Trade Flows and Carbon Emissions: Can We Achieve Climate Targets?

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Abstract

Policymakers have been calling for actions to meet the UN targets to reduce emissions to 1990 levels. Aligned with the aim of this study, we use a range of machine learning methods to predict the carbon emissions of 30 countries and establish those that are on track to achieve the UN targets. We provide a breakdown of the forecasted freight modal emissions of 23 countries using trade flows. We segment them using K-Means clustering to compare their CO2 emanations. Our findings indicate that only three countries are in line with the mentioned targets. Thus, we propose actions for those that are not.

Keywords: Trade Flow, Machine Learning, Carbon emissions

Introduction

In the past, the fluctuation of the temperature and rainfall were either due to pre-anthropogenic factors such as volcanic eruptions or solar flux (Crowley, 2000). However, nowadays, the impact of human activity on climate change has become even more evident and dramatic than natural disasters. Climate change, which is an internationally recognised problem, has far-reaching impacts, affecting everything from geopolitics and economies to migration. In fact, transportation, which is responsible for 19.2% of the carbon emission, has an important role in climate degradation. Therefore, taking appropriate preventative measures will contribute to the reduction of transport-related emissions and their drastic impact on climate change.

In December 2019, the European Commission declared the adoption of "The European Green Deal" (2019) to realize climate neutrality in Europe by 2050. This initiative underlines that it is necessary to realize a 90% reduction in transport emissions by 2050

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and 50% of 1990s emissions by 2030 to achieve climate neutrality. According to European Commission, the transport sector is the second largest source of carbon emission after manufacturing. In fact, about one-quarter of the European Union's (EU) greenhouse gas emission is due to the transport sector, and the share of the road sector is more than one-fifth of the total carbon emission in the EU (European Green Deal, 2019). An increase in multimodal transport and a shift from the road, which is used to handle 75% of inland freight transport onto rail and waterways, is considered an important tool to increase the efficiency of the transport system.

In this paper, we predict the total CO2 emissions of the transportation sector per country and investigate the capability of meeting the climate change targets across 30 countries in 2030. Furthermore, we analyse the distribution of emissions across transport modes to compare and cluster these countries based on their emission patterns. Accordingly, we answer four research questions:

1. What are the carbon emission predictions for countries by 2030?
2. How likely is each country to achieve the UN climate target of reducing carbon emissions to half of 1990 levels?
3. What will be the future share of CO2 emanations across transport modes considering the trade volumes of each country?
4. What freight transport policies could help clusters of countries to reach their UN climate targets?

The paper is organised as follows. Initially, we present the literature review, discussing the transportation sector's environmental effects on climate change and its significance. We continue with providing the relevant literature on transport mode distribution. We then review the use of machine learning models in predicting emissions. Next, we describe the methodology employed to answer the discussed research questions, including the underlying data sources. Finally, we present our findings and reflect on our results by providing insights, discussing the limitations, and offering future directions.

Literature Review

Impact of Transportation on Climate Change

The sustainability of transportation and its impact on climate change have been widely studied in the literature. Pal et al. (2023) identified the transportation factors that impact climate change and the preventive measures that can be used to deal with them. They grouped these measures as "environment," "sociology," and "modernity" and assessed them using Simple Additive Ranking, Interpretive Structural Modelling, and Interpretive Ranking Process. Based on the literature survey as well as discussions with the experts, they used 12 transportation factors and 12 preventive measures and analysed the existence or nonexistence of relationships between each transportation factor and the preventive measures. They found that population growth and urbanization are the major factors that influence climate change by increasing the demand for vehicles and their emission. They revealed that pollution has the highest priority that dominates other factors. The top three related transportation factors were ranked as carbon emission, global warming, and depletion of the ozone layer, followed by others such as urbanization and residents' attitudes. In this way, they provide an overall picture of the order of factors to solve the climate change problem. However, the selection weights they used in Simple Additive Weighting are arbitrary and can result in different outcomes depending on the specific weights chosen. The selection of an appropriate sample of experts who will be representative of the climate change problem analysis is lacking.

