A Model for Predicting Greenhouse Gas Emissions from Motorcycles in Kenya

Laureen Cherotich Cheruiyot

148461

A Dissertation Submitted to the School of Computing and Engineering Sciences in Partial Fulfilment of the Requirements of the Degree of Master of Science in Sustainable Energy Transitions at Strathmore University

School of Computing & Engineering Sciences

Strathmore University

Nairobi, Kenya

March 2024

Declaration and Approval

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself. No part of this thesis may be reproduced without the permission of the author and Strathmore University.

Name: Laureen Cherotich Cheruiyot

Registration Number:148461

Signature ……………………………

Date: 4/18/2024 ……………………………

Approval

The dissertation of Laureen Cherotich Cheruiyot was reviewed and approved by the following:
Dr. Bernard Shibwabo,
Senior Lecturer,
School of Computing and Engineering Sciences,
Strathmore University

Signature ……………………………

Date: 4/18/2024 ……………………………

Abstract

In Kenya, inefficient public transport systems coupled with rough terrains have made motorcycles the most preferred means of transport. The transport sector is a leading emitter of greenhouse gases, the main driver of global climate change. This is due to the reliance on fossil fuels which require Internal Combustion Engines to operate. The threat posed by climate change and variability has fueled the ongoing energy transition from fossil fuels to green technologies through E-mobility. Motorcycles have been described as low-hanging fruit in the E-mobility transition from fuel-based engines to electric-powered motors. However, this transition has shown little progress due to fewer and inadequate models to inform E-mobility policy and investment decisions. This study sought to develop a model for calculating GHG emissions from conventional and electric motorcycles under different scenarios. The scenarios were based on traffic conditions and engine efficiency. The study also aimed to analyze existing ICE and electric two-wheeler technologies in Kenya. A descriptive and experimental research design was adopted for the study. Primary data was collected using a structured questionnaire embedded in the Kobo Toolbox and was administered to motorcycle operators in Nairobi and Machakos counties. Secondary data was also collected from the NTSA database. The R-programming tool was used for data analysis and simulation of GHG emissions under different scenarios. The model was validated using experimental results to increase confidence in the findings. The study results provided comprehensive insights into the determinants of greenhouse gas emissions from both conventional Internal Combustion Engine (ICE) and electric motorcycles. Through an analysis of rider demographics, and electric and conventional motorcycle characteristics, the study revealed the multifaceted factors that contributed to the environmental impact of motorcycles. The specifics of electric motorcycle technologies, including battery characteristics, charging habits, and daily travel distances, were explored, offering valuable insights into the state of electric mobility in the country. Additionally, the study developed and applied a General Additive Model (GAM) for predicting motorcycle emissions, yielding high predictive accuracy and significant predictors. The model underscored the influence of fuel type and temporal trends on emissions, emphasizing the importance of considering both technological and temporal factors in policy formulation. Projection of emissions to 2045 revealed an alarming exponential increase, necessitating urgent intervention. ***Keywords: Predictive model, GHG emissions, electric two-wheelers***

Table of Contents

List of Figures

List of Tables

List of Formulas

List of Abbreviations

CFCs	**-**	Chlorofluorocarbons
CO	**-**	Carbon Monoxide
CO_2	**-**	Carbon Dioxide
E2Ws	**-**	Electric Two-Wheelers
EVs	**-**	Electric Vehicles
GHGs	**-**	Greenhouse Gases
ICE	**-**	Internal Combustion Engines
IPCC	**-**	Intergovernmental Panel on Climate Change
PM	**-**	Particulate Matter
SCLP	**-**	Short-Lived Climate Pollutants
TAM	**-**	Technology Adoption Model
UNFCCC	**-**	United Nations Framework Convention on Climate Change
VKT	**-**	Vehicle Kilometer Travelled

Definition of Terms

Greenhouse Gas Emissions: These are a range of gaseous elements within Earth's atmosphere that have the ability to absorb and emit radiation at specific wavelengths found in the thermal infrared spectrum. They are emitted by various sources, including the Earth's surface, the atmosphere itself, and cloud formations (IPCC, 2015).

Climate scenario: An achievable and frequently streamlined portrayal of forthcoming climate conditions, built upon a harmonious collection of climatic interconnections. This construct is deliberately designed to explore the potential outcomes of human-caused climate alterations and is commonly employed as input for impact models (IPCC, 2018).

Climate projection: An achievable and frequently streamlined portrayal of forthcoming climate conditions, built upon a harmonious collection of climatic interconnections (IPCC, 2018).

Climate model: In the realm of data analysis, a model refers to a streamlined depiction or mathematical description of an actual system, process, or interconnection between different factors (IPCC, 2015).

Acknowledgement

The accomplishment of this dissertation and its underlying endeavors resonates as a triumph, attributing its achievement to the unwavering assistance extended by numerous individuals. I hold profound gratitude for their tireless dedication. I extend my utmost thanks to Dr. Bernard Shibwabo and Dr. Eng. Fenwicks Musonye for their invaluable insights, constructive assessments, enthusiastic motivation, and ardent backing throughout this endeavor. Furthermore, I express heartfelt appreciation to my fellow classmates and my childhood friend, John Paul Wafula (a prospective graduate), for their collaborative efforts in sourcing reputable scholarly references and their priceless input during our classroom presentations. I acknowledge my colleagues at The Palladium Group's UK PACT programme and Conservation International's GEF Agency for the encouragement to forge forward. Lastly, my family deserves endless gratitude for their support and encouragement throughout my academic journey.

Dedication

I dedicate this work to God Almighty for the grace and might granted unto me to embark on this journey. To my ever-supportive parents Mr. and Mrs. Raymond Cheruiyot, and siblings for the encouragement to push forward. My academic success is a result of them not giving up on me. To my friends Lucia Munyao, Judy Komen, Beverly Kaluli and Caroline Mutheu for pushing me to continue with this journey, forever grateful for their support. A special thank you to REED TEA/LP scholarship for supporting this dream.

Chapter 1: Introduction

1.1 Background of the Study

The transport sector is heavily reliant on fossil fuels, which use Internal Combustion Engines (ICE) to operate. The sector is responsible for approximately 25% of Greenhouse Gas Emissions (GHGs) globally. It is also a leading emitter of short-live climate pollutants (SLCP). This significantly affects the human health and the environment. The global vehicle fleet is projected to double by the year 2050, with 90% of the change occurring in developing countries (Akumu, 2019). In the last two decades, all regions except Europe have recorded an increase in transport related GHG emissions, with developing countries recording the highest growth (United Nations, 2021). This Business-As-Usual (BAU) scenario is inconsistent with the United Nations Framework Convention on Climate Change (UNFCCC) global warming mitigation targets. The inevitable consequences of continued reliance on Internal combustion engine (ICE) vehicles calls for a shift to cleaner and sustainable transport systems such as electric powered vehicles (EVs) (Ayetor et al., 2023; Bakker et al., 2019; Vanatta et al., 2022).

Small vehicles such as 2 & 3 wheelers are already dominating the transport sector across Africa. Asia and Africa account for 95% of global motorcycle sales. Motorcycles are also the fastest growing mode of transport in Kenya (EPRA & UNEP, 2020). The increasing demand for motorcycle taxis commonly referred to as 'boda-boda' has been driven by an inefficient public transport system and their ability to access remote areas and different terrains. Even though motorcycles emit less per kilometer compared to Light Duty Vehicles (LDVs), studies have shown that they emit more short-lived climate pollutants (SLCPs) such as hydrocarbons, carbon monoxide and Nitrous Oxides (UNEP, 2020). A transition to electric two wheelers (E2Ws) could reduce the SLCPs emitted per km and significantly improve air quality (Longe, 2022).

Technological shift from conventional ICE engines to electric motors through adoption of E2Ws is projected to significantly impact future GHG emissions (Longe, 2022). A number of projections have been developed, simulating emission abatements. These projections are based on scenarios developed from different assumptions, simulated using mathematical models. Use of scenario building is a decision-making tool that can be applied by public and private institutions to inform public policy and strategies (Hultman & Edmonds, 2023). Use of such an approach in determining emissions in Kenya, using various factors, can be useful. Even though there exist such studies in Kenya, they do not consider factors like engine efficiency degradation, average distances covered in a day in various towns and topographies (Notter & Fussler, 2018; Sitati et al., 2022). This study, therefore, seeks to estimate and project GHG emissions from conventional ICE engines and E2Ws in Kenya using scenario modeling with improved modelling assumptions.

Electric-Two-Wheelers (E2Ws) are equipped with rechargeable lithium-ion batteries and electric motor which power the wheels. Common E2Ws include electric scooters and electric motorcycles. On a single charge, E2Ws have a range of up to 200km depending on several factors including battery capacity and weight (Ayetor et al., 2023). Compared to ICE vehicles, E2Ws offer more benefits in terms of low costs associated with maintenance and charging (Longe, 2022). Policy incentives such as reduction of excise duty from 20% to 10% by the government are also in place to promote adoption of e-mobilities (KOA LLP, 2022). Moreover, E2Ws offer a sustainable zero-emissions alternative to fossil fuel-dependent transport system as the world shifts towards green mobility. Therefore, focusing on E2Ws presents a viable path to low-emissions and electro-mobility transition in Kenya.

1.2 Problem Statement

The steady rise in the use of the conventional ICE vehicles exacerbates climate change impacts due to the accompanying increase in greenhouse gas emissions (United Nations, 2021). This reality highlights the urgent need to transform the transport sector from reliance on fossil fuels to sustainable modes of transport such as electric vehicles such as E2Ws (Government of Kenya, 2019). Despite the description of E2Ws as 'low-hanging fruit' in e-mobility transition, its potential is yet to be harnessed, with fewer and inadequate models that can guide policy intervention and investment into this mode of transport. There indeed exist models that can be used as a guide to policy and investment decision making. However, they have overlooked important factors such as engine sizes, changes in efficiencies of the E2Ws, topographies where the wheelers are used and the life cycle cost assessments. These factors are often place-based and greatly vary especially in developing countries. This study intends to address these gaps and contribute to the growing body of knowledge on scenario modeling of GHG emissions, in the Kenyan market.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this study is to develop a model for predicting greenhouse gas emissions from motorcycles in Kenya.

1.3.2 Specific Objectives

i. To determine the factors that influence GHG emissions from motorcycles.
ii. To analyze the existing models for predicting of GHG emissions.
iii. To develop a model for predicting GHG emissions from motorcycles.
iv. To validate the developed model.

1.4 Research Questions

i. How do different factors affect GHG emissions from motorcycles?
ii. What are the existing models used for predicting of GHG emissions?
iii. How can a model for predicting GHG emissions from motorcycles based on different factors be developed?
iv. How can the developed model be validated?

1.6 Justification

Climate change has emerged as a global challenge affecting nations worldwide. The impact of climate change is already visible across Africa and Kenya (Ayanlade et al., 2023; Kogo et al., 2021; Sasu, 2023). As a major contributor to GHG emissions, the transport sector presents both a challenge and an opportunity to address the climate change crisis. A challenge due to the threat it poses on human health and wellbeing through environmental pollution, and an opportunity to reverse this course through a transition to greener technologies such as E2Ws (Abbass et al., 2022; Opoku et al., 2021). By using predictive modelling to analyze GHG emissions from motorcycles, this study intends to develop an evidence-based tool that would inform low-emissions transition in Kenya such as e-mobility. Moreover, findings of this study will be beneficial to policy makers, businesses, scholars, researchers, and development partners interested in low-carbon development and energy transition. In addition, the study also reflects on the progress made towards meeting

Kenya's obligations under the Paris Agreement and attainment of sustainable development goals (SDGs).

1.7 Assumptions of the Study

The following presumptions will form the basis of this study;

1. All motorcycles imported into the country and registered with respective associations are operational and actively in use.
2. The current grid emission factor in Kenya will remain the same.
3. Performance of the motorcycles is not affected by road conditions.
4. Performance of the motorcycles is not affected by the tare weight.
5. Data collected and utilized in developing the predictive model represents all regions of the country.

Chapter 2: Literature Review

2.1 Introduction

Vehicles can be classified into three main groups: Internal Combustion Engine (ICE) vehicles, hybrid electric vehicle (HEV) and all-electric vehicles (AEV). Research and debate on the tradeoff between conventional vehicles and EVs have gained significant interest over the past decades. The need for sustainable, cost-effective, reliable and energy-efficient technologies has catalyzed the divestment from fossil-fuels towards greener technologies (Adnan et al., 2018). This momentum has been driven by several factors including environmental concerns, depleting fossil fuel reserves and advanced innovative technologies (Arif et al., 2021). This section reviewed basic concepts on conventional and electric vehicles with a focus on motorcycles. Approaches to modelling were also reviewed with a focus on predictive modelling. The terms "motorcycles" and "motorbikes" are often used interchangeably to refer to two-wheeled motor vehicles powered by internal combustion engines or electric motors.

2.2 Theoretical Literature

The study was underpinned by Technology Adoption Model (TAM) and the Information-Deficit Model (IDM) theories.

2.2.1 Technology Acceptance Model (TAM)

According to TAM, and as shown in Figure 2.1, perceived usefulness and ease of use of new technologies such as E2Ws influence individual intensions to adopt the technologies (Venkatesh & Davis, 1996). Zhang & Chang (2023) applied TAM to explore Generation Z's intention to use electric motorcycles in Taiwan. The study found that perceived usefulness and ease positively influenced their attitude to use electric motorcycles. Furthermore, the study also found that consumer attitude was also influenced by government policies. The inefficient public transport system coupled with rough terrains have made motorcycles the most preferred mode of transportation in Kenya. The usefulness and ease of use of motorcycles coupled by government policies on e-mobility transition will likely influence adoption of E2W technologies. This shift will also be spurred by the projected growth in population and rapid urbanization as individuals seek improvements in mobility.

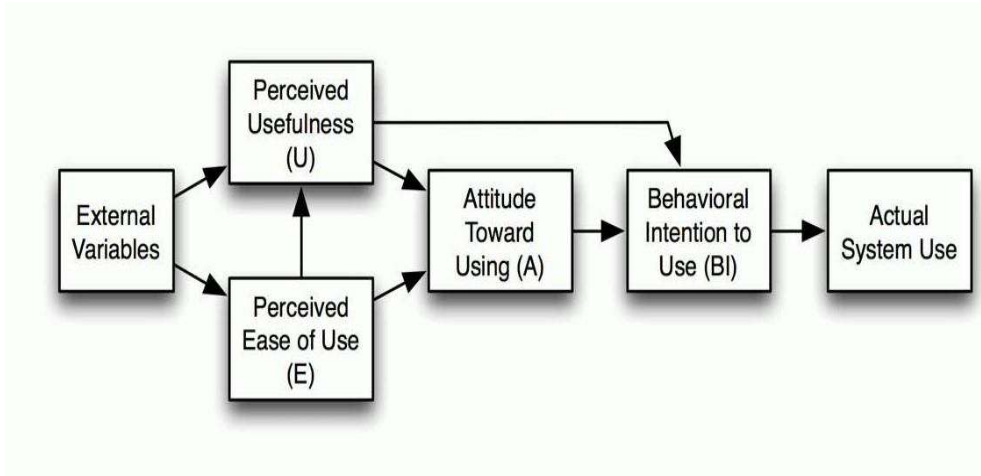


Figure 2.1: Technology Acceptance Model (Venkatesh & Davis, 1996).

2.2.2 Information-Deficit Model (IDM)

The Information-Deficit Model suggests that the mismatch in adoption of e-mobility is due to limited public knowledge. Limited knowledge on E2Ws and the benefits of adopting E2Ws, has contributed to the low adoption and use of the technology. At the same time, the lack of GHG predictive models has denied policymakers a critical decision-making and knowledge management tool that would inform short-term and Long-term GHG mitigation strategies such as E-mobility transition. Conversely, limited public knowledge on the negative wide-ranging impacts of continued use of ICE motorcycles due to the inevitable GHG emissions has contributed to the rising reliance on motorcycles especially in developing countries such as Kenya.

2.2.3 Conventional Vehicles

Conventional vehicles are operated by internal combustion engines which convert the chemical energy into mechanical power. Internal Combustion (IC) engines operate a wide range of devices including motorcycles, trucks, automobiles, ships, and aircrafts. IC engines rely on either gas or liquid fuels such as diesel, ethanol, biodiesel, biogas among others. The engines have 5 key primary components; cylinder, piston, crankshaft, combustion chamber and valves as shown in Figure 2.2.

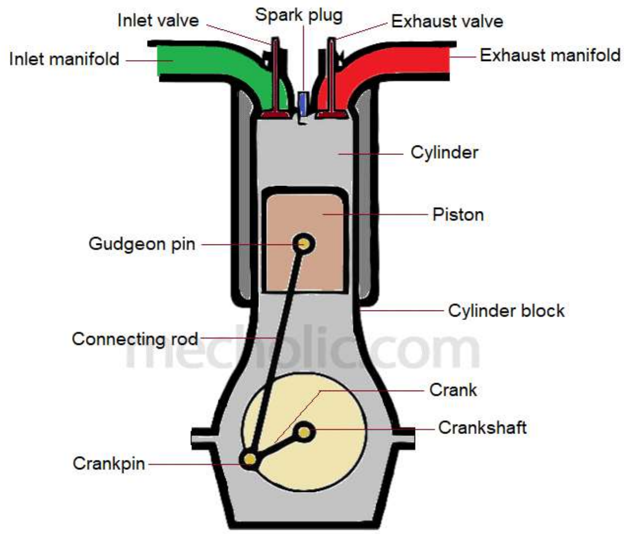


Figure 2.2: Basic components of an IC Engine (Basshuysen & Schäfer, 2016).

IC engines operate through two principles; four-stroke and two-stroke cycle (Kornhauser, 2004). The four-stroke cycle begins with an intake stroke where the inlet valve opens, and piston moves down drawing in the air-fuel mixture into the cylinder. This is followed by compression stroke where both valves are closed, and the piston moves upwards compressing the air-fuel mixture. The compressed mixture is then ignited causing expansion that forces the piston down (power stroke).

Moreover, the final stroke is exhaustion where the piston moves up and exhaust valve opens pushing out the flue gas. On the other hand, the two-stroke cycle involves; induction and compression stroke (exhaust blowdown) followed by expansion and pre-compression (scavenging). Exhaust blowdown combines both combustion and power stroke as the piston moves upwards compressing the fuel then ignition producing power. The piston moves down, valves open allowing new mixture in and expelling exhaust gases (Subramanian, 2018). Figure 2.3 shows the two-stroke and four-stroke engine cycle principles.

Figure 2.3: Two-Stroke and Four-Stroke Engine Cycles (Herold et al., 2011).

There has been an increase in the manufacture and use of motorcycles. This is because motorcycles have become the most preferred means of transport in the cities of the global south (Olvera et al., 2020). Motorcycles with 101-150kg tare weight and up to 250cc engine capacity dominate the Kenyan market. As of June 2018, 1.5million 2 & 3 wheelers had been registered in the Kenya and this is projected to increase to 5million by the year 2030. The average Vehicle Kilometer Travelled (VKT) for motorcycles is 31,200km annually (100-125km per day) with an estimated 58.65g of CO_2 emitted per km (UNEP, 2020).

Motorcycle engines are either four-stroke or two-stroke. Both types of engine use carburetors which cause high evaporative emissions (EEs) (UNEP, 2020). EEs emanate from evaporation of fuels in tanks, lines and conduits and have often been overlooked compared to exhaust emissions. This has contributed to release of volatile organic compounds (VOC), mostly hydrocarbons, to the atmosphere (Pawsey, 2014). Some of the advantages linked to two-stroke engines include simplicity, low-cost and high power per unit weight. However, the use of two-stroke engines in motorcycles has declined over the years due to poor efficiency attributed to fuel economy and GHG emissions. This is compounded by lack of regulatory standards for motorcycles as those placed on Light Duty Vehicles (LDV) (UNEP, 2020). Attempts to improve fuel efficiency and lower emissions have led to advancements in green engine technologies such as electric vehicles (EVs).

2.2.4 Electric Vehicle Technologies

Electric Vehicles have been the focus of research and development as the world seeks to shift from fossil-fuels to low-carbon technologies. Adnan et al., (2018) classified EVs into three categories; Hybrid-Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Fully Electric Vehicles (FEVs). Others such as Hossain et al., (2022) have grouped EVs into two main categories; Hybrid EVs (HEVs) and All-Electric Vehicles (AEVs). Classification of the three categories is provided in Table 2.1.

Table 2.1: Classification of EVs (Adnan et al., 2018)

EV	Engine type	Battery Charging
Hybrid-Electric Vehicles	ICE	Internal battery
Plug-in Electric Vehicles	ICE	Internal and/or external battery
Fully Electric Vehicles		External battery

2.2.4.1 Hybrid-Electric Vehicles (HEVs)

Hybrid-electric vehicles (HEVs) rely on both IC engines and electric motors for power. HEVs have 4 main components: IC engines, electric motor(s), battery pack and power electronics as shown in Figure 2.4. The IC engines in HEVs are smaller and more efficient. Battery packs which are often Lithium-ion battery store energy which powers the electric motor. The electric motors assist IC engines during acceleration and convert kinetic energy into electrical energy during deceleration thereby recharging the battery. Hybrid systems have improved fuel economy and fuel efficiency, and lower GHG emissions. They are a transition technology towards more improved models such as plug-in EVs and AEVs. Plug-in EVs is a type of HEVs that have a battery capacity equal to or more than 4kWh and can be powered directly from the grid i.e. power outlet or charging station (Adnan et al., 2018). Compared to HEVs, PHEVs store more electrical energy as they have a large battery pack giving it more range.

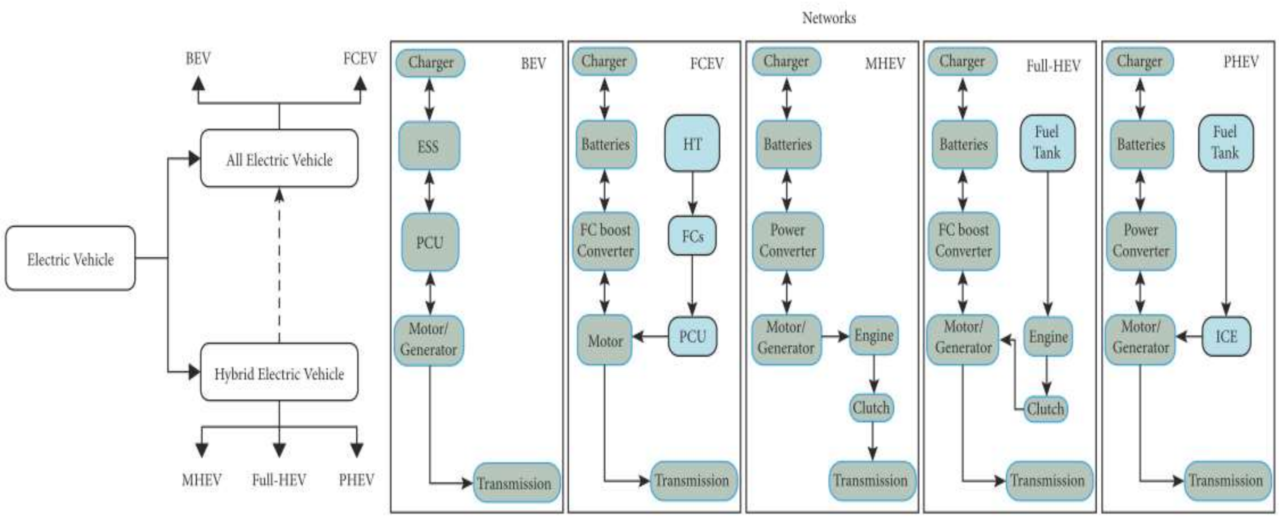


Figure 2.4: Classification of EVs (Hossain et al., 2022)

2.2.4.2 All-Electric Vehicles (AEVs)

Fully electric vehicles can be grouped further into Battery Electric Vehicles (BEV) and Fuel Cell Electric Vehicles (FCEV). BEVs rely on external power source while FCEV do not require external charging system. Modern AEVs are equipped with high performing Lithium-ion batteries capable to covering a wide range with top speed (Adnan et al., 2018). Battery capacity and charging infrastructure are crucial determinants of efficiency and sustainability of EV technologies. There are two main charging methods; conductive charging and battery swapping with prospects for wireless power transfer as technology advances (Arif et al., 2021; Hossain et al., 2022). As of March 2022, there were 29 public charging stations in Kenya, all within Nairobi (Mboa et al., 2022). Figure 2.5 shows the available charging techniques.

