of "carbon" is very broad. Most of the objects around us, such as wood, plastic, rubber, fuel oil, coal, natural gas, diamonds, etc., are composed of carbon substances. Besides, all the living things on earth, including humans, are carbon-based. It can be said that we live in a world made of carbon, and carbon elements are everywhere in our lives. Carbon dioxide emissions refer to all kinds of greenhouse gas emissions, while "carbon neutrality" means to reduce the greenhouse gas emissions in the social development to 0 through various means so as to achieve "carbon emissions <carbon absorption". Carbon dioxide emissions is a general term or short term for greenhouse gas emission. The sources of carbon emissions are divided into three categories: carbon dioxide released from energy (combustion), carbon dioxide released from other industrial production (non-combustion, such as carbon dioxide released from calcium carbonate in lime production), and carbon dioxide released from agriculture and other activities.

Generated directly from human activities, carbon emissions make the greatest influence on the climate (EPA)[1]. In view of its ever-increasing negative impacts, it has become a heated topic to predict the future emission levels based on the past data. This practice has been adopted by many leading authorities and organisations, including the United Nations Framework Convention on Climate Change (UNFCCC)[2] and European Environment Agency (EEA) (UNFCCC) [2].

These models range from non-mitigation scenarios to idealised long-term scenarios. As many projects resort to construction of models and algorithms to complete predictions, the study aims to investigate the differences and similarities among the existing approaches and summarises the findings.

2. Data

Predicting carbon dioxide (CO_2) emissions involves a combination of historical data analysis, modelling, and scenario planning. Predictions often start with an analysis of historical CO_2 emissions data [3]. Some typical data are shown in Fig .1. Traditionally, this data includes records of emissions from various sources such as energy production, transportation, industry, and land-use changes, for a considerable length of time [4].

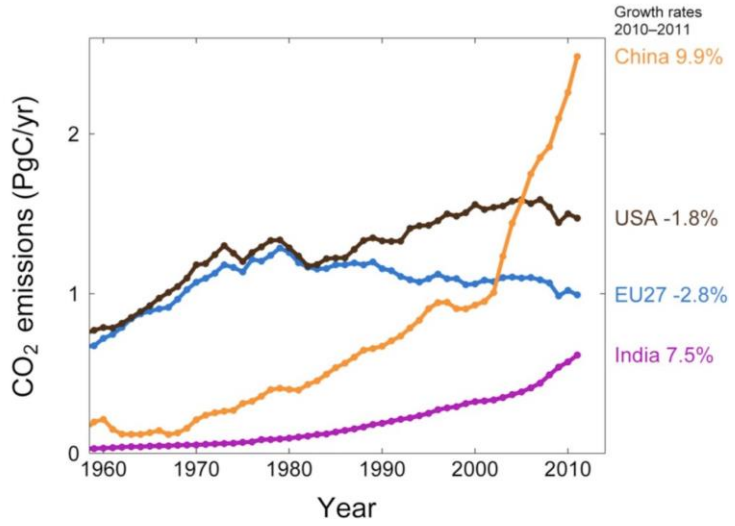


Fig. 1 Carbon emssion data during 1960-2018.

