

Design and Simulation of Regenerative Braking System for Light-Duty Electric Vehicle



Teressa Gizachew Abate

A Thesis Submitted to the Department of Mechanical Engineering

College of Mechanical, Chemical, and Materials Engineering

Presented in Partial Fulfillment of the Requirement for the Master of Science in
Automotive Engineering

Office of Graduate Studies

Adama Science and Technology University

May 2025

Adama, Ethiopia

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Advisor: Dr. Ramesh Babu Nallamothe (Ph.D.)

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DECLARATION

I, hereby declare that this Master's thesis entitled “**Design and Simulation of Regenerative Braking System for Light Duty Electric Vehicle**” is my work and has not been submitted to any university for a similar purpose. Proper citations duly recognize the references used in this proposal.

Teressa Gizachew Abate

Name of Student

Signature

Date

RECOMMENDATION

I, the major advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled “**Design and Simulation of Regenerative braking system for light duty electric vehicle**” prepared under my guidance by Teressa Gizachew Abate, submitted in partial fulfillment of the requirements for Master of Science in automotive engineering. Therefore, I recommend submitting the revised version of the thesis to the department following the applicable procedures.

Ramesh Babu Nallamothe (Ph. D.)

Major Advisor

Signature

Date

APPROVAL PAGE

I hereby certify that the recommendations and suggestions given by the thesis review committee are appropriately incorporated into to final thesis entitled “**Design and Simulation of Regenerative Braking System for Light Duty Electric Vehicle**” by Teresa Gizachew.

_____	_____	_____
Major Advisor	Signature	Date

We, the undersigned, members of the board of examiners of the M.Sc. thesis open defense by Teresa Gizachew, have read and evaluated by thesis entitled “**Design and Simulation of Regenerative Braking System for Light Duty Electric Vehicle**” and assessed the understanding of the candidate about the thesis. This is, therefore, to certify that the thesis is accepted and we recommend the implementation of the thesis.

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ACRONYMS AND ABBREVIATIONS

EV	Electric vehicle
RBS	Regenerative Braking System
ABS	Anti-Lock braking system
HEV	Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
SOC	State of Charge of the battery
SoH	State of Health of the battery
GPS	Global Positioning System
OBD-II	onboard Diagnosis two
LDEV	Light Duty Electric Vehicle
ECA	Economic Commission for Europe
EU	European Union
CVT	Continuously Variable Transmission
PID	Proportional-Integral-Derivative
MPC	Model Adaptive Control
FLC	Fuzzy Logic Control
ANN	Artificial Neural Network
NEDC	New European Driving Cycle
FTP75	Federal Test Procedure
JC08	Japan Chassis Dynamometer Test Cycle
WLTC	World Light Vehicle Test Cycle
WHLTP	Word Harmonized Light Duty Test Procedure

ABSTRACT

Regenerative braking systems (RBS) represent an advanced energy recovery mechanism that enhances the operational effectiveness of electrical vehicles (EVs) by changing kinetic energy during slowing down into electrical energy for battery recharge. This technology significantly improves vehicle range while reducing mechanical wear on braking components and mitigating environmental impact through enhanced energy utilization. This study investigated the design and modelling of light-duty electrical vehicles regenerative braking under diverse Ethiopian road conditions, specifically analyzing the Addis Ababa to Bishoftu corridor. Three distinct driving environments, urban, suburban, and highway, were systematically evaluated to assess system performance. The research employed a Changan E-Star EV as a test platform, with real-world operational data acquired through OBD-II interface telemetry, recorded via a smartphone-based Car Scanner application. Methodologically, the study implemented a dual computational approach: (1) system modeling through Artificial Neural Networks (ANN) and MATLAB/Simulink for component and subsystem simulation, and (2) performance optimization using Response Surface Method (RSM) in Design-Expert computer software. The integrated modeling framework enabled a comprehensive analysis of energy recovery potential across varying road topographies and traffic conditions. The study identified the average efficiency of the regenerative braking system as 28.6% in urban, 23.4% in suburban route, and 22.2% in highway route using experimental driving from Ayertena (328.4km) to Bishoftu, a total of 8.26 kWh energy recovered and 33.986 kWh energy consumed. MATLAB simulation results and ANN training results ($MSE < 1$ & $R = 0.99$) indicated that the amount of recovered energy according to the proposed model was acceptable and reduced prediction error by 3%. An optimization was carried out by considering main effect factors, which included initial speed of braking, braking strength, number of braking times, and road inclination. In this finding, 1.55 kWh. Optimum energy recovered at initial braking speed of 60km/h, 0.5 % braking strength, -2.04 m.s^2 deceleration rate and -1.67 % road angle.

Keywords: Regenerative braking System, Electric vehicles, Artificial Neural Network, simulation, design, and optimization.

