Potential Improvement in Sales of EVs through Effective Use of Sales Trend Analysis in Strategic Decision Making

Research Project
MSc in Data Analytics

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MSc Project Submission Sheet

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Potential Improvement in Sales of EVs through Effective Use of Sales Trend Analysis in Strategic Decision Making

Abstract

The automobile industry is gradually transitioning to EVs because the consumers have realized the importance of the environment and there are inventions in the industries that are employed in the vehicles. As for the Such an approach indicates that the market penetration of EVs during this period appears to have been augmented. to only 35% by the investigated automobile firm by the year 2023. The research goal of the present work is as follows: the analysis of the factors that may affect consumption, as well as the identification of measures to improve them. promotion. With this approach in defining sales trends, there is the need for research analysis. Interact with several products and services, customer's behaviour, and conditions in the marketplace. to generate recommendations for EV vendors. The purpose of this research study is to be contributing to the stream of knowledge in the existing body of literature when it comes to gaining a great and exhaustive understanding of the actual sales pattern and consumers' attitudes towards the promotion of the utilization of Regarding EV and providing concrete recommendations on how to boost the sales of the EV.

Keywords: Time series – EVs, sales, data by time-series, and multivariable. analysis, recommendation model.

1 Introduction

Automotive is an industry in transition going electric vehicles (EVs) due to advancement in technology and awareness of the adverse effects of climate change. These changes are important for the global transition from fossil fuel and for controlling environment pollution in line with other sustainability goals. This shift towards more sustainability within the automotive industry to deal with climate change has the potential to provide a significant shift within the societal standards for transportation practices in the countries of the global south. This shift is brought about by increased improvements in technology such as the battery life and efficiency, and positive regulation support for clean transport solutions (W. Sierzchula, S. Bakker, K. Maat, and B. van Wee; vol. 68, pp. 183–194, 2014). These shifts are not merely reactions to external pressures but also the result of shifts in the consumer audience which more and more appreciates green technology (Y. Huang and L. Qian; vol. 155, p. 112338, 2021).

Background

BEVs are significant markers of a new generation of vehicles, enabling by growth in battery technology and policy support of curtailing greenhouse gases. This evolution is happening because of raised level of environmental consciousness amongst consumers, which makes them to demand vehicles that have minimal impact on the environment. The market has been quick to adapt, and auto makers have been developing increasingly complex electric cars that target as many different consumer niches as possible [8]. This strategic shift is revolutionizing the automotive industry, forcing organisations to invent and evolve concurrently to the changing market environment (F. Liao, E. Molin, and B. van Wee; vol. 37, no. 3, pp. 252–275, 2010). Electric cars are not just the result of a technological advancement but are a concept of the AC and DC developing the aspect of sustainable development in a society.

Importance

The emergence of the electric cars is answers to global environmental issues and bring about new shift in consumer behaviour and industry revolution. To automotive sector stakeholders, including manufacturers, policymakers, investors and suppliers, it is of paramount importance to identify motivations which drive the adoption of electric vehicles (I.K. W. Lai, Y. Liu, X. Sun, H. Zhang, and W. Xu; vol. 7, no. 9, pp. 12564–12585, 2015). This is not just the rise in the variant or new model of EVs but an indication of new trends among consumers in a rapidly evolving automotive market. Manufacturers, policy makers, and users themselves therefore need to understand these trends to be better placed to respond and create. When it comes to the options for evaluating these aspects of factors affecting NEV adoption, they not only allow fine-tuning business approaches but also forming the policies that foster sustainable business practices and support environmental objectives in the economy.

Research Objectives and Questions

This study aims to unravel the complexities of the EV market by analysing the factors that influence consumer decisions to adopt electric vehicles and how these factors affect overall sales and market penetration (Y. Zhang, M. Zhong, N. Geng, and Y. Jiang; vol. 70, pp. 1–15, 2019). The research addresses critical questions that will aid stakeholders in understanding market trends and consumer preferences, such as: What makes up the chance of increase in sales for EV retailers? Such factors as these, are likely to affects total sales in what manner? Which strategies of the sales volume improvement can be regarded as suitable and effective? Addressing these questions will provide valuable insights into the evolving automotive market, helping to formulate strategies that promote the widespread adoption of electric vehicles.

Limitations

Several limitations are identified in the research; first, because of the dynamism in the technological sector which is expected to change rapidly during the data collection period, some of the data collected might be outdated by the time the analysis is under way. Furthermore, generalization of results may be a problem due to geographical limitation of the study and the target auditor's population, which restricts the transfer of conclusions of the study on various regions. However, the opportunity of the study is to make as objective estimation as possible in the framework of the set tasks and to reveal the contemporary key directions of thought that can be important for practical application. Another avenue for further research would be to generalize the findings geographically, and demographically, thereby further increasing the externality validity of the investigated research results.

Literature Review

Yong Zhang, Miner Zhong, Nana Geng, and Yunjian Jiang. Traditional models such as ARIMA and advanced methods like Singular Spectrum Analysis (SSA) and Vector Autoregressive (VAR) models are surveyed in a 2017 paper covering forecasting methods for EV sales. SSA works very well in trend analysis, but does not consider macroeconomic, such as fuel prices. By incorporating other variables such as prices and consumer confidence, we get better long-term accuracy of VAR.

Wenbo, Ruyin Long, Hong Chen, Jichao Geng, There are demographic, situational and psychological antecedents of consumer intentions to use battery electric vehicles (BEVs). Good educational attainment and or technical occupations, youth, and the perceived driving range, charging systems, and costs are the factors that may deter the automobile-form adopters of BEVs. For instance, numerous economic factors regarding governmental promotion bear influence on the BEV, which includes rebates and subsidies. Despite the advertisement of BEVs in terms of environmental friendliness, some of the consumers do not care much about this factor, or do not buy the car due to doubts about the production of batteries. Sample, especially Test Drives, and positive attitude towards innovation & environment promote BEV adoption.

Ivan K. W. Lai, Yide Liu, Xinbo Sun, Hao Zhang. In a study on the adoption of FEV in Macau, it is demonstrated that environmental concerns, government support (tax exemptions, subsidies), economic benefits such as lower fuel costs will positively affect intentions to adopt such technology. Policymakers should use environmental awareness and subsidies as well as promote charging infrastructure in order to increase sales, while on the other hand, consumers desire FEV savings and performance at an affordable price.

William Sierzchula, Sjoerd Bakker, Kees Maat, Bert van Wee,2014. Traditional and emerging chemistries such as lithium ion, solid state and metal air are reviewed when it comes to materials, lifespan, thermal regulation and recycling in the review on EV battery technologies. It conveys that it shows battery health, is cost optimized, and further development is needed in materials; thermal management; and recycling.

Virender Singh, Vedant Singh, S. Vaibhav 2020. Key drivers of EV adoption are determined to be cognitive factors such as attitudes, societal norms and behavioral control, as well as demographics, income, education and government policies in the analysis. Aleksej | Mechelen | EV Charging is raised awareness, provide incentives and improve Charging infrastructure to increase EV uses.

Gang Zhao, Xiaolin Wang, Michael Negnevitsky 2017. The analysis of the literature on electric vehicle research areas reveals four areas of focus known as research clusters charging infrastructure adoption of EVs; thermal management; and routing. EV research has expanded ever since 2010 in battery constitutions and structures and the transition from HEVs to BEVs, PHEVs. Research activity leaders are China and the USA majoring in electrical and computer engineering together with environmentalism. Some of the new branches are charging optimization and wireless power technology, and regulation policies of the governments, particularly the Chinese and the EU have a significant influence on research and market.