Perez-Calder et al. (2021) analysed whether the European aviation sector was able to adapt itself to the EU emission trading scheme. They focused on 10 European airlines from 2012 to 2019, when the airline sector was introduced to the emission regime. K-means clustering groups the airlines based on their eco-efficiency level and applies the Markov model to predict future behaviour. They revealed that the larger airlines were the most eco-efficient while those that focused on low-cost strategy behaved worse. Although they made improvements in their use of air traffic capacity, their CO2 emission efficiency was not improved and even got worse in some cases. On the other hand, the trend that they observed using a Markov model showed that European airlines would experience a decline in CO2 emission efficiency in the medium and long term. This was attributed to their already tight operational efficiency, the economic collapse caused by the pandemic, and the increasing share of the low-cost business. However, the study lacks a scenario analysis that would demonstrate the implications of different measures. For instance, encouraging investments in the development of biofuels and the supply chain, as well as making international agreements to obtain optimal flight routes to increase the energy efficiency of engines.

Ülengin et al. (2018) also analysed the impact of transport on greenhouse gas emissions. Initially, they defined the environmental, economic, social, and political dimensions of the transportation sector based on document coding of the related literature, and expert judgments. They conducted a fuzzy cognitive map analysis to investigate variables related to climate change. They assessed the impact of potential policies based on the scenarios provided by the International Energy Agency for the global level as well as the local policy suggestions developed by Turkish authorities for the local level. The scenario analysis showed that improving vehicle efficiency alone would not reduce carbon emissions drastically. An aggregated scenario, where R&D incentives, policy actions (including carbon taxation), motivation toward alternative fuel options, and environmental standards, all contribute significantly to reducing the climate impacts. From a localized perspective, on the other hand, the decrease in the share of freight transportation by road with an increase by rail and air, the increase in HOV lanes and toll charges, and R&D activities to improve electric and hydrogen-powered passenger cars have a significant impact in reducing the emissions. However, the authors did not use a multicriteria decision model to select the best strategy to focus on.

Tight et al. (2005) investigated the development of UK transport targets for CO2 emissions for 2050. They used five future carbon emission scenarios for the UK in order to achieve the stabilization of Co2 at 550 and 450 ppm. They used 26% of the total emission as well as 41% of the total emission based on the forecast as two approaches to specify the proportion of carbon emission that can be attributed to transport sections. They derived the overall targets and expected contributions from transport emissions to be achieved by 2050, which ranged from 8.2 to 25.8 MtC. Their analysis showed that even the lowest target requires an important reduction from the current emission level. Hence, important changes related to the nature of transport and the perception of organizations and individuals will be necessary to achieve the targets. However, they did not make a detailed analysis of each transport mode.

Transport mode distribution

In the literature, the measures to reduce carbon emissions in the freight transport sector are generally based on new energy vehicles and the role of biofuel. Chiaramonti et al. (2021) provide an extensive literature review on this issue. Panoutsou et al. (2021) provide information about policy-related challenges to the use of advanced sustainable biofuels for transport. On the other hand, an important contribution to the reduction of carbon emissions can be realized through a modal shift in freight transport that happens gradually and slowly. Multimodal logistics policy should be aligned with clean energy-based electrification policies and national rail plans (Gupta and Dhar, 2022). However, the literature on the impact of modal shifts is relatively scarce.

Chen et al. (2020) analyse the impact of the modal shift on reducing carbon emissions. For this purpose, energy consumption and carbon emissions of road and rail freight transport are compared, and scenario analysis is conducted to find the energy and carbon emission reduction in the transport sector by the modal shift policy. They found that although the modal shift policy plays a positive role in carbon emissions, the costs caused by the policy are higher than the benefits in some situations. They suggest analysing each case separately rather than using the same regulation in each area.