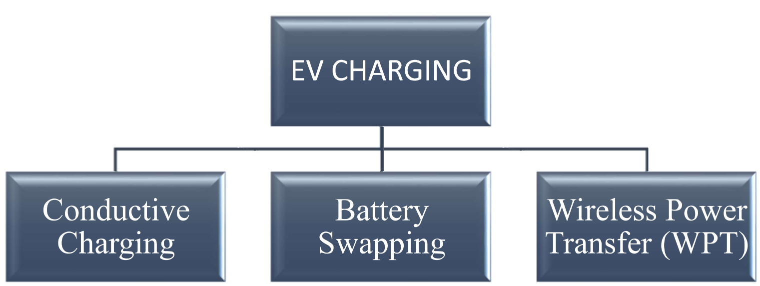


Figure 2.5: EV Charging techniques (Ahmad et al., 2018)

2.2.4.3 Electric Two-Wheeler Technologies

Electric two-wheelers (E2Ws) are powered by electric motors which rely on energy stored in the battery packs. Battery capacities vary widely and influence the performance efficiency and distance that can be covered on a single charge. They are also equipped with an electric throttle and controller which; regulate the amount of electric power supplied to the motor and control acceleration and deceleration. Another unique feature of E2Ws is regenerative breaking. This technique converts kinetic energy that would have been wasted during deceleration or braking into electric energy and feeds it back to the battery. E2Ws can be charged through standard electricity outlets or at charging stations. Battery swapping is also a common practice where a depleted battery is exchanged with a fully charged battery (Mboa et al., 2022). With fewer moving parts compared to IC engines, E2Ws are easy to maintain and have lower carbon footprints due to zero tailpipe emissions. An example of an electric motorcycle is captured in Figure 2.6.

Figure 2.6: An Electric Motorcycle (Roam Electric, 2023)

2.3 Empirical Literature

Discussions on greenhouse gas emissions have gained traction over the last few decades in light of the threats posed by climate change. The transport sector has been a significant contributor to GHG emissions through reliance on fossil fuels for power to operate. Ritchie et al., (2020) estimates that a transition to e-mobility platforms such as EVs could lower transport-related carbon emissions globally by 12%. In developing countries where 2 & 3 wheelers are gradually dominating the transport sector, a shift to E2Ws presents the most feasible path to e-mobility and low-carbon transition as noted by Akumu (2019). This section reviews research and discussions on greenhouse gas emissions from both conventional (ICE) and electric 2-wheelers. It also reviews existing GHG emission models and identify gaps in results and methodologies.

2.3.1 Greenhouse Gas Emissions

Climate change is one of the defining issues of this century. According to the World Economic Forum (WEF), climate change is in the top 10 of major risks confronting humanity (World Economic Forum, 2023). In 2020, The Alliance of World Scientists declared that the world was facing a climate emergency (Ripple et al., 2020). This 'emergency' was attributed to the damaging impact of rapidly increasing GHG emissions on the earth's climate, environment and the society due to human activities on both built and natural environment. Anthropogenic GHG emissions is the leading cause of climate change. Greenhouse emissions have been on the rise since the 19th century and peaked in 2019 at 54.8billion tonnes of CO_2 equivalent (Lamb et al., 2021). Abbass et al., (2022) in a global review of the impacts of climate change concluded that the climate crisis has precipitated a decline in agricultural productivity, biodiversity loss and, harm to human health and wellbeing.

A global review of sectoral trends in GHG emissions from 1990-2018 by Lamb et al., (2021) found that GHG emissions were increasing across all sectors globally. Due to disproportionate sectoral contribution to GHG emissions, the Intergovernmental Panel on Climate Change (IPCC) Working Group III classified GHG emissions to five major sources; energy, transport, industry, buildings and AFOLU (Agriculture, Forestry and Land use). Despite sectoral increases, Europe and North America recorded a decline in fossil fuel emissions due to increased uptake of renewable technologies and divestment from fossil fuels (Lamb et al., 2021).

Global emissions have risen from 4billion tonnes of CO_2 equivalent in 1850 to 54.6billion tonnes in 2021 (Ritchie et al., 2020a). A pictorial graph showing this trend is shown in Figure 2.7. Common GHGs include Carbon dioxide (CO_2), Methane (CH_4), Nitrous Oxide (N_2O), Hydrofluorocarbons (HFCs), Chlorofluorocarbons (CFCs) and Sulfur hexafluoride (SF_6) among others trace gases. CO_2 constitutes the largest share of total emissions at 74.4% while CH_4 and N_2O represents 17.3% and 6.2% respectively. Greenhouse gases have varying Global Warming Potential (GWP), therefore, carbon dioxide equivalents (CO_2e) are used as a single metric to calculate total emissions. The transport sector is the leading emitter of Short-Lived Climate

Pollutants (SLCPs) such as CH4, black carbon and CFCs. SLCPs have a much greater warming potential compared to CO_2 and account for 45% of global warming (Climate & Clean Air Coalition, 2023).

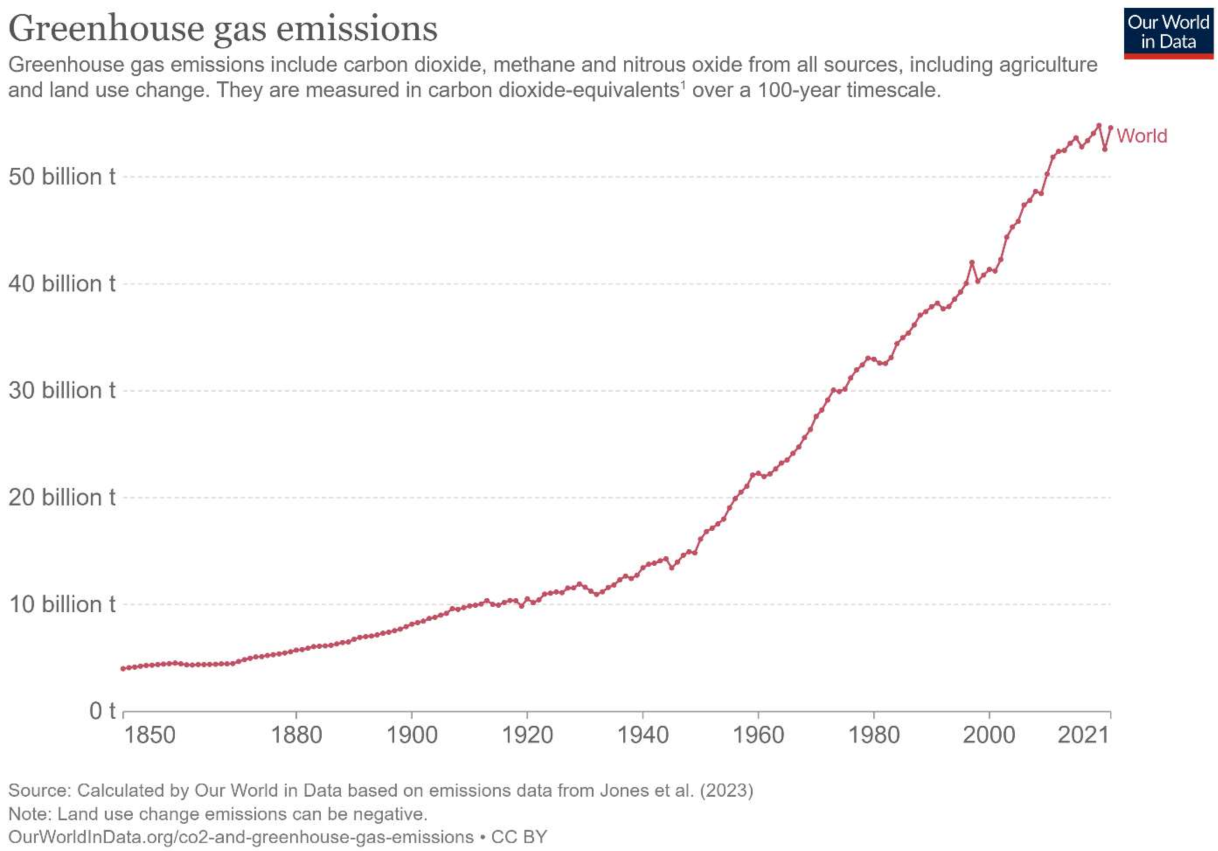


Figure 2.7: Global GHG Emissions from 1850-2021(Ritchie et al., 2020)

Poverty and extreme inequalities still define the socioeconomic landscape in Africa. In addition, it now grapples with the severe impacts of climate change. Even though Africa accounts for only 3.9% of global CO_2 emissions (Kamer, 2023), it is the most vulnerable region to climate impacts due to increased exposure, high sensitivity and low adaptive capacity. Some of the impacts include frequent extreme weather events such as drought and floods, leading to deaths and other socioeconomic impacts such as poverty and food insecurity (Sasu, 2023). According to Sasu (2023), the climate crisis has claimed more than 700,000 lives, impoverished 20million people and exposed 280million people to hunger and malnutrition in Africa. This situation has been exacerbated by conflicts and the global COVID-19 pandemic.

Ayompe et al., (2020) analyzed the trends of CO_2 emissions in Africa using the Kaya Framework from the year 1990 to 2017. The study revealed that CO_2 emissions were on the rise in Africa and had a positive correlation with population and economic growth (GDP). The study also found that 10 countries were responsible for 87% of Africa's total emissions. These are South Africa, Egypt, Algeria, Nigeria, Morocco, Libya, Tunisia, Sudan, Kenya and Angola. However, the true nature and scope of climate change in Africa is yet to be determined due to scarcity of data (Ayompe et al., 2020). The GHG emission trend from 1850-2021 is shown in Figure 2.8.

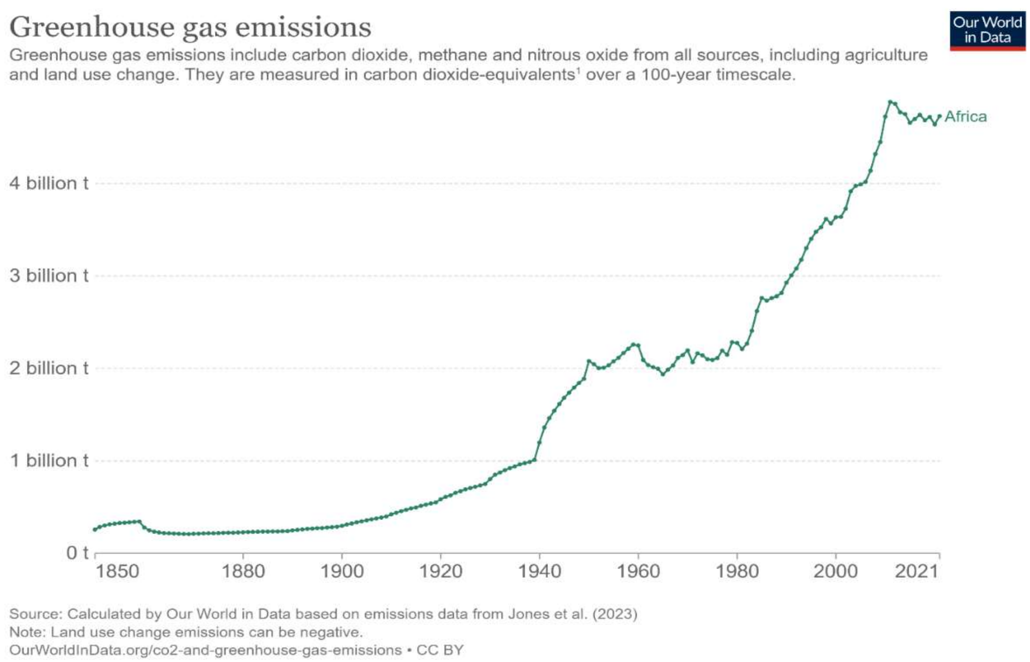


Figure 2.8: Africa GHG Emissions Chart from 1850-2021 (Ritchie et al., 2020)

Kenya is both a culprit and victim of climate change. Although the country accounts for less than 0.1% of global emissions, it is the leading GHG emitter in East Africa (Sun et al., 2022). Fossil fuel emissions account for 90% of the total emissions in the country and the transport sector is the leading and fastest growing emitter accounting for 60% of the total emissions. Oil demand driven by increase in conventional vehicles including two and three wheelers will further accelerate the transport-driven emissions (Akumu, 2019). Chemical, food and manufacturing industries are also leading sectoral emitters of GHGs in Kenya. Sun et al., (2022) while investigating emission drivers in East Africa also concluded that population growth and economic growth are the major drivers of GHG emissions in Kenya. Increasing energy demand occasioned by population growth, urbanization, and industrialization are projected to significantly contribute to the rising emissions.

Climate change and variability impacts are already visible in Kenya. Unpredictable climate patterns such as rainfall, temperatures and humidity due to changes in atmospheric CO_2 concentration are affecting agricultural production. Kogo et al., (2021) & Mugwika (2019) in investigating the impacts of climate change on agriculture and food security found that climate change climate change severely impacted Agriculture and food security by lowering crop production. Thereby, exposing vulnerable populations to food insecurity. The reliance on rain-fed agriculture poses a serious threat to developing countries experiencing population growth and rapid urbanization which demand a robust food security system to sustain.

A thesis by Abdikadir (2021) cautioned that climate change threatens human security by exacerbating scarcity of food and water, which ultimately affect human health and wellbeing. Air pollution caused by presence of Particulate Matter (PM) such as smoke, soot and dust in the atmosphere has become the leading environmental hazard globally (National Centre for Environmental Health, 2016). Fine particulate matter ($PM_{2.5}$) penetrate directly into the body's organs while larger particulate matter (PM_{10}) are common irritants. According to the World Health Organization (WHO), particle pollution from both indoor and ambient air pollution is responsible for more than 7million premature deaths annually (World Health Organization, 2016).

While acknowledging the severe impacts of climate change, several binding and non-binding agreements have been made to mitigate GHG emissions and avert the climate crisis. These include the first Climate Conference in Geneva (1979) to the 1992 Rio Summit, Kyoto Protocol of 1997 and the 2015 Paris Agreement. Despite the attempts, GHG emissions have remained on an upward trend. The Paris Agreement of 2015 ratified by 195 member states is a legally binding agreement that seeks to limit the rise in global temperatures to 2^0C above pre-industrial levels and to further raise ambition to 1.5^0C. In fulfillment of the agreement, Kenya committed to reduce its GHG emissions by 30% by 2030 as its Intended Nationally Determined Contribution (INDC) (Government of Kenya, 2015). This commitment, however, was subject to external support through financing, technology transfer and capacity building. In 2020, Kenya updated its Nationally Determined Contribution (NDC) from 30% to 32% relative to the BAU scenario of

143MtCO_2e (Government of Kenya, 2021). Low carbon and efficient transport systems is one of the priority areas targeted for GHG mitigation in the NDC.

Kenya has also put in place ambitious policies to support its NDC. These include; the Climate Change Act of 2016, National Climate Change Action Plan (NCCAP I & II) and the Climate Finance Policy among other sectoral policies. Even though the Climate Change Act (2016) was the pioneer climate change law in Africa, Wambua (2019) notes that effective implementation remains a challenge. The review emphasised on the need for stakeholder engagement in order to realize the goals of the law. Other emerging issues highlighted by Wambua (2019) include the need for political will, engagement of the justice system and local context in attempts address climate change.

2.3.2 Motorcycles and GHG Emissions

Motorcycles comprise of electric two wheelers and the conventional internal combustion engine bikes. Research on two-wheelers has mainly focused on mobility demands and conditions of both devices and operators. Few studies have investigated transport emissions related to ICE operated two-wheelers, moreover, the studies have mainly been done in Asia. Studies have also overlooked variations in specifications such as engine efficiencies in estimating GHG emissions. Suatmadi et al., (2019) in investigating the sustainability of on-demand motorcycle services in Asian cities argued that on-demand motorcycles taxis improved urban mobility by easing commute and congestion. Tong et al., (2023) found that short motorcycle trips significantly contributed to GHG emissions. The study which analyzed GHG emissions from short motorcycle trips in Vietnam concluded that behavior change to active travel modes such as biking and walking could abate 18% of motorized transport emissions in developing countries where motorcycles are a dominant means of transport. Similar conclusion was also reached by Mshelia et al., (2021) who assessed vehicular GHG emissions in Bayero State University Campus, Nigeria. The study also modelled a scenario where all motorcycles are banned and found that transport GHG emissions reduced by 21% (Mshelia et al., 2021).

Motorcycle emissions are driven by factors such as driving patterns, engine efficiency, tare weight and distance covered. Driving patterns such as accelerating, decelerating and idling, often influenced by traffic conditions, driving habits and road conditions, also impacts GHG emissions. Barth & Boriboonsomsin (2009) demonstrated that different traffic conditions had a significant impact on CO_2 emissions. For instance, a smooth stop-and-go pattern at a constant speed led to reduction in CO2 emissions while a free flow scenario at a speed of 45mph led to increased emissions (Barth & Boriboonsomsin, 2009). Other studies have linked traffic-related emissions to distance travelled (VKT) and fuel consumption (Adhi, 2018; Bharadwaj et al., 2017). According to Narváez-Villa et al., (2021), tare weight and engine size are significant predictors of VKT. Vehicles with higher tare weight and engine capacities cover longer distances and therefore contribute to more emissions. A street-level study of GHG emissions due to traffic congestion along Uhuru highway in Nairobi by Sitati et al., (2022) found that motorcycles had the least emissions compared to personal cars, passenger vehicles and heavy goods vehicles.

E2Ws are poised to lead the e-mobility transition in Kenya and Africa at large (UNEP, 2020). However, few studies have been conducted on the technical and environmental feasibility of E2Ws in Africa. Ayetor et al., (2023) explored the feasibility of electric 2 & 3 wheelers in Africa and covered technical, economic, environmental and market aspects. The study reported that most E2Ws covered a limited range of less than 50km on a single charge. This was attributed to the low energy density and short lifespan of lead acid batteries. Transitioning to lithium-ion batteries, known for their elevated energy densities, has the potential to extend the range to approximately 200km. Other challenges highlighted by Ayetor et al., (2023) include the limited load carrying capacity and fast battery discharge rate. Park et al., (2021) analyzed emissions from both conventional and electric motorcycle taxis in Uganda and found that a transition to E2Ws had a significant impact on GHG emissions. E-mobility transition led to environmental benefits through abated CO_2, CO, NO_2, $PM_{2.5}$ and PM_{10} emissions. Similar conclusion was also reached by Vanatta et al., (2022).

2.3.3 Impact of Traffic Conditions and Engine Efficiency on GHG Emissions

Motorcycle emissions are driven by factors such as driving patterns, engine efficiency, tare weight and distance covered. Driving patterns such as accelerating, decelerating and idling, often influenced by traffic conditions, driving habits and road conditions, also impacts GHG emissions. Barth & Boriboonsomsin (2009) demonstrated that different traffic conditions had a significant impact on CO_2 emissions. For instance, a smooth stop-and-go pattern at a constant speed led to reduction in CO2 emissions while a free flow scenario at a speed of 45mph led to increased emissions (Barth & Boriboonsomsin, 2009). Other studies have linked traffic-related emissions to distance travelled (VKT) and fuel consumption factors (Adhi, 2018; Bharadwaj et al., 2017).

According to Narváez-Villa et al., (2021), tare weight and engine size are significant predictors of VKT. Vehicles with higher tare weight and engine capacities cover longer distances and therefore contribute to more emissions. A street-level study of GHG emissions due to traffic congestion along Uhuru highway in Nairobi by Sitati et al., (2022) found that motorcycles had the least emissions compared to personal cars, passenger vehicles and heavy goods vehicles. Engine efficiency is also a determinant of GHG emissions in two-wheelers.

A dynamometric essay study by Weber et al., (2019) found that electric motorcycles were more energy efficient than liquid fueled (ICE) motorcycles. The assessment which was based on the bottom-up methodology and Primary Energy Factor (PEF) also concluded that emissions from electric conversion were less harmful. A similar study by Daemme et al., (2017) also found that electric motorcycle performed better in terms of energy efficiency and emissions compared to conventional motorcycles.

2.3.4 Predictive-modelling of GHG Emissions

Models are effective tools in climate mitigation and adaptation strategies as they link GHG emission drivers to different probable outcomes (Hultman & Edmonds, 2023). Predictive modelling of GHG emissions has been widely applied in research, policy and practice by both public and private actors for decades. Few studies have applied modelling equations in assessing GHG emissions in Kenya and Africa at large. Luo et al., (2020) modelled urban growth, energy use and GHG emissions in Dar es Salaam. The study projected increase in GHG emissions by modelling increases in household sizes and energy consumption patterns. Similarly, Afroz et al., (2021) also applied scenario-based modelling to estimate agricultural GHG emissions in the United States.

Furthermore, the analysis developed different climate change scenarios based on Global Warming Potential (GWP) and N_2O, however, the model was poorly validated. Other than predictive models, simplified equation models have also been used in estimating GHG emissions. Neya et al., (2021) developed simplified equation models to assess transport GHG emissions in Burkina Faso. The model was built on parameters such as distance travelled, fuel economy and emission factors.

However, the study relied heavily on secondary data and no primary data was used in order to improve the accuracy of the data.

2.4 Conceptual Framework

This study was guided by the conceptual framework presented in Figure 2.9.