Zhengwei Xia, Dongming Wu, Langlang Zhang, Diffusion of Innovation theory is applied to explain 63.7% of EV adoption variance. Perceived compatibility (the degree to which values align with the offering; perceived as being compatible vs. incompatibility), complexity (how easy the offering is to use), and relative advantage (environmental or cost advantages) are key factors. That just leaves us with monetary subsidies, which help increase adoption because they address complexity concerns while improving compatibility and advantages.

Youlin Huang, Lixian Qian, 2021 The paper on adoption of EV in alternate business models finds that NFU and highly innovative consumers are inclined to leverage sharing or leasing of EV, viewing shared EVs as modern and successful. Where adoption is fostered by positive psychosocial perceptions, risk-averse customers eschew non-ownership schemes but no direct purchase. Making models available for shared or lease increases adoption rates, and foster positive perceptions.
Fanchao Liao, Eric Molin, Bert Van Wee 2017. A review of EV preferences is conducted based on price, operating cost, driving range, charge time, and policy incentives influencing adoption. They also depend on socio-demographics, environmental concerns and battery reliability. This provides implications for future research focusing on real world data of preference, and consumer attitudes as technological advancements evolve.

1.1 Existing Methods

From the paper (Y. Zhang, M. Zhong, N. Geng, and Y. Jiang; vol. 70, pp. 1–15, 2019). This analysis uses two models: SSA and VAR for the prediction of EV sales in China refer to BEVs and PHEVs. These models were selected because of the dissimilarities in accuracy of time series forecasting, SSA for the univariate data set, VAR for the multivariate data set which contain exogenous variables.

SSA is a non-parametric technique, which does not make assumptions that the nature of the relationship, the variables are linear and normally distribution, and constant. SSA has divided the time series data into trends, periods and noise and is ideal for associated forecasts in environments of rapid dynamism. It originally includes the process of converting time related data into vector space, the decomposition and cauterization and reconstruction to provide a forecast of additional values. This method is particularly appropriate when targeting nonlinear relationships within the data which is very typical when analysing socio-economic and financial data.

On the hand the VAR model is used for simulation of the multivariate time series analysis because many variables are involved. This method results from accumulating the historical value of dependent and independent variables that include pegged economic factors of consumer price index, prices of vehicles as well as other factors from Baidu Consumer Surveys. The VAR model provides the interconnection of these variables thus, the forecast is more complete in regard to the influence of the external stock on the EV sales. The first requirement of applying the VAR model is the non-stationarity of the time series that can be eradicated through unit root tests. Thereafter analyses of the variables to determine the existence of the relationships in the development of the model involved application of the cointegration and Granger causality tests.

1.2 Proposed Methods for Forecasting EV Sales Growth

The purpose of this analysis is to try and estimate the sales of electric cars in 2030 a significant emphasis will be made on the fact that there are common factors that influence the adoption of such cars–infrastructure and population density, first and foremost. This forecast, consequently, will be done in two ways by employing the time series analysis as well as the demographic data and applying (ARIMA) (Dhankhar, S., Dhankhar, N., Sandhu, V., & Mehla, S. (2024)). For this analysis, the Region dataset which can be found on the IEA's website, population data from Kaggle, and charging infrastructure data from the Open Charge Maps shall be used.

Region Dataset from the IEA

The primary analysis focus of this work will be drawn from the Region dataset available in the IEA. The information about prior sales of EVs, principal attributes of regions, and energy consumption information are crucial for EV adoption analysis, which is why they are included in this data set. From the sales performance copy for the various years for the different regions I will have the flow of the EV usage in consecutive years (W. Li, R. Long, H. Chen, and J. Geng; vol. 78, pp. 318–328, 2017). This will afford the opportunity to establish a time series model by applying time series analysis such as the ARIMA to forecast the number of EV sales in 2030. In order to observe the impact on sales increases, regional characteristics and conditions, policies, as well as government incentives, will be taken as factors.

Charging Infrastructure Data from Open Charge Maps

The sales of the EVs depend with how frequently theses public charging stations are present. To quantify this, I will employ data of the distribution and type of charging stations obtained from Open Charge Map API, including, the data of charging stations around the world (Gnann, T., et al. (2018)). These data will be utilised in order to explore how charging infrastructure influences consumer intent regarding electric vehicles. Those regions with increased number of charging points are assumed to experience high electricity tariffs translating to increased EV tariffs. With this dataset, I will go further to look at the effect of charging infrastructure on sales of EVs by incorporating IEA sales data.

Population Data from Kaggle

The third dataset from Kaggle attempts to understand the impact demographic traits such as income, urbanization and incentive play in deciding to purchase EV. In particular, findings show that better infrastructure and incentive the higher income urban areas will adopt EVs. Despite linkage between EV models and consumer behavior, demographic data is excluded from direct forecasting of the EV market in order to prioritize observable, stable factors for forecasting market trends.

ARIMA Model for Time Series Forecasting

The ARIMA model will be applied on the historical sales data of EVs to forecast the number of EV sales that will occur in 2030. This means that as a part of the model we would have inbuilt tools that can demonstrate problems of trend, seasonality and auto correlation within the data. Moreover, the charging infrastructure and population data shall be integrated into the test of outside variables of the model to examine the effect on the sales of EVs. This will help the model to have the influence of these factors, in responding the better results for the purpose of predicting the results.

Factors Influencing EV Sales Growth

The degree of importance of these factors has comparatively less importance to market growth except for charging infrastructure for electric cars, and population density. These shall be taken into consideration as they influence the ARIMA model to work out the adoption of the EVs across different regions (F. Liao, E. Molin, and B. van Wee; vol. 37, no. 3, pp. 252–275, 2010). Given this backdrop, this paper, which will forecast the total EV sales in 2030, will help policymakers/decisions-makers, companies and consumers who require insight on the future mobility system.

2 Research Methodology

The purpose of the present work was to apply time series analysis to model and predict electric vehicle (EV) sales in different regions. The methodology encompassed several key stages: data preprocessing, preliminary data analysis, the tests of stationary and potential transformation, the model building, to provide sales forecast, the analysis of residuals to assess the performance of the model.

Data Collection and Preparation

Archival data concerning the sales of Electric Vehicles for some multiple regions were gathered to form a baseline with columns namely region, year and quantity to show the number of EVs that were sold. This was done through data washing that entails a thorough scrubbing of the data set, which includes checking for and handling missing data, data checking, and format conversion into a time series. The set of sales observations specific to each region was disaggregated and arranged as region-specific time series with year as the time index. This segmentation was important particularly when performing region analysis which enabled the model to incorporate regional characteristics and patterns of the markets.

Exploratory Data Analysis

In order to analyse the sales data of electric vehicles an exploratory data analysis (EDA) was carried out on the data set to identify the extent of any correlations and patterns. For each region, line plots of the sales data were created. What these visualizations showed were important things like trends whether sales were on the rise, falling, or rising and falling periodically, or taking on other patterns like seasonal patterns, as well as being able to identify bad data points that were skewing the overall patterns upward or downward. In order to select the appropriate analytical models, these patterns were critical for determining issues that could be expected during the modelling stage. The graphical analysis allowed decisions to be made about data transformation and the appropriateness of employing time series models.