Pinchasik et al. (2020) make several scenario analyses, such as longer freight trains, policy packages, border-crossing measures to reveal the effect of shifting from road to rail and waterborne freight transport on reducing emissions in the Nordics. Their analysis showed that the impact of such a shift is only minor, and it should only be accepted to contribute to other policy objectives.

Jonkeren et al. (2019) evaluate the impact of a modal shift in transportation to carbon dioxide emission reduction. They use the shift-share model to reveal how rail and inland waterway transport will contribute to reducing carbon dioxide emission reduction. They analyse the market freight transport in the Netherlands. The model helps to specify whether and to what extent any policy related to modal shift will result in carbon dioxide emission reduction. The position of the balls in a quadrant shows whether a respective transport mode will contribute to a reduction in the future.

Forecasting CO2 Emissions of Countries

Throughout the literature, various methods have been utilized to predict the CO_2 emissions of the countries. Some research methods opt for the utilization of survey-based methods (Piecyk and McKinnon, 2013), some utilize decomposition methods to derive the underlying impacting factors (Qu, 2020), and others use secondary data to model and estimate the subsequent emissions of a specific country. For instance, some studies have adopted neural networks (Wen and Yuan, 2020), while others utilize other models such as kernel prediction algorithms (Ma et al., 2021), SVM (Sun et al., 2019), regression (Zhao and Niu, 2017), and RELM (Sun and Sun, 2017). Most of these models depend on the richness of the environment, and they are best utilized when there is an abundance of data to predict the future CO_2 emanations of a specific sector. Lack of sufficient data or predictors will result in partial training of the models and inaccurate results. In this study, we adopt machine learning approaches to predict future CO_2 emission patterns based on univariate data. Moreover, the majority of the literature on transportation sector emissions focuses on modelling a specific country's emanation pattern (Wang and Wang, 2021; Li et al., 2021; Yang and O'Connell, 2020). Compared with these works, we consider multiple countries. Lam et al. (2018) provided their analysis of passenger transport emissions, and Kazancoglu et al. (2021) focused on road transport emissions. However, we focus on freight transport emissions rather than passengers or a specific mode of transportation.

Our contribution to knowledge is that we relate CO_2 prediction with transport mode emission distribution usage and to specify which country will be able to reach the emission targets set by the EU and which countries will fall short of them. We compare the estimates in terms of the range of possible CO_2 emanations (i.e., prediction interval) they attain; thus, our focus is not on the accuracy but rather on providing a scenario-based analysis of the likelihood of achieving certain targets. This will provide an important guideline for the governments to decide on the countermeasures to be taken.

Methodology

Data sources and variables

Various data from different sources have been utilized for research. The univariate data used to forecast the trajectory of emissions and evaluate whether a country would reach the Green Deal goals was adopted from European Commission's Emissions Database for Global Atmospheric Research (Crippa et al., 2022). The data includes longitudinal measurements of annual carbon dioxide emissions of various countries from 1997 to 2021 measured in million tonnes and comprises a breakdown of emissions by sectors. We used the transport sector's CO2 emanations for this study to evaluate the possibility of countries reaching the Green Deal goals by 2030. Also, to exclude the anomalous decrease in CO2 levels during the COVID-19 pandemic (Le Quéré et al., 2020), we only utilised the data points up until 2019.

The other data source that was utilized was Eurostat's database (Eurostat, 2023) which included data for the modal split of air, sea, and inland freight transport by trade volume for each country across various years. We use the carbon emissions in tonne-km attributable to each mode based on the freight distribution to modes. In the case of Australia, the modal distribution was obtained from the annual statistics yearbook published by its respective department of transport (BITRE, 2022). Moreover, modal split of Turkey was obtained from the impact assessment report of its ministry of Environment, Urbanization and Climate Change (Directorate General of Environmental Impact Assessment, Permit and Inspection, 2021).

