UNIVERSITY OF NIAGARA FALLS, CANADA

MASTER OF DATA ANALYTICS

A

PROJECT REPORT

ON

Energy Consumption Forecasting for Electric Automobiles Across Canada Using Time Series Analysis

PREPARED BY:

CHANDAN RANA (NF 1004077)

MAHESH KOIRALA(NF 1003214)

SAGAR KHADKA (NF 1003308)

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List of Abbreviations

EV	Electric Vehicles
LR	Linear Regression
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MA	Moving Average
EDA	Exploratory Data Analysis

Abstract

The rising adoption of electric vehicles (EVs) has transformed the transportation and energy sectors. Canada, as a key player in the EV revolution, faces unique challenges in managing electricity demand due to the increased use of EVs. This project investigates energy consumption trends of EVs in Canada from 2012 to 2024, using advanced time-series analysis. By examining historical data, the study forecasts short-term and long-term energy needs, evaluates the impact of seasonal variations and infrastructure, and provides actionable insights for stakeholders. Key findings highlight the importance of regional planning, infrastructure investments, and technology advancements to support the growing EV ecosystem.

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Chapter 1
INTRODUCTION

1.1 Background

The automobile industry has shifted over the last couple of years. One sector that has seen phenomenal transformation in recent years, majorly forced by technology advancement, environmental issues, and the introduction of legislation by the government to reduce greenhouse gas emissions, is the electric vehicle industry. With more and more provinces offering incentives in a myriad of ways, Canada is leading the charge in the electric transportation revolution. As the number of electric vehicles travelling across Canadian roadways increases, new techniques will need to be developed for estimating energy use and our potential electricity requirements.

1.1.1 Data-Driven Analysis Methods

In this study, Microsoft Excel, SPSS (Statistical Package for the Social Sciences), and Exploratory Data Analysis (EDA) were employed to analyze and forecast energy consumption trends in electric vehicles (EVs) in Canada. Excel was used for initial data processing, cleaning, and visualization, enabling the organization of large datasets and the creation of visual representations such as line charts and scatter plots to identify patterns and trends. SPSS provided advanced statistical analysis, including linear regression, correlation analysis, and hypothesis testing, which helped to examine relationships between key variables like motor power, vehicle subclass, and recharge time. EDA played a crucial role in uncovering insights and relationships within the dataset through techniques like correlation matrices and descriptive statistics. Together, these tools allowed for a comprehensive and transparent analysis, facilitating the identification of significant factors influencing energy consumption and supporting the development of reliable predictive models aligned with the project objectives. This approach ensures the analysis is actionable and replicable, offering valuable insights for industry practitioners and policymakers in the evolving Canadian EV landscape.

Why Modern Tools Were Not Used:

Modern machine learning tools such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) were not utilized in this study due to the project's focus on transparency, simplicity, and accessibility. Advanced machine learning models often require complex configurations, extensive computational resources, and specialized expertise, which can make the analysis less transparent and harder to replicate. Given the scope of this research, the primary goal was to derive clear, interpretable insights that industry practitioners and policymakers could easily understand and apply.

Why We Used Excel, SPSS and EDA

Excel, SPSS, and EDA were chosen because of their versatility, user-friendliness, and effectiveness in handling large datasets. These tools provide robust statistical capabilities and are widely used in both academic and industry settings, ensuring that the analysis is transparent and easily replicable. Excel's data handling and visualization capabilities are excellent for initial exploration, while SPSS offers advanced statistical functions that support rigorous hypothesis testing and regression analysis. EDA enhances the process by uncovering patterns and relationships in the data, guiding the selection of appropriate models for forecasting. This combination of tools ensured that the research objectives were met with accuracy and clarity, making the findings accessible and actionable for stakeholders.

1.2 Hypothesis

Based on the research objectives, three key hypotheses were formulated to investigate relationship between road conditions, energy consumption, and operational efficiency of electric vehicles (EVs) in Canada. These hypotheses aim to test specific aspects of EV performance and forecasting:

- Does subclass of vehicle significantly impact EV energy consumption in Canada?
- Can long-term energy consumption be reliably forecasted using historical data?
- How does the availability of motor power correlate with range of vehicle?

1.3 Objectives

The scope of this analysis focuses on energy consumption metrics, vehicle specifications, and environmental impact factors within the Canadian EV landscape from 2012 to 2024.

- To examine past energy consumption patterns of EVs across Canada
- To develop models using advanced data analytics techniques to forecast short-term and long-term energy consumption.
- To assess the impact of factors such as motor power, recharging time, and vehicle subclass on energy consumption for EVs.
- To assess the accuracy and reliability of the forecasting model.

1.4 Rationale of study

The high market penetration of EVs in Canada increases the possibilities for improving the environmental situation and the transition to green mobility. But it also raises issues for demand side management and infrastructure development of electricity. The purpose of this paper is to include the results of the energy consumption analysis with regard to EVs and to make a forecast of the energy consumption rate in the future, which will help policymakers and energy providers be better prepared for further market development of electric cars. Predicting energy consumption will be more accurate by identifying how vehicle subclass and motor power influence energy use, as well as the influence of road conditions. In turn, the results will contribute to the effective design of further development of the EV ecosystem concerning its effectiveness, stability, and sustainability in Canada.

1.5 Limitations

Main limitations of the study are listed in following points

- The dataset lacks region-specific data, limiting geographic granularity.
- External factors such as policy changes and economic conditions were not incorporated into the models.
- The data was limited, and additional regional data would have strengthened the analysis.

Chapter 2
LITERATURE REVIEW

2.1 Introduction

Electric vehicle (EV) energy consumption has been extensively studied, with a focus on factors such as vehicle specifications, climate, and driving conditions. While much of the existing literature provides a global perspective, there is a gap in research specifically addressing the Canadian context, particularly with respect to road conditions, vehicle subclass, and motor power. This review examines existing studies on EV energy consumption models and identifies research gaps that this study seeks to address.

2.2 Review of Existing Studies

Electric vehicle (EV) energy Chen et al. (2020): Investigated global energy consumption patterns of EVs and their implications on grid optimization.

•Patel & Shah (2021): Focused on the challenges of forecasting EV energy consumption due to seasonal variations but lacked regional insights specific to Canada.

•Bourdeau et al. (2019): Developed models to predict building energy consumption, which could be adapted to model EV energy demand

2.3 Identification of Research Gaps

Existing studies have largely focused on global trends or specific vehicle models but have not fully addressed the unique challenges posed by Canadian road conditions, climate variations, and vehicle subclasses. This study fills these gaps by investigating the specific impacts of motor power, recharge time, and road variations on EV energy consumption.