Stationarity Testing and Transformation

A dear assumption with time series data is that the series has a constant mean, variance and auto correlation structure over time. Check for stationarity was conducted by using the ADF test on each region's time series data. The ADF test checks the empirical hypothesis that the unit root in the time series exists hence suggesting non-stationary. On the other hand, if p-value is greater than 0.05, this becomes the case that null hypothesis must be accepted and therefore the series is non-stationary. For districts in which the time series data were determined to be non-stationary, techniques such as transformation were used to make the series stationary. First-order differencing was applied, where each data point yt is replaced by the difference between it and the preceding data point:

$$\Delta yt = yt - yt - 1$$

This process effectively removes linear trends and stabilizes the mean of the series. If differencing alone did not render the series stationary, a logarithmic transformation was applied to stabilize the variance, particularly useful for data exhibiting exponential growth patterns

$$y't = ln(yt)$$

If necessary, differencing was then applied to the log-transformed data:

$$\Delta y't = y't - y't - 1$$

After each transformation, the ADF test was reapplied to confirm that stationarity had been achieved before proceeding to model building

ARIMA Model Construction

Cross sectional data in most cases resulted to development of Autoregressive Integrated Moving Average (ARIMA) models for every region. ARIMA, a popular method for time series forecasting, captures data trends and seasonal effects using three parameters: From the equation, symbols include p that refers to autoregressive order , d that is degree of differencing and q that refers to moving average order. In order to choose the model order we used the ACF and PACF plots which can help to recognize the necessary lags. Choice of d, p and q For 'd' the differencing parameter we chose this based on the amount of differencing required to make the series stationary For 'p' and 'q' From the ACF and PACF plots we chose the number of lags in the autoregressive and the moving average respectively. Each model was then estimated, based on the maximum likelihood estimation, in order to estimate the likelihood of getting the observed data. At last, the diagnostic checks were run to identify any serious misspecification and to test the coefficients which were found to be significant at $p < 0.05$.

The maximum likelihood estimation method was used to estimate each ARIMA model to the corresponding region's time series data. This process included the assessment of the model parameters. Parameters are those values that make the probability density function of the observed data largest under the model. Property of the fitted models was evaluated through diagnostics checks such as evaluating coefficients and signs of model features.

Forecasting and Inverse Transformation

Once they have been fitted, they are then utilised in order to predict future levels of sales for EVs in each of the regions of interest. Therefore, forecast horizon of the 5 years was adopted as it offers medium-long term predictions on consumption rate. The models produced point forecasts along with the interval forecasts providing a range within which the actual future values are expected to take place within a certain level of confidence (usually 95%). For the regions where transformation have been made on the data, reverse transformation was done on the forecast values to bring back the results to the desired form.
For differenced data, the forecasts were cumulatively summed to reverse the differencing:

$$yt = \hat{y}t - 1 + \Delta\hat{y}t$$

For log-transformed data, the forecasts were exponentiated to reverse the logarithmic transformation:

$$yt = e\hat{y}'t$$

If both transformations were applied, the inverse differencing was performed on the Log transformed forecasts before exponentiating.

Residual Analysis

To check the robustness of these models for accurate forecasting, the residuals were checked for whiteness. This entails the residuals to have zero mean, constant variance and must lack first order autocorrelation. We employed several methods to examine the residuals:

- Histogram and Q-Q Plot: These were used to assess the normality of the residuals.
- ACF Plot of Residuals: This checked for any remaining autocorrelation, indicating the model's effectiveness in capturing the time series structure.
- Ljung-Box Test: This statistical test checks for autocorrelation across multiple lags. A p-value above 0.05 supports the null hypothesis that residuals are independent, affirming the model's adequacy.

$$Q = n(n+2)\sum_{k=1}^{h} \frac{\rho_k^2}{n-k}$$

Where:

- Q is the test statistic,
- n is the sample size,
- h is the number of lags being tested,
- $\hat{\rho}k$ is the sample autocorrelation at lag k.

The data are cleaned and processed and analysis performed on the combined APIs before merging using the project. Charging points by country, charger distribution by type of power, and regional trends of the technology of charging are examined as EDA. Insights include the top 10 countries bolstering chargers, the average power (kW) of chargers by charger type, and global power distribution providing a thorough read on existing and future EV charging systems.
The EV model distribution, type (PHEVs, BEVs), electric range, and regional availability are analyzed using EDA in the approach to model the EV population. Market evolution, and the correlations in the features, are explored across model years.
We use ARIMA for the time series forecasting of EV counts, while ACF/PACF plots work to choose a model using auto ARIMA. Residual validation, Q-Q normality and the Ljung-Box test for autocorrelation are the diagnostics. RMSE is used to evaluate forecasting accuracy and the actual vs. predicted values are compared visually.

Evaluation of ARIMA Forecasting Accuracy:

A formal validation procedure confirmed forecasting reliability through testing of residual normality and independence followed by the Ljung-Box test for detecting white noise patterns. ARIMA models were evaluated using AIC and BIC for both their complexity and performance assessment while the forecast accuracy relied on MAE, RMSE and MAPE. The analysis split its dataset into training and testing partitions before implementing rolling window forecasting as a method to simulate practical scenarios. The model performance resulted in a series of evaluations involving both SARIMA and Prophet alongside LSTM. Whenever competitor models showed better predictive outcomes than ARIMA models ARIMA parameters were modified for enhanced forecasting precision.

Justification for Selecting the p, d, q Values in ARIMA:

The initial step involved testing for stationarity with Augmented Dickey-Fuller before deciding whether to apply first-order differencing (d=1) or keep the original values (d=0). When trends persisted, second-order differencing (d=2) became necessary. The analysis included PACF and ACF plot evaluation for significant lags before applying a grid search to pick p and q values through AIC/BIC selection of the simplest model with strongest performance capabilities.

3 Design Specification

The IEA dataset consists of some parameters on drivers to EV, total energy, and oil. Charging point therefore means the number of public or private outlets which determine the degree of use of electric vehicles. Total electric vehicle sales and the sales of electric vehicles as a percentage of total vehicle sales could also be used. EV stock is the total number of electric vehicles that are currently in use, while EV stock share gives a modified figure of the percentage of total vehicles in circulation that are electric. Electricity demand demonstrate the amount of electricity to electric vehicles and Oil displacement (Mbd) is the measure of oil meters substituted by electric vehicles stated in millions of barrels per day. Last, Oil displacement, million quantifies the level of oil displacement in millions of Liters of gasoline equivalent. These parameters appear to be interrelated; firms' adoption of EVs, the expansion of charging infrastructure, and the displacement of oil are intrinsically linked and must be seen as such when developing sustainable transportation strategies.

The dataset analyzes EVs by region and factors, with 12,654 records across 54 regions, 8 parameters, and a timeframe from 2010 to 2035 (base year: 2019). Values are related with EV stock, charging points, sales, and oil displacement in various units, constituting parameters. The "World" and "Historical" categories hold most values. The richness of the variables and time logged metrics of the dataset lends it to the trend analysis and forecasting.
It has location details of charger stations in terms of charging station ID, Town, State, Country, PowerKW (charging rate), Quantity (no of chargers), Connection/Current Type (e.g. CCS, AC/DC), and Date Created. It can evaluate the charging station region and country density and capacity.
As part of the EV charging station, dataset with 519,675 rows of EV charging station details like ID, Town, State, PowerKW, and Quantity. Key insights from EDA show a mean PowerKW of 47.38 kW (SD: 72.Quantity ranges from 2.75 (2 chargers per station) with a wide variation, to a median of 2, and a skew skewed lower. Of which, most of stations have low power power output, not more than 500 kW.

AC (Single Phase) Charging: Common in homes and public areas, AC (Single Phase) charging gives you 3.7–7.4 kW of power suitable for overnight and slow charges. Low power density means longer charging times, which is fine for places where you don't need to charge rides instantly.

AC (Three Phase) Charging: Three Phase AC (11–22 kW) charging that is used in commercial and public stations, can charge faster than single phase systems. DC fast charging is faster, but slower than that on charging stations located at shopping centers, offices where vehicles are parked for hours.

DC (Direct Current) Charging: The fastest EV charging option is called DC (Direct Current) charging; this provides 50–350+ kW, permitting an 80% charge in less than 30 minutes. The onboard charger is by passed and the power is fed directly to the battery, making it the perfect fast charger for highways and areas where rapid charging is required.