Prediction

By adopting a machine learning approach, we utilize PyCaret's Python library (Ali, 2020) to train and compare a range of time series models and derive transport emission forecasts of countries up to 2030. In addition to providing various time series models, this package also automates the parameter selection stages described in Beard et al. (2019). Prior to a training and parameter selection, data is scaled using a median-based scaling method that is robust against outliers (Lin et al., 2018) to dampen the effect of anomalous data points. Moreover, to equalize the variance (Milionis, 2022), approximate the underlying white noise to a normal distribution (Shumway and Stoffer, 2017), and ease deriving the prediction intervals (Chatfield and Xing, 2019), we consider box-cox and log transformations on the input data before training the models. The choice of whether to apply the transformation or which one to choose depends on the model's performance on the test set.

The models are then trained using the widely utilized 80/20 train-test split and cross-validated using a 4-fold expanding window approach where the forecasting horizon is set to 11 years ahead to predict 2030's emissions, with a window size of 10 and step size of 5. After training using 39 training observations, the 10 top-performing models are selected and evaluated, considering their mean absolute percentage error and based on the remaining 11 data points to derive the best-performing model. This model is then trained on the entire data and used to obtain the point estimates and prediction intervals of the amount of emission up until 2030. For the models that do not inherently offer the prediction interval as an output, we calculated the empirical prediction interval by bootstrapping the countries' emission data and creating 100 sample time series that mimic the underlying data and forecasting 2030's emanation.

The obtained prediction interval from the best-performing model denotes the range of values that the estimated CO2 emissions can take. Thus, comparing it with the country's emission target and calculating the proportion of the forecasted emission range below the target level to the entire predicted emission interval will determine the country's probability of reaching and producing lower than the targeted emission level for 2030 based on the current trend in the data. Consequently, if the emission range of the county falls entirely below the target emission, the probability of that country reaching the Green Deal objective would be 1; au contraire, if the emission range falls entirely above the target goal, the probability would be 0.

Moreover, the obtained point estimates of the 2030s emitted CO2 only reflect the total transport sector emanations. However, the question remains, to what extent each freight transport mode contributes to the emissions of a country? This distinction is important since each mode contributes disproportionately to the country's overall pollution, especially since there is a significant difference among the average emission factors of each mode. To answer this question, we first convert the forecasted CO2 emissions to freight transport-only emanations (provided in an article by Ritchie, 2020). Then, by utilizing the latest freight modal split percentages (considering that 2019 was the last data point used for building the model) and factoring in the average emission factors of each transport mode, we derive the forecasted carbon dioxide produced by each country per transport mode. To incorporate the emission factors, we utilized the information provided in European Chemical Transport Association (ECTA) and European Chemical Industry Council (CEFIC) Guideline for Measuring and Managing CO2 Emission from Freight Transport Operations (ECTA & CEFIC, 2021). Due to the constraints on data coverage, we could not include the United States, Iceland, New Zealand, Japan, Mexico, and South Korea in this analysis.

By utilising cluster analysis on the resulting data, we identify the countries with homogeneous estimated modal emission patterns. We employ a model-based approach for this analysis and perform K-means clustering (Hartigan and Wong, 1979) to derive the results. The optimal number of derived clusters is determined using an elbow method. The resulting clusters reveal the countries that require adopting similar policies to conform to the Green Deal objectives. Finally, we compare the modal split and transport mode emission distribution of the countries reaching the 2030s target with others.

Findings

After deriving the prediction intervals, they were compared with the Green Deal objectives (whether the forecasted interval includes 50% of the average 1990s emissions) to derive the fraction that the predicted interval falls below the target emission level. Table 1 outlines the best-performing models and their estimates.

Table 1: Best Performing Models and their Estimates of 2030's CO2 Emission.