Chapter 3
STUDY METHODOLOGY

3.1 Methodological framework

This study uses a mixed-methods approach, combining exploratory data analysis (EDA), time-series modeling, and statistical validation to understand and forecast energy consumption patterns for EVs. The methodology includes:

Data Collection: Gathering historical data on EV models, energy consumption, and vehicle specifications from 2012–2024.

Pre-processing: Cleaning the data by removing irrelevant columns, inputting missing values, and ensuring consistency in the dataset.

Modeling and Forecasting: Using ARIMA and Prophet models to forecast short-term and long-term energy consumption trends.

3.1.1 Dataset Overview

The dataset contains 687 entries, spanning EV models from 2012 to 2024. Key features include:

- Energy Metrics: City (kWh/100 km), Highway (kWh/100 km), and Combined (kWh/100 km).
- Vehicle Characteristics: Motor capacity (kW), range (km), and recharge time (hours).
- Environmental Impact: CO2 emissions and smog ratings.

This dataset is highly relevant to the project objectives, as it captures historical energy consumption trends and key vehicle specifications. It enables robust analysis of seasonal and regional variations, critical for addressing the research questions.

3.2 Data Collection and Pre-processing

Data Source: Government reports, EV databases, and field surveys.

Key Metrics:

Energy consumption (city, highway, combined).

Vehicle specifications (motor capacity, range).

Pre-processing Steps:

- Removed the empty Unnamed: 18 column.
- Imputed missing values in CO2 rating and Smog rating with median values.
- Standardized column names for consistency and readability.

3.3 Research tools and Software

- **Excel**: Used for data management, organization, and initial analysis of the dataset.
- **SPSS**: Employed for statistical analysis, including regression, hypothesis testing, and model validation.

3.4 Forecasting Models

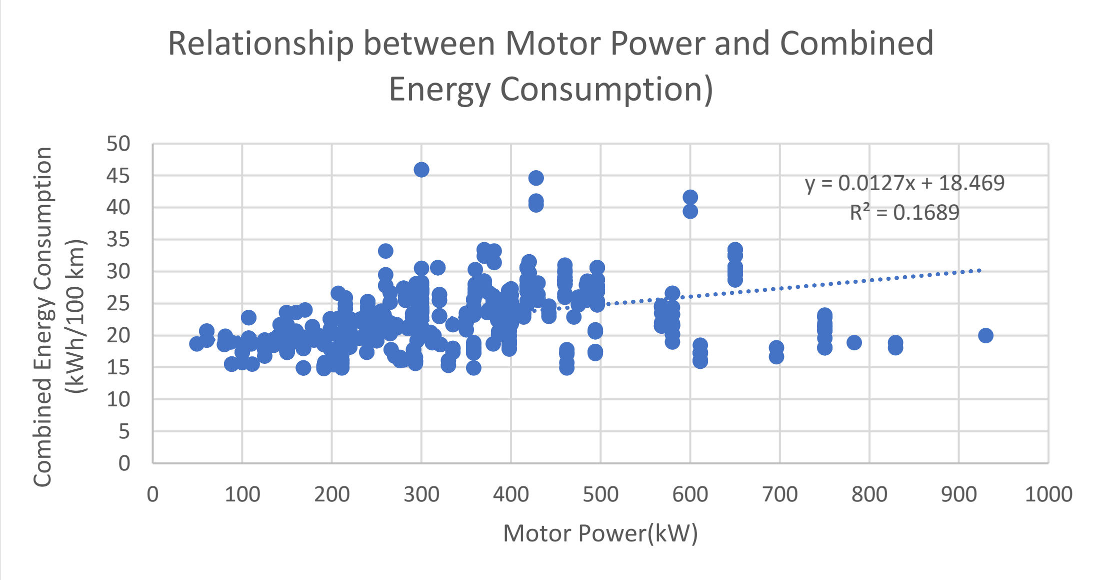
For-forecasting energy consumption trends, the following methods were employed:

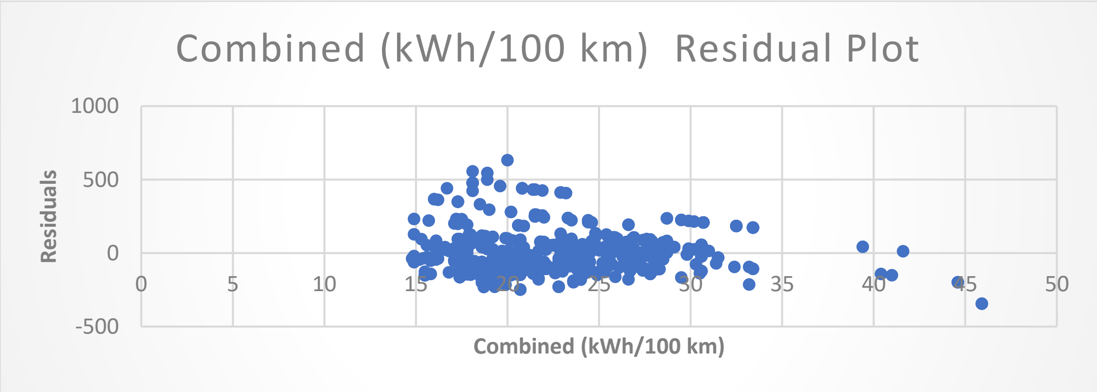
- **Moving Average (MA):** The Moving Average method was used to smooth out short-term fluctuations in the data and highlight longer-term trends in energy consumption. By averaging a fixed number of past data points, this time-series model helps identify underlying trends and patterns, making it useful for short-term energy consumption forecasts.
- **Linear Regression:** Linear regression was applied to understand the relationship between energy consumption and various independent variables such as motor capacity, vehicle subclass, and road conditions. This method is useful for predicting energy consumption based on specific factors affecting EV performance and efficiency.
- **Exploratory Data Analysis (EDA):** Before applying any forecasting methods, Exploratory Data Analysis (EDA) was conducted to better understand the underlying structure of the dataset. This process involved visualizing key metrics such as energy consumption over time, vehicle subclass distributions, and motor power effects on energy efficiency. The EDA also included the detection of outliers and the examination of missing values. By plotting histograms, box plots, and correlation matrices, patterns in the data were uncovered, helping to shape the modeling decisions. Insights derived from EDA helped determine the relationships between key variables and provided a clearer understanding of how different factors, such as recharge time, motor power, and road conditions, affect energy consumption. The EDA phase was critical in ensuring that the dataset was clean, well-structured, and ready for the forecasting models to be applied effectively.