CHAPTER ONE

INTRODUCTION

1.1. Background of the study

The consequences of the global economic crisis and the rise of issues related to global warming raised demand for electric vehicles in an effort to decrease carbon emissions and reliance on oil (Chan, 2007). Modern transportation systems are primarily dominated by three distinct vehicle architectures, each characterized by unique propulsion mechanisms: Internal Combustion Engine Vehicles (ICEVs): Conventional vehicles powered exclusively through the combustion of fuels, Battery Electric Vehicles (BEVs), Electrified transport solutions utilizing solely electrochemical energy storage systems for propulsion and Hybrid Electric Vehicles (HEVs): Transitional technologies combining both internal combustion engines and electric powertrain components (Rind et al., 2017). Internal combustion engines lose a significant amount of energy; waste heat accounts for about 62.4% of the energy from the fuel. On the other hand, contemporary electric drivetrains exhibit exceptional energy conversion efficiency, usually converting between 59 and 62% of battery charge into power that can be used to move the wheels (Doshi & Doshi, 2015). The main factor hindering EV adoption was a phenomenon called range anxiety, which means fear among drivers that the vehicle will not reach the desired charging station. As a result, it is difficult to drive those cars on lengthy trips in rural and highway locations where the travel distance exceeds the driving range (Adnan et al., 2017).

Researchers were motivated to increase electric vehicle driving range by optimizing energy efficiency, promoting renewable energy sources for recharging the battery, rather than increasing battery capacity and electric motor, which resulted in the development of lightweight materials and improved aerodynamics (Alanazi, 2023). Similarly, in 1967, the American automotive manufacturing (AMC) invented a regeneration braking system for a theoretical electric car, the AMC Amitron, but RBS technology was initially introduced to the market by Toyota in their Prius series of hybrid vehicles. Vehicle energy recuperation systems gained popularity after being used in racing cars as an energy-saving feature (Tie & Tan, 2013). The regenerative braking system (RBS) uses its driving motor in opposite which functions in place of a generator while decelerating in order to transform kinetic energy into electrical energy. At the moment, RBS is a standard function included in all EVs to increase vehicle energy efficiency, driving safety, and range (Wager, 2017).

Regenerative braking systems were applicable in various industries, especially in transportation and cyclic working conditions (Bosch Rexroth, 2015). Regenerative braking technology first found practical application in electrified rail systems during the early 20th century, where the substantial mass of trains and frequent stop-start operations made energy recovery particularly advantageous. The technology subsequently transitioned to road transportation with the advent of modern electric vehicles (EVs), enabled by three key technological advancements. Implementing a regenerative braking system in ICEV is complicated due to irreversible energy conversion processes in ICEV compared to electric vehicles. In hybrid electric vehicles, the regeneration process starts when the vehicle is working in ICE mode, resulting in excessive power converted into electrical energy. As a result, a dual source of power is needed (Perktold, 2016).

According to reports, the regenerative braking potential of storing regenerated current ranges from 16% to 90% (Boretti, 2013). Regenerative braking can increase a vehicle driving distance by 30%, based on driving conditions, and other variable quantity (Vasiljević et al., 2022). The maximum regeneration power, varying from 50 kW for small cars to 300 kW for the most powerful based on motor characteristics, battery performance, and the model of the vehicle. Driving conditions affect a vehicle's range, whereas unbalanced load and fluctuating SOC limit the amount of regenerated current (López-López et al., 2014). RBS uses electrical motor to decelerate the vehicle, which can reduce the brake pedal feel, making it difficult to use for some drivers (Islameka et al., 2022). Driving route has an impact on RBS utilization; continuous driving without braking renders effective RBS useless for enhancing system performance, efficiency, and range (Wager, 2017). The severity of regenerative braking, battery temperature, charging rate, and SOC regulate the quantity of energy recovered. Overall engine efficiency, as well as its power, speed, and torque, affect regenerative energy (Crolla & Cao, 2012).

Ethiopia was the first country to ban the import of internal combustion engine vehicle to comply with environmental and green initiative goals and to reduce fuel consumption and shortage of fuel because half of the fuel imported in the country was consumed by vehicles, according to (MOTL,2024). While the government planned the number of EVs in Ethiopia to be 95% of ICE vehicles in the next decades, recharging the EV battery is the main problem hindering EV adoption in Ethiopia due to limited charging and road infrastructure. This study focused on design, optimization, and analysis of a regenerative braking to extend the driving distance, reducing fuel consumption and environmental pollution impact of RBS for light-duty electric vehicles, which contribute to sustainable transportation solutions within Ethiopia.



Figure 1. 1. Charging station in Addis Ababa

1.2. Statement of the problem

In Ethiopia adoption of EVs was mainly hindered by limited charging infrastructure and longer times to recharge the battery. Currently most common charging techniques are charging at home (level-1), public charging (level-2), and (level-3) DC fast charging, but in Ethiopia, there is a small number of public charging stations compared to the increasing number of electric vehicles. Additionally, shorter driving distances per single charge, lack of skilled technicians, and availability of spare parts also had a significant impact on the EV industry. Previous studies deal with increased energy storage capacity, multiple electric motors, drive train modelling, hybrid electric vehicle modelling, and regenerative braking systems to maximize EV driving range. But not all researchers have addressed the problem of Ethiopian road conditions by testing electric vehicles on actual road conditions, including urban, suburban, and highway routes. So, this thesis work addressed the gaps created by those researchers applying the distinctive driving conditions, geographic diversity, and infrastructure of Ethiopia, which make the deployment of such systems particularly difficult here. The effectiveness and efficiency of regenerative braking systems are impacted by Ethiopia's varied geography, which includes metropolitan areas, highland regions, and rural roadways. Effective handling of this fluctuation is necessary for the regenerative braking system to optimize energy recovery under various road conditions. Different driving surroundings, frequent stops, and fluctuating speeds are characteristics of the Ethiopian driving situation. To optimize energy recovery and improve vehicle efficiency, light-duty electric vehicles' (EVs') regenerative braking system was designed, simulated, and analyzed.