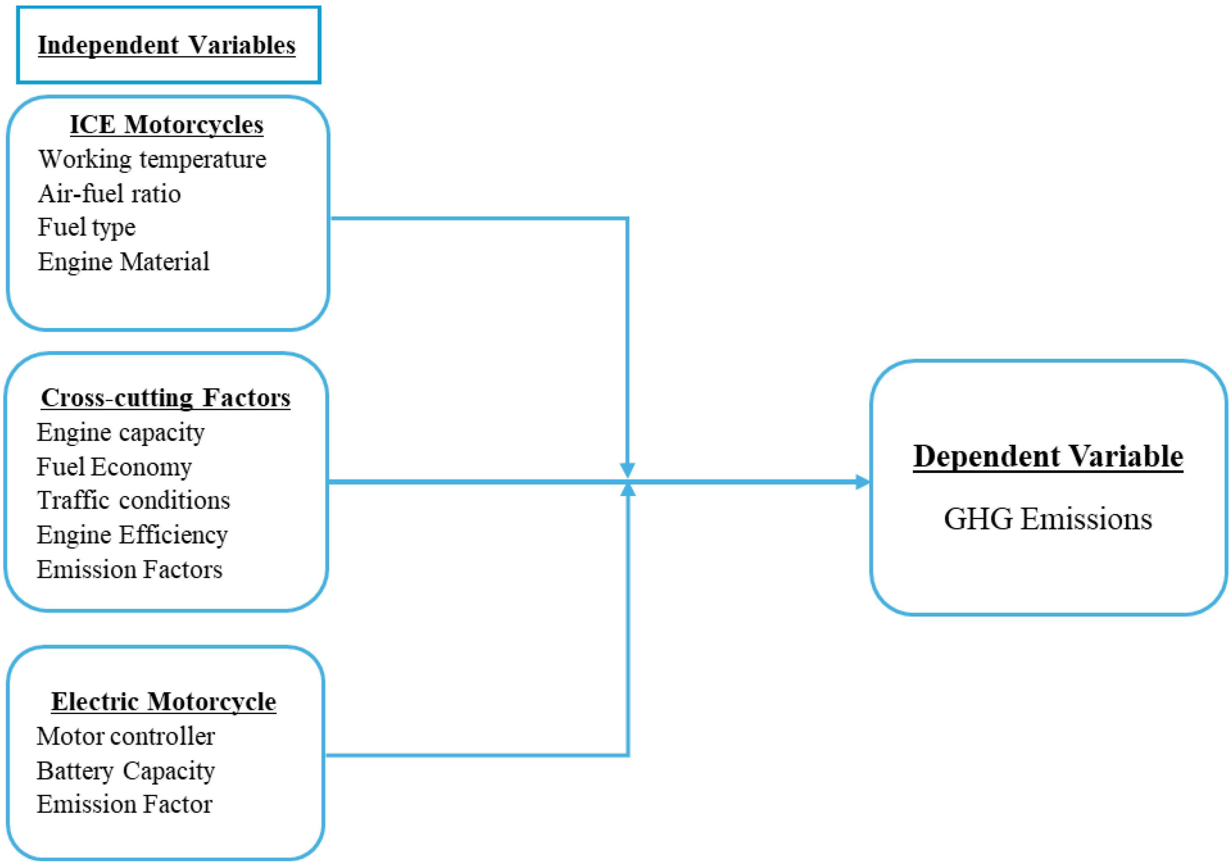


Figure 2.9: Conceptual Framework

Chapter 3: Methodology

3.1 Introduction

This chapter outlines the system development methodology employed to attain the objectives in researching and development of a model for predicting GHG emissions from motorcycles. The study relied on two major data sources; primary data collected through a questionnaire survey and content analysis from existing literature. Primary data was collected to provide a true representation of factors influencing GHG emissions from motorbike operators in Kenya while secondary data provided complimentary data.

3.2 Research Design

A research design is a detailed plan for carrying out a study that ensures all its components function logically and consistently to respond to the research question. It can be used as a template for research and analysis (Mishra & Alok, 2011). The study adopted both descriptive and experimental research design. Descriptive research design entailed using data collected on motorcycles using a questionnaire to find out the information such as the average fuel used, type of motorcycles, distance covered, time used and engine size to calculate the current and future GHG emissions. The experimental research design of the study emerged from its comparative nature, involving the manipulation of variables under specific assumptions to create diverse scenarios and predictions and showcased in form of graphs and pictograms.

3.3 Study Area

The research was conducted in Kenya, a country with a population of 47.5 million according to the 2019 national census. Notably, Kenya boasts one of the largest markets for two and three-wheelers across the entire African continent, with considerable challenges foreseen for growth in the forthcoming decade (Makundi, 2018). The increasing utilization of these vehicles in Kenya is attributed to their scalability and the established backward and forward linkages with various sectors of the Kenyan economy. Currently, an estimated 300,000 motorcycles are operational on Kenyan roads, serving both passenger and cargo transportation needs (Khanbhai & Lutomia, 2012).

3.4 Target Population

The target population refers to the extensive group of individuals that captures the researcher's interest, from which the sample respondents are selected Maxwel (2012). The target population for this study was motorcycles operators in Kenya, a country divided into 47 semi-autonomous counties that are headed by governors. The proliferation of motorcycles in Kenya has exhibited a consistent upward trend over the years, raising questions about the potential implications for our already delicate transportation system. A recent survey by Kenya National Bureau of Statistics revealed that there are over 2 million motorcycles registered in Kenya. Estimates put the total number of registered motorcycles in the wider East African region at well over 5 million motorcycles, all of which are essentially internal combustion engine motorcycles (KNBS, 2022). This research focused on motorcycle operators, seeking to comprehend how various variables influence the development of the model.

3.5 Sampling Strategy

The study used purposive sampling strategy to identify the sample from which information will be obtained. The sampling strategy is appropriate as the target population share specific characteristics that align with the research objectives. As of February 2018, 1,393,390 motorcycles were registered in Kenya, according to the National Transport and Safety Authority (NTSA). Therefore, the researcher will purposively select motorcycle operators in Kenya. Purposive sampling was applied to derive the sample (size) based on the national level data obtained from NTSA on the number of motorcycles registered.

3.6 Data Collection

3.6.1 Questionnaire Survey

A structured questionnaire was developed and used to collect information from motorcycle operators. The questionnaires (attached as Appendix 1) were administered to motorcycle operators using the Kobo tool. A pilot study was conducted to pre-test the tool prior to data collection exercise. The purpose of the pilot was to establish validity and reliability of the questionnaire and the Kobo tool. The information to be collected includes the type of engine, engine capacity, Vehicle Kilometer Travelled (VKT) per day, and fuel used by the motorcycles.

Data collection employed a structured questionnaire integrated into the Kobo Collect toolbox as shown in Figure 4.1 administered in person. The data collection period was from September 4th to October 31st, 2023, as depicted in Figure 4.2. Subsequent data cleaning and analysis were executed utilizing the R Statistical Computing software. The data cleaning process involved consolidating records for Internal Combustion Engine (ICE) and electric motorcycles into a unified file, rectifying discrepancies in the motorcycles' registration dates and aggregating the records to obtain total counts of registered motorcycles based on the year and month of registration. Figures 3.1. and 3.2 shows the representation of the questionnaire in the Kobo Collect Tool. Figure 3.3 shows the data collection points in form of a map.

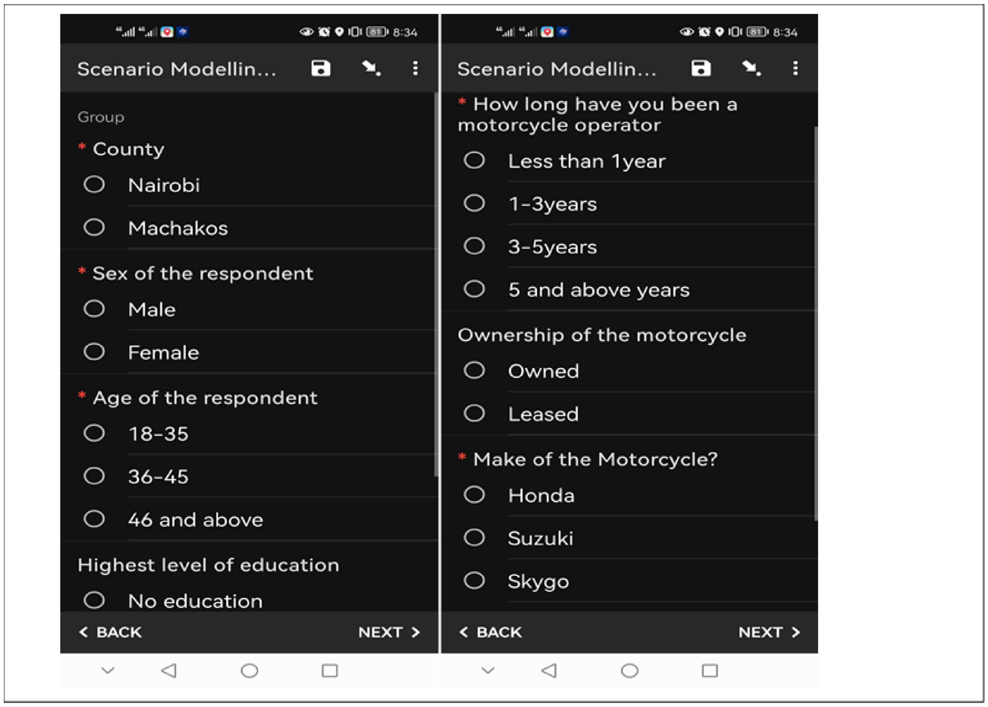


Figure 3.1: Representation of the questionnaire in the Kobo Tool

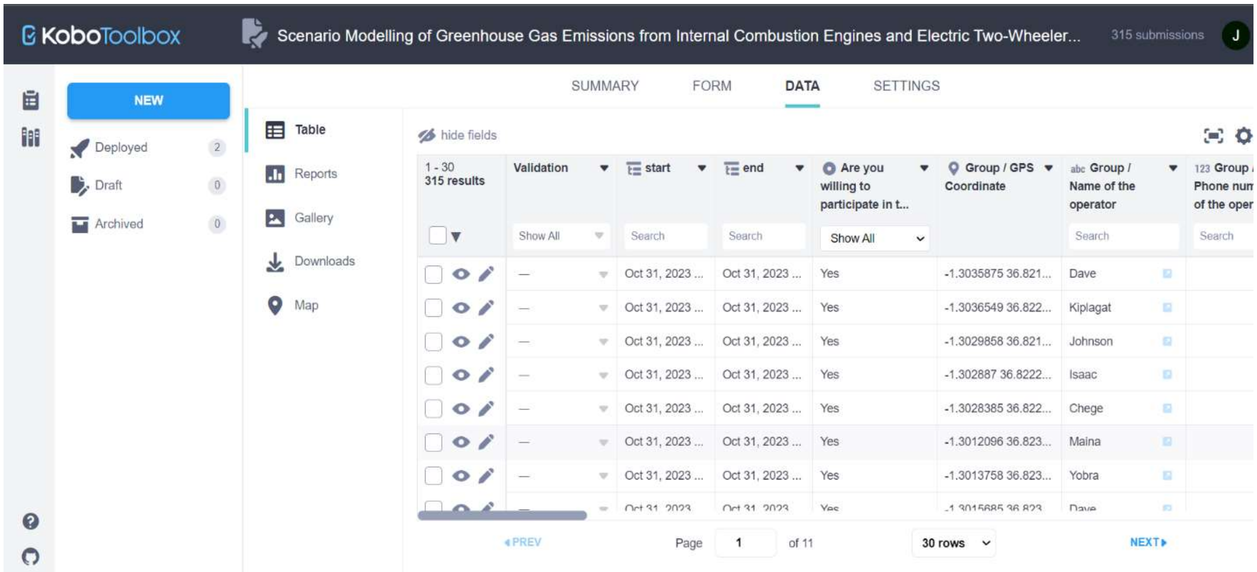


Figure 3.2: Data collection dashboard

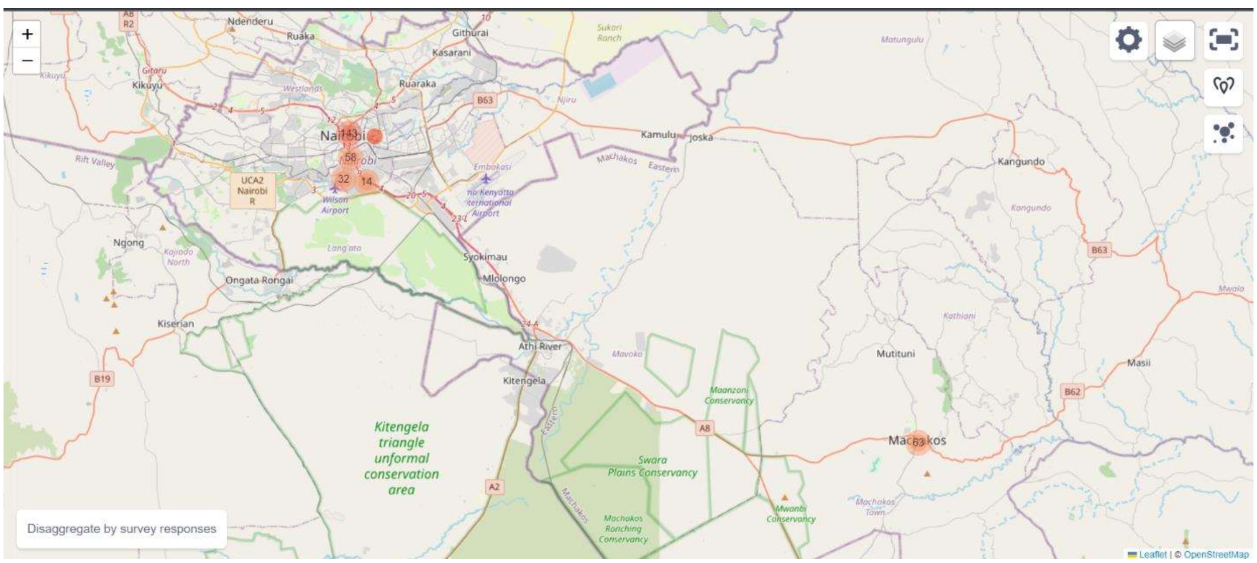


Figure 3.3: Map showing data collection points.

3.6.2 Secondary Sources

The study relied on secondary data sources such as scholarly journals, reports and government databases. Secondary sources such as the motorcycle inventory data compiled by National Transport and Safety Authority (NTSA) was used. The following data was obtained from the NTSA database; Total number of motorcycles registered, Year of manufacture, Year of registration, fuel type, engine capacity, tare weight, distance covered per day, make and model number of the motorcycles for the past ten years. The study also relied on data from Bodaboda associations on the number of motorcycles currently registered with them. Content analysis was useful in obtaining the national grid emission factor and the average efficiency deterioration percentage for the different motorcycle technologies.

3.7 Data Analysis and Interpretation

Data collected was cleaned using MS Excel and then analyzed using R software. The outputs were presented using graphs. Error analysis was done through ANOVA in order to keep the error rate at the set α.

3.7.1 Estimation of CO2 Emissions

IPCC Tier 3 methodology was used to calculate CO_2 emissions;

GHG Emissions of a Transport Activity = Transport Activity X GHG Emissions Factor

The formula was modified by Adhi (2018) as used by Sitati et al., (2022) to;

$$\mathbf{E = A \times f \times l \times Ef}$$

Formulae 1.1: IPCC Tier 3 methodology for calculating GHG emissions

In this study, the Sitati et al., (2022) methodology, was modified further where the distance covered by the motorcycle per day was used instead of the length of the road *(l),* this provided a more accurate data on distance covered in a day instead of focusing only on the length of a single road.

E is the total CO_2 Emissions (gCO_2 per day)

A is the average number of motorcycles operating per day

F fuel consumption per motorcycle (fuel economy in litres/km)

L is the distance covered per day in kilometres (km)

Ef is the emissions factor in gCO_2/litres

The average fuel economy is 2.45litres/100km(UNEP, 2020). Therefore, the data requirements for this methodology are; Traffic flow/count, distance covered, fuel economy and the emissions factor. This study further modelled CO_2 emissions based on the efficiency decay over time.

Engine efficiency decay was determined by efficiency deterioration formulae below.

The exponential decay formula describes the process of decrease over time in a quantity that decreases at a constant percentage rate. It is commonly expressed as:

$Y=ab^{xt}$

Where:

Y is the final amount or value,

a is the initial amount or value at t=0,

b is the base of the exponential function,

x is the time or the independent variable, and

t is the exponent.

Formulae 1.2: Engine efficiency decay formulae

The formula represents the exponential decay curve, which illustrates how a quantity diminishes as time progresses. In this case, exponential decay was injected in the developed model to determine efficiency decay in motorcycles up to 2045. To get the desired results, the formula above was modified as follows.

$$Efficiency = P_o * e^{-0.28t}$$

The exponential decay formula was modified by adding the greenhouse gas (GHG) emission formula to include the exponential decay component. The breakdown of the main components is explained as follows:

GHG Emission Formula: $E = A \times f \times l \times Ef$

Emission at half Life:

This represents the GHG emissions at half-life, where t is time, k is the decay constant, and e is the base of natural logarithms.

Decay Formula:

$P = Po*e^{-0.28t}$

(P): Final GHG emissions

(Po): Initial GHG emissions

(t): Time (in this case, 25 years)

$e^{-0.28t}$: The decay factor based on the decay constant k= 0.028

The decay formula accounts for a decreasing emission rate over the specified time, providing insights into how emissions reduce over a 25-year period based on the given decay constant.

3.8 Model Formulation

The model was formulated using R software to predict greenhouse emissions from motorcycles. Dataset included engine size, traffic conditions, fuel type, age of the bike as independent variables and the corresponding greenhouse emission values as the dependent variable. Details about the model formulation is provided in section 5.5.2.

In general, formulation of the model followed the following steps:

a) Data Preparation: The collected data was imported into R software online in saved datasets where the data structure and contents were explored. Missing data was sorted and cleaned, then divided into a training set and a testing set. The training set was used in the model, and the testing set was used to validate its performance.

b) Model Training: Once the data is cleaned, the training data was fed into the R software using the chosen algorithm and formulas. The model parameters in this case the independent variables were tuned to optimize performance if needed. At this stage, comparison of GHG emissions from the motorcycle technologies were compared.

c) Model Evaluation: The testing dataset was used to evaluate the model's performance and to calculate metrics such as mean squared error, R-squared, or other relevant evaluation metrics to assess how well the model predicts greenhouse emissions over the next 45 years.

d) Model Deployment and Prediction: Once the evaluation is done, the results were deployed to make predictions in sequences of 5 years up to the next 45 years. The predictions were packaged in the form of graphs and charts.

3.9 Validation

This study developed a deterministic model, employing a deterministic approach whereby the scenarios developed follow the same parameters exactly, without the involvement of randomness. Data collected was used to predict the GHG emission outcome. The model was validated using the using the IPCC (2006) guidelines for assessing GHG emissions. Specifically, the study validated the predictive model for GHG emissions from motorcycles by employing the IPCC tier 1 method in order to gain higher confidence in the results.

3.10 Ethical Consideration

This study promoted ethics by ensuring the following considerations are made. Consent was sought from the participants, confidentiality maintained, and the researcher did not deceive participants in order to gather information from them. Furthermore, the data collected by this study was used for the intended purpose, to develop the predictive model. The researcher declared any conflicts of interest that may affect the integrity of the research, in this case there were none. Ethical approval was obtained from Strathmore University institutional scientific and ethical review committee prior to data collection.

Chapter 4: Results

4.1 Introduction

The chapter presents the results of the study. The results are presented in three sections. The first section discusses the respondents of the study. This section is followed by the analysis of the characteristics of the ICE and electric motorcycles. Finally, the chapter presents the results of the General Additive Model (GAM) for projecting GHG emissions emanating from motorcycles in Kenya.

4.2 Descriptive Analysis

Research has consistently highlighted the direct correlation between rider demographics and greenhouse gas emissions from motorcycles (Chiou & Chen, 2010). Table 4.1 offers a detailed overview of survey participants, encompassing information such as county of residence, gender, age, highest level of education attained, and years of operational experience.

Table 4.1: Respondents characteristics

Description	Electric (*N*=84)	Petrol (*N*=231)	Total (*N*=315)
Sex of the respondent			
Female	4 (4.8%)	3 (1.3%)	7 (2.2%)
Male	80 (95.2%)	228 (98.7%)	308 (97.8%)
Age of the respondent			
18-35	66 (78.6%)	177 (76.6%)	243 (77.1%)
36-45	14 (16.7%)	43 (18.6%)	57 (18.1%)
46 and above	4 (4.8%)	11 (4.8%)	15 (4.8%)
Highest level of education			
No education	1 (1.2%)	4 (1.7%)	5 (1.6%)
Primary	1 (1.2%)	32 (13.9%)	33 (10.5%)
Secondary	55 (65.5%)	119 (51.5%)	174 (55.2%)
Tertiary/College	20 (23.8%)	54 (23.4%)	74 (23.5%)
University	7 (8.3%)	22 (9.5%)	29 (9.2%)
Years of operation			

Description	Electric (*N*=84)	Petrol (*N*=231)	Total (*N*=315)
1-3years	25 (29.8%)	58 (25.1%)	83 (26.3%)
3-5years	6 (7.1%)	45 (19.5%)	51 (16.2%)
5 and above years	20 (23.8%)	119 (51.5%)	139 (44.1%)
Less than 1year	33 (39.3%)	9 (3.9%)	42 (13.3%)

4.2.1 Sex of the Respondents

Our findings reveal that 97.8% of participants were male, while 2.2% were female. Among electric motorcycles, 4.8% were operated by females, whereas 95.2% were operated by males. Similarly, conventional vehicles were predominantly operated by males (98.7%), with only 1.3% being operated by females. Interestingly, a greater proportion of women (4.8%) opted for electric motorcycles compared to conventional ones (1.3%), indicating a potential preference for electric vehicles among female riders. Despite the predominantly male composition of riders, the higher proportion of women operating electric motorcycles presents an opportunity to mitigate transport-related emissions. This finding is also supported by (Chiou & Chen (2010) who identified a positive correlation between higher emissions and male riders, emphasizing the significant influence of sex on greenhouse gas emissions. Figure 4.1 provides an overview of the sex of respondents.

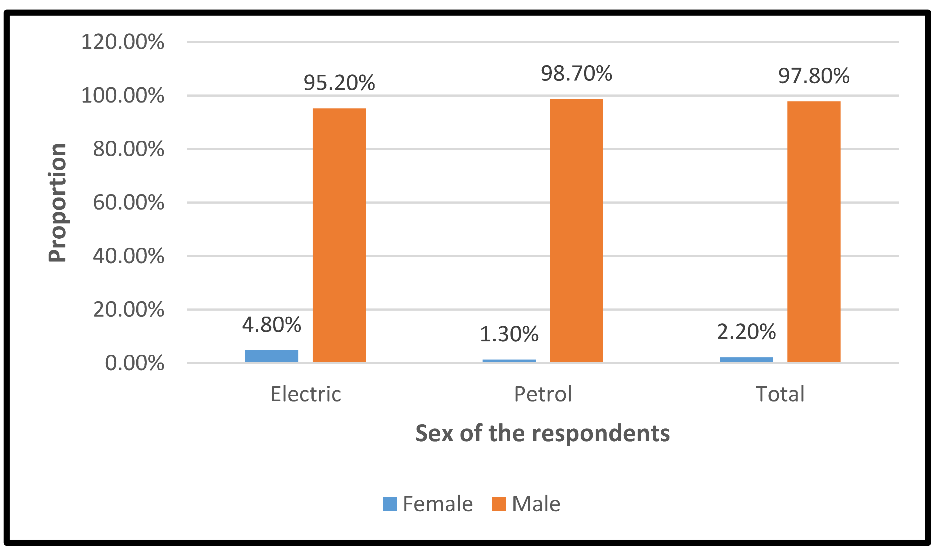


Figure 4.1: Sex of the respondents

4.2.2 Age of the Respondents

A study by Chiou & Chen (2010) revealed a positive correlation between higher emissions and older riders, highlighting the significant influence of age on greenhouse gas emissions. Nevertheless, this research results indicate that 77% of respondents fall within the youthful age range of 18 to 35. Among the participants, 97.8% were male, while 2.2% were female. Electric motorcycles were operated by 4.8% of females and 95.2% of males, whereas conventional vehicles were predominantly operated by males (98.7%), with only 1.3% being operated by females. Notably, a higher proportion of women (4.8%) chose electric motorcycles over conventional ones (1.3%), suggesting a potential preference for electric vehicles among female riders. Based on these findings, the large proportion of youth can be interpreted as that they are the primary demographic for transitioning to electric two-wheelers. Figure 4.2 provides an overview of the age of respondents.

