Assessing the impact of Electric Vehicles on CO_2 emissions and Air Pollution

Brian Riera
National College of Ireland
Dublin, Ireland
x23186771@student.ncirl.ie

Nicholas Stancill
National College of Ireland
Dublin, Ireland
x22225668@student.ncirl.ie

Ramesh Thoppe
National College of Ireland
Dublin, Ireland
x23206446@student.ncirl.ie

***Abstract*— The objectives of the study are to predict the growth of electric vehicle sales in the EU and the impact on factors which affect climate change. The correlation between air pollution, CO_2 emissions, and electric vehicle sales were investigated. Forecast models of predicted future data were generated using time series. The trend suggests that as electric vehicle sales increase, CO_2 emissions and air pollution should decrease.**

I. Introduction

Fossil-fuelled vehicles play a substantial role in the emission of greenhouse gasses (GHGs), accounting for approximately one fifth of global CO_2 emissions in 2022 [1] and have a significant role in contributing towards air pollution. As the global number of vehicles is projected to triple by 2050, associated GHG emissions are expected to increase at a pace surpassing that of any other emission sources [2].

The increasing global concern over climate change has prompted a paradigm shift towards sustainable transportation solutions. Electric vehicles (EVs) have emerged as a promising alternative, with growing adoption aimed at reducing both air pollution ($PM_{2.5}$) and carbon dioxide (CO_2) emissions. Research and development of EVs have surged since the 1990s, evidenced by a notable increase in patent registrations [3]. This growth has been aided by government initiatives worldwide, including the imposition of stricter tail-pipe CO_2 targets on the automotive industry by the EU resulting in a notable rise in the market presence of EVs [4].

Despite a significant expansion of the global electric vehicle fleet to align with zero-emission objectives, it remains a minority within the overall global fleet. Furthermore, the majority of these electric vehicles are concentrated in areas characterized by a substantial market share in EV adoption, such as China, Europe, and the United States [5].

A study in 2020 discovered that a 25% transition to electric cars in the United States, factoring in the existing electricity mix, would result in marginal reductions in air pollution. However, a more substantial 75% adoption, particularly in conjunction with a cleaner grid, holds the potential for a significant decrease in pollution levels [6].

This study endeavors to investigate the relationship between electric vehicle sales, carbon dioxide (CO_2) emissions, and air pollution levels, specifically focusing on particulate matter ($PM_{2.5}$). The investigation aims to explore these interconnections at a macroscopic level, considering the broader environmental implications and dynamics that influence the transition towards a more sustainable and eco-friendly landscape.

II. Related Work

To comprehensively investigate the interplay between EVs, air pollution, and CO_2 emissions, a systematic search strategy was implemented. The criteria for selecting literature aimed to include recent, peer-reviewed studies with a focus on empirical research related to the adoption of electric vehicles, their impact on air pollution, and the associated changes in CO_2 emissions. In each study, the measurement of air pollution was predominantly focused on the particulate matter $PM_{2.5,}$ a key indicator of fine particulate pollution with known implications for respiratory health.

A 2014 study observing air quality in Barcelona and Madrid following EV introduction discovered significant air quality improvements despite additional electricity generation emissions [7]. However, it is important to note that the conclusions drawn were based on a short episode of time. In the study's own words, "The conclusions shown in this study are derived from the study of an air pollution episode in 2011 (worst-case). Although it cannot be considered a large period, it is an episode with significant air pollution."[7] This recognition of a limited time frame highlights the need for caution in generalizing the findings to broader contexts, emphasizing the importance of considering temporal variability in assessing the impact of EVs on air quality.

A study assessing the contribution of diesel vehicle emissions to the concentrations of $PM_{2.5}$ in Dublin, found that the second-largest contributor at a road site was diesel vehicle emissions (22%). The research was small-scale and specific to certain zones, raising concerns about the representativeness of the concentrations for general urban air quality in Dublin, particularly when extrapolating to broader contexts. As the study acknowledges, "The differences between Site A and all other monitoring stations give rise to concerns about the representativeness of these concentrations of general urban air quality in Dublin." [8] During the full Covid lockdown in China, it was found that the substantial traffic reductions were near linearly linked to reductions of $PM_{2.5}$ and NO_2 [9]. Further extrapolation of a full conversion to EVs showed a significant reduction of $PM_{2.5}$ (30-70%) in most of China. Similarly, in a more recent study, the relationship between EV adoption and local $PM_{2.5}$ reductions across 31 provinces in China was investigated. The findings of the research are particularly inspiring, demonstrating a significant alleviation of $PM_{2.5}$ pollution with increased EV adoption. Stating that a 1 additional unit of EV sales can reduce 1.75×10^{-5} μg/m^3 of $PM_{2.5}$, underscoring the potential impact of EV adoption at a local level [10].