1.3. Objectives

1.3.1. General objective

- The general objective of the thesis work was to design, optimize, simulate, and analyze a regenerative braking system for a light-duty electric vehicle according to Ethiopian road conditions.

1.3.2. Specific objectives

- Designing light-duty electric vehicle regenerative braking.
- Simulating light-duty electric vehicle regenerative braking.
- Analyzing light-duty electric vehicle regenerative braking.
- Optimizing light-duty electric vehicle regenerative braking.

1.4. Significance of the study

The study aimed to optimize energy regeneration during deceleration which extend electric vehicle range satisfying braking regulations and safety considerations based on real driving data for light-duty electric vehicles. The findings of this study offer a promising outlook for the advancement of electric vehicle (EV) technology in Ethiopia. By simulating a regenerative braking system tailored to the Ethiopian driving conditions, significant insights were gained into optimizing energy efficiency for local conditions. This research not only reveals the potential for enhanced vehicle performance but also underscores the necessity for collaboration between government, industry stakeholders, and research institutions to foster innovation in sustainable transport solutions. Similarly, it reduces carbon emissions and increases the economic benefit of the country while addressing environmental fates.

1.5. Scope of the study

The scope of the thesis was included the following tasks:

- Developing a design framework that considered Ethiopia's particular road conditions, traffic patterns, and weather.
- The regenerative braking system's performance was simulated via the use of simulation tools using MATLAB Simulink software and ANN training in a variety of driving scenarios that are representative of Ethiopian settings.
- Developing localized insights using simulation analysis to provide insightful advice and recommendations to support Ethiopia's electric vehicle adoption and the improvement of regenerative braking systems.
- Optimization of the best suitable parameters and components using Design Expert software.

1.6. Limitations

Previous Electric vehicle-related research and literature in the case of Ethiopia was very limited since Ethiopia has no long history of EV technology, and no local driving data was available to gather relevant information on those vehicles. Instruments for the data collection system were the second limitation of this work, and awareness of Ethiopian EV technology within governmental offices and stakeholders was among the main limitations faced in this thesis work.

1.7. Organization of thesis

There were five chapters in this work. The study's aims, scope, limitations, and importance were all outlined in the first chapter, which served as an introduction to the thesis work. The second chapter discussed the literature review for the thesis, which concentrated on the research gaps. The resources and procedures needed to finish the thesis were included in the third chapter. The results and discussion of the thesis were presented in the fourth chapter. Chapter 5 concluded with a suggestion.

CHAPTER TWO

LITERATURE REVIEW

2.1. Regenerative braking systems theory

Electric braking systems are primarily classified into three distinct methods: dynamic braking, which dissipates kinetic energy as heat through resistive elements; counter-current braking, which generates a reverse torque by reversing motor polarity for rapid deceleration, and regenerative braking enhances electric vehicle (EV) efficiency by recovering kinetic energy during slowing down, transforming it into electric energy to charge the battery, offering superior energy efficiency compared to other methods (Wager, 2017). Unlike traditional braking systems, which dissipate energy as heat through friction, RBS reduces mechanical wear, prolonging brake component lifespan (Saiteja et al., 2022). The system operates by applying negative torque via the electric motor, simultaneously slowing the vehicle and storing reusable energy (Patil et al., 2018). RBS can be classified into three basic categories depending on their energy conversion and storage mechanisms (Tawadros et al., 2014).

Mechanical regenerative braking

Mechanical kinetic energy recovery systems (KERS) utilize a flywheel mechanism coupled to the vehicle's drivetrain through a clutch system. During braking, the kinetic energy is transferred to accelerate flywheel, converting motion into rotational energy storage while simultaneously braking the vehicle. Conversely, during acceleration, the flywheel's stored angular momentum is transferred back to the drivetrain, providing supplemental torque to assist the powertrain. This bidirectional energy transfer creates a closed-loop mechanical energy recovery system that enhances overall vehicle efficiency (Tawadros et al., 2014). However, integrating KRES into to small vehicle was difficult (Boretti, 2011) .

Electrical regenerative braking

Electrical regenerative braking utilizes an electric machine (motor/generator) to transform a kinetic energy into electricity during slowing down, and stored as chemical energy in the battery. During acceleration, this energy is converted back to electrical energy to power the motor. However, this system suffers from relatively low round-trip efficiency due to cumulative losses across multiple energy conversions. Additionally, efficiency is further constrained by battery-specific energy limitations and packaging challenges, as optimal energy recovery requires careful integration of power electronics, motor control, and energy storage systems within the vehicle's design framework. Despite these drawbacks, electrical regeneration remains the most widely adopted method due to its compatibility with existing electric drivetrains and scalability across vehicle types (Cross, 2009).