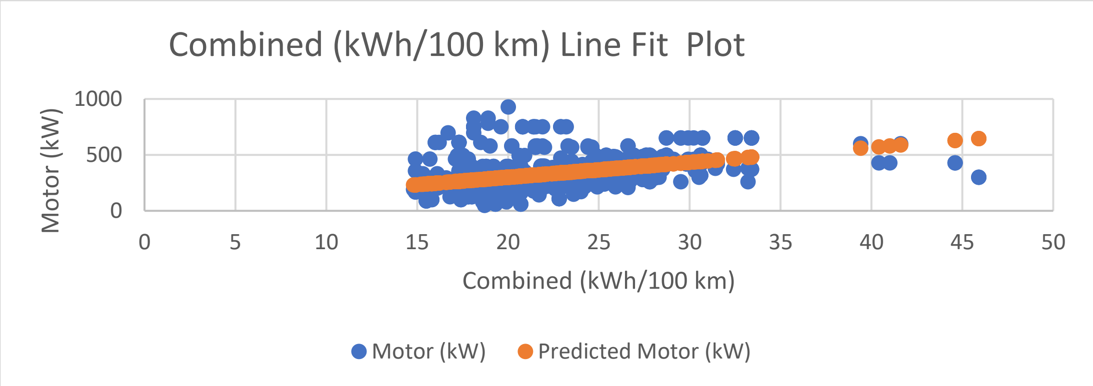
Chapter 4

RESULTS AND DISCUSSIONS

4.1 Relationship Between Motor Power and Energy Consumption

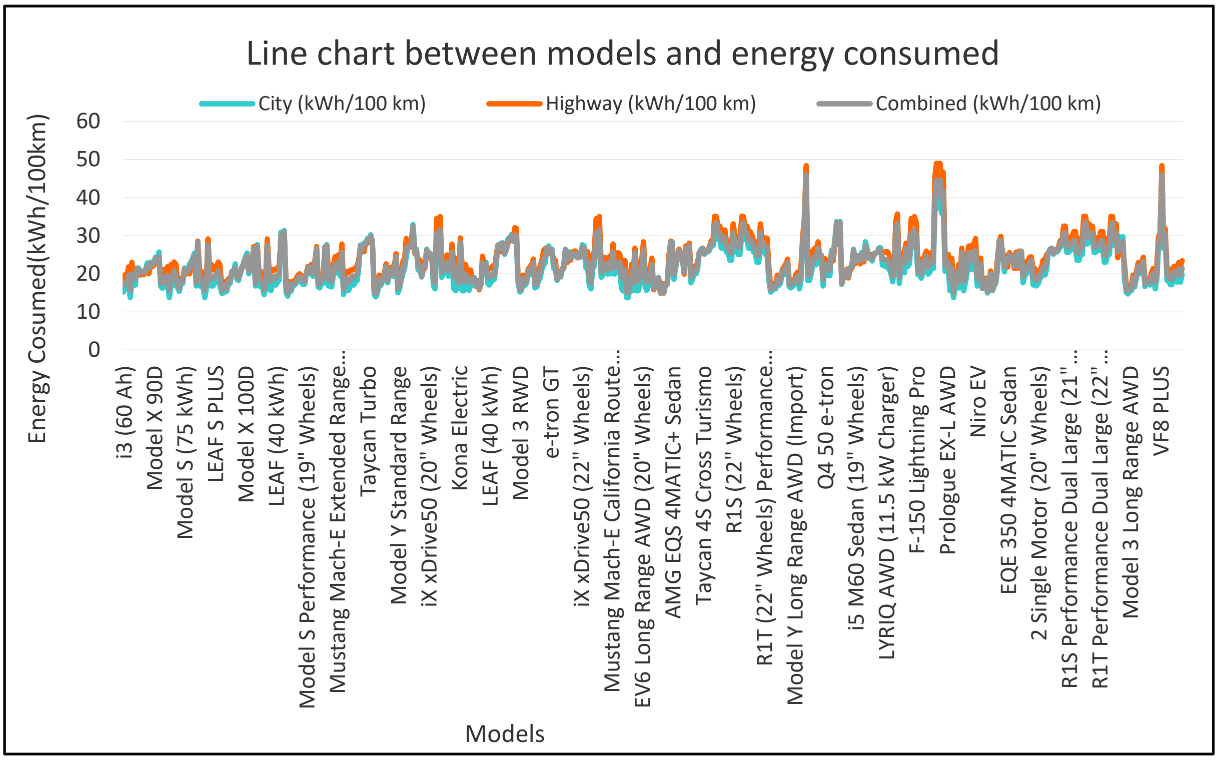




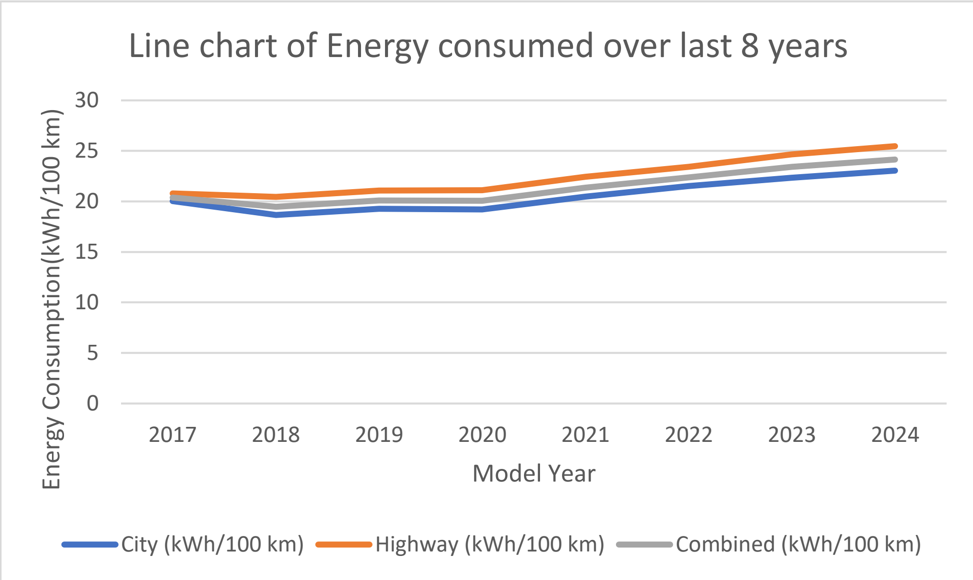


Analyzing the dependence of motor power on total electrical energy consumption in electric vehicles provides an understanding of several important tendencies connected with efficiency parameters of EVs. Using the scatter plot analysis, the positive correlation is very low; in fact, the R-squared is at 0.1689 – this means that 17% of the fluctuation in energy consumption can be associated with motor power changes. According to the linear regression equation y = 0.0127x + 18.469, with the increase of the motor power, the energy consumption does not significantly grow, but it grows steadily adding 0,0127 kWh per 100 km for each kilowatt of motor power. The distribution of the dataset represents motor power from around fifty kW to a thousand kW and has significant variation from the regression line with most of the energy consumption values between fifteen to thirty-five kWh per one hundred kilometers This is nevertheless shifted downwards in the case of several hundred to four hundred kilowatts with the consumption rate of roughly forty-five kWh/100km. That the correlation coefficient is relatively small, and hence the distribution pattern of the data points is scattered, again indicates that motor power cannot solely account for energy consumption. This discovery carries general implications for efficiency improvement of EV and reveals that factors like aerodynamics, mass, drivetrain layout, and operational states might be as or even more influential on energy utilization. The observed trend of falling efficiency at higher power levels also indicates that raises in the motor power output do not necessarily correspond to enhanced energy consumption, which sheds light on the analysis of the intricacy of powertrain efficiency specificity in EVs.