4 Implementation

The ARIMA model is proposed to be created for all the regions in the dataset in accord with a precise sequence of construction. First, when looking at the time series data of each region, we need to decide which column to use. Differencing is used to remove trend and seasonality from the series as a first step towards meeting the requirement of stationarity needed for ARIMA modelling. Next, for each region, the model picks the right time series data where value_diff = 1 is used the data is log-differenced, otherwise the data is first-differenced for both, the differencing order d is set.
The order of the ARIMA model is decided next (G. Zhao, X. Wang, and M. Negnevitsky; vol. 77, pp. 1–20, 2017). In the code a less astute method is used where both the autoregressive term p and the moving average term; q is set to 1. There is a basic model of this which can be fine tuned using the AIC/BIC criteria or ACF/PACF plots to determine the best values for p and q. After identifying the right data and model order, the actual model is developed and estimated using ARIMA function from the stats models library.

For Ireland's time series data the preliminary analysis shows that it is non stationing (ADF statistic of 3.0737 p value = 1.0000 which suggest a unit root). Higher order differencing was performed to span the statistic to 8.3758, but the element was still non-stationary and did not produce accurate forecast; further transformations were applied to remove trends and seasonality and then higher order differencing was performed to obtain accurate forecast.

EV charging station data visualizations analyze the infrastructure. A pie chart shows charger type distribution globally (AC: 68.With DC chargers able to provide higher power, 9% (DC: 31.1%). A bar plot shows average power (kW) of chargers per country by type, and a histogram rendered with a density estimate confirms our observation of a right skew in the power distribution: most chargers have power in the order of 100 kW or less. These insights reveal the types of chargers in existence globally, the regional power differences, as well as the overall direction and depth of charging infrastructure.

5 Evaluation

The graph that you have shared here presents the global EV sales year over year. The x-axis of the given graph is marked in terms of years which ranges from 2010 to 2035 whereas on the y axis a number of vehicles sold is depicted. This brings a concern on the fact that total EV sales seems to be the major variable under consideration for this dataset whereby a clear disaggregation by regions and grouped by distinct years. As viewed in the graph, the sales position itself is not very high from the year 2010 to the year 2019 and a slight increase is observed only in few years.

Fig1: Overall sales visualization from IEA Data

Yet there is a steep upward trend beginning in the year 2020, and increasing gradually up to 2035. This increase might be as a result of the following reasons Technology Lavish charging facilities The World heading towards Sustainable transportation etc. The entire trend is shown by the straight line through the data points and the individual points for each year are also shown by the black dots. This furthers the hypothesis that the expectation of exponential growth for the EV sales exists, and that growth may plateau by 2035. This graph assists in understanding how the technology transition in automotive mobility is steadily happening around the world.

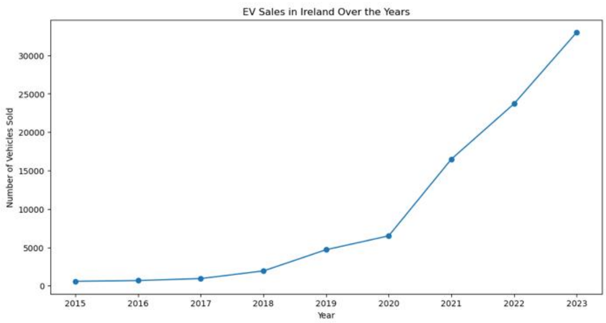

Fig2: Ireland sales from IEA Data

The two graphs give a concentred outline of electric vehicle (EV) revenue in Ireland and equally illustrates the past data and the expected coming years data. The first graph represents the level of EVs adopted by the Ireland between the year 2015 and 2023. First, the total amount of sales is relatively small, which suggests that take-up of electric cars was rather slow in the first years. This could have been due to issues like limited models, costly, and relatively fewer charging stations for EVs. But starting from 2020, the numbers show a gradual upward trend, year in and year out. This growth could be attributed to several reasons such as higher government subsidies towards the use of electric vehicles, global awareness of environmental sustainment, and better advancement in technological infrastructure of electric vehicles like improved batteries charge. The increase in uptake of EVs could also be explained by change in consumers perception and preference towards EVs as a viable substitute for conventional EVs.

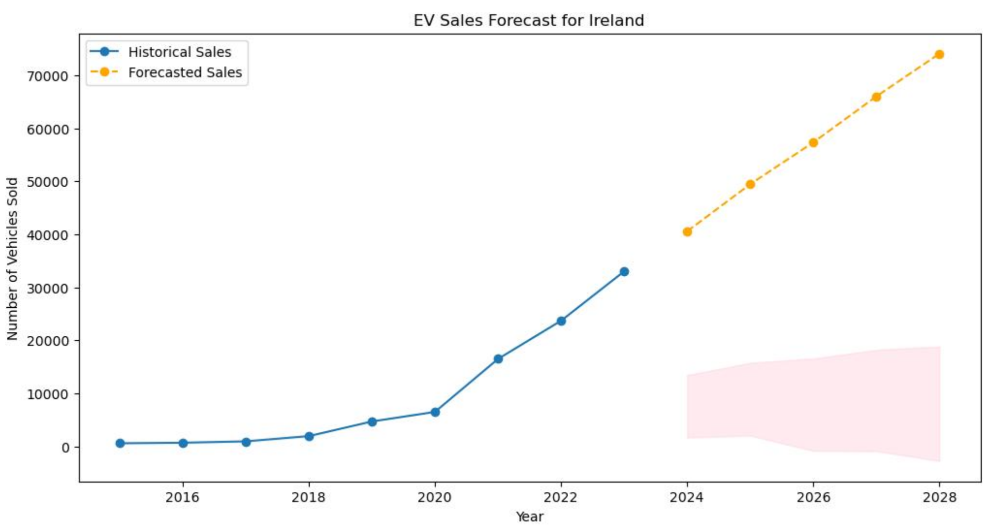

Fig3: Ireland sales with applied ARIMA forecasting

On the other hand, the second graph depicts the projected sales of EVs for Ireland while graphing a continuation of the sales trend through 2028. We can get a better picture by referring to the forecast where even more increase is seen in the given years as the sales of EV are expected to grow steeply thereafter and is marked by a dashed orange line at this point in the graph going well beyond 2023. This forecast is based on statistical models that measure the historical pattern of sales and the probable rate of expansion from this data (Kley, F., et al. (2011)). This shaded area around the forecast line is known as confidence interval to show what the result could be if the model assumptions prove right and the market condition change. Based on the forecasted data, Ireland is set for comparable or even greater a rise in the usage of EVs because of the better technology, strong supporting structure, and potentially higher requirements for emissions. This analysis of past and future sales offers insight into EV revolution in Ireland and polices, industries, and consumers can thus plan for future of transport in Ireland.