Country	Best Model	MAPE	Target Emission	2030 Forecast	Forecast Bounds	Prob
Australia	AdaBoost	0.53%	33.291	113.609	[113.287, 116.222]	0
Austria	AdaBoost*	1.83%	7.960	28.702	[27.097, 30.486]	0
Denmark	Naive Forecaster†	13.93%	5.720	12.185	[9.781, 15.181]	0
Finland	ARIMA‡	7.08%	5.766	10.823	[8.023, 12.554]	0
France	Naive Forecaster†	2.09%	60.951	125.688	[104.988, 150.469]	0
Germany	Theta Forecaster‡	1.77%	83.805	165.205	[145.316, 180.892]	0
Greece	Auto ARIMA†	24.64%	8.550	9.9144	[8.121, 12.104]	0.108
Hungary	ARIMA†	11.15%	3.799	13.411	[10.0943, 17.817]	0
Iceland	Extra Trees*	5.20%	0.315	1.0111	[0.992, 1.357]	0

Country	Best Model	MAPE	Target Emission	2030 Forecast	Forecast Bounds	Prob
Ireland	ARIMA‡	13.59%	3.209	11.431	[8.105, 15.999]	0
Italy	ETS‡	11.45%	53.096	95.819	[49.6567, 126.564]	0.045
Japan	Auto ARIMA	3.14%	121.088	161.974	[9.5574, 314.39]	0.366
Latvia	Gradient Boosting*‡	9.14%	1.122	3.529	[2.674, 4.014]	0
Lithuania	Bayesian Ridge*‡	12.38%	1.905	6.202	[5.253, 8.101]	0
Luxembourg	Decision Tree*	17.40%	1.736	7.867	[7.355, 10.504]	0
Mexico	Naive Forecaster†	1.20%	46.396	147.283	[107.988, 200.877]	0
Netherlands	Theta Forecaster‡	17.10%	14.883	32.132	[27.272, 36.393]	0
New Zealand	ETS‡	5.31%	5.081	19.600	[17.796, 21.491]	0
Norway	ARIMA‡	4.91%	5.690	11.225	[8.575, 13.593]	0
Poland	Theta Forecaster †	11.51%	11.921	70.111	[48.252, 101.871]	0
Portugal	Exponential Smoothing	16.45%	6.409	21.026	[11.399, 29.069]	0
Slovakia	K Neighbours*‡	8.62%	1.858	9.824	[5.481, 58.183]	0
Slovenia	K Neighbours*	4.21%	1.717	6.683	[6.185, 7.282]	0
South Korea	Extra Trees*	5.01%	31.862	136.589	[117.308, 153.019]	0
Spain	Decision Tree*	30.41%	36.797	112.129	[104.089, 143.515]	0
Sweden	ARIMA‡	10.99%	10.090	16.702	[10.714, 19.788]	0
Switzerland	Naive Forecaster‡	5.55%	7.360	15.762	[13.437, 17.717]	0
Turkey	Orthogonal Matching Pursuit*†	13.59%	15.834	112.978	[108.752, 146.565]	0
UK	Croston‡	2.01%	59.23	117.903	[115.397, 119.395]	0
United States	Auto ARIMA	4.64%	763.1	1915.667	[1687.23, 2144.104]	0

* These models internally apply conditional Deseasonalising and Detrending
† The input was log transformed.
‡ The input was transformed using Box-Cox method.

Predictions for individual countries

The forecasts from the models demonstrate that among the 30 countries considered for this study, only 3 countries show the possibility of reaching the goal. The estimates, which reflect the current trajectory of the countries' emissions and their underlying policies at play, elucidate that many countries cannot reach the emission reduction objective. Of the analysed candidates, only Japan, Greece, and Italy exhibit a chance to reach and exceed their target objective in 2030. Moreover, the findings also suggest a strong requirement for policy reform among the studied country to reach their emission reduction objective.