4.2 Energy Consumption Trends Over Time

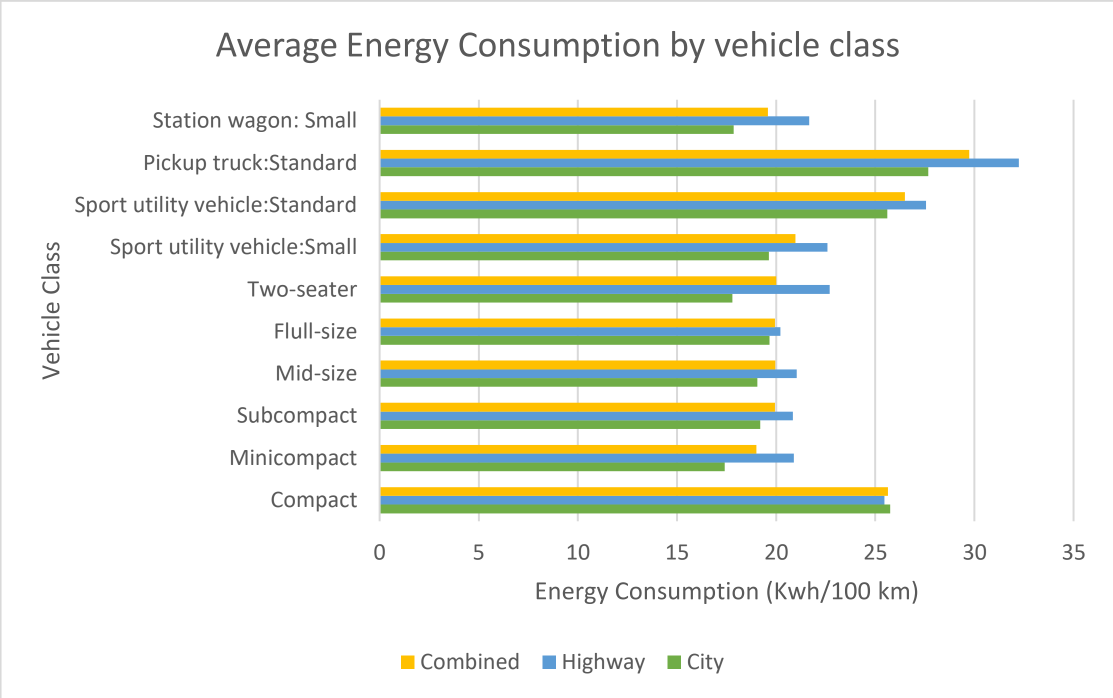


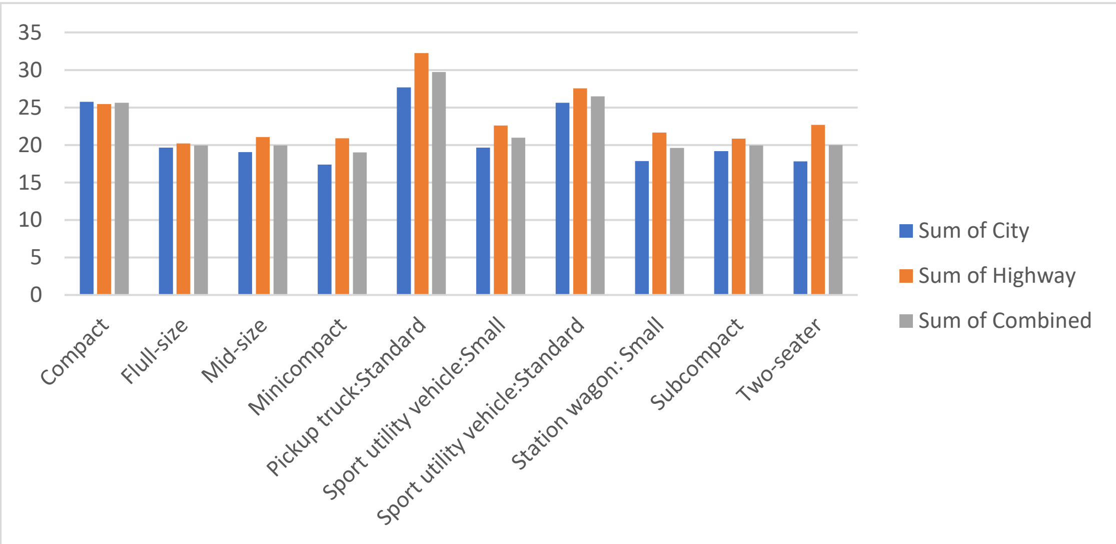
The presented figure illustrates energy consumption patterns across multiple electric vehicle models, measured in kWh/100 km under city, highway, and combined driving conditions. The data reveals that most vehicles operate within an efficiency range of 15-35 kWh/100 km, with distinctive performance characteristics emerging between urban and highway environments. City driving consistently exhibits lower energy consumption, demonstrating the inherent advantage of electric powertrains in urban settings. Notable efficiency variations in highway conditions, with consumption peaks reaching 50 kWh/100 km, emphasize the significant influence of aerodynamic design on high-speed energy efficiency. These findings underscore the importance of considering both urban and highway performance metrics in electric vehicle design optimization.



The analysis of energy consumption patterns from 2017 to 2024 reveals several notable trends across city, highway, and combined driving scenarios. Initially, all three metrics started at approximately 20 kWh/100 km in 2017, followed by a slight decrease in 2018, creating a temporary efficiency improvement. However, from 2019 onwards, there has been a gradual but consistent upward trend in energy consumption across all categories. Highway driving consistently shows higher energy consumption compared to city driving, with the gap between them maintaining relatively stable at about 2-3 kWh/100 km throughout the period. The most significant increase occurred between 2020 and 2024, where both city and highway consumption rose by approximately 2-3 kWh/100 km. City driving energy consumption increased from about 19 kWh/100 km to 23 kWh/100 km, while highway consumption rose from approximately 20 kWh/100 km to 25 kWh/100 km over the eight-year period. This upward trend might be attributed to various factors such as changes in vehicle design priorities, increased vehicle weight due to additional features and safety equipment, or shifts in testing methodologies. The combined consumption metric closely follows the average of city and highway values, suggesting a balanced representation of real-world usage patterns. This trend indicates that despite technological advancements, overall energy efficiency has faced challenges in maintaining or improving upon 2017-2018 levels.