While these studies provide valuable insights into the local dynamics of EV adoption and its effect on air quality in China, the current study takes a broader perspective. Building upon the findings garnered from studies in Barcelona, Madrid, and Dublin, our research seeks to examine the relationship between electric vehicle adoption, CO_2 emissions, and air quality on a larger scale, specifically within the context of Europe. By shifting our focus from individual provinces to a more extensive geographical coverage across Europe, this study aims to contribute to the understanding of the broader environmental benefits associated with widespread electric vehicle adoption in the European context.

III. METHODOLOGY

Total CO_2 Emissions is a semi-structured XML dataset, derived from Climate Watch Historical GHG Emissions for the years 1990-2020, quantifying total CO_2 emissions in Metric Tonnes per Capita (MTPC) at a country level. The dataset's structure allows for granular, country-level insights into the historical trends of CO_2 emissions. Enabling the examination of the relationship between electric vehicle adoption, air pollution, and CO_2 emissions, contributing to a comprehensive understanding of the environmental impact of sustainable transportation. The Electric Vehicle (EV) dataset is a structured CSV dataset derived from the International Energy Agency. The dataset comprises of information that contains country wise sales, stock, EV share percentage and sales percentage. The Air pollution dataset used in this analysis is a semi-structured XML file derived from the Global Burden of Disease Study 2019 (GBD 2019). The dataset encompasses an air pollution metric, specifically the concentration of particulate matter (PM2.5) in micrograms per cubic meter (µg/m³), for the years 1990 to 2019, across various countries highlighting their mean annual exposure. Its inclusion, allows the correlation and contextualization of environmental data related to EV car sales, and CO2 emissions. To ensure the most current information, additional data for the years 2020, 2021, and 2022 was web-scraped from Wikipedia for 131 countries.

The greenhouse gas emissions dataset is sent by countries to UNFCCC and the EU Greenhouse Gas Monitoring Mechanism (EU Member States). This data set reflects the GHG inventory data by year as reported under the United Nations Framework Convention for Climate Change. This data set is available under the European Environment Agency website containing different types of Greenhouse Gas emissions and the CO_2 equivalent measures at every European country level, as well as aggregated measure at EU level. The dataset also covers every sector's/industry's contribution to greenhouse gas. For the purpose of this study only data pertaining to cars has been used. It is also important to note that, with changes in EU membership, the UK is no longer a member state of the EU since 2020, while Croatia joined in 2013.

Python was chosen as the programming language for this project due to its versatility and extensive set of libraries tailored for efficient Extract, Transform, Load (ETL) processes. The language's readability and integration with databases such as MongoDB and PostgreSQL, allowed for effective handling of diverse data formats, ensuring a streamlined ETL workflow throughout the project. The project initiated with files being read into Python, facilitated by the 'with' statement, a concise resource management tool. The use of a context manager aimed to bolster code robustness as it automates resource management, ensuring proper file closure and minimizing the risk of errors.

The initial XML files were stored in MongoDB as binary files using pymongo, allowing interaction between Python and the database. MongoDB was selected for storage due to its NoSQL document-oriented structure, and suitability for semi-structured data. The decision to store the files directly as binary objects, without conversion to a dictionary, was influenced by the project's brief. MongoDB's support for BSON (Binary JSON) facilitated the storage and retrieval of both XML files for subsequent processing stages.

In the ETL process, XML files retrieved from MongoDB were parsed using ElementTree, allowing systematic extraction from the hierarchical format of the original files, as well as extraction of specific elements and attributes. Subsequently, the extracted data were transformed into Pandas DataFrames, providing a structured tabular format, standardizing the data representation for efficient cleaning and transformation. Pandas was chosen for its powerful data manipulation and analysis capabilities, making it an ideal tool for the ETL process.