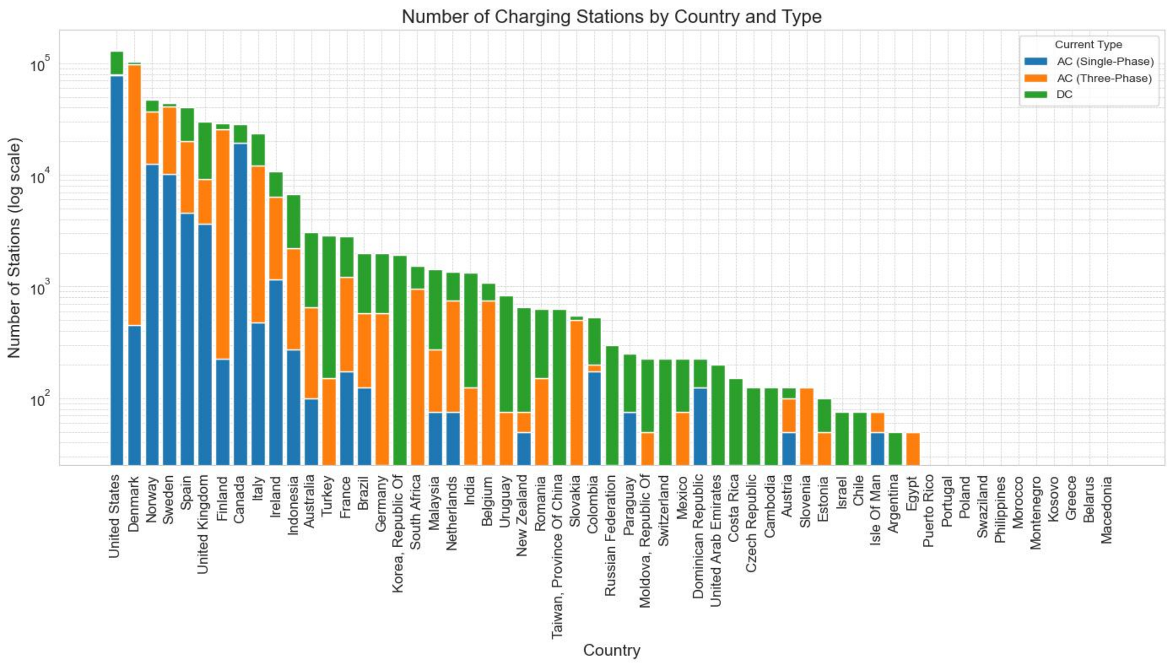

Fig4: Types of Chargers in various countries

The plot visualizes charging station numbers by country, categorized by current type: AC Single Phase, AC Three Phase and DC. It further uses a log scale on the y axis, with bars split by current type (blue for AC Single Phase, orange for AC Three Phase, and green for DC). (Hu X, Martinez CM, Yang Y; 2017; 87:4–16). Other countries in the top ten include Denmark, Norway, and Sweden, where there's a move towards DC fast chargers. Meanwhile, AC chargers for home use only offer fewer stations in regions such as Latin America and Southeast Asia. Log scale makes countries with lower infrastructure visibility, which highlights gaps and shows the need for investment to serve growing demand.

The pie chart "Global Distribution of Charger Types" illustrates the proportion of electric vehicle (EV) chargers categorized by their type Alternating current or AC and Direct current or DC. The chart also demarcates the number of charging stations worldwide where a dominant proportion (68.9%) of the facilities is found to be AC chargers distinguished by grey-shaded colour. This is so because AC chargers are more popular, predominantly for residential and for slower charging applications, due to their lower costs and fewer requirements in terms of infrastructure. On the other hand, stations with DC chargers which are shown in a soft orange colour make up 31,1% of total stations. The DC chargers are mainly employed for fast charging at stations and provide significantly higher power density than AC chargers which main purpose is to provide quick charge facilities mainly at highway rest stations, industrial areas and other such places where time is an important factor.

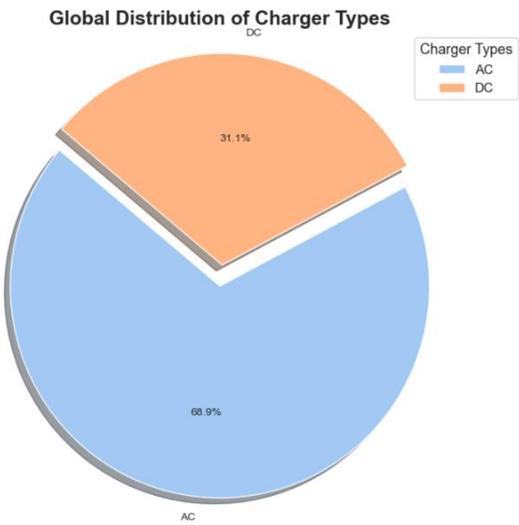

Fig5: Global Distribution of AC & DC Type

The used charting design modified on the DC section with a minor explode to underscore the role of that segment with the distribution. Also, the overall Pastel colour and the neat professional appearance of the chart assist in the understanding of the chart On the same account, the percentages shown on the slices also provide the relative proportions of the different charger types. This figure emphasizes on the current usage of AC chargers in the global EV infrastructure in combination with emphasizing on DC chargers focus on their necessity to expand the fast-charging station network along with the rise of widespread EV market.

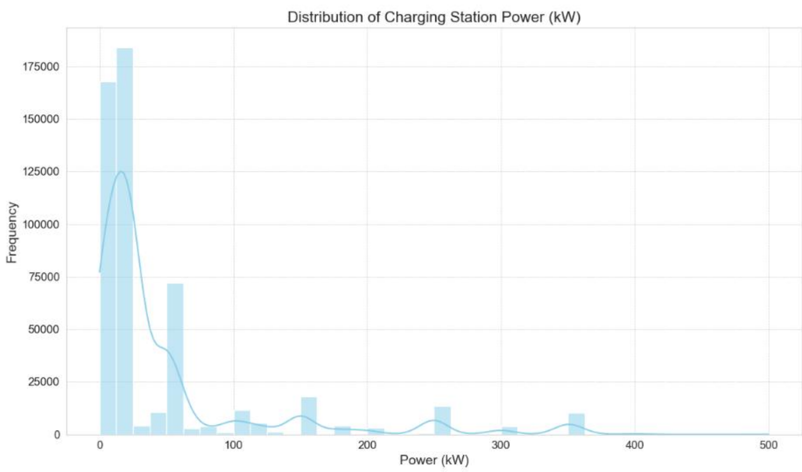

Fig6: Different distribution of Charging Station Power

The "Distribution of Charging Station Power (kW)" plot measures different variables related to charging stations and their power ratings out in the world globally. Most stations appear as low power chargers that charge our batteries at night near 0 kW (0.39 horsepower), usually found in residential areas or places of work where a trickle charge is adequate. Station frequency by power range is plotted on the y-axis, and power in kW on the x-axis. Where power increases, the density of available charging stations drops substantially, with most stations staying below 100 kW. High power DC fast chargers are needed but rare, signalling a need for greater supporting fast charging infrastructure. The plot details that slow chargers dominate the world, and therefore demand for high power stations is critical to meet EV adoption and long range and urban transportation.

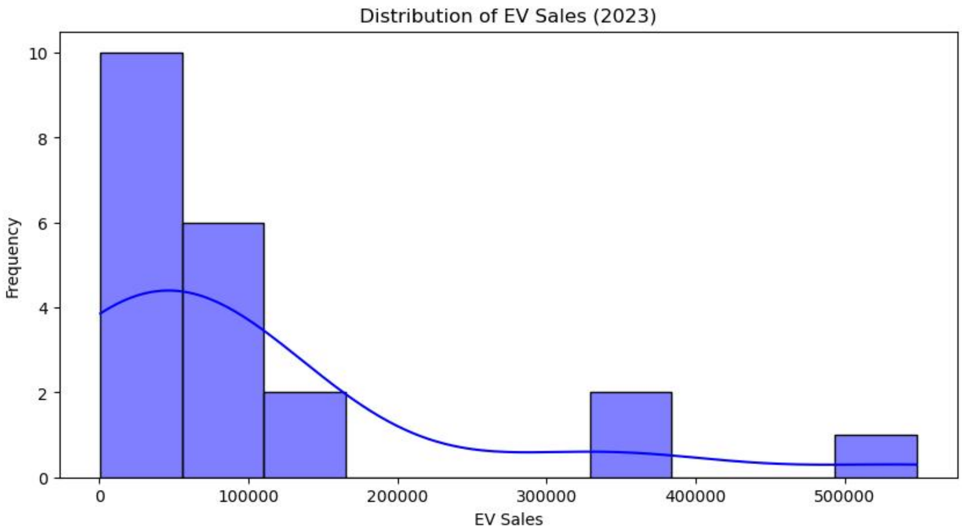

Fig7: Distribution of EV Sales (2023)

The sales of electric vehicle (EV) and the charging infrastructure have been an important area of study to understand the global distribution for 2023. First, data from two datasets, ‘ev_sales_agg’ including data on the sales of EV and infrastructure including data on the charging points are combined by using pd.merge() . This join operation is done according to the region and year only data for the same year, 2023 in this case must be produced. The final dataset is therefore a combination of the total EV sales and charging points per region to facilitate comparison of the figures since they provide information about the successfully completed EV sales and the charging points available for use.