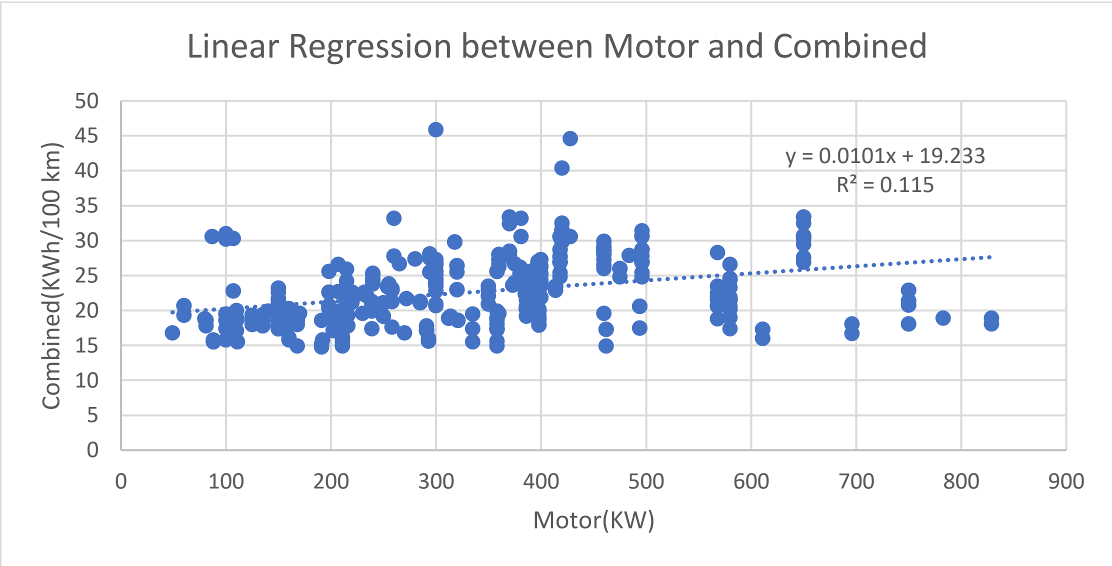
4.3 Energy Consumption by Vehicle Class





Based on the comprehensive data analysis of energy consumption across different vehicle classes, several significant patterns emerge. The results demonstrate that Pickup truck-Standard vehicles exhibit the highest energy consumption across all driving conditions, with notably high highway consumption of 32.25 kWh/100 km and city consumption of 27.67 kWh/100 km. Conversely, Minicompact vehicles show the most efficient energy utilization, consuming only 17.4 kWh/100 km in city driving and 20.9 kWh/100 km on highways. Sport utility vehicles, both Standard and Small classifications, display intermediate consumption patterns, with highway driving consistently demanding more energy than city operation. An interesting observation is that across all vehicle classes, highway driving consistently requires higher energy consumption compared to city driving, with differences ranging from 2-5 kWh/100 km. This comprehensive analysis of vehicle classes and their respective energy consumption patterns provides valuable insights for electric vehicle design optimization and consumer decision-making, highlighting the significant impact of vehicle size and class on overall energy efficiency.

4.4 Model Performance and Forecasting



Based on the regression analysis conducted to evaluate the relationship between motor power and combined energy consumption in electric vehicles, the results indicate a statistically significant positive correlation. The linear regression model yielded an R-square value of 0.115 (adjusted R-square = 0.113), with a regression equation of y = 0.001x + 19.233. The model's statistical significance is substantiated by an F-statistic of 55.49 and a p-value of 5.24219E-13. Analysis of 429 observations revealed that while motor power demonstrates a clear influence on energy consumption, the relatively modest R-square value suggests that approximately 11.5% of the variance in energy consumption can be attributed to motor power variations. This finding indicates that while motor power is a significant predictor, additional variables are likely to contribute to the overall energy consumption patterns in electric vehicles.