In the extraction process of CO_2 emissions data from the XML file, a list comprehension and for loop were used to extract unique column names from the 'fields' elements within the first 'record'. This combination was then employed to iterate through each 'record' element. To account for scenarios with no 'record' elements or an empty XML file, the 'None' condition was incorporated. The '.text' method was utilized to extract data from each 'field' element, and the extracted data was appended into a list for subsequent storage as a dataframe. As the (GBD 2019) air pollution dataset had the same structure to that of the CO_2 xml file, the same code was implemented. To incorporate air pollution data for the years 2020-2022, web scraping using Beautiful Soup was employed on a static Wikipedia page. Beautiful Soup was selected for this task due to its effectiveness in parsing HTML and XML documents.

Inspecting the webpage and identifying table headers and rows facilitated data extraction. Each 'heading' element nested under the 'headings' element was examined to identify the column names. Simultaneously, each 'row' element was processed to extract the text content of 'cell' elements within. The webscraped air pollution XML file's hierarchical structure contained nested 'heading' elements representing column titles, and 'rows' for individual data records. Data were gathered similarly to the previous XML files, using list comprehensions and for loops to extract text from the 'heading' elements to form a list of column names, and iterate through 'rows' to gather text from each 'cell' element.

Upon creation of the dataframes, data transformation operations were conducted, including dropping redundant columns and converting data types to numeric, ensuring data consistency and enabling the data for aggregation, analysis, and visualization. Additionally, techniques like forward and backward fill were applied to address missing values. The decision to use forward and backward fill was driven by the temporal nature of the data, where adjacent time points were likely to have similar values. In cases where there was insufficient information, missing values were dropped to maintain data integrity and quality throughout the analysis process. The transposition by year facilitated visual trend analysis, ensuring alignment with project goals. Following data preparation, descriptive statistics were computed to provide a comprehensive overview of the datasets.

The structured CSV and cleaned dataframes were stored in a PostgreSQL database due to its support for structured data and as a robust relational database management system (RDBMS), it aligned well with the organized rows and columns of the dataframes. Libraries psycopg2 and SQLAlchemy's (an Object-Relational Mapping (ORM) library for python) compatibility with PostgreSQL, allowing database interactions, made it an optimal choice for managing the upload of the dataframes.

IV. Results and Evaluation

Table I shows the correlation coefficients for each of the three variables Air Pollution, EV Sales, and Total CO_2 Emissions. There was a moderate negative correlation between Air Pollution and EV Sales (r= -0.59), while there was a weak negative correlation between EV Sales and Car Emissions (r= -0.055). A strong negative correlation was found between EV Sales and total CO_2 emissions (r= -0.84) suggesting that as EV sales increase CO_2 emissions decrease. The data suggests that as EV Sales increase, air pollution and CO_2 emissions tend to decrease while there is a slight reduction in Car Emissions.

TABLE I. The Correlation Coefficients Between the Variables

	Air Pollution	EV sales	Total CO2 emissions	Car emissions
Air Pollution	1.00	-0.59	0.88	0.084
EV Sales	-0.59	1.00	-0.84	-.055
Total CO2 Emissions	0.88	-0.84	1.00	0.34
Car Emissions	0.084	-0.55	0.34	1.00

A strong positive relationship was found between Air pollution and Total CO_2 Emissions (r= 0.88) indicating that as one increases so does the other. A weak positive relationship was found between Air Pollution and Car Emissions (r= 0.084) with almost no linear relationship between the two based on the data. For total CO_2 emissions and Car emissions the correlation coefficient is (r= 0.34), indicating a weak positive relationship, so as CO_2 emissions increase, car emissions tend to increase slightly.

Time series forecasting modelling using Python library statsmodels was applied to predict patterns and trends in the data to obtain future insights on the EU27 countries. ARIMA model was used to forecast EV Stock for the next 10 years . The forecasting model (Table II) shows that EV sales represent 2.3% of total car sales for the year 2022 and this is predicted to increase to 25.73% of total car sales by the year 2032. Exponential Smoothing forecasting model was used on Greenhouse gas emissions to forecast its emission from 2022 to 2032. Later then it was merged with EV forecast data to project CO_2 emissions reflecting EV car's share percentage.