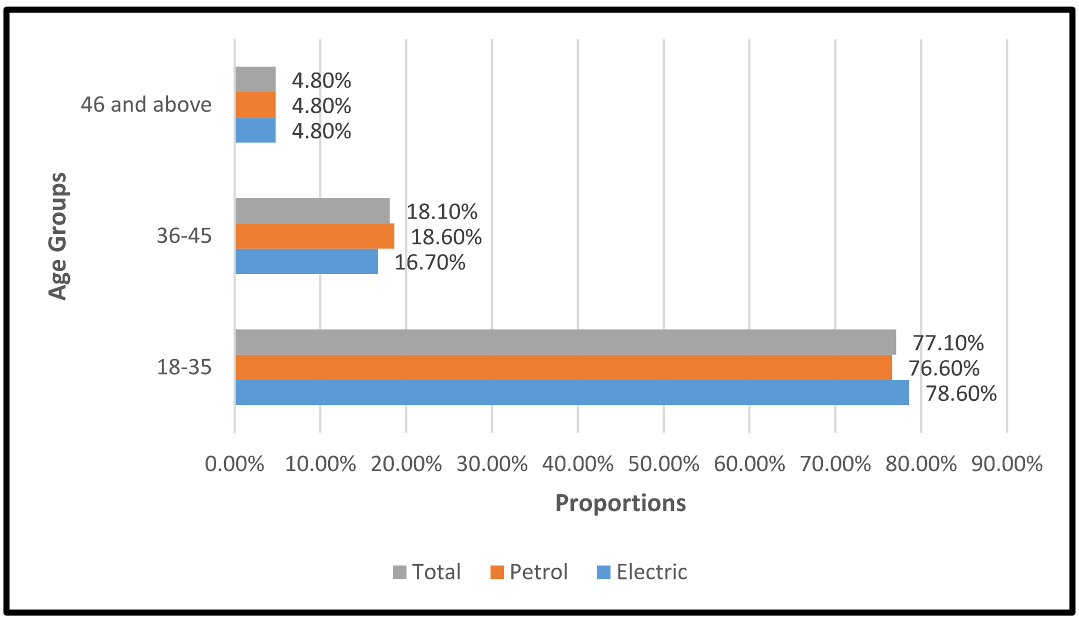


Figure 4.2: Age of the respondents

4.2.3 Level of Education

In a study by Chiou & Chen (2010), there is a linear correlation between lower levels of education and higher greenhouse gas emissions, indicating the significant influence of education on emissions. More than half of the respondents in the study, comprising 55.2%, had completed secondary education, while 23.5% had pursued tertiary education, and 10.5% had achieved primary education. Furthermore, 9.2% of the respondents had attained a university education. Among those operating electric motorcycles, 65.5% had completed secondary education. This underscores the role of literacy in curbing greenhouse gas emissions especially in the transport sector. Detailed overview of level of education is shown in Figure 4.3.

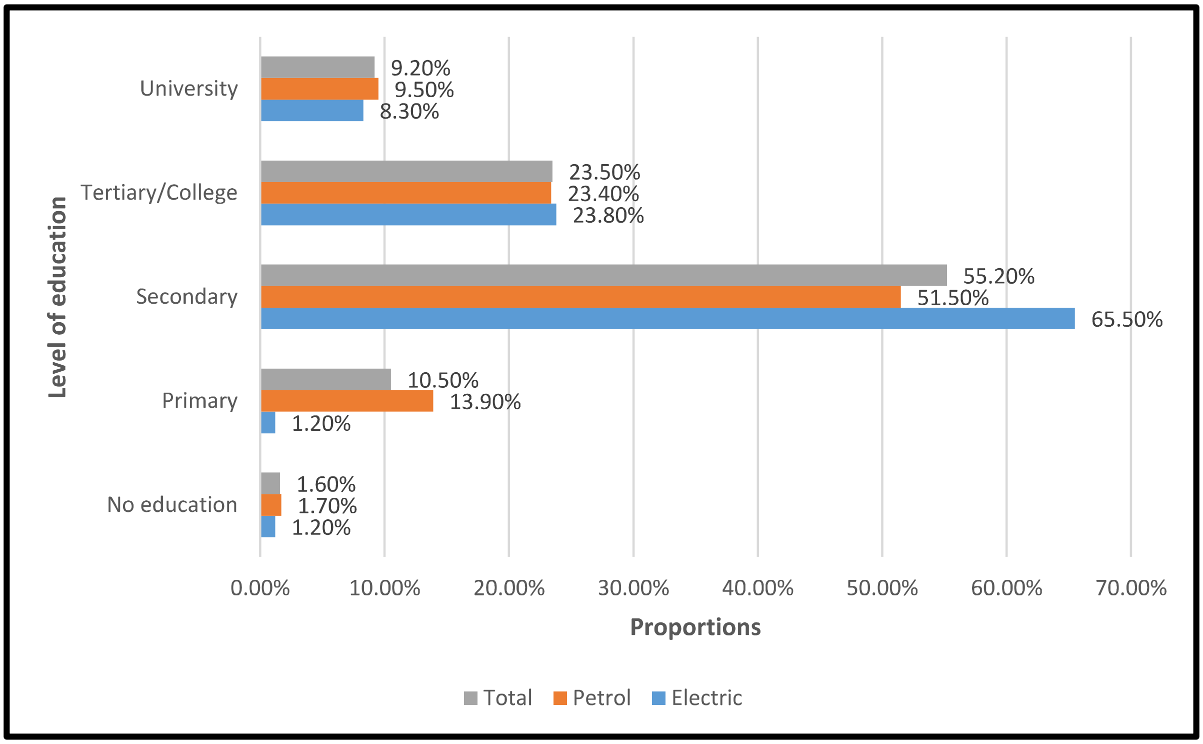


Figure 4.3: Level of education

4.2.4 Years of Operation

Extensive driving experience has been linked to higher greenhouse gas emissions (Chiou & Chen, 2010), as demonstrated by the findings that 44.1% of respondents had operated as riders for 5 years or longer. As is evident in Figure 4.4, this proportion was even higher among those operating conventional motorcycles, with 51.5% reporting an extensive driving experience of 5 years or more. Nevertheless, a majority of electric motorcycle operators had minimal driving experience as 39.3% of respondents reported to have operated electric motorcycles for less than one year, suggesting a recent surge in the adoption of electric motorcycles.

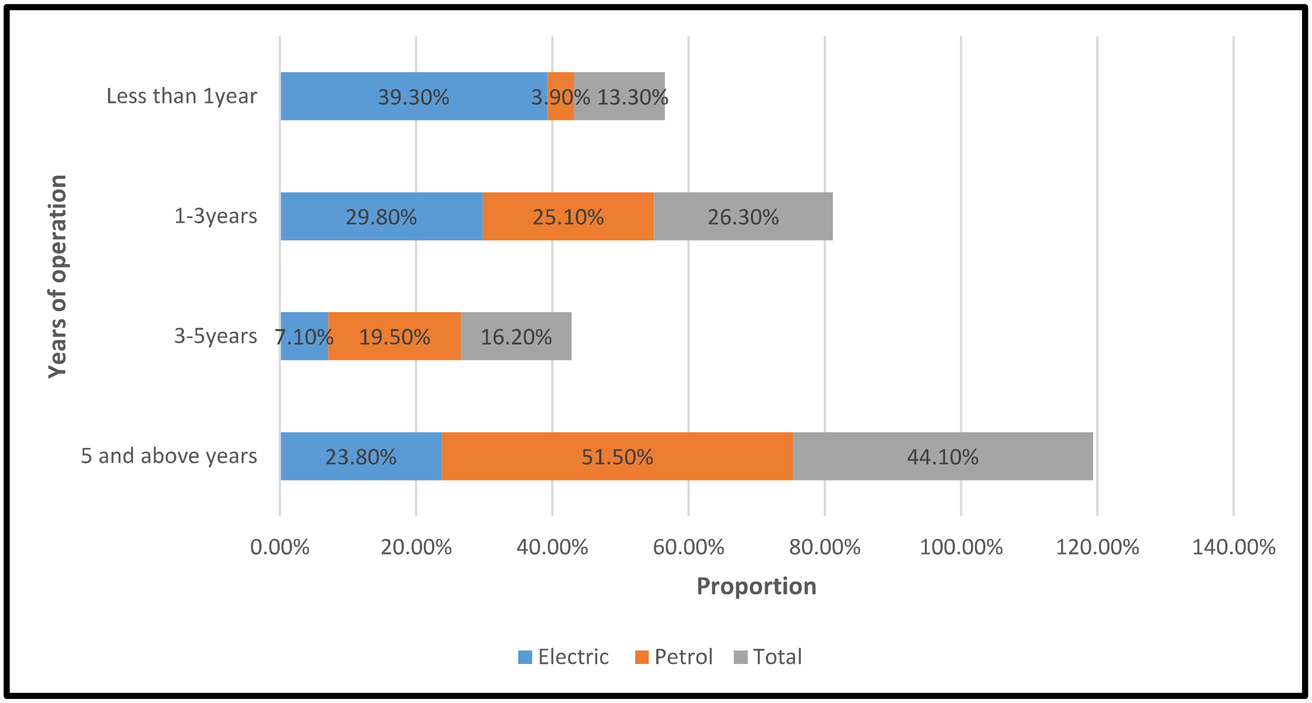


Figure 4.4: Year of Operation

4.3 Motorcycle Characteristics

Table 4.2 presents a comprehensive overview of key characteristics associated with motorcycles, providing valuable insights into their diverse specifications, features, and performance attributes.

Table 4.2: Motorcycle characteristics

	Electric (N=84)	**Petrol (N=231)**	**Total (N=315)**
Ownership			
Leased	65 (77.4%)	33 (14.3%)	98 (31.1%)
Owned	19 (22.6%)	198 (85.7%)	217 (68.9%)
Make of the motorcycle			
Others	84 (100%)	41 (17.7%)	125 (39.7%)
Bajaj	0 (0%)	47 (20.3%)	47 (14.9%)
Honda	0 (0%)	59 (25.5%)	59 (18.7%)
Skygo	0 (0%)	21 (9.1%)	21 (6.7%)
TVS	0 (0%)	63 (27.3%)	63 (20.0%)
Year of manufacture			

	Electric (N=84)	Petrol (N=231)	Total (N=315)
<2011	1 (1.2%)	3 (1.3%)	4 (1.3%)
>2020	70 (83.3%)	62 (26.8%)	132 (41.9%)
2016-2020	13 (15.5%)	145 (62.8%)	158 (50.2%)
2011-2015	0 (0%)	21 (9.1%)	21 (6.7%)
Year of registration			
<2011	1 (1.2%)	1 (0.4%)	2 (0.6%)
>2020	82 (97.6%)	100 (43.3%)	182 (57.8%)
2016-2020	1 (1.2%)	111 (48.1%)	112 (35.6%)
2011-2015	0 (0%)	19 (8.2%)	19 (6.0%)
Engine size (cc)			
100	NA	13 (7.7%)	13 (7.7%)
110	NA	2 (1.2%)	2 (1.2%)
125	NA	50 (29.6%)	50 (29.6%)
150	NA	97 (57.4%)	97 (57.4%)
160	NA	1 (0.6%)	1 (0.6%)
170	NA	1 (0.6%)	1 (0.6%)
180	NA	5 (3.0%)	5(3.0%)
Fuel use (Ltrs per day)			
Mean (SD)	NA	3.80 (1.50)	3.80 (1.50)
Median (Min, Max)	NA	4.00(1.00, 15.00)	4.00 (1.00, 15.00)

4.3.1 Ownership of the Motorcycles

The findings of the study, based on a sample of 315 motorcycles, reveal that the majority of motorcycles (approximately 69%) were owned by their operators, while 31% were acquired through leasing arrangements. Notably, a significant proportion (85.7%) of conventional motorcycles were owned by operators, whereas the majority (77.4%) of electric motorcycles were obtained through leasing agreements. Most of the electric motorcycles sampled in the study were owned and serviced by the parent company and were only leased to riders on a daily basis. The parent companies include ROAM electric, Stima Boda, KIRI EV and EWAKA among others. This may be attributed to the high cost of acquiring and maintaining the EVs, which has prohibited ownership of the E2Ws. Overview of motorcycle ownership is captured in Figure 4.5.

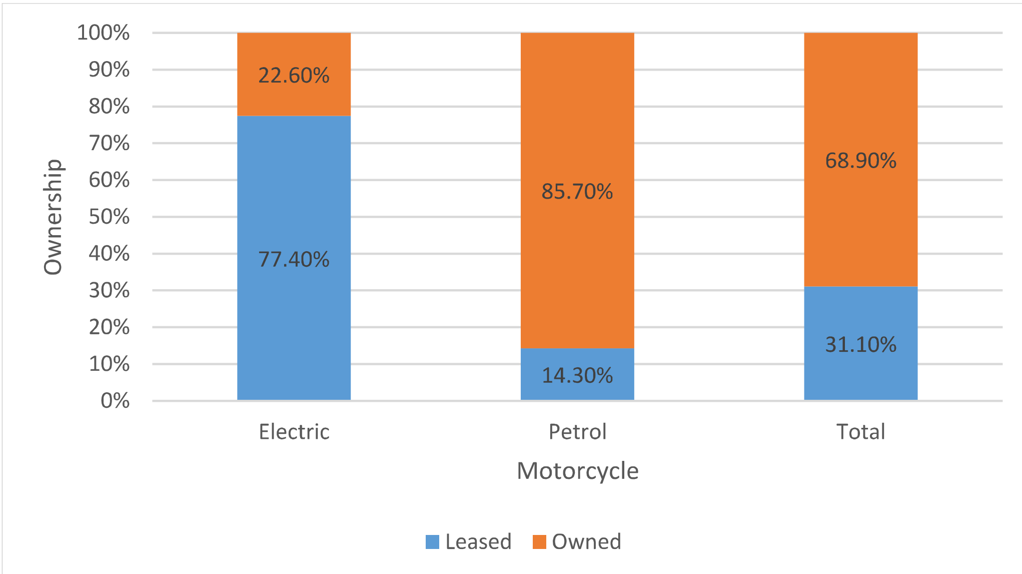


Figure 4.5: Ownership of Motorcycles

4.3.2 Year of Manufacture and Registration

Regarding the manufacturing period, nearly 98% of electric motorcycles were manufactured after the year 2020. This suggests a recent uptake of newly manufactured EVs in the country. Thereby signifying a positive trend in the adoption of electric two-wheelers within the last three years. In contrast, more than 60% of the conventional motorcycles sampled were manufactured between the years 2016 and 2020, suggesting a shorter lifespan due to exposure to accidents, poor terrains and deteriorating engine efficiency. The percentage of motorcycles manufactured against the years is shown in Figure 4.6.

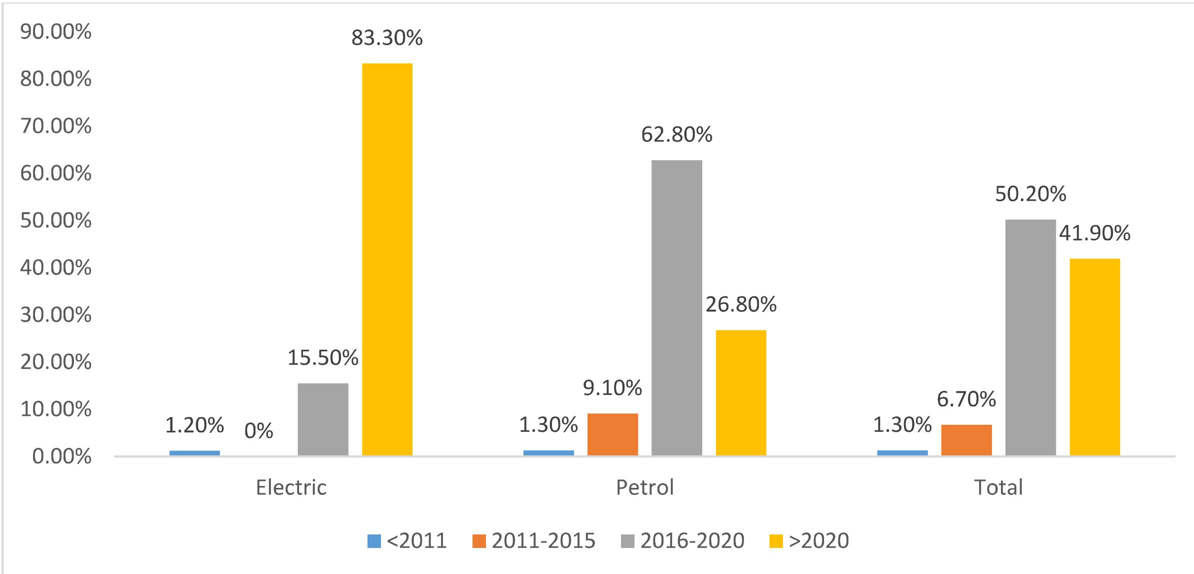


Figure 4.6: Year of Manufacture

The results also indicate that close to 98% of electric motorcycles were registered after the year 2020. The surge in registration of the EVs is also a positive indicator of adoption of the technology. On the other hand, 91.4% of conventional motorcycles sampled in the study were registered since the year 2016 as shown in Figure 4.7.

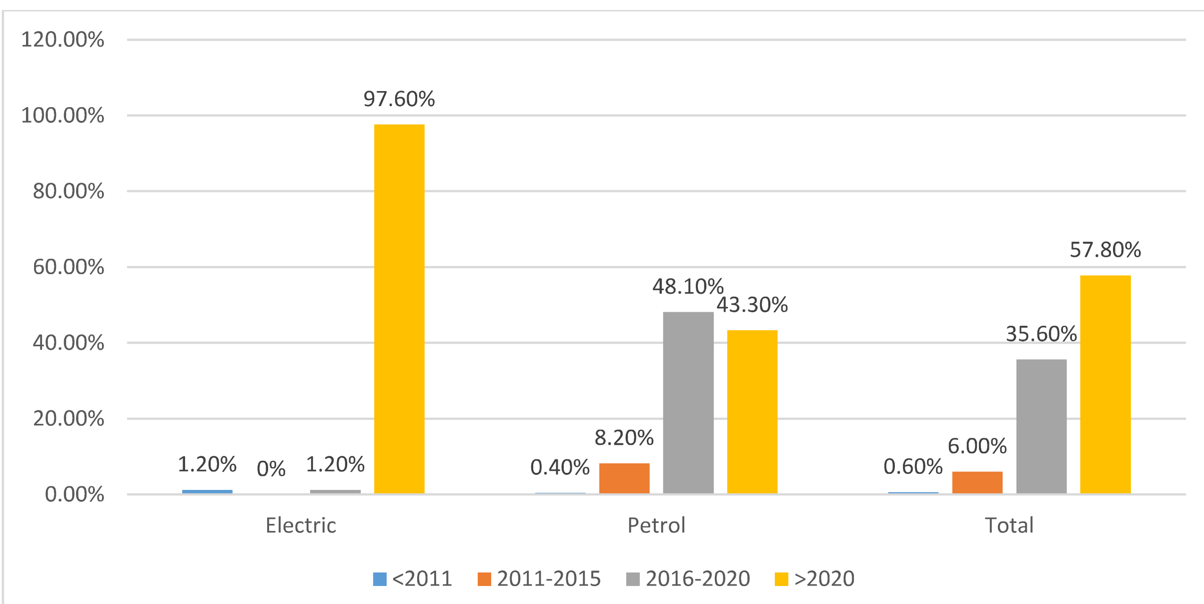


Figure 4.7: Year of Registration

4.3.3 Engine Size

The second objective of this study aimed to evaluate the prevailing technologies in Internal Combustion Engine (ICE) and electric motorcycles in Kenya. The findings indicate that only 26.7% of the surveyed riders operated electric motorcycles, while 73.3% opted for conventional motorcycles. These Figures align with national statistics highlighted in section 2.2 of the literature review, underscoring the dominance of ICE motorcycles in the Kenyan market. Additionally, the study revealed that the engine sizes of the sampled motorcycles varied between 100cc and 180cc. Notably, 57% of the motorcycles had a 150cc engine, while 30% possessed a 125cc engine capacity. Moreover, the study found that the average amount of fuel used per day across all conventional motorcycles was 3.8litres. These findings provide valuable insights into the ownership, manufacturing, and fuel consumption patterns of conventional motorcycles in the sampled population. The battery usage and motorcycle performance are shown in Table 4.3.

Table 4.3: Battery usage and performance of motorcycles

	Electric (N=84)	**Petrol (N=231)**	**Total (N=315)**
Type of battery			
Lead Acid Battery	1 (1.2%)	NA	1 (1.2%)
Lithium Ion Battery	83 (98.8%)	NA	83 (98.8%)
Battery capacity (V)			
72	33 (39.3%)	NA	33 (39.3%)
77	22 (26.2%)	NA	22 (26.2%)
80	3 (3.6%)	NA	3 (3.6%)
84	25 (29.8%)	NA	25 (29.8%)
85	1 (1.2%)	NA	1 (1.2%)
Battery capacity (Ah)			
40	9 (10.8%)	NA	9 (10.8%)
42	2 (2.4%)	NA	2 (2.4%)
45	72 (86.7%)	NA	72 (86.7%)
Charging time (hrs per day)			
Mean (SD)	4.19 (1.24)	NA (NA)	4.19 (1.24)
Median [Min, Max]	4.00 [3.00, 8.00]	NA [NA, NA]	4.00 [3.00, 8.00]

	Electric (N=84)	Petrol (N=231)	Total (N=315)
Distance covered per day (km)			
Mean (SD)	126 (61.6)	153 (71.6)	146 (70.0)
Median [Min, Max]	95.0 [4.00, 300]	135 [40.0, 500]	120 [4.00, 500]

4.4 Motorcycle Characteristics

The study revealed that Lithium-ion batteries were the predominant source of power for the electric motorcycles. These batteries exhibited a voltage capacity range of 72 to 85 volts. Notably, a substantial majority of the electric motorcycles featured a battery capacity of 45 ampere-hours (Ah). The study also investigated the charging requirement of the batteries. On average, the study found that electric motorcycle owners spent 4.2 hours per day charging their two-wheelers. This metric provides valuable insights into the practical implications and habits associated with maintaining electric motorcycle batteries.