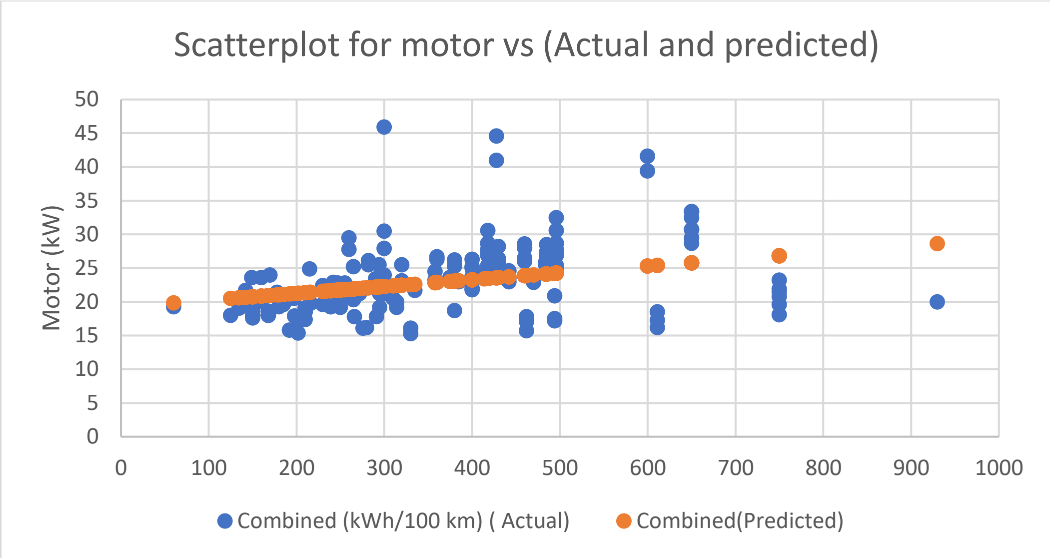
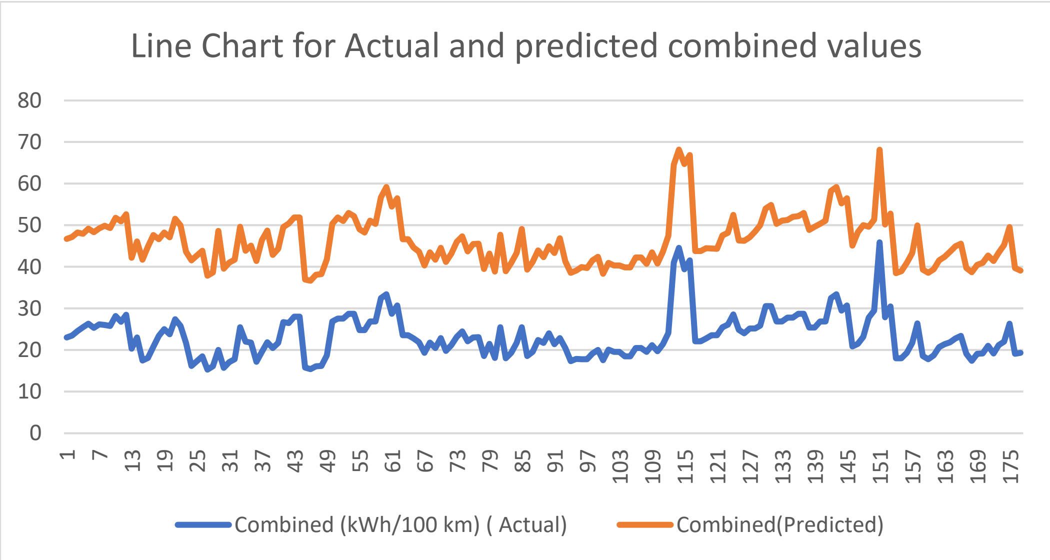
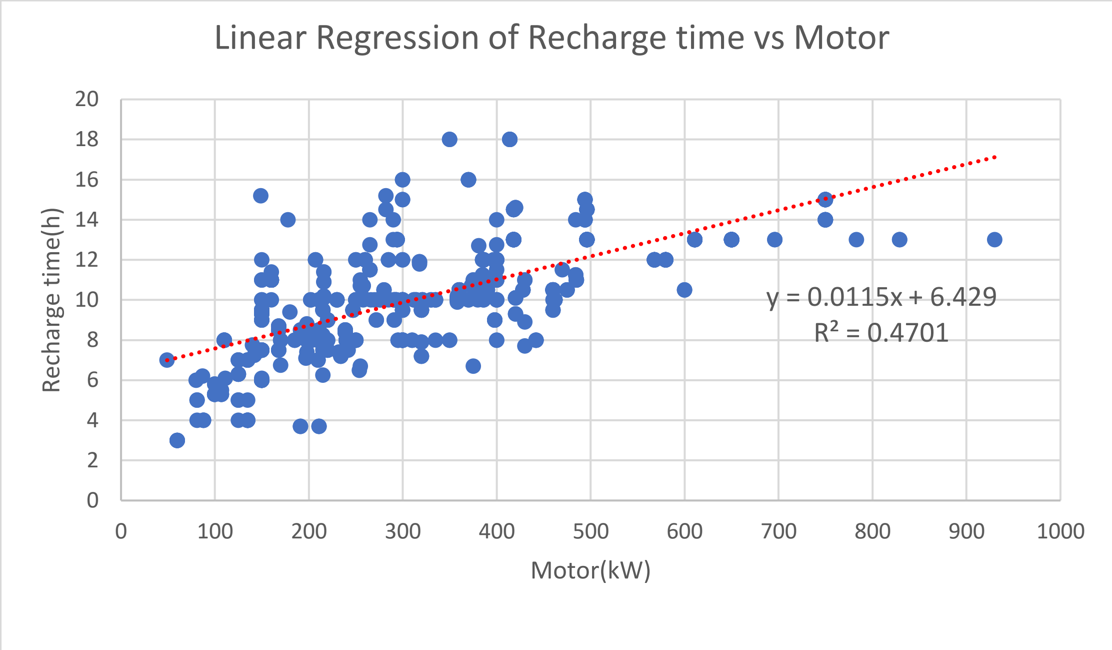


Table 1: Training Dataset



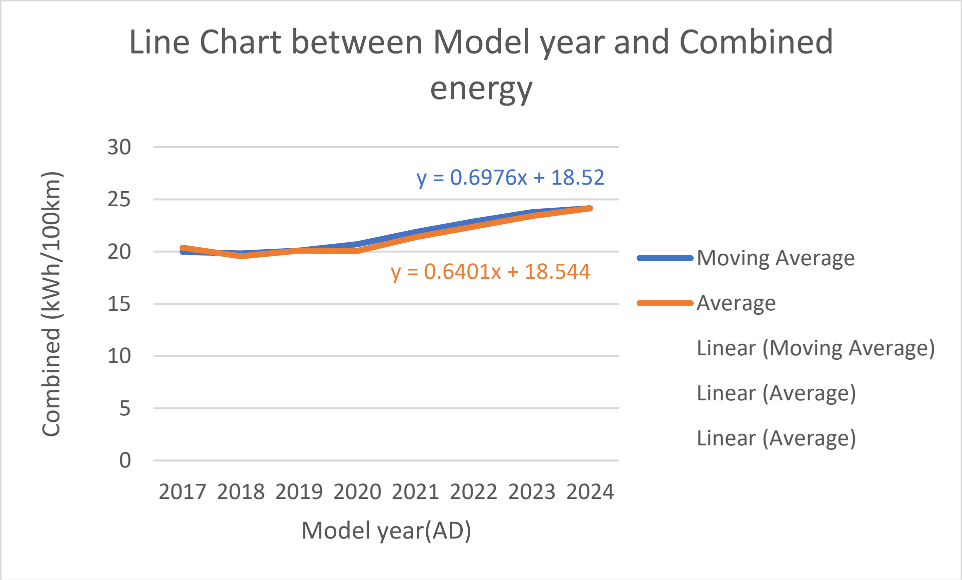
The testing phase of the regression model revealed robust statistical performance, as evidenced by the perfect Multiple R and R-square values of 1.0, indicating exceptional model fit across 177 test observations. The model's predictive accuracy is demonstrated through an extremely low standard error of 1.678E-13. The ANOVA results show a highly significant F-statistic (7.9985E+31) with a p-value of 0, confirming the model's statistical validity. The scatter plot comparison between actual and predicted values demonstrates consistent tracking, though with some notable variations in higher power ranges. The line chart visualization of actual versus predicted combined values reveals that while the model generally captures the trend of energy consumption, there appears to be a systematic overestimation in the predicted values, as indicated by the consistently higher orange line (predicted values) compared to the blue line (actual values). This suggests that while the model exhibits strong statistical indicators, there may be room for refinement in its predictive capabilities, particularly in accounting for real-world variations in energy consumption patterns.