TABLE II. Time Series Forecasting Model

Year	Cars CO_2 Emission	All Cars	EV Cars	EV Cars %
2010	470,815	202,857,150	2,840	0.00
2011	464,551	208,600,005	10,430	0.01
2012	446,070	220,714,279	30,900	0.01
2013	448,657	219,999,999	77,000	0.04
2014	458,350	221,666,672	133,000	0.06
2015	466,628	227,272,729	250,000	0.11
2016	477,580	217,647,057	370,000	0.17
2017	483,452	221,739,126	510,000	0.23
2018	480,336	227,272,718	750,000	0.33
2019	483,220	242,222,229	1,090,000	0.45
2020	406,561	253,488,368	2,180,000	0.86
2021	440,487	243,749,996	3,900,000	1.60
2022	473,316	247,826,092	5,700,000	2.30
2023	470,192	250,496,052	7,192,458	3.19
2024	465,705	253,047,692	9,920,844	4.36
2025	459,620	255,486,254	13,436,784	5.84
2026	451,963	257,816,749	17,738,363	7.64
2027	442,690	260,043,968	22,856,679	9.77
2028	431,761	262,172,486	28,818,970	12.21
2029	419,729	264,206,677	35,365,289	14.87
2030	405,380	266,150,722	43,086,164	17.99
2031	388,120	268,008,616	52,279,134	21.67
2032	368,920	269,784,176	62,481,116	25.73

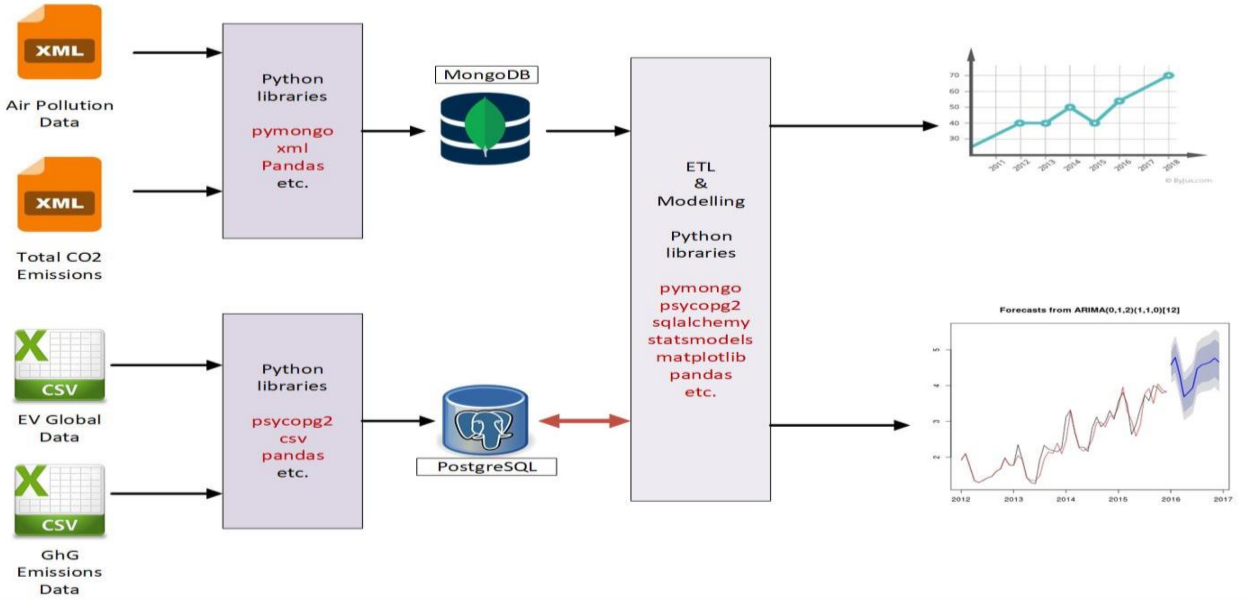

Fig. 1. Methodology of Data Storage and Modelling

Exponential smoothing was used to combine CO_2 Emissions with EV Car Sales to predict future impacts on CO_2 emissions. The final model shows the total CO_2 emissions of all cars and those of electric vehicles. The model shows that the CO_2 emissions for all cars show a small linear growth whereas electric vehicles show an exponential decrease in carbon emissions. Therefore, the assumption can be made that as the population of electric vehicles increase then the CO_2 emissions from cars will also decrease for the EU27 countries.