Comparing the daily travel distances of electric motorcycles to their conventional counterparts, the study found that electric motorcycles covered an average distance of 126 kilometers per day. In contrast, conventional motorcycles covered a slightly higher average distance of 153 kilometers per day. This information sheds light on the current limitations and capabilities of electric motorcycles in terms of daily commuting range.

In conclusion, the study findings highlight the prevalent use of Lithium-ion batteries in electric motorcycles, with specific voltage and capacity ranges as shown in Table 4.5 above. The observed charging patterns and daily travel distances provide valuable insights into the practical aspects of electric motorcycle usage and performance. These findings contribute to a better understanding of the current state of electric motorcycle technology in Kenya.

Chapter 5: Model Development

5.1 Modelling of GHG Emissions

5.5.1 Introduction

This section presents the modelling of CO_2 emissions from motorcycles in Kenya using data from 2010 to 2022. The records for 2023 were dropped because data for the full year was incomplete. The secondary data used was obtained from the National Transport and Safety Authority (NTSA). Secondary and primary data collected was used for prediction to 2045.

5.5.2 General Additive Model Formulation

A generalized additive model (GAM) with a Poisson family provided a better fit to the data compared to a linear model, and even compared to a GAMs with a Gaussian and negative binominal families. This is because the number of motorcycles registered per unit time, in this case per year, was the Poisson function. The overall structure of a GAM was given as;

$$y_t = \sum_{i=1}^{l} f_i(x_t) + \epsilon_t$$

Formulae 5.1: Generalized Additive Model (GAM) structure

Where $y_t$is the outcome at time t, f_i are constant or continuous transfer functions over x_t, the vector of co-variates, and ϵ_t is the noise term, assumed to be Gaussian, independent and identically distributed with mean zero and finite variance (Pathak, Ba, Ploennigs, & Roy, 2018).

5.5.3 Data Preparation and Analysis

5.5.3.1 Data Cleaning

Data cleaning and analysis was conducted use the R Statistical Computing software. Data cleaning entailed appending the record for ICE and electric motorcycles into a single file, as they were downloaded from Kobo tool in separate files, cleaning out the date of registration of the motorcycles, and collapsing the records into total sums of registered motorcycles by year and month of registration. Table 5.1 shows a sample of cleaned data.

Table 5.1: Sample Table of Clean Data

Registration date	Registration _month	Registration _year	Type	Number bikes
1-Jan-2010	1	2010	Petrol	9343
1-Feb-2010	2	2010	Petrol	13933
1-Mar-2010	3	2010	Petrol	8733
1-Apr-2010	4	2010	Petrol	9782
1-May-2010	5	2010	Petrol	7459
1-Jun-2010	6	2010	Petrol	9591
1-Jul-2010	7	2010	Petrol	8062
1-Aug-2010	8	2010	Petrol	9051
1-Sep-2010	9	2010	Electric	2

Outliers within the dataset were detected and managed using a method based on the interquartile range (IQR), which reflects the range containing the middle 50% of the data. Outliers were identified as values greater than the third quartile (Q3) plus 1.5 times the IQR, which represented the upper whisker of the data distribution in a boxplot in Figure 5.1. To address these outliers, the researcher replaced the outliers with the geometric mean of the dataset. This choice of replacement helps to stabilize the data analysis by mitigating the influence of extreme values, which could otherwise skew the results and distort statistical measures.

By replacing outliers with the geometric mean, a measure less sensitive to extreme values compared to the mean, the dataset becomes more robust and better suited for further statistical analysis, ensuring that conclusions drawn from the data are more representative and reliable.

Further, the data exhibited outliers, and these were removed by replacing values greater than 3rd quartile plus 1.5 times of interquartile range (greater than upper whisker) with the median.

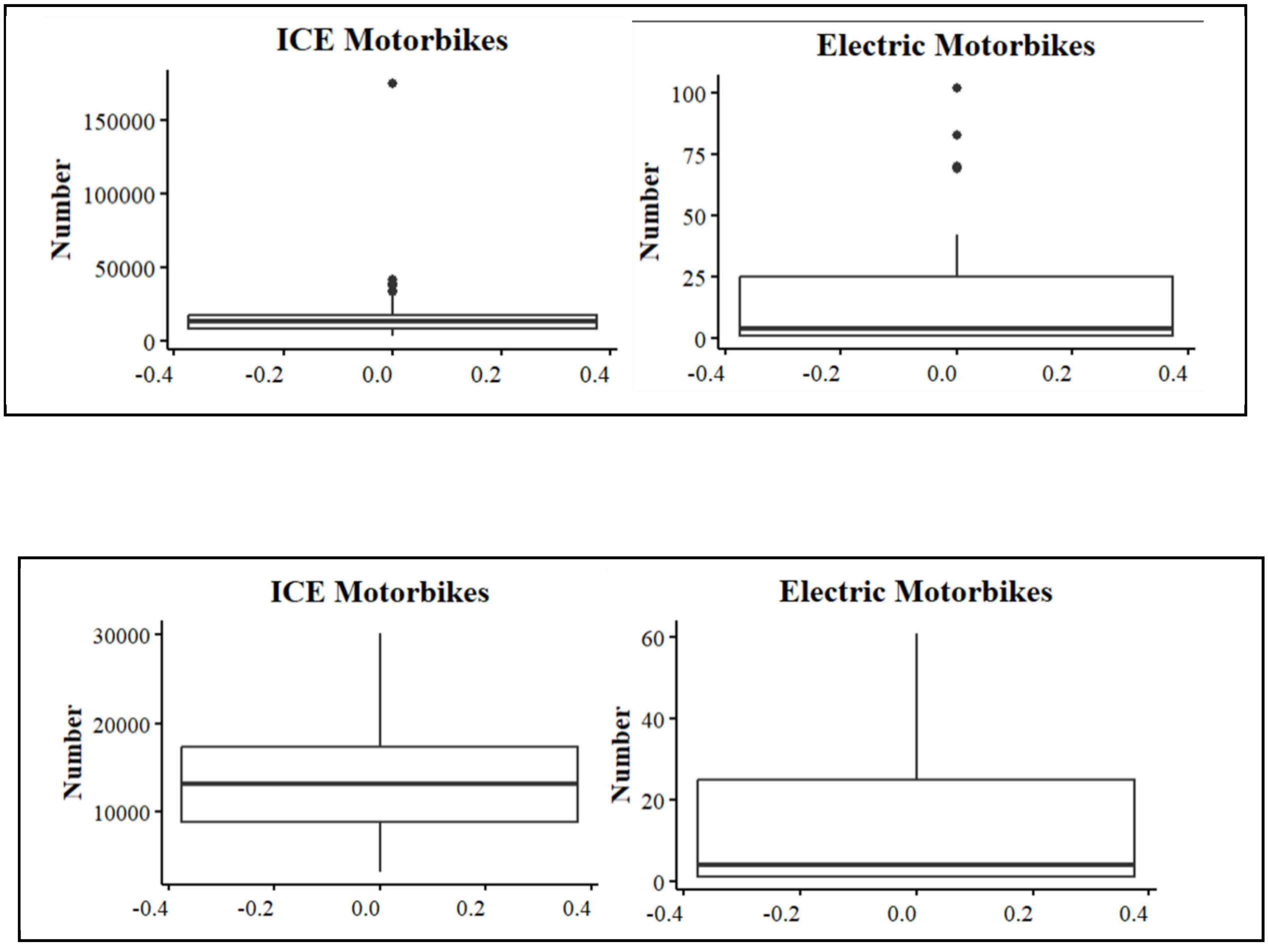


Figure 5.1: Outliers were managed using the 1.5IQR rule.

After the cleaning of the outliers on the number of registered motorcycles, the median number of ICE motorcycles was 13,100, and that of electric motorcycles was 4, and this difference was statistically significant (p-value < 0.001) as shown in Table 5.2.

Table 5.2: Comparison of Motorcycle Characteristics: Petrol vs. Electric

	Petrol (N=156)	**Electric(N=41)**	**Total (N=197)**	**P-value**
Number of bikes				
Mean (SD)	13700 (6360)	15.3 (19.4)	10800 (7940)	<0.001

	Petrol (N=156)	Electric(N=41)	Total (N=197)	P-value
Median [Min, Max]	13100 [3180, 30100]	4.00 [1.00, 61.0]	10600 [1.00, 30100]	

The clean secondary data in Table 5.1 was then merged with the primary data, using the year of registration and the type of fuel as the primary keys, utilizing a many-to-many relationship to preserve all records. The resulting data exhibited missingness in instances where there should be no missing data, as missingness would negatively impact modelling (Emmanuel, et al., 2021).

As shown in Figure 5.2, the missingness was non-monotone, which means that missing data in one variable does not impact the missingness in another. Blue represents observed data, while red is missing values.

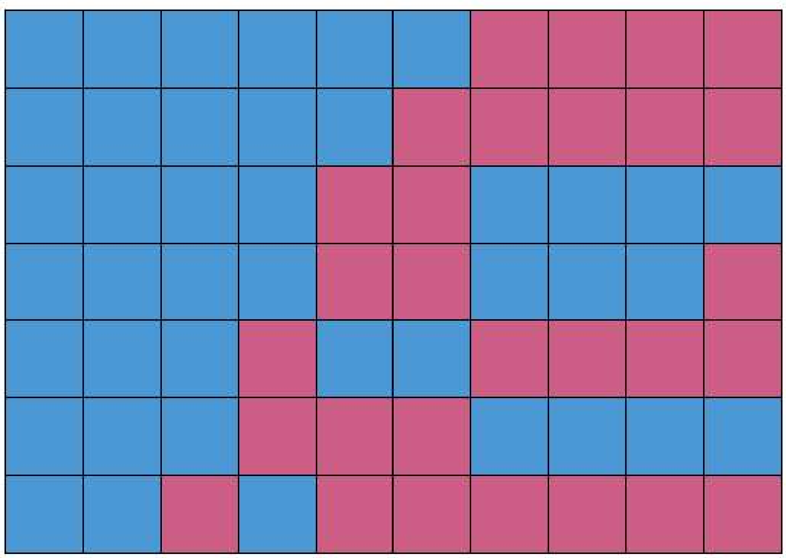


Figure 5.2: Non-monotone missing data.

Using the {mice} package in R, missing continuous variables were imputed using Predictive Mean Matching (PMM) method, while missing categorical variables were imputed using Classification and Regression Trees (CART) method.

Computation of emissions was then performed using the formula; $E = A \times f \times l \times Ef$, where;

E = total CO2 Emissions (gCO2 per day)

A = the average number of motorcycles operating per day

F = fuel consumption per motorcycle (fuel economy in liters/km)

L = the distance covered per day in kilometers (km)

Ef = the emissions factor in gCO2/liters, taken to be 0.4999

In the now imputed data, the calculation was done as follows;

$$Emissions = (Avg\_Num\_Mbikes\_per\_day * Fuel\_Consumption * dist\_per\_day * emissions\_factor)/1000000)$$

Where $Fuel\_Consumption$ for ICE motorbikes is equivalent to "fuel per day", a field collected in the primary data as "Amount of fuel used per day (liters)". On the other hand, $Fuel\_Consumption$ for electric bikes was computed as $battery\_capacity * battery\_capacity\_ah * charging\_time$ / 1000 where $battery\_capacity$ is in volts, $battery\_capacity\_ah$ in Ampere hours, $charging\_time$ in hours, and 1000 convers the resulting value to kWh, while the overall $'1000000$' converts emissions to metric tonnes.

The emissions variable was further summarized by aggregating the values by year and fuel type, and outliers managed the same way outliers in number of motorbikes were handled. Figure 5.3 shows comparison of total emissions before and after removing outliers. This was done so that the model can better capture the underlying patterns in the data and make more accurate predictions.

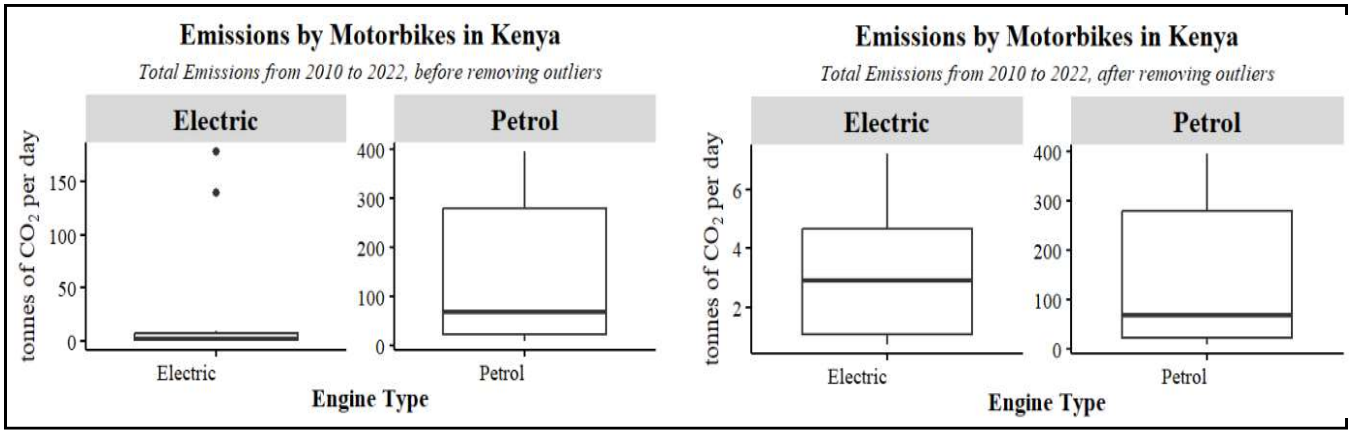


Figure 5.3: Emissions value before and after outlier management.

5.5.4 Generalized Additive Modelling (GAM)

In Figure 5.4, emissions from both electric and Internal Combustion Engine (ICE) motorbikes are plotted against time. The plot includes a trend line (in blue) generated using Generalized Additive Models (GAM) smoothing technique, which offers a flexible approach for capturing underlying patterns in data. Additionally, a 95% confidence band (in gray) surrounds the trend line, illustrating the uncertainty associated with the estimated trend and the black line showing the plotted data.

By leveraging the flexibility of GAMs, the trend line in Figure 5.4 provides a more nuanced depiction of how emissions from electric and ICE motorbikes evolve over time. Comparing emissions from petrol motorcycles show an increasing trend, this can be attributed to the increased use and popularity in Kenya which directly contributes to emissions per day.

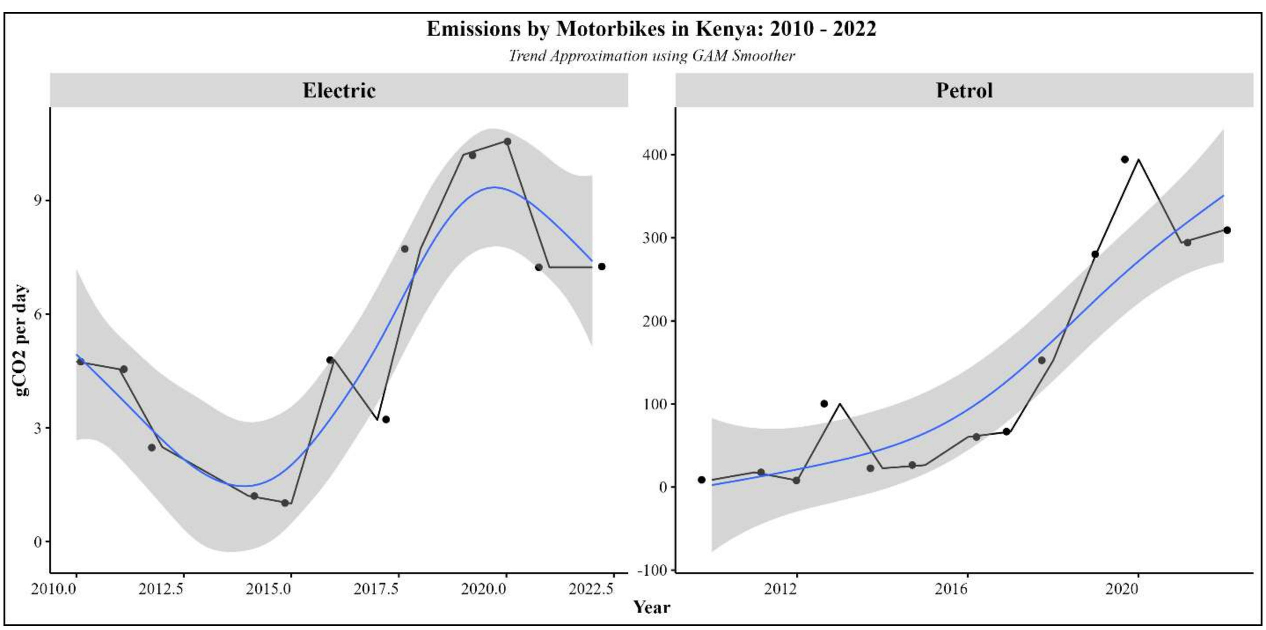


Figure 5.4: Emissions by motorbikes from 2010-2022

The researcher then applied the GAM smoother into the data as follows.

$$y_t = \sum_{i=1}^{l} f_i(x_t) + \epsilon_t$$

Formulae 5.2: Generalized Additive Model (GAM)

This is broken down into.

$$Emissions = s(Years, k = n_{years}, bs = \text{"cs"}) + FuelType$$

Where $k = n_{years}$ is the knots, that is, the number of unique $Years$ in the data, and $bs = \text{"cs"}$ is the b-spline that specifies "cyclic shrinkage", the shrinkage version of "cr", the "cubic regression". The model performs reliably, with an explained deviance of 99.40%.

Table 5.3 shows the output of 'summary (GAM_Emissions)', and most notably the high R-squared and high deviance parameters, indicating a good fit. Also, at 95% level of confidence, FuelType and Years are significant predictors of emissions (both p-values are <0.001).

Table 5.3: Model Performance Metrics

Parametric Coefficients				
	Estimate	Std. Error	z value	Pr (>|Z|)
Intercept	0.45	0.17	2.655	0.008
Fuel Type: Petrol	3.78	0.17	22.87	<0.001
Fuel Type: Electric	Ref	Ref	Ref	Ref
Approximate Significance of Smooth Terms				
	edf	Ref. df	Chi. sq	p-value
s(Years)	12	12	1053	<0.001
R-sq.(adj)	0.99			
Deviance explained	99.40%			
UBRE	1.034			
Scale est.	1			
N	25			

Figure 5.5 and Figure 5.6 shows the model performance metrics. As depicted in Figure 5.5, the fitted values align linear with observed values (response axis). Figure 5.6 shows the fitted Data against observed data shows GAM adapting well to the data. From the graph, the data set aligns with a line of best fit as shown in Figure 5.5. The model performed quite well, as demonstrated by the metrices, and this implies that it is fit for even forecasting and other predictive uses.

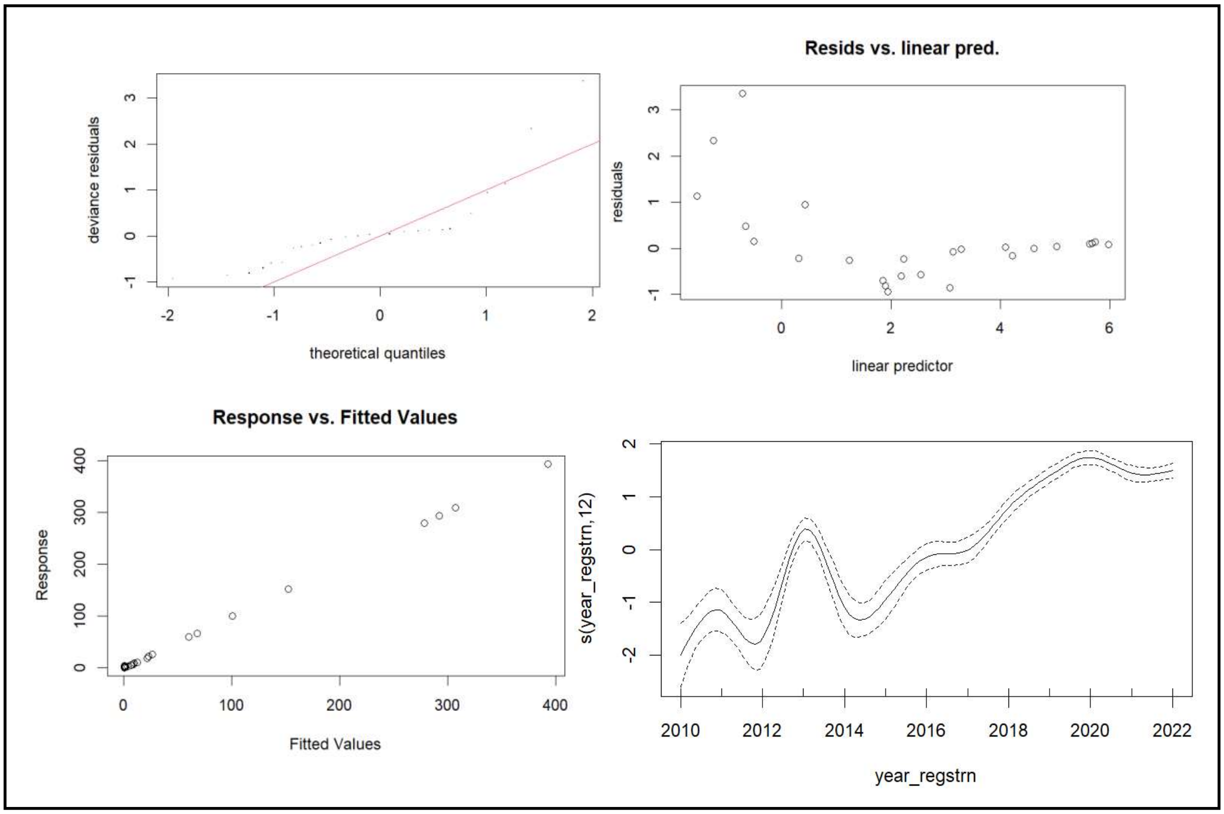


Figure 5.5: Model Performance Metrics, visualized.