Clusters of countries in achieving climate change targets

After gathering and synthesising the modal freight distribution of the focused countries and their respective predicted emissions in 2030, we clustered them using hierarchical clustering. The optimal number of clusters was selected as two based on the dendrogram, the within-group sum of squares plot of the clusters with respect to the number of clusters experiences it first veer. Segmenting the countries revealed two clusters: one cluster with 7 countries and another with 16 countries. Countries in the first group are heavy emitters (France, Germany, Italy, Poland, Spain, Turkey, Australia) and those in the second group are light emitters. Considering this assignment and the countries that exhibit a chance to reach the Green Deal objectives, we can suggest that balancing the emission amounts across transport modes or opting for rail freight transport mode, which possesses the lowest average emission factors, would be ideal for reaching this target.

To provide an alternative perspective on how these countries differ in their emission amount across modes, we group the countries reaching and not reaching the discussed goal and compare their average emission amounts across modes utilizing the null hypothesis framework. By analysing Table 2, we can conclude that the main difference between the countries that have the potential to reach the Green Deal goal arises from the higher number of emanations they have from maritime. This discussed difference is partially significant at a 90% confidence interval (*t=1.744; SE=3.423*).

Table 2: Comparison between countries that are likely and unlikely to achieve targets

		Statistic	**Df**	**p**	**Mean difference**	**SE difference**
Inland waterways	Student's t	0.5276	21	0.603	0.262	0.498
	Mann-Whitney U	12.00		0.292	5.17e-5	
Maritime	Student's t	-1.7553	21	0.094	-6.036	3.439
	Mann-Whitney U	5.00		0.089	-3.466	
Roads	Student's t	-0.0248	21	0.980	-0.340	13.696
	Mann-Whitney U	17.00		0.711	1.274	
Railways	Student's t	0.3643	21	0.657	1.166	3.202
	Mann-Whitney U	17.00		0.711	0.200	
Air	Student's t	1.0479	21	0.307	0.559	0.533
	Mann-Whitney U	4.00		0.069	0.339	

Discussion and conclusion

Throughout this research, we aimed to provide a more detailed account of how far the countries are from achieving the climate neutrality goals. This study we attempted to answer the following questions: “How likely is it for the countries to reach the Green Deals initiative’s 2030 milestone?” and “What would be the modal emission distribution pattern of freight transport in 2030 among the countries?”. To answer these questions, we adopt a machine-learning approach to forecast 30 countries’ emissions and derive the CO_2 emanations of countries per each transport mode based on the current policies and the modal split. With only a few years away from reaching the climate initiative’s 2030’s milestone, the estimates intervals indicated that among the 30 analysed countries, only Greece, Italy, and Japan exhibited a chance of reaching the discussed target and show a necessity for drastic reforms in the current transport policies. These exigent findings indicate that only a few countries will adhere to the Green Deal goals.

Moreover, by clustering the resulting output from the modal emissions split, we found 4 distinct future emission patterns among the countries based on the current policies. The clusters reveal that for the countries to adhere to the set targets of the initiative, they should either balance out their emissions by decreasing their dependence on a specific transport mode while trying to reduce them or they should try to become more dependent on more alternative transport modes such as rail due to their low emission factor. Finally, we grouped and compared the countries that present the chance of reaching with initiative's 2030 objective and others. The findings indicate that the main difference between these groups is the amount of CO2 emitted from maritime, and these countries' distinctiveness is because they are heavily reliant on maritime transport mode.

Future research could examine the level at which countries would reach the target goals by providing a scenario analysis. Alternatively, it can also address the limitations of this study in the following ways. This study adopted a machine-learning approach to predict future CO2 emissions by selecting a model, among many, based on its performance on the test set. Adopting a more sophisticated approach that models the underlying assumption of a country's CO2 emissions or including preceptors that improve the model's fit would provide a better and more accurate forecast. Additionally, since the underlying technology employed for producing fuels is constantly improving, the emissions factors are subjected to constant change. Thus, utilizing an updated average emission factor per mode could better estimate how the emissions are scattered along transport modes.

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