V. Conclusions and Future Work

In summary, this study delves into the relationships between EV sales, CO_2 emissions, and air pollution (PM2.5), shedding light on dynamics in the evolving landscape of sustainable transportation. The findings underscore a positive trajectory for electric vehicle sales, with projections indicating a sustained increase in adoption. This would lead to a significant environmental impact as electric cars purchased in 2030 are projected to reduce CO_2 emissions four-fold due to an EU grid relying more heavily on renewables [12], aligning with the global shift towards cleaner and more environmentally conscious modes of transportation.

Although on-road transport has been the largest contributor to atmospheric pollutant emissions in urban areas [13], fleet electrification should not be viewed as an exclusive solution, and alternative management strategies need consideration. This is particularly crucial in addressing particulate matter emissions, as fleet electrification yields minimal reductions (<5%) [7], primarily due to the substantial contribution of non-exhaust emissions. Secondly, achieving a noteworthy enhancement in urban air quality necessitates a substantial adoption of electric vehicles (26–40%) across all vehicle categories [7].

The current study faced limitations due to a lack of granularity, hindering its ability to discern intricate relationships and interactions. Although this study predicted decreasing CO_2 emissions with increased electric vehicle sales, variables like Vehicle-use Intensity (VKT) play a crucial role in influencing fuel use and emissions, impacting the accuracy of estimates related to EV adoption and CO_2 emissions [14]. This analysis, conducted at a yearly level, may overlook nuanced seasonal changes that can influence air pollution levels.

Additionally, conducting longitudinal studies requires a substantial amount of historical data to offer insights into the long-term trends and impacts. This study faced limitations due to lack of complete historical data, highlighting the need for a more comprehensive datasets to thoroughly investigate the complex relationships between electric vehicles, CO_2 emissions, and air pollution.

Future research should aim for a finer level of granularity when examining the predicted trend of decreasing CO_2 to unravel subtler patterns and nuances that may exist, taking into account seasonal variations, incorporating in variables like VKT, infrastructure development, and other factors that may offer a more comprehensive understanding of the interplay between EV adoption, CO_2 emissions, and air pollution.

In conclusion, this study serves as a stepping stone in understanding the relationship between electric vehicles, CO_2 emissions, and air pollution. Recognizing its limitations opens doors for future research to explore these relationships with greater depth and precision, contributing to the ongoing discourse on sustainable transportation and environmental stewardship.

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<u>Brian Riera x23186771</u>

Coding:

Files on github:

air_pollution.ipynb + co2_emissions.ipynb combined as Code_artefact.ipynb or .py

global_temperature.ipynb (not used)

Sourced Air pollution XML file & Webscraped additional data - ETL + Descriptive Statistics

co2 emissions file XML - ETL + Descriptive Statistics (After Nicks CSV file was not used)

Temperature JSON - ETL + Descriptive Statistics (Not used)

Correlation **Matrix**

Linear Regression Model (Not used)

Report:

Wrote Intro, Literature Review, and conclusion including all references

Methodology – Description of XML datasets, ETL processes, webscraping and justifications for libraries & Databases

<u>**Nicholas Stancill** x**22225668**</u>

Coding:

Files on github:

Co2_Emissions ipynb (CSV)

Global_temperature ipynb (CSV)

Ev_car sales ipynb (CSV) – included Postgresql database (code to create original database)

Co2_emissions Postgresql upload

Create Output Table & Output Table edit – created output tables for databases and trimmed output tables

Time Series plots ipynb & updated global temp time series ipynb – Created Time series plots for all databases that were used in the final report

Report:

Wrote results section and abstract of the report. Added to methodology in the report. Completed initial report checks making changes to the document, completed second draft of the report, final draft of the report and worked on the final report edit to get the report in the IEEE template.

Ramesh Thoppe x23206446

Coding:

ev_sales.py
eu_ghg_emissions.py
Etc.

Identified a data set on Greenhouse Gas (GHG) emissions from various industries which included breakdown of Greenhouse GHG for cars.

Worked with GHG and Electric Vehicles dataset to ingest into PostgreSQL DB (using library psycopg2)

As part of ETL, extracted data from the DB to analyze these two dataset, applied timeseries modelling using ARIMA and Exponential Smoothing forecasting (python library statsmodels)

End to End Integration of various components. Once DB configurations are set in constants.py entire project could be kicked off by starting Main.py

Report:

Prepared the E2E Design diagram using MS Visio. Added to report section

Prepared documentation for group presentation