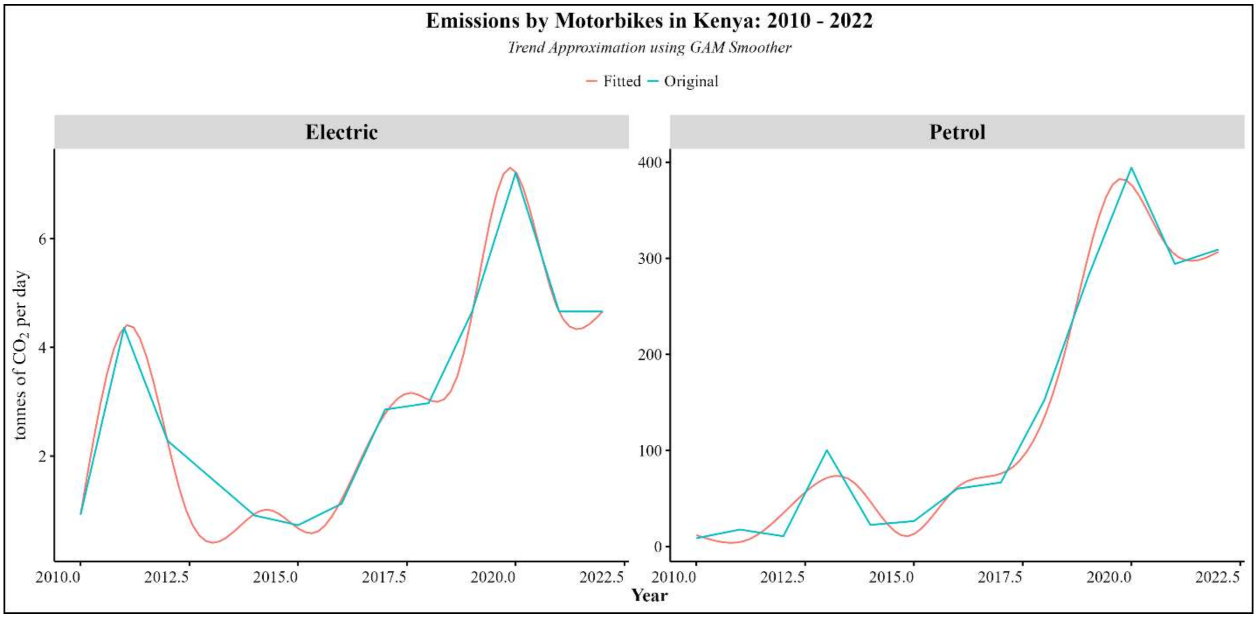


Figure 5.6: Fitted Data against observed data shows GAM adapting well to the data.

5.2 Forecasting Emissions

The data for this modelling was available spanning 12 years (2010 to 2022), and because this is a relatively short span of time series data, reliable forecasting can be computed to 15 years. Beyond that, the estimates are no longer strongly reliable. The researcher demonstrates in Figure 5.7 a projection to 2045, which show an exponential rise in the emissions. A further dive into the statistical properties of the projections reveal that they follow an exponential distribution $f(x) = \lambda e^{-\lambda x}$ with rates (λ) of 0.00009551 and 0.002665 for Petrol and Electric motorbikes respectively.

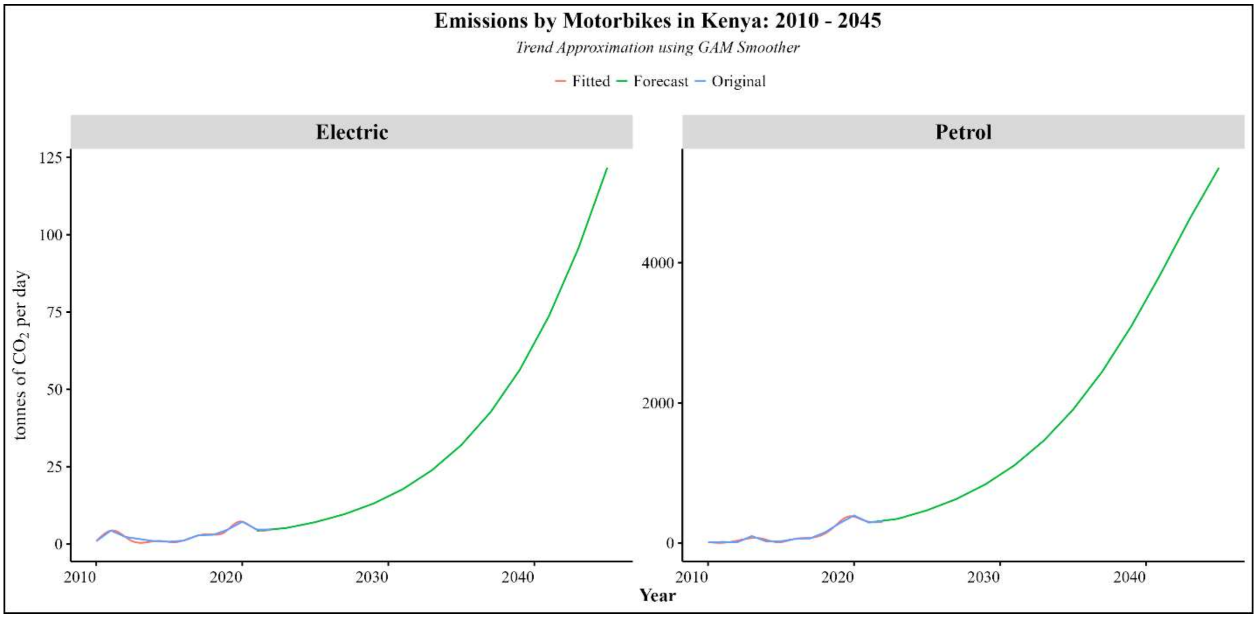


Figure 5.7: The GAM model shows a steady rise in emissions from 2022 through 2045.

5.2.1 Modelling Motorcycle Engine Efficiency

A model of the motorbike energy efficiency for 50 years is presented in Figures 5.7 and 5.8. To further predict emissions, this study assessed the impact of exponential decay on emissions from ICE and electric motorcycles using the following formula.

Data from 2022 formed the base year in the exponential decay formula;

$$Efficiency = P_o * e^{-0.28t}$$

Formulae 5.3: exponential decay formula

Where P_o is the value of the GHG emissions for the base year 2022. This value is 7,637,931 grams of CO_2 per day for electric motorbikes, and 309,238,140 grams of CO_2 per day for petrol motorbikes. The e in the formula is the natural base of logarithms, i.e. the constant Euler's number taken to be 2.718282. The t is a vector of years into the future, in this case 50 years starting from 2023 to 2072, inclusive of the latter. Plugging the values into the formula in R Software generates forecast values for both types of motorcycles, as shown in Figure 5.8.

While GHG emissions follow a growing exponential distribution, efficiency of the other hand conforms to a decaying exponential distribution. GHG emissions are increasing rapidly, indicating a worsening environmental impact, while efficiency improvements are occurring but at a decreasing rate, suggesting that it becomes progressively more difficult to achieve further efficiency gains over time.

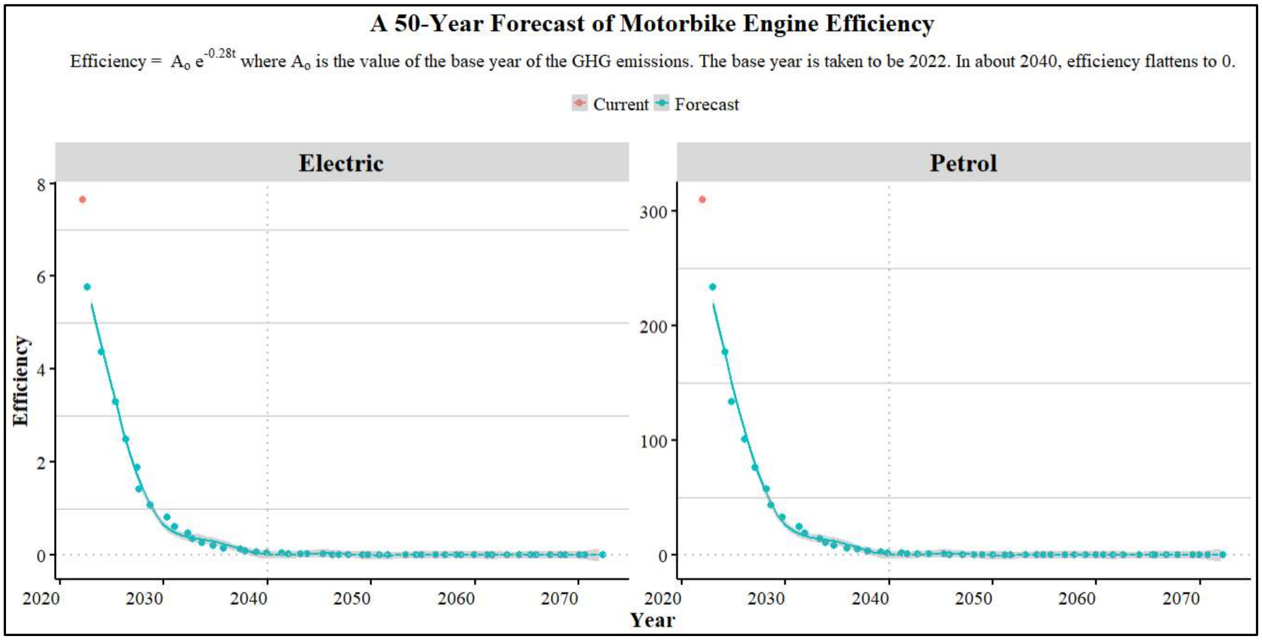


Figure 5.8: Forecasting motorcycle engine efficiency

Table 5.4 provides descriptive statistics for the forecasted efficiency data, comparing electric and petrol motorcycles, as well as the overall dataset.

Table 5.4: Descriptive Statistics of the Forecasted Efficiency Data

	Electric (N=50)	**Petrol (N=50)**	**Overall (N=100)**
Mean (SD)	0.473 (1.17)	19.1 (47.2)	9.81 (34.5)
Median [Min, Max]	0.00611 [0.00000635, 5.77]	0.248 [0.000257, 234]	0.0385 [0.00000635, 234]

The mean efficiency for electric motorcycles is 0.473 (SD = 1.17), while petrol motorcycles exhibit a higher mean efficiency of 19.1 (SD = 47.2). The overall dataset, combining both electric and petrol motorcycles, has a mean efficiency of 9.81 (SD = 34.5). Median efficiency values and their corresponding ranges (Min to Max) are also presented for each subgroup, emphasizing the variability within the datasets. The median efficiency for electric motorcycles is 0.00611 (range: 0.00000635 to 5.77), petrol motorcycles have a median efficiency of 0.248 (range: 0.000257 to 234), and the overall dataset has a median efficiency of 0.0385 (range: 0.00000635 to 234). These descriptive statistics offer a comprehensive summary of the forecasted efficiency data, highlighting both central tendencies and the dispersion of values within each subgroup and the overall dataset.

5.3 Validation of the Model

The emissions from motorcycles were calculated using the IPCC (2006) guidelines for assessing GHG emissions. Specifically, the study validated the predictive model for GHG emissions from motorbikes by employing the IPCC tier 1 method. This method, known for its default emission factors obtained from literature, provides a foundational approach for estimating emissions. While less detailed than tier 2 and tier 3 methods, which incorporate more specific emission factors, the tier 1 model equation was instrumental in combining default emission factors with activity data to determine the total emissions from the motorcycles.

The model equation used was;

$$AE = NV \times ATD \times EF \times 365$$

Formulae 5.4: IPCC tier 1 for calculating GHG emissions

Where;

AE = Annual Emission
NV = Number of each category of vehicle
ATD = Average Travel Distance
EF = Emission Factor.

The model equation, derived from IPCC guidelines, underwent validation using field data collected from 315 sampled motorbikes, which were categorized into petrol and electric variants. Emissions were projected on a daily and yearly basis, extending up to the year 2045. The results revealed a striking resemblance between the forecasted emissions derived from the IPCC model and those generated by the predictive model. Notably, both exhibited an exponential increase in GHG emissions over the forecast period.

However, disparity emerged in the emission trends between conventional and electric motorcycles. The emissions trajectory for conventional motorbikes displayed a steep curve, indicating a rapid escalation compared to that of electric motorcycles. Under the Business-as-Usual (BAU) scenario, it is projected that conventional motorcycles in this study will emit 597 metric tonnes of CO2 equivalent (MTCO2e) by the year 2045. In stark contrast, electric motorcycles are anticipated to emit a significantly lower amount, with emissions totaling only 38 MTCO2e by the same year. This stark variation underscores the potential environmental benefits associated with the adoption of electric motorcycles over conventional counterparts.

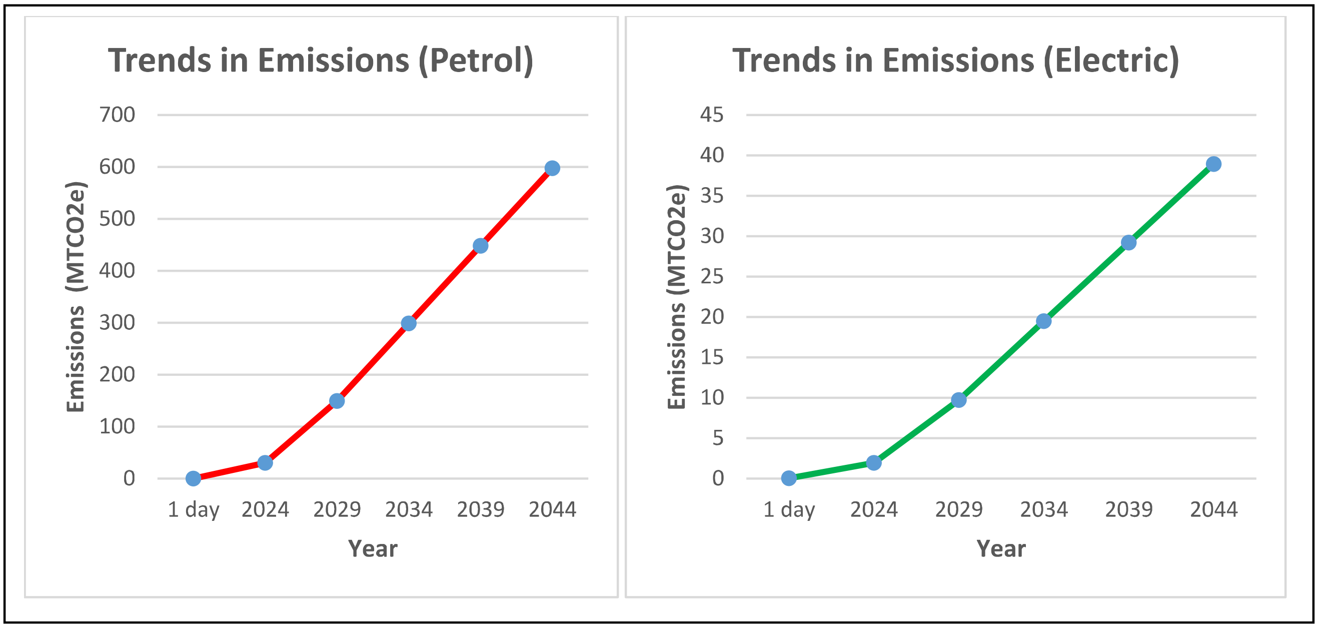


Figure 5.9: Emission trend for petrol and electric motorcycles over time

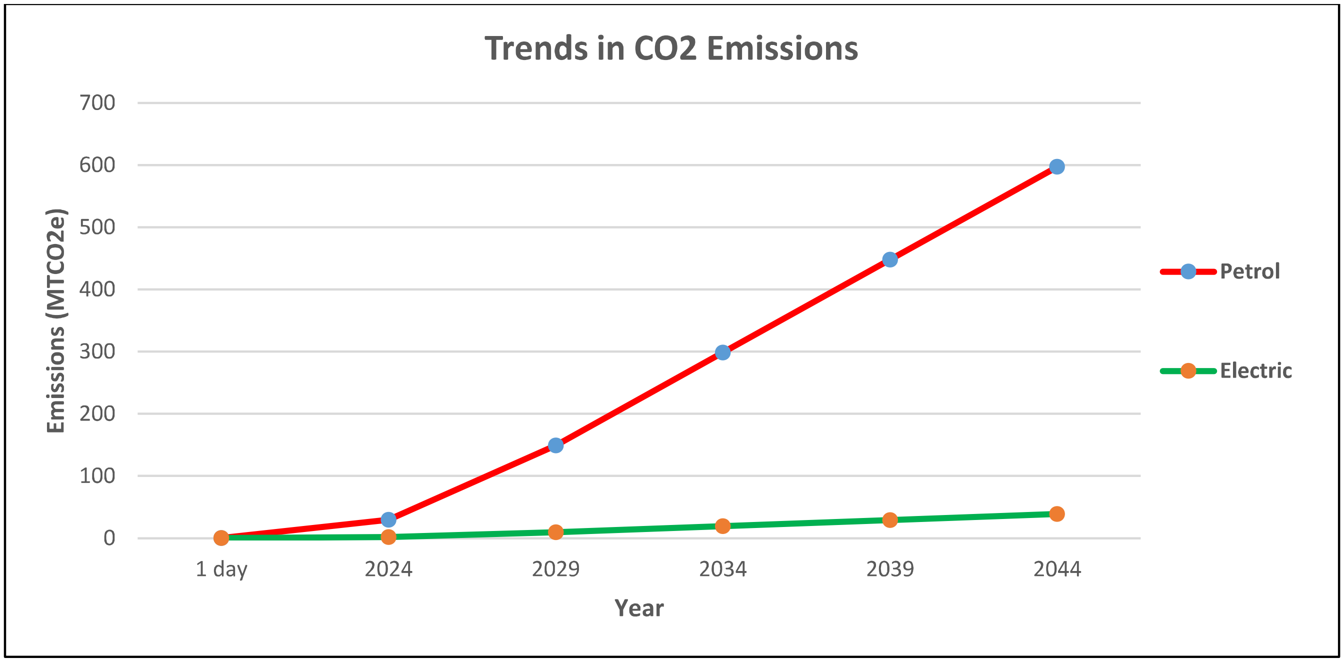


Figure 5.10: Fitted emission trend for petrol and electric motorcycles over time.

Chapter 6: Discussion

6.1 Introduction

This section compiles the study's findings and discusses them in comparison to the objectives.

6.2 Factors that Influence GHG Emissions from Motorbikes

The first objective of this study was to identify the various factors influencing greenhouse gas (GHG) emissions from motorcycles. A comprehensive literature review highlighted key determinants, including engine load, road characteristics, traffic flow, behavioral considerations, and technological advancements (Chen et al., 2003). In scenarios characterized by slow-moving traffic, motorcycles tend to operate at lower speeds and engage lower gears. Operating at lower gears with a higher engine load correlates with increased fuel consumption and emissions. The exertion required to overcome traffic-induced resistance prompts the engine to burn more fuel, consequently emitting greater amounts of greenhouse gases. In contrast, motorcycles function more efficiently in smooth traffic flow at higher speeds. Maintaining constant speeds and employing higher gears enhances fuel efficiency, resulting in reduced greenhouse gas emissions. However, fluctuating traffic conditions with frequent acceleration and deceleration diminish fuel efficiency and also increase electricity consumption in E2Ws, leading to higher emissions (Kusalaphirom et al., 2023).

Rider behavior emerges as a significant factor influencing emissions, with aggressive acceleration and braking practices exacerbating the release of pollutants (Seedam et al., 2017). Notably, the practice of lane-splitting, where motorcycles navigate between lanes in slow-moving or stationary traffic, holds the potential to alleviate congestion. This maneuver not only reduces idle time but also improves fuel efficiency, thereby leading to a decrease in emissions. Chiou & Chen (2010) research additionally underscores the impact of rider demographics on greenhouse gas (GHG) emissions. Their study, employing structural equation modeling, revealed that factors such as age, gender, education level, and income play a role in influencing emissions.

Modern motorcycles are often equipped with advanced technologies such as fuel injection and catalytic converters, contributing to emission reduction. Nevertheless, the effectiveness of these technologies varies with speeds and engine loads, potentially being limited in heavy traffic conditions. In congested traffic, motorcycles experience frequent stops and starts, resulting in heightened fuel consumption and increased emissions. Such conditions render motorcycles less fuel-efficient, emitting greater quantities of greenhouse gases per mile traveled.

Moreover, motorcycles, like their automotive counterparts, emit pollutants while idling. In densely congested traffic, motorcycles often experience extended periods of idling, especially at traffic signals or in gridlocked conditions. This prolonged idling substantially contributes to increased greenhouse gas emissions. A study conducted by Seedam et al., (2017) affirmed that idle time played a significant role in escalating fuel consumption and emissions in congested urban roads.

These results are consistent with a UNEP, EPRA, and IKI commissioned study, which disclosed that motorcycles with engine capacities in the range of 101-150cc held sway in the Kenyan market and were the preferred choice among riders (UNEP, 2020). Popular brands included Honda, Bajaj, TVS, Skygo, and others.

The findings of this study also show the prevalence of Lithium-ion batteries as the primary power source for electric motorcycles, with a notable voltage capacity range of 72 to 85 volts. These results align with existing literature emphasizing the widespread adoption of Lithium-ion technology in electric vehicles due to its high energy density and long cycle life (Lu et al., 2013; Zubi et al., 2018). In terms of battery capacity, a significant majority of electric motorcycles featured a 45 ampere-hours (Ah) battery. This aligns with the work of Manzetti & Mariasiu (2015) who highlighted the common usage of 45 Ah batteries in electric motorcycles, emphasizing their balance between weight, size, and performance.

Regarding charging requirements, the study revealed that electric motorcycle owners spent an average of 4.2 hours per day charging their vehicles. This finding provides practical insights into the charging habits and requirements of electric motorcycle users. The literature supports this by acknowledging the critical role charging infrastructure and user behavior play in the adoption and acceptance of electric vehicles (He et al., 2022).

Comparative analysis of daily travel distances highlighted those electric motorcycles covered an average of 126 kilometers per day, while conventional motorcycles covered a slightly higher average distance of 153 kilometers per day. This information offers valuable insights into the current limitations and capabilities of electric motorcycles in terms of daily commuting range. The literature supports this discussion by emphasizing the ongoing efforts to improve the range of electric motorcycles through advancements in battery technology and charging infrastructure (Miao et al., 2019; Ullah et al., 2023).

6.3 Existing Models for Predicting of GHG Emissions

The second objective of this study was to analyze the existing models for predicting GHG emissions. Models serve as crucial tools in climate mitigation and adaptation strategies, linking GHG emission drivers to various potential outcomes (Hultman & Edmonds, 2023). Predictive modeling of GHG emissions has seen widespread application in research, policy, and practice by both public and private entities over decades. However, there has been limited application of modeling equations in assessing GHG emissions in Kenya and Africa at large.

For instance, Luo et al. (2020) employed modeling techniques to project urban growth, energy use, and GHG emissions in Dar es Salaam, demonstrating an increase in emissions by modeling changes in household sizes and energy consumption patterns. Similarly, Afroz et al. (2021) utilized scenario-based modeling to estimate agricultural GHG emissions in the United States. In addition to predictive models, simplified equation models have also been utilized in estimating GHG emissions. Neya et al. (2021) developed simplified equation models to assess transport GHG emissions in Burkina Faso, incorporating parameters such as distance traveled, fuel economy, and emission factors. However, this study heavily relied on secondary data without incorporating primary data, potentially compromising the accuracy of the model.

The model used in this study, addresses these identified gaps by employing a General Additive Model (GAM) fitted using R software. Unlike some previous models that lacked validation or relied solely on secondary data, the model in this study utilized both primary and secondary data and demonstrated a rigorous statistical approach, with a high R-squared value of 0.99 and 99.4% of the deviance explained, indicating a strong fit to the observed data. Furthermore, significant predictors such as the type of fuel used and temporal trends were identified, enhancing the model's predictive power and applicability. Thus, the model used in this study represents a significant advancement in the field, offering a robust framework for predicting GHG emissions from motorcycles and informing effective mitigation strategies.