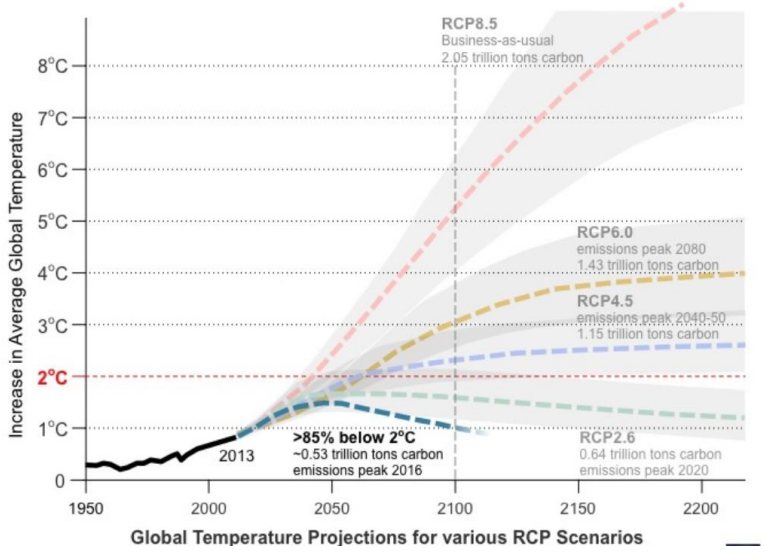


Fig. 2 Carbon emssion prediction to 2200.

Examining trends over time provides insights into past emissions patterns and helps establish models that cater to physical mechanisms, such as dynamic scenario simulation models [5]. In approaches of this kind, experts consider factors of human activities regarding their influences on energy consumption patterns and hence CO2 emissions:

Demographic economics, including economic growth, population growth, and urbanisation rates in their predictions, as these factors directly influence the scope of energy consumption and hence CO2 emissions.

Energy consumption trends: Predictions incorporate trends in energy consumption, including shifts from fossil fuels (coal, oil, natural gas) to cleaner energy sources like renewables (solar, wind, hydro) and nuclear power [6]. As technology evolves and energy efficiency improves, these trends can significantly affect emissions.

Technological advancements: Predictions consider the development and adoption of clean energy technologies, such as electric vehicles, carbon capture and storage (CCS), and energy-efficient appliances. Technological advancements can accelerate emissions reductions.

Climate Goals and Agreements: International climate agreements, like the Paris Agreement, set targets for reducing CO_2 emissions. Countries' commitments to these agreements influence predictions, as they indicate their intent to reduce emissions over time.

Predictions often rely on carbon intensity data, which quantifies CO2 emissions per unit of economic activity or energy consumption. Energy sources of different forms are also converted to carbon emissions equivalent [7]. Some typical prediction results are given in Fig. 2 and Fig. 3.

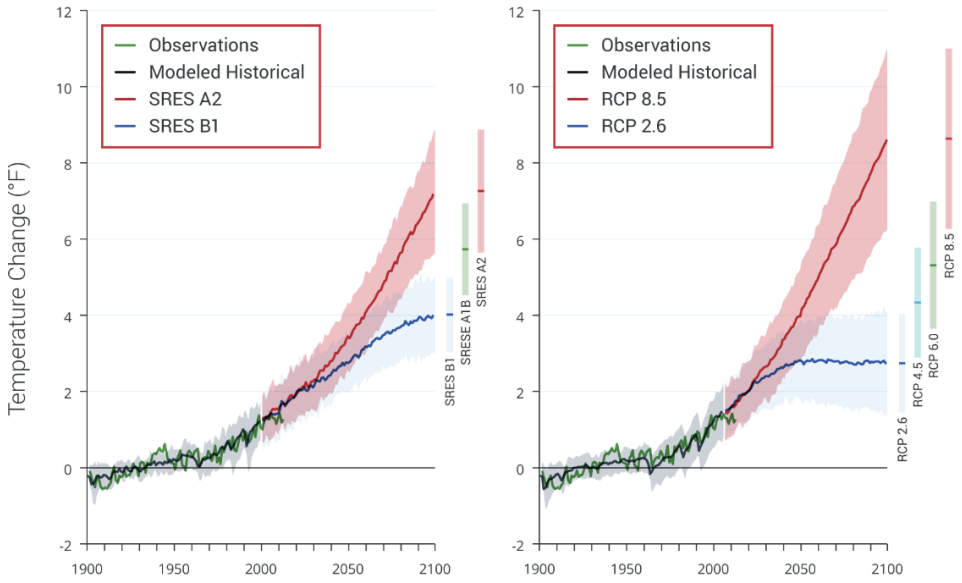


Fig. 3 Carbon emssion data prediction under differet conditions.