Hydraulic regenerative braking

Hydraulic regenerative systems utilize a fluid-based mechanism that includes a low-pressure reservoir, a hydraulic pump/motor, and a high-pressure accumulator. During deceleration, kinetic energy drives a pump to transfer fluid from the reservoir into the accumulator, compressing an inert gas to store energy. The pressurized fluid reverses flow through the hydraulic motor during acceleration, delivering energy back to the drivetrain. While cost-effective for heavy-duty applications due to robust components and manageable weight impact, these systems face limitations in energy density and require higher maintenance than electrical systems. Their suitability for buses and commercial vehicles stems from durability under frequent stop-start cycles, despite lower efficiency than battery-based regeneration (Tawadros et al., 2014).

Components of regenerative braking systems

RBS comprises five core components: (1) an actuator (typically an electric machine, hydraulic pump-motor, or continuously variable transmission) that converts kinetic energy into storable energy forms during deceleration; (2) an energy storage device (batteries, ultracapacitors, flywheels, or hydraulic accumulators) to retain recovered energy; (3) a control unit to maximize the distribution of torque between friction and regenerative braking; (4) sensors to monitor variables like speed, torque, and state of charge; and (5) software algorithms to manage energy recuperation efficiency. This integrated design ensures adaptive energy recovery across diverse driving conditions while maintaining braking performance (Szumska, 2025).

2.2. Regenerative braking classification and requirements

To ensure safe deceleration, braking force is distributed between the electric motor, friction brakes (front/rear), and regenerative braking according to EU regulations (ECE 13H/13.11). These classify regenerative braking into: Category A (throttle-release activation only), Category B Non-Phased (parallel blending of regenerative and friction torque simultaneously), and Category B Phased (series strategy prioritizing regenerative braking until supplemental friction is needed). For Category B systems, regulations mandate: (1) friction brakes must compensate for regenerative torque variations (e.g., from battery state of charge or motor temperature), and (2) ABS must actively control regenerative torque while maintaining wheel adhesion (UN Regulation No 13H, 2023). This ensures consistent braking performance while maximizing energy recovery (UN Regulation No 13H, 2023).

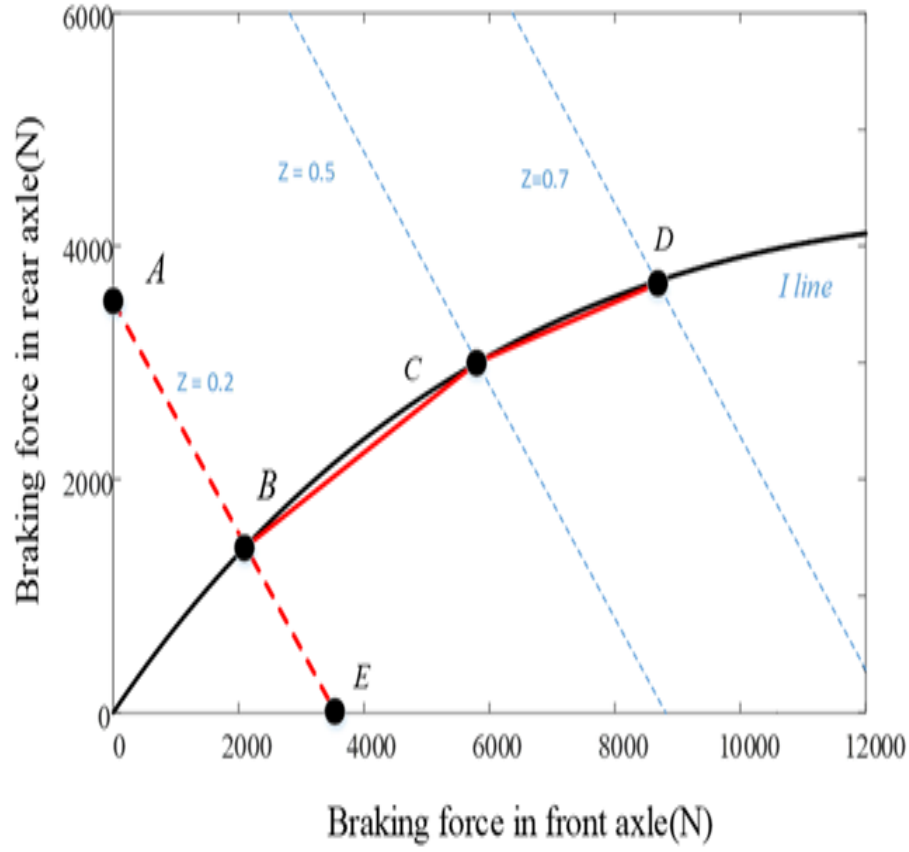


Figure 2. 1. Braking force distribution curve diagram (Ali et al., 2017)

2.3. Control Algorithms

The regenerative braking control algorithm processes real-time sensor data (vehicle speed and brake pedal position) to calculate the required braking intensity (Szumska, 2025). The central brake controller links the actuator and energy storage device, monitoring wheel speed, determining optimal braking torque, and directing recovered energy to storage (Yoong et al., 2010). This controller converts driver pedal inputs into operational commands while employing advanced control algorithms to optimize energy recovery, ensure smooth deceleration, and maintain braking effectiveness.