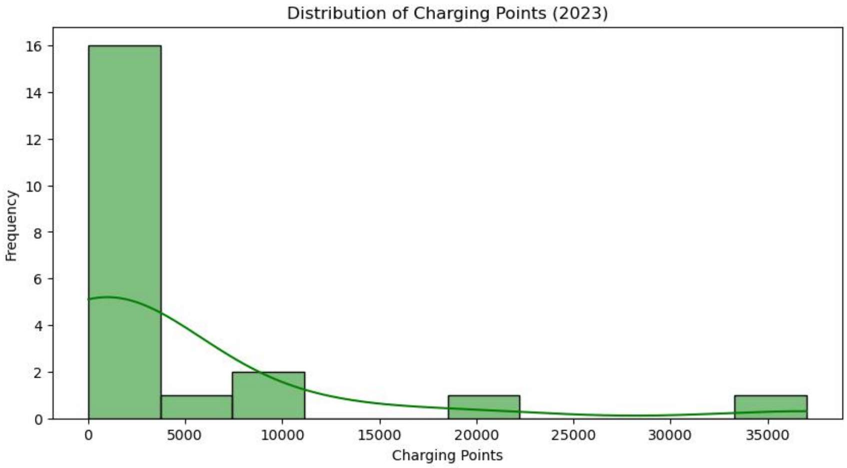

Fig8: Distribution of EV Charge Points (2023)

It revealed the total EV service and charging point for regions including Australia, Austria, and Canada. The distribution of EV sales in 2023 is visualised in a histogram, made using Seaborn with a KDE overlay indicating patterns (Namdeo A, Tiwary A, Dziurla R;2013; 89:188–200). EV distribution has a long tail or uneven global adoption with some regions such as Canada dominating sales, while others are lacklustre.

The second histogram labelled, "Charging Points (2023)" denotes the distribution of charging station locations in the same regions, in green. Like the earlier histogram, a kernel density estimate curve is laid on top of the data points to help the viewer understand the density's shape. The plot demonstrates that the majority of regions has the charges point below a certain number while a few has many times the number of charges point (as the case with Canada again). This also underscores the same problem of the imbalance of infrastructure development regarding EV charging where some countries are moving a level up while others are behind.

Global differences in EV sales and charging stations are called out using histograms showing a correlation between high EV sales and more chargers, while exceptions are where low EV adoption is associated with high charger presence (Hu X, Martinez CM, Yang Y; 2017; 87:4–16). KDE curves expose data spread and trends, facilitating understanding of market segment challenges (such as working class), infrastructure requirements and regional inequity to promote equitable EV development, globally.

By addressing key success factors for a sustainable EV market such as infrastructure availability, demographics, and economic drivers, this study helps increase the sustainable growth of the market. Using statistical models such as ARIMA, it decomposes retail determinants to guide EV sales priorities so that retail environment becomes competitive and EV sales strategies are as optimal as possible. It comprises a detailed plan of work specifying activities, timelines and resources necessary to attack key constraints and opportunity, resulting in a process to execute strategies. These strategies are established into unambiguous indicators for measuring the effectiveness of them, so that continuous refinement can be made. Moreover, the study also proposes, in favor of effective conditions, some policy measures such as financial incentives and effortless bureaucratic procedures. Furthermore, this framework aims at promoting long term EV adoption, promoting the performance of the retail, and being sustainable for the environment through strategic infrastructure, technology and policy initiatives.

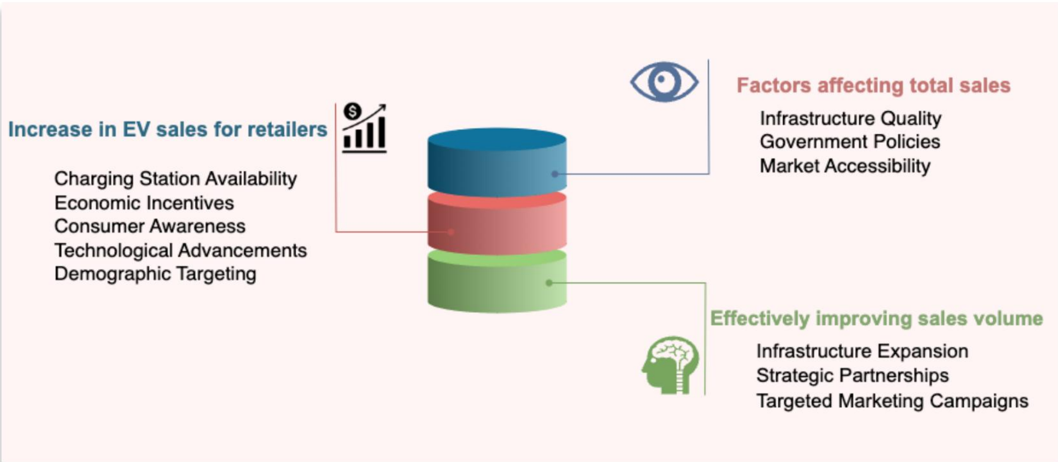

Fig9: Overall Strategies can be applied for increasing the EV Sales

critical success factors that may have an impact on the expansion of EV market, highlighting the external factors which contribute to the overall market size as well guidelines that can be used by retailers to enhance the numbers of vehicles sold. The section called "Change in EV Sale for Retailers" focuses on factors like accessibility of charging stations that makes EV ownership less difficult, subsidies/tax credit that brings down the cost implied in the purchase of an EV for consumers. Consumer sensitivity towards environment and its exploitation, consciousness about the efficiency of the electric cars also contributes to high demand besides technological research enacted on the batteries and the cars themselves that enhances the long range usability also contributes (Hidrue MK, Parsons GR, Kempton W, Gardner MP;2011; 33(3):686–705). Moreover, demographic targeting, which directs promoting messages at certain categories of consumers, contributes to retailers' improved opportunity to reach the client base. In presented "Factors affecting total sales" the aspects related to external environment are concentrated, including, quality of infrastructure (charging outlets should be reliable and widely spread), government actions (stimulates, restrictions), and market accessibility, (charging outlets should be available and not so expensive).

5.1 Case Study 1

Sub data for this case study was obtained from the International Energy Agency (IEA) regional database. The charts presented below reveal similarities and differences between different regions, with historical sales and the model's forecast shown underneath. These forecasts are helpful in developing the strategies that depend on accurate data and realistic acknowledgements. The following visuals contain and compare past data regarding sales along with forecasted data generated using ARIMA model.