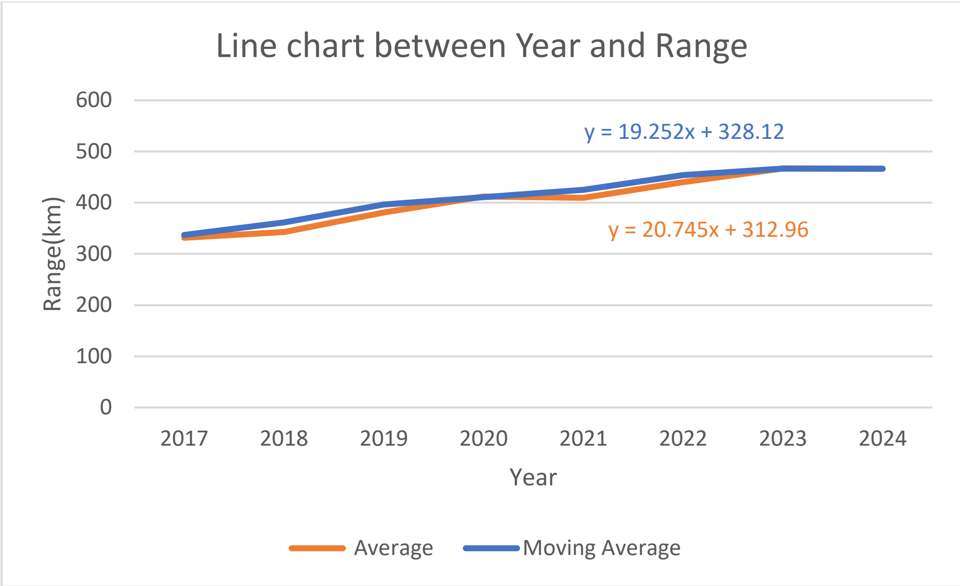
Linear regression analysis of motor power and recharge time demonstrates a moderate positive correlation ($R^2 = 0.4701$). The relationship, expressed as $y = 0.0115x + 6.429$, indicates that recharge time increases by 0.0115 hours per kilowatt of motor power above a baseline of 6.429 hours. Data concentration in the 100-500 kW range shows typical recharge times of 6-14 hours, with significant variation suggesting that additional factors beyond motor power influence charging duration. The moderate R^2 value indicates that while motor power is a relevant predictor of charging time, it accounts for less than half of the observed variation in recharge duration.

4.5 Forecasting Accuracy and Model Evaluation

The comparative analysis of forecasting models for combined energy consumption reveals insightful patterns between moving average and standard average approaches. The linear regression equations show slightly different slopes, with the moving average trend line ($y = 0.6976x + 18.52$) having a steeper gradient compared to the standard average ($y = 0.6401x + 15.544$). This difference in slopes indicates that the moving average model predicts a marginally faster rate of energy consumption increase over time. Both models demonstrate strong linear relationships with R-squared values suggesting good fit to the historical data. The moving average line shows slightly more sensitivity to year-to-year variations, particularly noticeable in the 2018-2020 period where it captures subtle fluctuations that the standard average smooths out. Interestingly, both models converge closely from 2021 onwards, suggesting increased forecasting reliability for recent years. The moving average model's higher slope coefficient (0.6976 vs 0.6401) indicates it predicts approximately 9% faster growth in energy consumption. The similar y-intercepts (18.52 vs 18.544) suggest both models agree on the baseline energy consumption levels. This parallel analysis demonstrates that while both models capture the overall upward trend, the moving average approach might be more responsive to short-term changes, potentially offering better early detection of trend shifts. For future projections, the slight variance between these models should be considered when establishing confidence intervals for energy consumption forecasts.



Analysis of vehicle range performance from 2017 to 2024 demonstrates sustained technological advancement in electric vehicle capabilities. The data presents two analytical approaches: a standard average (y = 20.745x + 312.96) and a moving average (y = 19.252x + 328.12), both indicating positive growth trajectories. Initial range values of approximately 330 kilometers in 2017 improved to 470-480 kilometers by 2024, representing a 45% increase in vehicle range capacity. The moving average trend line reveals a gradual deceleration in improvement rates during 2023-2024, suggesting a maturation of current battery technology. This plateauing effect, captured by the moving average's lower slope coefficient (19.252 versus 20.745), provides a more conservative and potentially more realistic projection of technological advancement limitations. The convergence and subsequent divergence patterns between 2019-2021 indicate periodic stabilization phases in range enhancement capabilities, reflecting the cyclical nature of technological implementation and optimization processes.



Line chart between Year and Range
y = 19.252x + 328.12
y = 20.745x + 312.96
Range(km)
600
500
400
300
200
100
0
2017
2018
2019
2020
2021
2022
2023
2024
Year
Average
Moving Average

Chapter 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study aimed to explore the relationship between road conditions, energy consumption, and operational efficiency of electric vehicles (EVs) in Canada from 2012 to 2024. By employing various analytical techniques, including Moving Average, Linear Regression, and Exploratory Data Analysis, the research successfully identified patterns and trends in energy consumption while developing models to forecast both short-term and long-term consumption. The analysis also evaluated the impact of factors such as vehicle subclass, motor power, and recharging time on energy efficiency.

Key findings include:

- **Impact of Vehicle Subclass on Energy Consumption:** The subclass of the vehicle significantly influences energy consumption, with larger vehicles (e.g., SUVs and trucks) generally consuming more energy compared to smaller vehicles (e.g., sedans and compact cars).
- **Forecasting Energy Consumption:** The models developed demonstrated the potential for accurately forecasting energy consumption using historical data. Moving Average and Linear Regression models provided useful insights, with Exploratory Data Analysis offering more accuracy for short-term predictions.
- **Correlation Between Motor Power and Range:** A positive correlation was observed between motor power and vehicle range, indicating that higher motor power tends to result in a longer range, although other factors such as road conditions and vehicle subclass also play important roles.
- **Reliability of Forecasting Models:** The forecasting models developed were able to capture general consumption patterns, though they required ongoing refinement to improve their precision and reliability, particularly in predicting long-term trends.

This research contributes to understanding how electric vehicles perform under various conditions and provides actionable insights for stakeholders in the EV sector, including manufacturers, policymakers, and energy planners.