Fuzzy logic control (FLC)

FLC optimizes regenerative braking by dynamically distributing torque between electrical and mechanical systems based on real-time inputs (speed, brake pedal position, battery state-of-charge) and predefined rules (Nian et al., 2014). The system adapts to driving conditions, prioritizing rapid deceleration for hard braking or energy recovery for gentle stops (Aswathi E.R. et al., 2018). While hybrid FLC-PID controllers enhance torque allocation precision, Reinforcement learning further refines FLC models using field data (Çeven et al., 2020), and fuzzy slip-ratio control prevents wheel lock in ABS (HongWen et al., 2018). Though FLC has inherent limitations in maximizing torque distribution efficiency.

Artificial Neural Network (ANN)

Neural networks (NNs) offer advanced control for regenerative braking through their self-learning, adaptive, and non-linear processing capabilities (Cao et al., 2007). Comprising input, hidden, and output layers, NNs analyze real-time data (speed, brake pedal position, battery state-of-charge) to optimize braking torque distribution (Vodovozov et al., 2021). Unlike fuzzy logic systems, NNs minimize reliance on predefined rules, instead using trained models such as radial basis functions with backpropagation to dynamically adjust PID parameters and predict optimal front-wheel braking force (Saiteja et al., 2022). However, NN performance depends heavily on training quality; inadequate data can compromise energy recovery efficiency and vehicle stability. While NNs maximize motor efficiency for energy recuperation, they struggle with steady-state tracking errors, necessitating supplemental model predictive control for precise future-state adjustment under varying conditions.

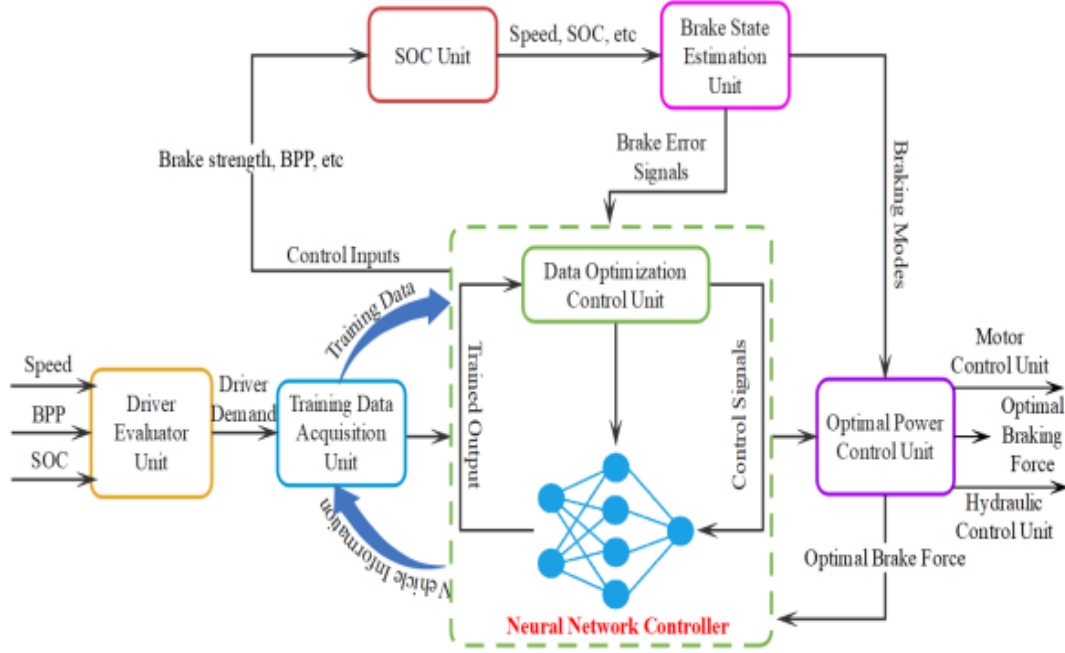


Figure 2. 2. ANN to control RBS for EV (Saiteja et al., 2022).

Model Predictive Control (MPC)

MPC is a sophisticated control strategy which optimizes braking performance by predicting future vehicle states (speed, road conditions, battery SOC) over a defined horizon. This approach calculates the optimal balance between regenerative and friction braking while adhering to system constraints (Sajadi-Alamdari et al., 2019). MPC's predictive capability enables proactive adjustments, making it ideal for complex automotive systems like RBS. The process involves inputting real-time sensor data into a prediction algorithm and generating optimized outputs for braking power distribution. Its ability to anticipate driving conditions and adapt control actions ensures efficient energy recovery without compromising safety.

Adaptive control

Adaptive controllers dynamically adjust their control laws to accommodate unpredictable system variables, which includes deceleration demand, speed, and battery SOC (Saiteja et al., 2022). These systems utilize a driver model unit to process real-time inputs and an optimal power control unit to distribute braking force accordingly. While adaptive control excels at handling variable conditions, its inability to learn from historical data limits long-term optimization.