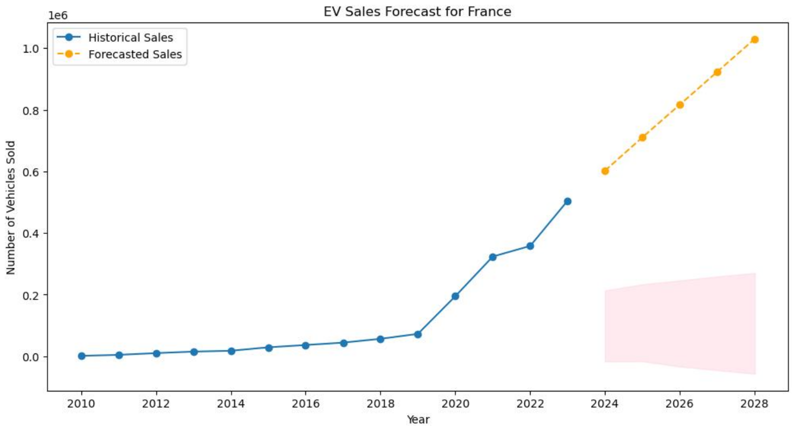

Fig10: Forecasting for France (IEA data ARIMA Applied)

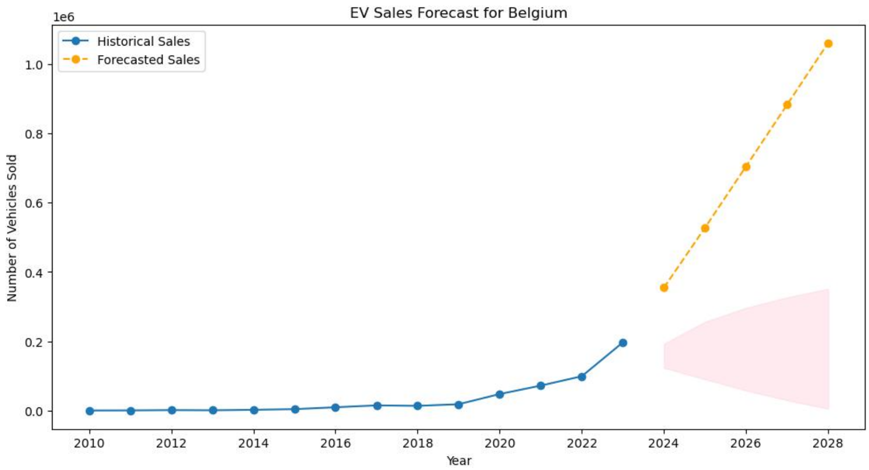

Fig11: Forecasting for Belgium (IEA data ARIMA Applied)

5.2 Case Study 2

This research employs confined data peculiar to the type of location and is obtained from the Open Charge Map API; hence, the type of data used is efficient for analyzing the EV sale in the specific location (Wu, M.; Chen, W; 2022, 14, 2206). In the analysis on how infrastructure impacts on sales across the various regions, the data is used extensively. The plots given below show the infrastructure rate in terms of different countries for the analysis. Public charging is highlighted, including a plot indicating the preliminary ten countries with the most developed EV infrastructure (Hall, D., & Lutsey, N. (2020)). Furthermore, there is a detailed power to distribution chart showing the various power outputs employed on the various charging station categories. These visual data in a way help in explaining how infrastructure differences affect Electric Vehicles adoption and sales in these areas.

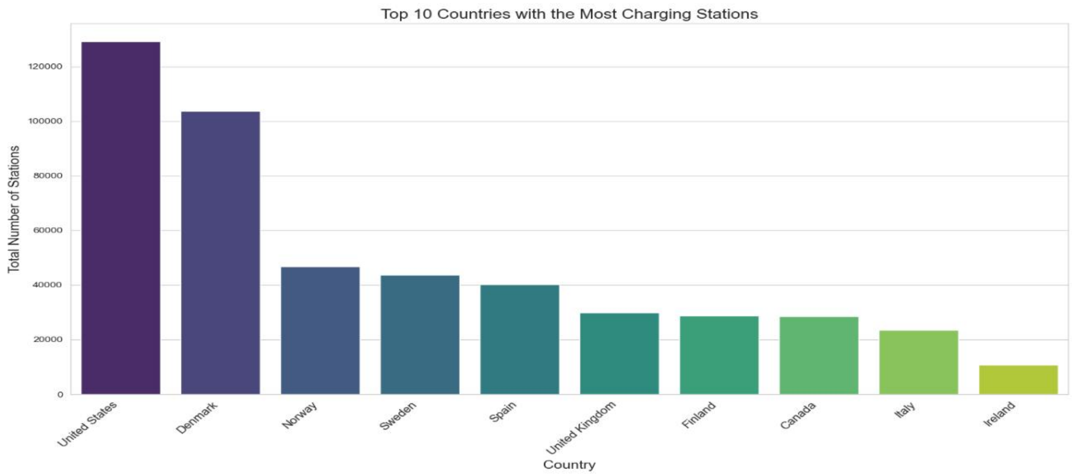

Fig12: Top 10 countries with number of Charge Stations

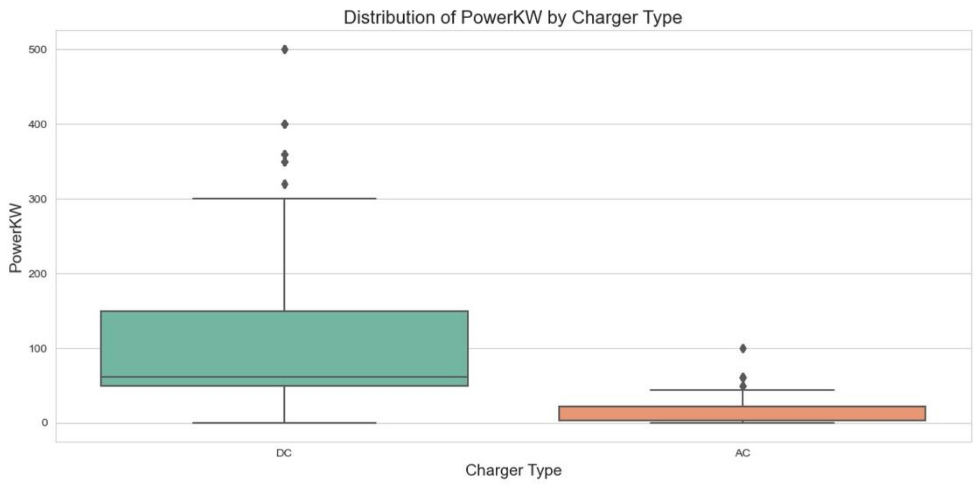

Fig13: Charger type power distribution (kWh)

5.3 Case Study 3

General forecasting was carried out using ARIMA, while seasonal factors were treated with SARIMA on the case study combining charge point data and IEA Regional Data. Detailed outcomes and objectives are provided in combined analyses of infrastructure's impact on EV market dynamics. These strategies are tabulated systematically to make the role of strategies more clear in the research framework.