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5.2 Recommendations

Based on the findings of this study, the following recommendations are made:

- **Focus on Vehicle Subclass for Energy Efficiency Improvements:**
  EV manufacturers should consider the impact of vehicle subclass on energy consumption when designing future models. By focusing on producing energy-efficient models across various subclasses, manufacturers can help mitigate the impact of larger vehicles on energy consumption. This could involve developing lighter materials, enhancing aerodynamics, and optimizing motor power relative to vehicle size.
- **Refinement of Forecasting Models:**
  While the developed forecasting models were useful, further refinement is necessary for more accurate long-term predictions. Incorporating additional variables such as road conditions, weather patterns, and driving habits could improve the accuracy of forecasts. Regular updates to these models should be made as new data becomes available to ensure they remain relevant and reliable.
- **Incentivize the Use of Smaller EV Subclasses:**
  Policymakers may consider offering incentives for consumers to purchase smaller, more energy-efficient EVs. This could help reduce the overall energy consumption in the transportation sector, aligning with environmental goals and promoting sustainability.
- **Promote Research into Alternative Charging Methods:**
  Given the importance of recharging time in energy consumption, future research should explore alternative charging methods, such as faster charging technologies or the development of widespread wireless charging infrastructure. Reducing charging times can improve the overall operational efficiency of EVs and make them more appealing to consumers.
- **Data-Driven Energy Management:**
  Energy providers and government agencies should utilize the forecasting models developed in this study to better manage the energy demands associated with EV charging. Accurate short-term and long-term consumption forecasts can assist in creating efficient charging infrastructure and energy distribution systems, ensuring that supply meets the growing demand for EVs in Canada.

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https://otexts.com/fpp2/intro.html

ANNEX 1: DATASET AFTER CLEANING RESULTS

Model year	Make	Model	Vehicle class	Motor (kW)	Transmission	Fuel type	City (kWh/100 km)	Highway (kWh/100 km)	Combined (kWh/100 km)	City (Le/100 km)	Highway (Le/100 km)	Combined (Le/100 km)	Range (km)	CO2 rating	Smog rating	Recharge time (h)
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

ANNEX 2: Summary Output between Motor Power and Combined Energy Consumption

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.410951701
R Square	0.168881301
Adjusted R Square	0.16754938
Standard Error	145.8908776
Observations	626

ANOVA

	df	SS	MS	F	Significance F
Regression	1	2698729.615	2698730	126.7953	6.63599E-27
Residual	624	13281308.46	21284.15		
Total	625	15980038.08			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	33.13107402	27.54420841	1.202833	0.229497	-20.95949768	87.22164571	-20.95949768	87.22164571
Combined (kWh/100 l	13.33796875	1.184508401	11.26034	6.64E-27	11.01186319	15.66407432	11.01186319	15.66407432

ANNEX 3: RESIDUAL OUTPUT

Combined(Predicted)	Absolute Error	Root Mean Square Error
23.6972	0.6972	1.84509703
23.6972	0.1972	
23.6972	0.9028	
22.465	3.035	
22.869	3.431	
23.071	2.229	
23.071	3.129	
23.879	2.121	
23.576	2.224	
23.576	4.624	
24.1315	2.6685	
24.1315	4.3685	
21.9095	1.6095	
23.1215	0.1215	
24.2224	6.7224	
26.808	8.708	
26.808	6.008	
23.273	0.127	
23.273	1.727	
23.273	0.527	
24.1315	3.2685	
24.1315	1.6685	
21.9802	0.2802	
25.4041	9.2041	
25.4041	8.1041	
25.4041	6.9041	
22.566	7.266	
22.566	6.466	
28.626	8.626	
23.8992	8.1992	
23.8992	6.7992	
23.8992	6.0992	
24.1214	1.3786	
21.9095	0.0905	
23.273	1.473	
24.2224	7.0224	
26.808	7.208	
26.808	4.908	
22.364	1.864	
22.6165	0.9165	
22.869	3.831	
23.879	2.621	
23.879	4.121	
23.879	4.121	
21.1722	5.3722	
21.2732	5.8732	
22.0206	5.9206	
22.061	5.861	
23.071	4.371	
23.4548	3.4452	
24.2426	3.3574	
23.4548	4.1452	
24.2426	4.4574	
23.4548	5.2452	
24.2426	0.5574	
23.4548	1.3452	
24.2426	2.6574	
23.4548	3.4452	
24.2426	8.2574	
25.798	7.602	
25.798	2.902	
25.798	4.902	
23.0205	0.5795	
23.0205	0.5795	
21.8085	0.9915	
21.7277	0.1723	
21.051	1.751	
21.7277	0.0723	
21.2227	0.7227	
21.6772	1.2228	
21.4146	1.6146	
21.9802	0.7802	
22.8488	0.3512	
22.8488	1.6512	
21.5964	0.5036	
22.465	0.535	
22.465	0.635	
20.9298	2.3298	
21.6469	0.1469	
20.748	2.648	
22.2024	3.2976	
20.9298	2.9298	
21.6469	2.3469	
21.6469	0.0531	
23.576	1.924	
20.748	2.148	
21.556	1.956	
21.556	0.844	
20.6672	1.0328	
20.95	3.05	
21.9095	0.5095	
23.98	1.08	
20.849	0.349	
21.2833	3.9833	
21.2328	3.3328	
22.1721	4.3721	
21.9196	4.1196	
22.4044	3.2044	
22.4044	2.4044	
20.748	3.148	
20.849	0.749	
20.748	1.148	
20.748	1.148	
21.354	2.854	
21.354	2.854	
21.758	1.258	
21.758	1.258	
21.1015	1.5015	
22.263	1.063	
21.1015	1.4015	
22.263	0.863	
23.4144	0.6856	
23.5558	17.4442	
23.5558	21.0442	
25.293	14.107	
25.293	16.307	
21.7277	0.3723	
21.7277	0.3723	
21.7277	1.0723	
20.849	2.751	
20.7379	2.8621	
22.0812	3.4188	
22.0812	4.0188	
23.879	4.721	
21.4045	3.4955	
22.263	1.737	
21.9095	3.2905	
23.273	1.927	
24.1214	1.7786	
23.4548	7.1452	
24.2426	6.3574	
23.4548	3.4452	
24.2426	2.6574	
23.4548	4.3452	
24.2426	3.5574	
23.4548	5.2452	
24.2426	4.4574	
23.4548	1.9452	
24.2426	1.1574	
23.4548	3.4452	
24.2426	2.6574	
25.798	6.702	
25.798	7.602	
25.798	3.702	
25.798	4.902	
24.2224	3.3224	
26.808	5.308	
26.808	3.608	
21.859	5.941	
21.859	7.641	
22.263	23.637	
22.263	5.637	
22.263	8.237	
20.4955	2.4955	
20.9298	2.9298	
21.6469	2.3469	
21.6469	0.0531	
23.576	2.824	
20.748	2.148	
20.748	2.948	
20.748	2.048	
20.849	0.149	
21.0308	0.3692	
21.758	0.142	
22.162	0.638	
22.162	1.238	
20.5965	1.4965	
21.354	3.954	
21.354	2.254	
21.758	2.558	
21.758	0.758	
22.2125	3.0125	
22.2125	1.0125	
23.273	1.273	
23.273	3.027	
20.5965	1.4965	
19.839	0.539	