Learning-based control algorithm

Learning-based algorithms autonomously optimize regenerative braking performance through continuous self-improvement. Techniques like fuzzy Q-learning adapt to diverse driving cycles, achieving optimal motor torque recovery, while hybrid approaches enable sensor-less braking control by classifying brake intensity and estimating pressures (Muñoz et al., 2017). These algorithms integrate with intelligent transportation systems via cloud platforms and vehicle-to-infrastructure (V2I) communication, leveraging real-time data to refine speed profiles and braking actions at traffic signals (Vajedi & Azad, 2016). By mimicking human learning patterns, such methods enhance energy recovery efficiency, vehicle-to-vehicle coordination, and adaptive braking strategies, demonstrating superior long-term performance in dynamic driving conditions.

2.4. Driving Cycles Analysis

Driving cycles are standardized speed-time profiles to evaluate vehicle performance with distinct applications for a vehicle running on fuel and battery powered vehicles. For EVs, drive cycles simulate propulsion systems to estimate energy consumption, predict range under varying conditions (acceleration, deceleration, traffic), and compare component configurations during development. ICE vehicles primarily use these cycles for emission and fuel efficiency testing. Conducted on dynamometer test beds, these protocols measure key parameters: traction force, battery state of charge (EVs), fuel consumption (ICEs), and emissions (ICEs). Driving cycles also enable regenerative braking analysis by quantifying recoverable energy during deceleration phases. While legislative cycles like the NEDC provide standardized test conditions for regulatory approval, real-world driving cycles offer more transient, realistic scenarios. These protocols vary globally to reflect regional differences in traffic patterns, road topography, and climate (Barlow et al., 2009).

Japan Chassis Dynamometer Test Cycle (JC08)

JC08 evaluates light vehicles less than 3,500 kg through two phases: a 25% cold-start segment and a 75% hot-start segment. This 1,204-second cycle covers 8.171 km, reaches average speed at 24.4 km/h and peak speed at 81.6 km/h. Designed to reflect urban and highway conditions, the JC08 standard assesses emissions, fuel efficiency, and energy consumption for electric vehicles under realistic Japanese driving patterns.

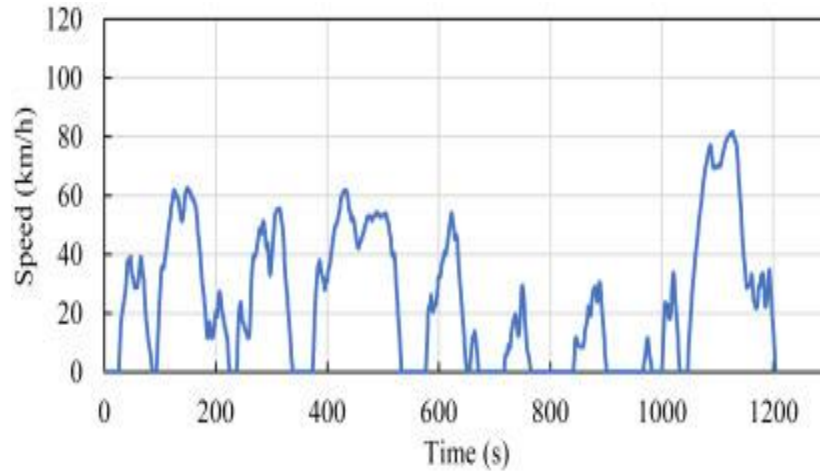


Figure 2. 3. JC08 drive cycle

Federal Test Procedure (FTP75)

The FTP-75 standard evaluates light-duty vehicles through three phases: cold start (505 s), stabilized operation, and hot start (505 s). This 2,474-second cycle achieves average speed at 25.6 km/h and, peak speed at 91.2 km/h. Designed with pronounced speed variations; it rigorously tests emissions and fuel efficiency under urban driving conditions.

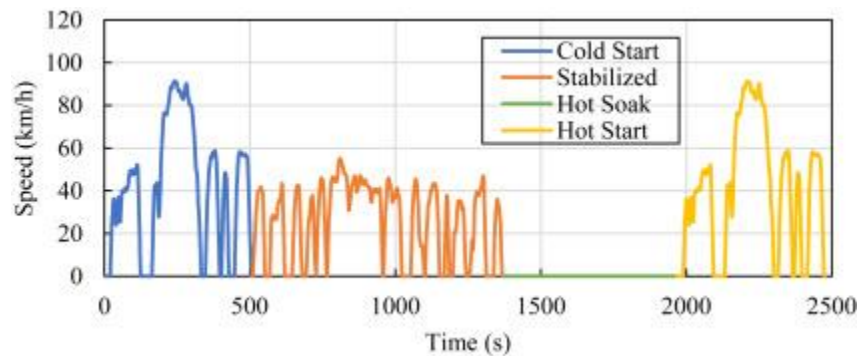


Figure 2. 4. FTP75 driving cycle

New European driving cycle (NEDC)

NEDC evaluates light-duty vehicles through two phases: urban (4×ECE15 cycles) and extra-urban (EUDC) driving conditions. This 1,180-second cycle (avg. speed 33.3 km/h, max 120 km/h) begins with 780 seconds of urban simulation before transitioning to highway conditions. Designed for European regulatory testing, it assesses emissions and fuel efficiency across diverse driving scenarios.