6.4 A Model for Predicting GHG Emissions from Motorcycles

The third objective of developing a model for predicting greenhouse gas (GHG) emissions from motorcycles is a crucial step in understanding and addressing the environmental impact of these vehicles. The utilization of a General Additive Model (GAM) fitted using R software demonstrates a statistical approach to capture the complexity of the relationship between predictor variables and GHG emissions. The high R-squared value of 0.99 indicates a strong fit of the model to the observed data. An R-squared value close to 1 suggests that the model explains a significant proportion of the variance in the dependent variable, in this case, GHG emissions from motorcycles. Additionally, the 99.4% deviance explained further reinforces the model's ability to account for the variability in the data.

The significance of the predictors, namely the type of fuel used and the years, is highlighted by their associated p-values being less than 0.001 at a 95% confidence level. This suggests a high level of confidence in the predictive power of these variables in determining GHG emissions. The inclusion of these variables aligns with existing literature, as the type of fuel is a well-established factor influencing emissions, and the consideration of temporal trends (years) acknowledges the dynamic nature of emissions over time. It is essential to emphasize the reliability and robustness of the model, as indicated by the high R-squared value and significant predictors. This lends credibility to its application for forecasting and other predictive uses. Policymakers, researchers, and energy industry stakeholders can leverage such models to make informed decisions regarding emissions reduction strategies and regulatory frameworks for motorcycles.

6.5 Model Validation and Testing

The 4th objective was to validate the proposed model. The extension of the model's predictions from the original 12-year dataset (2010-2022) to 2045 provides a glimpse into the future trajectory of GHG emissions from motorcycles. The observed exponential rise in GHG emissions over this extended period, as depicted in Figure 5.6, underscores the urgency of addressing environmental concerns associated with these vehicles. Numerous studies have pointed out the alarming trend of greenhouse gas emissions exhibiting exponential growth. The Intergovernmental Panel on Climate Change (IPCC) has consistently reported increases in GHG emissions, particularly carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O) (IPCC, 2014). The growth in emissions is attributed to various factors, including industrial activities, deforestation, and the burning of fossil fuels. This projection serves as a valuable tool for policymakers and industry stakeholders to anticipate and implement measures to curb emissions, promoting sustainability and mitigating the environmental impact of motorcycles.

The modelling results also indicated that while GHG emissions follow a growing exponential distribution, engine efficiency on the other hand conforms to a decaying exponential distribution. The efficiency of internal combustion engines, which are widely used in transportation and industry, tends to follow a decaying exponential distribution. This is a result of technological advancements, including improvements in fuel efficiency, combustion processes, and overall engine design. Research and development efforts, driven by environmental regulations and market demands, contribute to the continuous improvement of engine efficiency.

In conclusion, the development and validation of a General Additive Model for predicting GHG emissions from motorcycles, as outlined in the study, represent a significant contribution to the field. The robustness of the model, coupled with the inclusion of pertinent predictor variables and its successful application in forecasting, positions it as a valuable tool for guiding future decisions and interventions aimed at reducing the environmental footprint of motorcycles.

Chapter 7: Conclusion and Recommendations

7.1 Conclusions

Based on the descriptive results, several insightful conclusions can be drawn:

Gender Disparity in Motorcycle Operation and Emissions. The study reaffirms the existing correlation between gender and greenhouse gas emissions from motorcycles. Predominantly, male riders contribute to higher emissions. However, there's a noteworthy trend suggesting that a higher proportion of female riders opt for electric motorcycles compared to conventional ones, potentially indicating a preference for eco-friendly vehicles among women. This presents an opportunity to address emission concerns by encouraging the adoption of electric motorcycles, particularly among male riders.

Age Composition and Emission Patterns. While previous research suggested that older riders tend to emit more greenhouse gases, the current study indicates a youthful age distribution among respondents, with the majority falling within the 18 to 35 age range. This demographic shift could imply a positive outlook for emissions reduction in the future, as younger riders may be more inclined towards adopting environmentally friendly transportation options.

Educational Attainment and Emissions Reduction. The study underscores the significance of education in mitigating greenhouse gas emissions. A notable portion of respondents had completed secondary education, suggesting that promoting environmental literacy could potentially lead to more sustainable transportation choices. Additionally, the preference for electric motorcycles among those with secondary education further highlights the role of education in fostering environmentally conscious behavior.

Impact of Driving Experience on Emissions. The findings suggest a correlation between driving experience and emissions, with extensive driving experience associated with higher emissions. However, the emergence of a significant proportion of respondents with minimal experience in operating electric motorcycles indicates a recent surge in the adoption of eco-friendly transportation options. This shift could contribute positively to reducing overall emissions from motorcycle usage.

In conclusion, the study highlights various demographic factors influencing motorcycle emissions, including gender, age, education, and driving experience. While certain demographics, such as male riders and those with extensive driving experience, contribute more to emissions, there are promising trends suggesting a growing interest in environmentally friendly transportation options, particularly among younger and more educated individuals. Addressing these demographic patterns could inform targeted interventions aimed at promoting the adoption of electric motorcycles and reducing greenhouse gas emissions in the transportation sector.

7.1.1 Motorcycle Characteristics and Technologies

Based on the comprehensive findings presented, several insightful conclusions can be drawn regarding the ownership, adoption, technology, and usage patterns of electric and conventional motorcycles in Kenya:

Ownership and Acquisition Trends: The study highlights a notable disparity in ownership models between electric and conventional motorcycles. While the majority of conventional motorcycles are owned by their operators, a significant proportion of electric motorcycles are acquired through leasing arrangements. This phenomenon is likely attributed to the high initial costs associated with electric vehicles (EVs), making ownership prohibitive for many riders. The involvement of parent companies in owning and leasing electric motorcycles underscores the need for innovative financing solutions to facilitate broader adoption of EVs in the market.

Manufacturing and Registration Trends: The findings reveal a positive trend in the adoption of electric motorcycles, with a significant proportion of them being manufactured and registered after 2020. This surge in production and registration indicates increasing acceptance and uptake of EV technology within the last few years. Conversely, the majority of conventional motorcycles sampled were manufactured and registered between 2016 and 2020, suggesting a relatively shorter lifespan due to various factors such as accidents and engine efficiency issues.

Technology and Fuel Consumption Patterns: The study provides valuable insights into the prevailing technologies and fuel consumption patterns of both electric and conventional motorcycles. It is noted that Lithium-ion batteries are the predominant power source for electric motorcycles, with a majority featuring a battery capacity of 45 ampere-hours (Ah). Additionally, the study highlights the average amount of fuel used per day by conventional motorcycles, offering crucial data for understanding fuel consumption trends in the sampled population.

Charging and Travel Distance: Insights into the charging requirements and daily travel distances of electric motorcycles provide valuable information regarding the practical implications and usage habits associated with EV ownership. The study reveals that electric motorcycle owners spend an average of 4.2 hours per day charging their vehicles, while covering an average daily distance of 126 kilometers. In comparison, conventional motorcycles cover a slightly higher average distance of 153 kilometers per day. These findings shed light on the current capabilities and limitations of electric motorcycles in terms of daily commuting range and charging infrastructure requirements.

In conclusion, the study underscores the evolving landscape of motorcycle ownership, technology adoption, and usage patterns in Kenya. While conventional motorcycles continue to dominate the market, there is a noticeable shift towards the adoption of electric motorcycles, driven by factors such as environmental concerns and technological advancements. Addressing barriers to EV ownership, such as high upfront costs and charging infrastructure limitations, will be crucial in promoting further adoption and realizing the potential environmental and economic benefits of electric mobility in the region.

7.1.2 Model Development and Performance

Moreover, the development and successful application of a General Additive Model (GAM) for predicting greenhouse gas (GHG) emissions from motorcycles provide valuable insights into the environmental impact of these vehicles. The high R-squared value, significant predictors, and the model's suitability for forecasting indicate a robust tool for understanding and addressing emissions in this sector. The significance of the type of fuel used and temporal trends in predicting GHG emissions underscores the importance of considering both technological and temporal factors in formulating policies and strategies.

The projection of GHG emissions to 2045, revealing an exponential rise, also serves as a stark warning of the potential environmental consequences if no intervention occurs. Urgent action is needed to curb this upward trajectory, and the model provides a roadmap for identifying key areas for intervention. Policymakers should consider implementing stringent emission standards, promoting the adoption of cleaner technologies, and incentivizing the use of environmentally friendly fuels in the motorcycle industry.

Furthermore, collaboration between government bodies, industry stakeholders, and environmental organizations is crucial in developing and implementing effective strategies. The model's reliability and predictive capabilities make it a valuable tool for scenario analysis and impact assessment, aiding in the formulation of evidence-based policies.

7.2 Recommendations

In light of the study's findings, continued monitoring and periodic updates to the model are recommended to ensure its relevance in the face of evolving technologies and market trends. Research efforts should also be directed towards exploring additional predictors and refining the model to enhance its accuracy.

Other recommendations include:

I. Promotion of Electric Motorcycles: Given the environmental benefits associated with E2Ws, there is a need for targeted initiatives to promote their adoption. This could involve incentivizing electric motorcycle purchases, developing charging infrastructure, and raising awareness about the ecological advantages.

II. Behavioral Awareness Programs: Implementing awareness programs to educate motorcycle riders about the environmental impact of aggressive acceleration and braking can contribute to a reduction in emissions. Encouraging eco-friendly riding habits and promoting responsible behavior can positively influence emissions.

III. Infrastructure Development: To enhance the feasibility of electric motorcycles, there is a requirement for the development of robust charging infrastructure. Governments and private entities should collaborate to establish charging stations at strategic locations, facilitating convenient charging for electric motorcycle owners.

IV. Research and Development: Continuous investment in research and development is crucial for improving the range and efficiency of electric motorcycles. This includes advancements in battery technologies, aerodynamics, and energy recovery systems to address the current limitations and enhance the overall performance of electric motorcycles.

V. Policy Support: Governments should enhance existing policies, such as tax incentives and regulatory frameworks, to catalyze the adoption of electric motorcycles. Aligning policies with sustainability goals can foster an eco-friendlier transportation landscape.

VI. Collaboration with Manufacturers: Collaboration between policymakers, environmental agencies such as NEMA, and motorcycle manufacturers is essential. This partnership can lead to the development of eco-friendly technologies, the establishment of emission standards, and the creation of a more sustainable motorcycle industry.

7.3 Future Studies

1) Whereas this work developed a successful GAM for predicting GHG emissions in motorcycles, it did not factor in grid emissions, tare weight among other key factors. Future studies could focus on exploring alternative modeling approaches and incorporating additional variables in order enhance the predictive capabilities and provide a more comprehensive understanding of the factors influencing GHG emissions.
2) Future studies should focus on comparative analyses across different regions and countries could offer insights into variations in GHG emissions based on regional policies, infrastructure, and socio-economic factors. Understanding these differences can inform the development of tailored strategies for mitigating emissions on a global scale.
3) Moreover, in recognizing that the dynamic nature of emissions is essential. Future research could investigate how external factors, such as economic fluctuations, changes in transportation infrastructure, and global events, impact GHG emissions from motorcycles. This will contribute to a more nuanced understanding of the forces shaping emission trends.

Lastly, exploring emissions level comparisons between prevalent vehicle models and motorcycle models on Kenyan roads presents an intriguing avenue for future research. This investigation could provide valuable insights into the environmental impact of different modes of transportation, shedding light on the potential advantages of motorbikes, particularly in situations such as traffic congestion. Examining the emissions profiles of various vehicle types under different traffic conditions and usage patterns could contribute to a more comprehensive understanding of the environmental implications of urban transportation. This area of research holds promise for uncovering nuanced aspects of emissions dynamics and may pave the way for developing sustainable and eco-friendly transportation strategies in the future.

References

Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental Science and Pollution Research 2022 29:28*, *29*(28), 42539–42559. https://doi.org/10.1007/S11356-022-19718-6

Abdikadir, S. A. (2021). *Climate Change and Human Security in the 21st Century International System: the Case of Kenya*. http://erepository.uonbi.ac.ke/handle/11295/157067

Adhi, R. P. (2018). Top-Down and Bottom-Up Method on Measuring CO2 Emission from Road-Based Transportation System (Case Study: Entire Fuel Consumption, Bus Rapid Transit, and Highway in Jakarta, Indonesia). *Jurnal Teknologi Lingkungan*, *19*(2), 249–258. https://doi.org/10.29122/JTL.V19I2.2840

Adnan, N., Nordin, S. M., Rahman, I., Vasant, P., & Noor, M. A. (2018). An overview of electric vehicle technology: A vision towards sustainable transportation. *Intelligent Transportation and Planning: Breakthroughs in Research and Practice*, *October*, 292–309. https://doi.org/10.4018/978-1-5225-5210-9.ch013

Afroz, M., Li, R., Chen, G., & Anandhi, A. (2021). Agricultural greenhouse gas emissions in a data-scarce region using a scenario-based modeling approach: A case study in southeastern USA. *Agronomy*, *11*(7). https://doi.org/10.3390/agronomy11071323

Akumu, J. (2019). *The Electric Mobility Programme*.

Arif, S. M., Lie, T. T., Seet, B. C., Ayyadi, S., & Jensen, K. (2021). Review of Electric Vehicle Technologies, Charging Methods, Standards and Optimization Techniques. *Electronics 2021, Vol. 10, Page 1910*, *10*(16), 1910. https://doi.org/10.3390/ELECTRONICS10161910

Ayanlade, A., Smucker, T. A., Nyasimi, M., Sterly, H., Weldemariam, L. F., & Simpson, N. P. (2023). Complex climate change risk and emerging directions for vulnerability research in Africa. *Climate Risk Management*, *40*, 100497. https://doi.org/10.1016/J.CRM.2023.100497

Ayetor, G. K., Mbonigaba, I., & Mashele, J. (2023). Feasibility of Electric Two and Three-Wheelers in Africa. *Green Energy and Intelligent Transportation*, *July*, 100106. https://doi.org/10.1016/j.geits.2023.100106

Ayompe, L. M., Davis, S. J., & Egoh, B. N. (2020). Trends and drivers of African fossil fuel CO2 emissions 1990-2017. *Environmental Research Letters*, *15*(12). https://doi.org/10.1088/1748-9326/abc64f

Bakker, S., Haq, G., Peet, K., Gota, S., Medimorec, N., Yiu, A., Jennings, G., & Rogers, J. (2019). Low-carbon quick wins: Integrating short-term sustainable transport options in climate policy in low-income countries. *Sustainability (Switzerland)*, *11*(16), 1–17. https://doi.org/10.3390/su11164369

Barth, M., & Boriboonsomsin, K. (2009). Traffic Congestion and Greenhouse Gases. *ACCESS Magazine*.

Bharadwaj, S., Ballare, S., Rohit, & Chandel, M. K. (2017). Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region. *Transportation Research Procedia*, *25*, 3538–3551. https://doi.org/10.1016/J.TRPRO.2017.05.282

Chen, K. S., Wang, W. C., Chen, H. M., Lin, C. F., Hsu, H. C., Kao, J. H., & Hu, M. T. (2003). Motorcycle emissions and fuel consumption in urban and rural driving conditions. *Science of The Total Environment*, *312*(1–3), 113–122. https://doi.org/10.1016/S0048-9697(03)00196-7

Chiou, Y. C., & Chen, T. C. (2010). Direct and indirect factors affecting emissions of cars and motorcycles in Taiwan. *Transportmetrica*, *6*(3), 215–233. https://doi.org/10.1080/18128600903168108

Climate & Clean Air Coalition. (2023). *Short-Lived Climate Pollutants (SLCPs)*. https://www.ccacoalition.org/en/content/short-lived-climate-pollutants-slcps

Daemme, L. C., Penteado, R., Schneider, P. S., Da Rocha, B. P., Piccoli, B. D. S., Errera, M. R., & Corrêa, S. M. (2017). Study of the Energy Efficiency and Greenhouse Emissions from Motorcycles Powered by Electric and Internal Combustion Engines. *SAE Technical Papers*, *2017-November*(November). https://doi.org/10.4271/2017-36-0155

Government of Kenya. (2015). *Kenya ' s Intended Nationally Determined Contribution (INDC)* (Issue July).

Government of Kenya. (2019). *Transport Sector Climate Change Annual Report: Performance* *and Implementation of Climate Change Actions.*

Government of Kenya. (2021). *Kenya ' s updated Nationally Determined Contribution (NDC) and JCM Activities*.

He, S. Y., Sun, K. K., & Luo, S. (2022). Factors affecting electric vehicle adoption intention: The impact of objective, perceived, and prospective charger accessibility. *Journal of Transport and Land Use*, *15*(1), 779–801. https://doi.org/10.5198/JTLU.2022.2113

Hossain, M. S., Kumar, L., El Haj Assad, M., & Alayi, R. (2022). Advancements and Future Prospects of Electric Vehicle Technologies: A Comprehensive Review. *Complexity*, *2022*. https://doi.org/10.1155/2022/3304796

Hultman, N., & Edmonds, J. (2023). Scenarios to Model Long-term Climate Strategies Can Help Focus Action Today. In *Creating Transformational Pathways*.

IPCC. (2014). the IPCC'S Fifth Assessment Report (AR5). *Table of Content*, *September 2013*, 4.

IPCC. (2015). Glossary of terms. *Adoption and Fostering*, *39*(3), 195–196. https://doi.org/10.1177/0308575915599121

Kamer, L. (2023). *Africa: share in global CO2 emissions*. Statista. https://www.statista.com/statistics/1287508/africa-share-in-global-co2-emissions/

Khanbhai, M., & Lutomia, M. B. L. (2012). Motorcycle accident injuries seen at Kakamega Provincial Hospital in Kenya. East and Central African Journal of Surgery, 17(1), 43-46.

KOA LLP. (2022). *Opportunities and Challenges for Electric Mobility in Kenya*. *September*, 1–19.

Kogo, B. K., Kumar, L., & Koech, R. (2021). Climate change and variability in Kenya: a review of impacts on agriculture and food security. *Environment, Development and Sustainability*, *23*(1), 23–43. https://doi.org/10.1007/S10668-020-00589-1/METRICS

Kornhauser, A. A. (2004). Internal combustion engines. *The Engineering Handbook, Second Edition*, 68-1-68–15. https://doi.org/10.5958/2455-7110.2016.00013.6

Kusalaphirom, T., Satiennam, T., & Satiennam, W. (2023). Factors Influencing the Real-World

Electricity Consumption of Electric Motorcycles. *Energies 2023, Vol. 16, Page 6369*, *16*(17), 6369. https://doi.org/10.3390/EN16176369

Lamb, W. F., Wiedmann, T., Pongratz, J., Andrew, R., Crippa, M., Olivier, J. G. J., Wiedenhofer, D., Mattioli, G., Khourdajie, A. Al, House, J., Pachauri, S., Figueroa, M., Saheb, Y., Slade, R., Hubacek, K., Sun, L., Ribeiro, S. K., Khennas, S., De La Rue Du Can, S., … Minx, J. (2021). A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. *Environmental Research Letters*, *16*(7), 073005. https://doi.org/10.1088/1748-9326/ABEE4E

Longe, O. M. (2022). A Review on the Motivations, Challenges and Adoption Strategies for Electromobility in Africa. *The Institute of Electrical and Electronics Engineers, Inc. (IEEE) Conference Proceedings*. https://doi.org/10.1109/POWERAFRICA53997.2022.9905241

Lu, L., Han, X., Li, J., Hua, J., & Ouyang, M. (2013). A review on the key issues for lithium-ion battery management in electric vehicles. *Journal of Power Sources*, *226*(March), 272–288. https://doi.org/10.1016/j.jpowsour.2012.10.060

Luo, C., Posen, I. D., Hoornweg, D., & MacLean, H. L. (2020). Modelling future patterns of urbanization, residential energy use and greenhouse gas emissions in Dar es Salaam with the Shared Socio-Economic Pathways. *Journal of Cleaner Production*, *254*(October). https://doi.org/10.1016/j.jclepro.2020.119998

Makundi, B. (2018). *Stuck in neutral: A case study of the challenges facing the Kenyan automotive sector* (Master's thesis, University of Cape Town).

Manzetti, S., & Mariasiu, F. (2015). Electric vehicle battery technologies: From present state to future systems. *Renewable and Sustainable Energy Reviews*, *51*, 1004–1012. https://doi.org/10.1016/J.RSER.2015.07.010

Mboa, A. S., Njoroge, R. N., & Maranga, I. W. (2022). *Review of Electric Vehicle Charging and Battery Swapping Infrastructure in Kenya and International Best Practices*.

Miao, Y., Hynan, P., Von Jouanne, A., & Yokochi, A. (2019). Current Li-Ion Battery Technologies in Electric Vehicles and Opportunities for Advancements. *Energies 2019, Vol. 12, Page 1074*, *12*(6), 1074. https://doi.org/10.3390/EN12061074

Mshelia, R., Yusuf Jibatswen, T., Babarinde, F., Yusuf, R., & Mshelia, R. B. (2021). Assessment of Vehicular Greenhouse Gas Emissions and Potentials for Reduction in A University Campus: Case Study of Bayero University Kano. *International Journal of Environment and Geoinformatics*, *8*(3), 301–306. https://doi.org/10.30897/IJEGEO.837262

Mugwika, P. K. (2019). *Assessment of the Impacts of Climate Change and Variability on Food Security in Kenya: a Case Study of Kisii County*. http://erepository.uonbi.ac.ke/handle/11295/127466

Narváez-Villa, P., Arenas-Ramírez, B., Mira, J., & Aparicio-Izquierdo, F. (2021). Analysis and Prediction of Vehicle Kilometers Traveled: A Case Study in Spain. *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 8327*, *18*(16), 8327. https://doi.org/10.3390/IJERPH18168327

National Centre for Environmental Health. (2016). *Particle Pollution & Air Quality*. https://www.cdc.gov/air/particulate_matter.html

Neya, T., Yanon, G., Sylla, M. B., Neya, O., & Sawadogo, J. (2021). Simplified Equation Models for Greenhouses Gases Assessment in Road Transport Sector in Burkina Faso. *Journal of Atmospheric Science Research*, *4*(4), 11–18. https://doi.org/10.30564/jasr.v4i4.3758

Notter, B., & Fussler, J. (2018). *Road transport GHG emission factors for Kenya; Pilot study for 2015*.