3. Modelling and Comaprison

There are three main directions of modelling for existing literatures: machine learning models, statistical models as well as stimulation models [3]. Despite difference in mechanisms, machine learning and statistical models mainly achieve the establishment of relationship between factors through regressions based on previous data, be it linear or not [8]. One of the greatest differences lies in the pre-processing of the data. For instance, in autoregressive integrated moving average (ARIMA) models, lagged moving averages are implemented to smooth out the fluctuations [9].

The Atmosphere-Ocean General Circulation Model (AOGCM) has been another heated choice in this field, as one of the stimulation models [3]. This approach seeks to approximate the climate through a process focusing on the physical mechanisms behind different factors (Global Modelling) [10]. The implementation of such model would be more accurate in terms of the physics of climate but also more resources-consuming due to high computational complexity; it would also have limited accuracy on the human-nature interactions (ipcc) [11].

Most models would agree to each other for the period at the beginning of the 21 century, the fluctuation of prediction of the temperature rise does not exceed 0.05 degree celsius [3]. However, the divergence starts to grow greater as time factor proceeds. Since the mid-century, the influence of past emission levels on the climate has declined and that of concurrent human responses has increased [3]. The choosing of different levels of human activities would impact the global climate significantly. When it comes to the end of this century, the difference would grow to more than 80% [3].

For instance, “business as usual,” “promises kept,” and “sustainable pathways” represent contrasting approaches or scenarios in various contexts, including environmental sustainability, economic development, and resource management. As the name implies, “business as usual” models the path assuming no further regulation is put in place to facilitate climate preservation; “promises kept” assumes all current political promises are enforced; “sustainable pathways” represents the best solution available to humanity.

In the context of environmental sustainability, “business as usual” (BAU) typically results in the continuation of high resource consumption, pollution, and greenhouse gas emissions, contributing to environmental degradation and climate change. In the meanwhile, sustainable pathways emphasise reduced resource consumption, transitioning to cleaner energy sources, and implementing conservation and restoration measures to protect ecosystems. Sustainable pathways often involve strategies to mitigate climate change, such as reducing greenhouse gas emissions, increasing energy efficiency, and promoting renewable energy sources. It aims to build systems that are adaptable and resilient to changes, including those related to climate, resource availability, and social dynamics, achieving of which often requires innovation and change in technology, business models, and policies. It acknowledges that transformative shifts may be necessary.

At the same time, uncertainties prevail regardless of the models implemented. For instance, a "Post-epidemic consumption peaks" is suspected to exist, which refers to a significant surge in consumption and production after the end of an epidemic or pandemic [3, 4]. This may lead to a subsequent rise in carbon emissions that defers the previous trends in data, or in other words, that represents a change-point in the data, rendering previous models less accurate [3]. To combat the above-mentioned problem in accuracy, scholars resort to the use of grey systems, a system characterised by limited or incomplete information and associated uncertainties [12, 13]. It allows the system to assess the relevance of information and hence improve the prediction results [14-16].

4. Conclusion

To sum up, this study focuses on predicting carbon dioxide (CO_2) emissions and climate changes based on past data using various algorithms and models. Carbon dioxide is a critical greenhouse gas generated from human activities and has a significant impact on climate change. The study investigates existing approaches and summarises the findings. The methodology involves historical data analysis, modelling, and scenario planning. Data analysis includes examining emissions from energy production, transportation, industry, and land-use changes over time. Factors like economic growth, energy consumption trends, technological advancements, and international climate agreements are considered in predictions. Carbon intensity data is also used to quantify emissions per unit of economic activity or energy consumption. Modelling approaches include machine learning, statistical models, and simulation models like the Atmosphere-Ocean General Circulation Model (AOGCM). Machine learning and statistical models establish relationships between factors through regressions, while AOGCM spend extra focus on physical mechanisms. AOGCM is more accurate in terms of physics but less so when it comes to human influences, and is more computationally intensive. The uncertainty of prediction increases overtime, and special events would also hinder the accuracy of models. Grey models are implemented to mitigate this problem. In the end, the past carbon emissions would have decreasing influence as the time horizon expands, while the decisions on regulation would continue to play an increasingly important role.