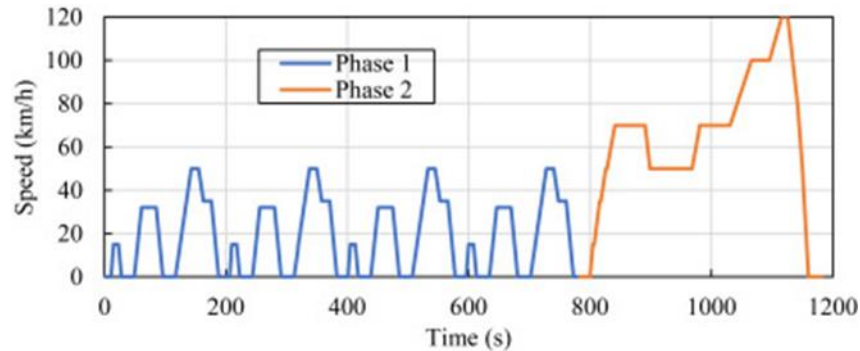


Figure 2. 5. NEDC driving cycle

Worldwide harmonized light vehicles test procedure (WLTP)

Automotive markets have developed regional driving cycles to evaluate vehicle performance, but these standards limit global comparability. To address this, the EU introduced WLTP in 2017, which classifies vehicles by power-to-weight ratio (PWR) into three categories: Class 1 (PWR<22) tests low/medium speeds with phase adjustments below 70 km/h; Class 2 (PWR 22-34) includes high-speed phases (adjusted below 90 km/h); and Class 3 (PWR>34) incorporates extra-high-speed segments (modified below 135 km/h). Unlike regional cycles, WLTP ensures uniform global benchmarking by tailoring tests to vehicle capabilities while maintaining standardized evaluation criteria.

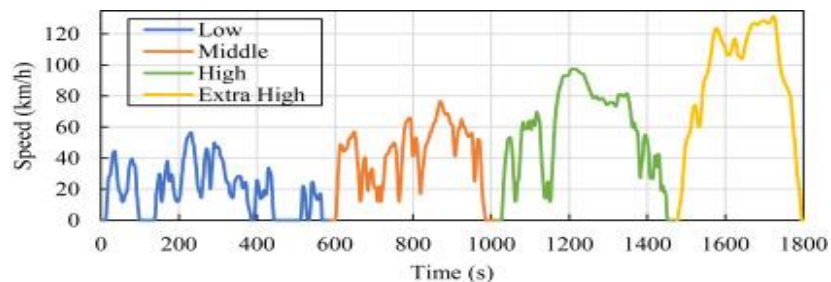


Figure 2. 6. WLTP driving cycle

2.5. Summary of literature related to Regenerative Braking Systems

Recent research on regenerative braking systems (RBS) demonstrated their critical role in enhancing electric vehicle efficiency, with studies showing 15-30% energy recovery during deceleration (Wager, 2017). Advanced control strategies like fuzzy logic (Geng et al., 2021) and neural networks (Rezk & Abuzied, 2023) Optimize performance by balancing multiple variables, which include vehicle speed, applied braking intensity, and battery SOC, while hybrid energy storage using batteries along with supercapacitors achieve up to 88% conversion efficiency (Zou et al., 2015) . However, implementation challenges persist, including battery degradation risks from high charging currents (Balagopal & Chow, 2015) , system complexity (Nanda Kumar & Subramanian, 2019) , and variable real-world conditions like road gradient (Bian & Qiu, 2018), That affects braking force distribution. Current research focuses on adaptive algorithms and hybrid storage solutions to improve RBS performance across diverse driving scenarios, with findings confirming significant benefits for vehicle range and energy efficiency when properly implemented and managed.

2.6. Research gap

While existing research on regenerative braking systems (RBS) has predominantly targeted medium and heavy-duty EVs, but still there is a big need in optimized solutions for light-duty electric vehicles (LDEVs), particularly in developing regions like Ethiopia. The design of lightweight, cost-effective RBS for LDEVs must account for critical factors such as vehicle weight, energy efficiency, and challenging road conditions elements, often overlooked in conventional studies. Recent advancements in battery technology and motor efficiency now enable the development of more compact and adaptive regenerative braking systems, which could be tailored to local infrastructure needs. This thesis addresses this research gap by evaluating RBS performance under real-world Ethiopian driving conditions, including variable road angles, traffic patterns, and terrain-specific challenge factors not previously incorporated in LDEV RBS design. Unlike prior studies reliant on standardized driving cycles, this work utilizes actual local driving data to optimize energy recovery efficiency, ensuring the system is both contextually relevant and technically viable for light-duty applications in emerging markets.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Materials

(OBD-II) have been used to record selected Electric vehicle data.

Hardware

- OBD-II ELM327 (Figure 3.1).
- Test vehicle (Electric Vehicle) Changan E-star 2023 (Figure 3.4).
- Smartphone A05s Android version 14.
- Laptop HP 64-bit operating system Windows 10Pro.

Software

- MATLAB Simulink R2024b.
- Design expert software 13.
- Artificial Neural Network.
- Car scanner App.
- Orgin Pro22.



Figure 3. 1. On-board diagnostic-II ELM327 interface

Table 3. 1. Specification of OBD-II

Working	Specification
ECU protocol	ISO 15765-4 CAN (11-bit ID, 500kbaud)
ECU address	7E8
VIN	LS6A3E032NB459022
Compatibility	All 1996 and new OBD-II
Connection	OBD-port
Data acquisition	Vehicle onboard computer
Data transmission	Bluetooth/wife/USB

3.2. Method

Flow chart of the thesis work was indicated as the following Figure (3.2).