Olvera, L., Plat, D., & Pochet, P. (2020). Looking for the obvious: Motorcycle taxi services in Sub-Saharan African cities. *Journal of Transport Geography*, *88*. https://doi.org/10.1016/j.jtrangeo.2019.102476

Opoku, S. K., Filho, W. L., Hubert, F., & Adejumo, O. (2021). Climate Change and Health Preparedness in Africa: Analysing Trends in Six African Countries. *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 4672*, *18*(9), 4672. https://doi.org/10.3390/IJERPH18094672

Park, J., Calzavara, J., & Courtright, T. (2021). *Environmental and Social Impact Assessment of Electric Motorcycle Taxis in Kampala, Uganda*. *April 2021*, 43. https://deepblue.lib.umich.edu/bitstream/handle/2027.42/167362/ESIAZembo_36.pdf?sequ ence=1&isAllowed=y

Pawsey, C. (2014). *Evaporative Emission Regulations and EVAP Systems*. IQ Automotive. https://www.automotive-iq.com/exhaust/articles/evaporative-emission-regulations-and-evap-systems

Ripple, W. J., Wolf, C., Newsome, T. M., Barnard, P., & Moomaw, W. R. (2020). World Scientists' Warning of a Climate Emergency. *BioScience*, *70*(1), 8–12. https://doi.org/10.1093/BIOSCI/BIZ088

Ritchie, H., Roser, M., & Rosado, P. (2020a). CO_2 and Greenhouse Gas Emissions. *Our World in Data*. https://ourworldindata.org/co2-and-greenhouse-gas-emissions

Ritchie, H., Roser, M., & Rosado, P. (2020b). *Greenhouse gas emissions*. Our World in Data. https://ourworldindata.org/greenhouse-gas-emissions#citation

Sasu, D. (2023). *Climate change in Africa - statistics & facts*. Statista. https://www.statista.com/topics/9715/climate-change-in-africa/#editorsPicks

Seedam, A., Satiennam, T., Radpukdee, T., Satiennam, W., & Ratanavaraha, V. (2017). Motorcycle on-road driving parameters influencing fuel consumption and emissions on congested signalized urban corridor. *Journal of Advanced Transportation*, *2017*. https://doi.org/10.1155/2017/5859789

Sitati, C. N., Oludhe, C., Oyake, L., & Mbandi, A. M. (2022). A street-level assessment of greenhouse gas emissions associated with traffic congestion in the city of Nairobi, Kenya. *Clean Air Journal*, *32*(1), 1–12. https://doi.org/10.17159/CAJ/2022/32/1.12546

Suatmadi, A. Y., Creutzig, F., & Otto, I. M. (2019). On-demand motorcycle taxis improve mobility, not sustainability. *Case Studies on Transport Policy*, *7*(2), 218–229. https://doi.org/10.1016/j.cstp.2019.04.005

Subramanian, K. A. (2018). Introduction to Internal Combustion Engines. *Biofueled Reciprocating Internal Combustion Engines*, 61–102. https://doi.org/10.4324/9781315116785-4

Sun, Y., Hao, Q., Cui, C., Shan, Y., Zhao, W., Wang, D., Zhang, Z., & Guan, D. (2022). Emission accounting and drivers in East African countries. *Applied Energy*, *312*, 118805.

https://doi.org/10.1016/J.APENERGY.2022.118805

Tong, Y. D., Maraseni, T., Nguyen, P. D., An-Vo, D. A., Mancuso Tradenta, J., & Tran, T. A. D. (2023). Potential for greenhouse gas (GHG) emissions savings from replacing short motorcycle trips with active travel modes in Vietnam. *Transportation*, *0123456789*. https://doi.org/10.1007/s11116-023-10394-0

Ullah, I., Zheng, J., Jamal, A., Zahid, M., Almoshageh, M., & Safdar, M. (2023). Electric vehicles charging infrastructure planning: a review. *International Journal of Green Energy*. https://doi.org/10.1080/15435075.2023.2259975

UNEP. (2020). Integrating Electric 2 and 3 wheelers into existing Urban Transport Modes in Kenya. In *Combined Reports on the Development of Electric Mobility Policies in Kenya* (Issue January).

United Nations. (2021). Sustainable Transport. *UN Sustainable Transport Conference*, 2–3.

Vanatta, M., Rathod, B., Calzavara, J., Courtright, T., Sims, T., Saint-Sernin, É., Clack, H., Jagger, P., & Craig, M. (2022). Emissions impacts of electrifying motorcycle taxis in Kampala, Uganda. *Transportation Research Part D: Transport and Environment*, *104*. https://doi.org/10.1016/j.trd.2022.103193

Venkatesh, V., & Davis, F. D. (1996). A Model of the Antecedents of Perceived Ease of Use: Development and Test*. *Decision Sciences*, *27*(3), 451–481. https://doi.org/10.1111/J.1540-5915.1996.TB00860.X

Wambua, C. (2019). The Kenya climate change act 2016: Emerging lessons from a pioneer law. *Carbon and Climate Law Review*, *13*(4), 257–269. https://doi.org/10.21552/CCLR/2019/4/6

Weber, N., da Rocha, B. P., Smith Schneider, P., Daemme, L. C., & de Arruda Penteado Neto, R. (2019). Energy and emission impacts of liquid fueled engines compared to electric motors for small size motorcycles based on the Brazilian scenario. *Energy*, *168*, 70–79. https://doi.org/10.1016/j.energy.2018.11.051

World Economic Forum. (2023). *The Global Risks Report 2023 - 18th Edition*. www.weforum.org

World Health Organization. (2016). *Ambient air pollution: A global assessment of exposure and* *burden of disease*. https://apps.who.int/iris/handle/10665/250141

Zhang, X., & Chang, M. (2023). Applying the Extended Technology Acceptance Model to Explore Taiwan's Generation Z's Behavioral Intentions toward Using Electric Motorcycles. *Sustainability 2023, Vol. 15, Page 3787*, *15*(4), 3787. https://doi.org/10.3390/SU15043787

Zubi, G., Dufo-López, R., Carvalho, M., & Pasaoglu, G. (2018). The lithium-ion battery: State of the art and future perspectives. *Renewable and Sustainable Energy Reviews*, *89*, 292–308. https://doi.org/10.1016/J.RSER.2018.03.002

Appendices

Appendix A: Questionnaire

English Version

Introduction and Consent Form

Greetings, I am **Laureen Cherotich Cheruiyot**. I am a Master of Science in Sustainable Energy Transitions Student at Strathmore University School of Computing and Engineering Sciences. I am currently conducting a study on **'A Model for Predicting Greenhouse Gas Emissions from Motorcycles in Kenya'.** I would like to ask you some questions related to the motorcycle *(bodaboda)* that you operate. The information you provide will be useful in shaping E-mobility transition and transport-related GHG mitigation strategies in Kenya. Your participation in this study is voluntary and you are free to withdraw from it anytime. The research data collected will only be utilized for academic purposes and treated with the utmost confidentiality. Your individual identity will be concealed, and a pseudonym assigned to you. The findings of my research may be availed to you upon request.

The survey will last about 15 minutes.

Are you willing to participate in the survey?

Yes ( ) No ( )

Name: __________________

Signature: __________________ Date: _________________

SECTION A: BIODATA

1. Gender
   Male ( ) Female ( )
2. Age

18-35 ( ) 36-45 ( ) 46 and above ( )

3. County

   Nairobi ( ) Machakos ( )

4. Highest level of education
   No schooling ( ) Primary ( ) Secondary ( ) College ( ) University ( )

5. How long have you been a motorcycle operator?
   Less than 1 year ( ) 1-3years ( ) 4-5years ( ) More than 5 years ( )

SECTION B: Motorcycle Inventory Data

6. Ownership of the motorcycle
   Owned ( ) Leased ( )

7. Make of the motorcycle
   Honda ( ) Skygo ( ) Suzuki ( ) Bajaj ( ) Other (Please specify):

8. Year of Manufacture
   ( )

9. Year of Registration
   ( )

10. Fuel type
    Petrol ( ) Diesel ( ) Electric ( ) Hybrid ( )

For fuel-based Engines;

11. Engine size (cc)
    ( )

12. Average amount of fuel used per day.
    ( )

For electric motorcycles;

13. Type of battery
    Lithium Ion Battery ( ) Lead Acid Battery ( )
14. Battery capacity (V)
    ( )
15. Average time used per day to charge the battery (Hrs).
    ( )
16. Average Distance covered per day.
    ( )

Swahili Version: Hojaji kwa Kiswahili

Hujambo, majina yangu ni Laureen Cherotich Cheruiyot. Mimi ni Mwanafunzi wa somo la Master of Science in Sustainable Energy Transitions Student at Strathmore University School of Computing and Engineering Sciences. Kwa sasa ninafanya utafiti kuhusu **'A Model for Predicting Greenhouse Gas Emissions from Motorbikes in Kenya'**. Ningependa kukuuliza baadhi ya maswali kuhusiana na pikipiki (bodaboda) unayoendesha. Maelezo utakayotoa yatakuwa muhimu katika kuchagiza mpito wa E-mobility na mikakati ya kupunguza uzalishaji wa hewa chafu inayohusiana na usafiri nchini Kenya. Ushiriki wako katika utafiti huu ni wa hiari na uko huru kujiondoa katika utafiti huu wakati wowote. Data ya utafiti iliyokusanywa itatumika tu kwa madhumuni ya kitaaluma na kushughulikiwa kwa usiri wa hali ya juu. Utambulisho wako binafsi utafichwa na utapewa jina bandia. Data ya utafiti iliyokusanywa itatumika tu kwa madhumuni ya kitaaluma na kushughulikiwa kwa usiri wa hali ya juu. Utambulisho wako binafsi utafichwa na utapewa jina bandia. Matokeo ya utafiti wangu yanaweza kupatikana kwako kwa ombi.

Utafiti utachukua kama dakika 15.

Je, uko tayari kushiriki katika utafiti?

Ndio ( ) la ( )

Jina: ________________

Sahihi: ______________________ Tarehe: ________________

<u>SEHEMU A: BIODATA</u>

1. Jinsia

Mwanaume ( ) Mwanamke ( )

2. Umri

18-35 ( ) 36-45 ( ) 46 na zaidi ( )

3. Wilaya

Nairobi ( ) Machakos ( )

4. Kiwango cha juu cha elimu

Hakuna shule ( ) Msingi ( ) Sekondari ( ) Chuo ( ) Chuo Kikuu ( )

5. Umekuwa mwendeshaji pikipiki kwa muda gani?

Chini ya mwaka 1 ( ) Miaka 1-3 ( ) Miaka 4-5 ( ) Zaidi ya miaka 5 ( )

<u>SEHEMU B: Data ya Malipo ya Pikipiki</u>

6. Umiliki wa pikipiki

Inamilikiwa ( ) Imekodishwa ( )

7. Tengeneza pikipiki

Honda ( ) Skygo ( ) Suzuki ( ) Bajaj ( ) Nyingine (Tafadhali taja):

8. Mwaka wa Utengenezaji

( )

9. Mwaka wa Usajili

( )

10. Aina ya mafuta

Petroli ( ) Dizeli ( ) Umeme ( )

11. Ukubwa wa injini (cc)

( )

12. Wastani wa kiasi cha mafuta kinachotumika kwa siku.

( )

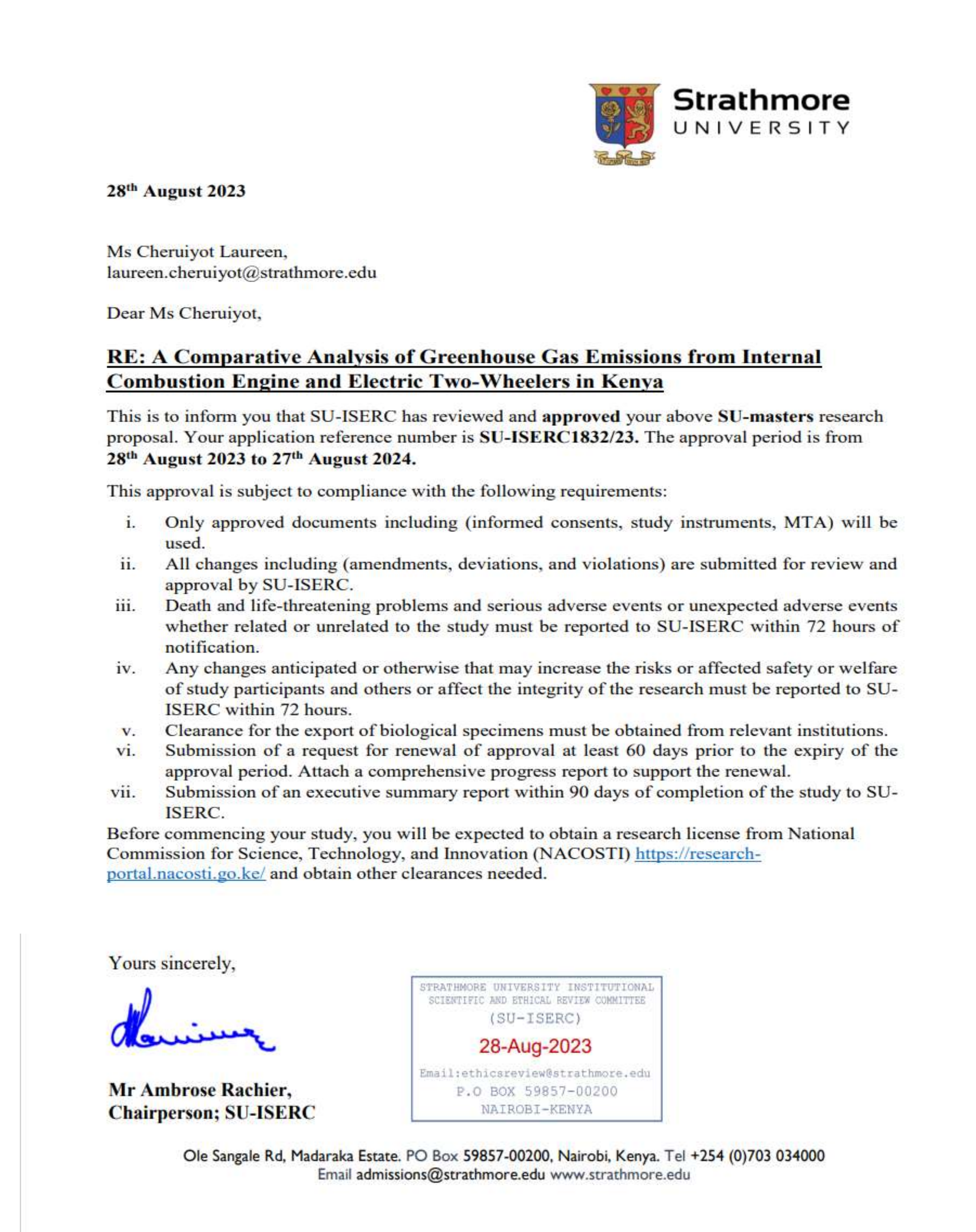
13. Wastani wa Umbali unaolipwa kwa siku.

( )

14. Kwa magurudumu mawili ya umeme, Wastani wa muda unaotumika kwa siku kuchaji betri.

( )

Appendix B: Ethical Clearance Confirmation



Strathmore UNIVERSITY

28th August 2023

Ms Cheruiyot Laureen,
laureen.cheruiyot@strathmore.edu

Dear Ms Cheruiyot,

<u>RE: A Comparative Analysis of Greenhouse Gas Emissions from Internal Combustion Engine and Electric Two-Wheelers in Kenya</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1832/23.** The approval period is from **28th August 2023 to 27th August 2024.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

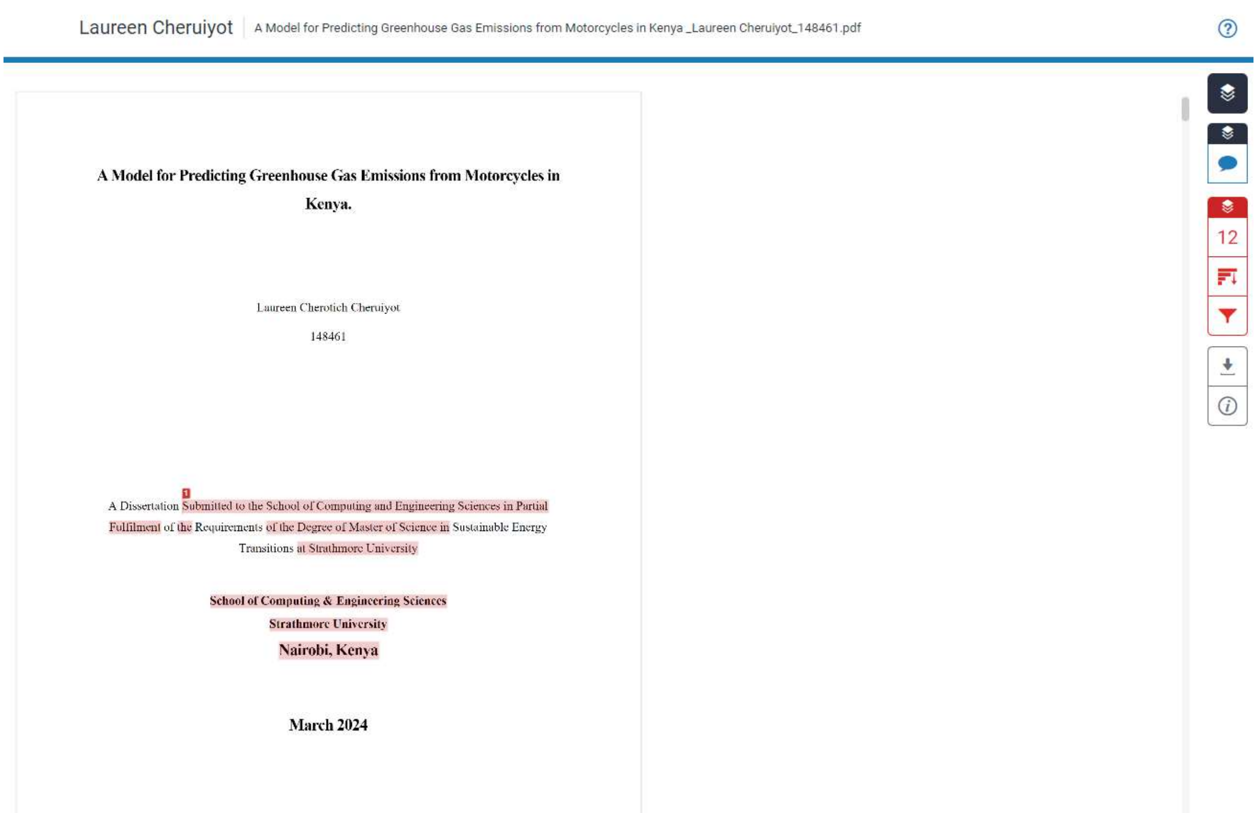
Yours sincerely,

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
28-Aug-2023
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

Appendix C: Turnitin Similarity Report



Appendix D: NACOSTI Clearance Form

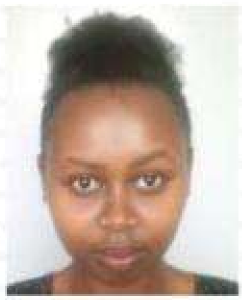
REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **209175**

Date of Issue: **05/September/2023**

RESEARCH LICENSE



This is to Certify that Miss.. Laureen Cherotich Cheruiyot of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Machakos, Nairobi on the topic: A COMPARATIVE ANALYSIS OF GREENHOUSE GAS EMISSIONS FROM INTERNAL COMBUSTION ENGINE AND ELECTRIC TWO-WHEELERS IN KENYA for the period ending : 05/September/2024.

License No: **NACOSTI/P/23/29158**

209175

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013 (Rev. 2014)

Legal Notice No. 108: The Science, Technology and Innovation (Research Licensing) Regulations, 2014

The National Commission for Science, Technology and Innovation, hereafter referred to as the Commission, was the established under the Science, Technology and Innovation Act 2013 (Revised 2014) herein after referred to as the Act. The objective of the Commission shall be to regulate and assure quality in the science, technology and innovation sector and advise the Government in matters related thereto.

CONDITIONS OF THE RESEARCH LICENSE

1. The License is granted subject to provisions of the Constitution of Kenya, the Science, Technology and Innovation Act, and other relevant laws, policies and regulations. Accordingly, the licensee shall adhere to such procedures, standards, code of ethics and guidelines as may be prescribed by regulations made under the Act. or prescribed by provisions of International treaties of which Kenya is a signatory to
2. The research and its related activities as well as outcomes shall be beneficial to the country and shall not in any way;
    i. Endanger national security
    ii. Adversely affect the lives of Kenyans
    iii. Be in contravention of Kenya's international obligations including Biological Weapons Convention (BWC), Comprehensive Nuclear-Test-Ban Treaty Organization (CTBTO), Chemical, Biological, Radiological and Nuclear (CBRN).
    iv. Result in exploitation of intellectual property rights of communities in Kenya
    v. Adversely affect the environment
    vi. Adversely affect the rights of communities
    vii. Endanger public safety and national cohesion
    viii. Plagiarize someone else's work
3. The License is valid for the proposed research, location and specified period.
4. The license any rights thereunder are non-transferable
5. The Commission reserves the right to cancel the research at any time during the research period if in the opinion of the Commission the research is not implemented in conformity with the provisions of the Act or any other written law.
6. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research.
7. Excavation, filming, movement, and collection of specimens are subject to further necessary clearance from relevant Government Agencies.
8. The License does not give authority to transfer research materials.
9. The Commission may monitor and evaluate the licensed research project for the purpose of assessing and evaluating compliance with the conditions of the License.
10. The Licensee shall submit one hard copy, and upload a soft copy of their final report (thesis) onto a platform designated by the Commission within one year of completion of the research.
11. The Commission reserves the right to modify the conditions of the License including cancellation without prior notice.
12. Research, findings and information regarding research systems shall be stored or disseminated, utilized or applied in such a manner as may be prescribed by the Commission from time to time.
13. The Licensee shall disclose to the Commission, the relevant Institutional Scientific and Ethical Review Committee, and the relevant national agencies any inventions and discoveries that are of National strategic importance.
14. The Commission shall have powers to acquire from any person the right in, or to, any scientific innovation, invention or patent of strategic importance to the country.
15. Relevant Institutional Scientific and Ethical Review Committee shall monitor and evaluate the research periodically, and make a report of its findings to the Commission for necessary action.

Appendix E: Steps to Fitting a Generalized Additive Model in R Software

After cleaning the data, the following steps were used to fit a GAM in R.

1. Load the {mgcv} package (Wood, 2011) in R
2. Load the clean dataset, call it 'Emissions_Data'. It should have the variables 'Emissions', 'Years', and 'FuelType'. The first 2 variables are numerical while the last is a typical R factor with two levels, i.e. Electric and Petrol.
3. Compute the k (unique number of years)
4. Create the model;

```
GAM_Emissions <- mgcv::gam(Emissions ~ s(Years,
                                          bs = "cs", fx = TRUE,
                                          k = n_years) + YuelType,
                            family = Poisson,
                            data = Emissions_Data)
```

5. Run the model and check the summary and the fit parameters;

```
Summary (GAM_Emissions)
mgcv:GAM.check (GAM_Emissions)
plot (GAM_Emissions, pages = 1)
```

6. To plot fitted values against the original values, extract the fitted values as below;

```
Emissions_Data $Original <- "Original"
Emissions_Data1 <- Emissions_Data
Emissions_Data1$Original <- "Fitted"

Emissions_Data1$Emissions <- GAM_Emissions$fitted.values

Emissions_Data_Full <- dplyr::bind_rows(Emissions_Data, Emissions_Data1)
```

7. The 'Emissions_Data_Full' can then be passed into {ggplot2} *(Wickham, 2016)* to visualize the fitted values against the original values.

```
GAM_plot <- Emissions_Data_Full %>%
  ggplot2::ggplot(aes(x = Years,
                      y = Emissions,
                      color = Original)) +
  ggplot2:geom_line (linewidth = 0.5) +
  labs (title = "Emissions by Motorbikes in Kenya: 2010 - 2022",
       subtitle = "Trend Approximation using GAM Smoother",
       x = "Year",
       y = expression (tonnes ~ of ~ CO [2] ~ per ~ day),
       color = NULL) +
  ggplot2::facet_wrap(~ FueType, scales = "free")
```

8. Optionally format 'GAM_plot' to look cleaner using the 'theme ()' function in {ggplot2}, and print the graph.