Author Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

[1] United States Environmental Protection Agency, "Greenhouse gases: What are the trends in greenhouse gas emissions and concentrations and their impacts on human health and the environment?" Report on the Environment, Retrieved from: https://www.epa.gov/report-environment/greenhouse-gases#:~:text=Carbon%20dioxide%20is%20widely%20reported,warming%20associated%20with%20human%20activities.

[2] United Nations Framework Convention on Climate Change. Science: why is there a need to act? Introduction to Science in the UNFCCC, Retrieved from: https://unfccc.int/topics/science/the-big-picture/introduction-science?gclid=Cj0KCQjwx5qoBhDyARIsAPbMagCA9jiBrbvY4x-tN7DXYbYSoPBjXcNszX4VHtzWMsawlMtpGDwEDrAaAt1EEALw_wcB.

[3] Yin F. Prediction of carbon dioxide emissions in China using a novel grey model with multi-parameter combination optimization. Journal of Cleaner Production, 2023, 404: 136889.

[4] Gou X, Zeng B, Ying G. Application of the novel four-parameter discrete optimized grey model to forecast the wastewater discharged in Chongqing China. Engineering Applications of Artificial Intelligence, 2022, 107: 104522.

[5] Huo T, Xu L, Feng W, et al. Dynamic scenario simulations of carbon emission peak in China's city-scale urban residential building sector through 2050. Energy Policy, 2021, 159: 112612.

[6] Mardani A, Liao H, Nilashi M, et al. A multi-stage method to predict carbon dioxide emissions using dimensionality reduction, clustering, and machine learning techniques. Journal of Cleaner Production, 2020, 275: 122942.

[7] Sterligov V V. Prediction of carbon dioxide emissions from fuel combustion. IOP Conference Series: Materials Science and Engineering, 2020, 1: 866.

[8] Shivammiglani09. Difference between Statistical Model and Machine Learning. Class method vs Static method in Python, Geeks for Geeks, Retrieved from: https://www.geeksforgeeks.org/difference-between-statistical-model-and-machine-learning/.

[9] Wabomba M S, Mutwiri M P, Fredrick M. Modeling and forecasting Kenyan GDP using autoregressive integrated moving average (ARIMA) models. Science Journal of Applied Mathematics and Statistics, 2016, 4(2): 64-73.

[10] Geoffroy O, Saint-Martin D, Olivié D J L, et al. Transient climate response in a two-layer energy-balance model. Part I: Analytical solution and parameter calibration using CMIP5 AOGCM experiments. Journal of climate, 2013, 26(6): 1841-1857.

[11] Intergovernmental Panel on Climate Change, Working Group I: The Scientific Basis. Retrieved from: https://archive.ipcc.ch/ipccreports/tar/wg1/378.htm.

[12] Cao Y, Yin K, Li X, et al. Forecasting CO2 emissions from Chinese marine fleets using multivariable trend interaction grey model. Applied Soft Computing, 2021, 104: 107220.

[13] Duan H, Luo X. A novel multivariable grey prediction model and its application in forecasting coal consumption. ISA transactions,2022, 120: 110-127.

[14] Deng J. Introduction to grey system theory. The Journal of grey system 1989, 1(1): 1-24.

[15] Meng Y, Hossain N. Predicting CO2 Emission Footprint Using AI through Machine Learning. Atmosphere, 2022, 13(11): 1871.

[16] Mardani A, Van Fan Y, Nilashi M, et al. A two-stage methodology based on ensemble Adaptive Neuro-Fuzzy Inference System to predict carbon dioxide emissions. Journal of cleaner production, 2019, 231: 446-461.