The graph below displayed merges observed data with forecasted projections which used two different sets of data so as make improve the projections. This forecast takes into consideration some of the major seasons together with an exponential model to forecast the growth rate of electrical vehicle (EV) sales. The trend line as such raises the growth outlook to a higher level, which points towards a significant scaling up of EVs in the years to come. The shaded area at the end of this model's forecast gives a graphical representation of potential future variability with its defined confidence interval. The fact of incorporating the historical data observation with sophisticated over-forecasting methodology provides the best insights into the trends paving the way for further studies to fine-tune these over-forecasting indications and examine the factors causing those trends

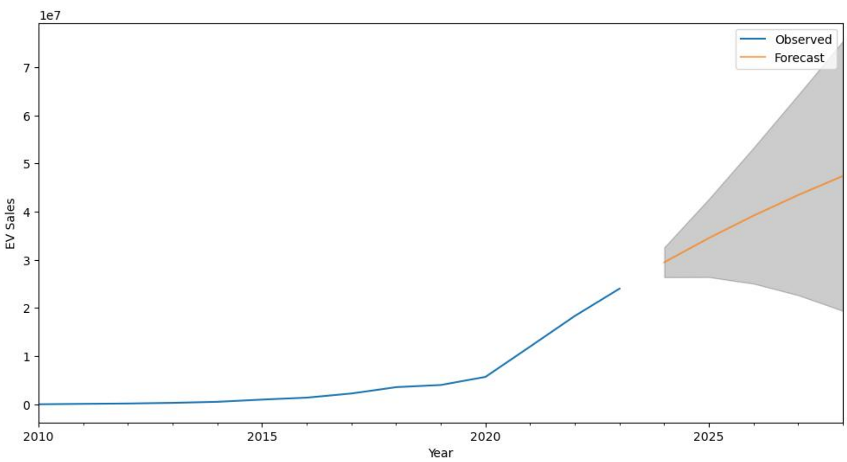

Fig15: Forecasting EV sales placing Infrastructure as a Factor

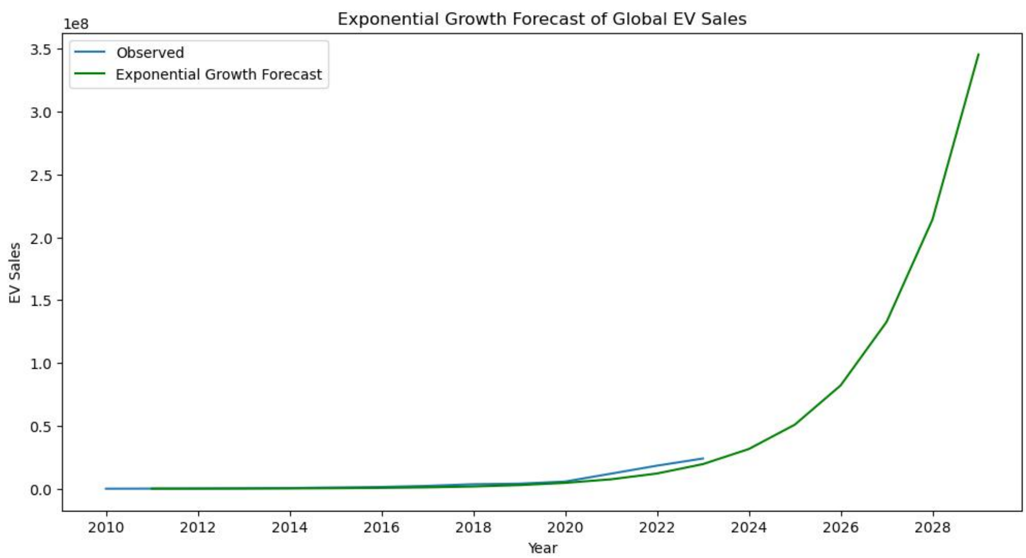

Fig16: Forecasting EV sales with applied (Seasonal) SARIMA

Research Question	Vision Outcome	Mission Outcomes
What factors contribute to the increase in EV sales for retailers?	Empowered Retailers- Sustainable Growth	Identification of Key Drivers- Data-Driven Insights- Enhanced Market Understanding
How do these factors affect total sales?	Optimized Sales Strategies- Market Responsiveness	Quantitative Impact Analysis- Model Validation- Strategic Insights
Which strategies can effectively improve sales volume?	Strategic Excellence- Sustainable Market Expansion	Actionable Strategies- Implementation Roadmap- Performance Metrics- Policy Recommendations

5.4 Discussion

In this study, the EV market growth is mapped through the study of barriers and drivers emphasizing a strong positive association between the infrastructure expansion and EV demand. In dense urban areas, the conversion to EVs is subject to availability of charging points and consumer decisions to switch from the internal combustion engine are significantly affected by the availability of charging points (Iii HAB, Lusk AC; 2016; 83:63–73). The study is consistent with previous research and IEA reports that infrastructure is a key factor in reducing range fear and servicing consumers' desires. Valuable insights are provided to business strategies of fast charging stations.
Sales trends and seasonality are modeled with ARIMA and SARIMA data consistency limits the outcome. Real time data could be integrated in future to give a more accurate forecasting. The study stresses government and municipal funding, consumer incentives and sustainability actions to encourage EVs use (Kumar, S., Singh, V., & Goel, R. (2024)). Although there are regional and consumer group differences in EV uptake, the research emphasizes enhancing infrastructure, facilitating targeted incentives and reforming policies as key to speeding the introduction of electric mobility.

6 Conclusion and Future Work

The objective of this research was to assess the trends of EV sales using the IEA region dataset with special emphasis to the role of infrastructure in facilitating these sales. Based on these assumptions, our research questions embraced the scope of determining essential drivers of EVs, their effects on sales, as well as patterns that can help boost the market even further. In this research pipeline, we achieved our goal of using statistical models such as ARIMA to forecast the future sales patterns through an analyst is of historical trends while giving a strong foundation for the analysis of the evolution of the EV market (Li, Z., Fan, H.,

& Dong, S. (2023);). A separate focus is made on the analysis of the main findings, which confirm the relationship between the density of charging stations and the sales of electric vehicles. This result supports our hypothesis and confirms the need to strengthen the infrastructure to advance the use of electric vehicles. Thus, we have found that regions with better charging facilities are likely to see higher sales indicating that infrastructure investment is a potent strategic tool for increasing EV consumption.

Implications and Efficacy

Therefore, our study brings a set of recommendations for policymakers and market players and advances the knowledge about the nature of market forces in the context of the global EV industry. In doing so, the research backs the efforts being taken to extend charging infrastructure to boost the market for electric cars (Brown M; 2013; 16(2):5). However, the study also recognizes some limitations, for instance other factors such as governmental policies and economic incentives that could explain other relations that might further improve sales forecasts are not included .

Limitations

These development and limitation include the use of aggregated regional information where the outcomes of EV adoption may vary at the local level. Moreover, it was used forecasting models seem to be helpful however, it is reinforced to integrate real-time data and to make use of machine learning algorithms for improving forecasting exactness and for the reason of market fluctuations.

Future Work

Future research agenda to refine the model immature factor and capture nuanced reality of consumers and geography in real time would include more specific and detailed data feeds such as transactional data at individual level or dynamic consumer data obtained through surveys which capture the behavior at a more fine grained spatial level (Braz da Silva, M., & Moura, F; (2016) 10(2), 49–64.). Additional research questions related to newly developed technologies including battery advances or driving automation can also be investigated for the examination of their effect on the acceptance and consequently the total usage of EVs. The follow-up project can focus on the comparison of various countries' policies to identify the efficiency at the encouragement of EVs. This could mean establishment of a policy impact index by assessing different countries' data and comparing it to the EVs adoption trends.

Potential for Commercialization

From a commercial point of view, this research could help create an algorithm that a company or a federal agency could use to predict future demand for EVs given predictions about infrastructure." This tool we have been discussing could assist in SWOT analysis and venture decisions that would add value to strategic applications in the EV sector, the efficiency to allocate resources.

Meaningful Future Research

Appropriate future research may focus on collaborations with automotive manufacturers and energy providers to understand new and effective business models for influencing fast purchase of EVs. For example, the exploration of new charging models such as subscription-based or pay-per-use charging services to meet clients' needs and expand market access was discussed (Orbach Y, Fruchter GE; 2011; 78(7):1210–26.). Thus, despite these achievements, the further advance of this investigation and the discovery of factors that affect EV sales requires the ongoing exploration of new sources of data, new methods, and new technologies related to this rapidly evolving filed. Future research should try to extend from this by filling the above mentioned research gaps and by including new trends and innovative concepts in the market of EVs.

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