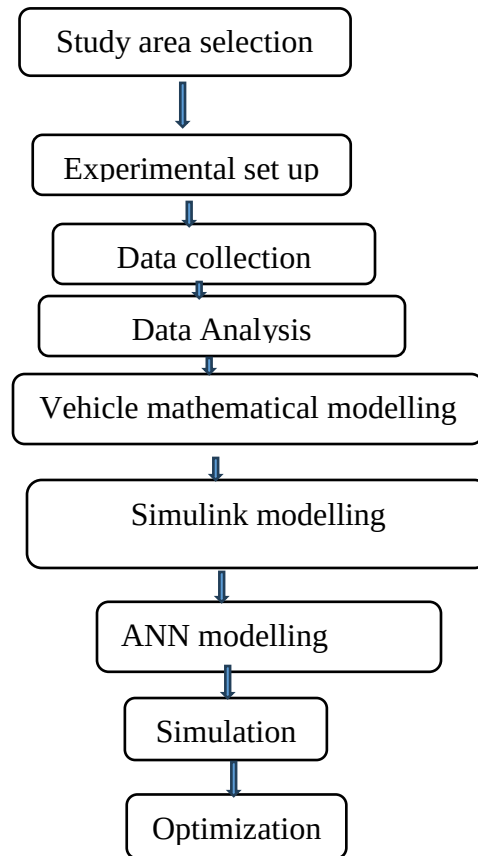


Figure 3.2. Thesis work conceptual model

3.2.1. Study area selection

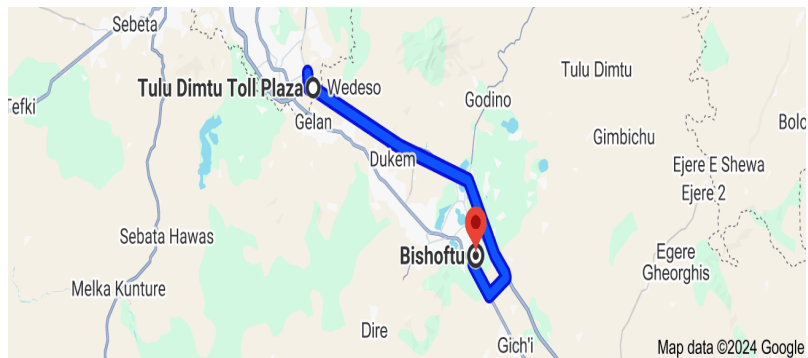
The thesis work was done in the area of Addis Ababa to Bishoftu town, which had a total distance of 82.1 km, following a two-way data collection system. The vehicle was started and driven in the direction of Ayer Tena Secondary school to Bishoftu town. This was separated into three categories to collect vehicle parameters, which include urban (19.3km), suburban (33.4 km), and expressway (29.4km), as shown in Figure 3.3. The framework used in this thesis is essentially based on a previous study, such as the WLTP, in which the route must incorporate motorway, suburban, and urban traffic. Routes were selected to capture a wide range of braking scenarios after carefully observing traffic density and road conditions in the study area (Gebisa et al., 2022).



Route 1(19.3 km via A1)



Route 2 (33.4 km via A1)



Route 3 (29.4 km via Addis Adama Express)

Figure 3. 3. Geographical location of the driving route map

3.2.2. Experimental setup

The vehicle was initially charged to 80% SOC with home-installed level 3 charger before starting the voyage. The vehicle had three driving modes: economy (prioritize energy efficiency and provide a lower level of regenerative braking), sport (highest level of regenerative braking and aggressive deceleration), and normal mode (moderate level of regenerative braking usually for everyday driving). The driver followed his usual driving habits. The regenerative braking setting of the test vehicle had two modes: B⁺, more aggressive deceleration, a stronger braking force, and more energy recovery; and B⁻, less aggressive deceleration, a softer braking force, and less energy recovery. For this thesis work light-duty electric vehicle popular in the Ethiopian market with an affordable price was tested to design and simulate a regenerative braking system, considering gross vehicle weight, load capacity, expected range, and regenerative braking system settings.



Figure 3. 4. Tested vehicle



Figure 3. 5. Locating OBD -II port

Table 3. 2. Technical specification of the tested vehicle.

Specification	Value
Model	Changan E-star2023
Type	Pure electric car
Made in	China
Body style	Hatch back
Gear type	Automatic
Number of seats	5 seat,5 door
Loading capacity	300 kg
Curb Weight	1160 kg
Wheelbase	2.4 meters
Drag Coefficient (Cd)	0.30
Top Speed	130 km/hr.
Driving range	310 km/hr.
Tyre Size	175/55 R16

Source: Changan EV specification from EV database.

3.2.3. Data collection

Primary data collected through on-road experimental test driving the vehicle starting point to the end point. The secondary data source was gathered from internet sources and publications. The driving test was performed two times, each with a total of four trips returning to the starting point along the established route. The entire data set comprised 15,840s speed-time points from 328.4 km of raw data. Data extraction was performed by connecting the OBD-II Bluetooth to a smartphone through a car scanner application.

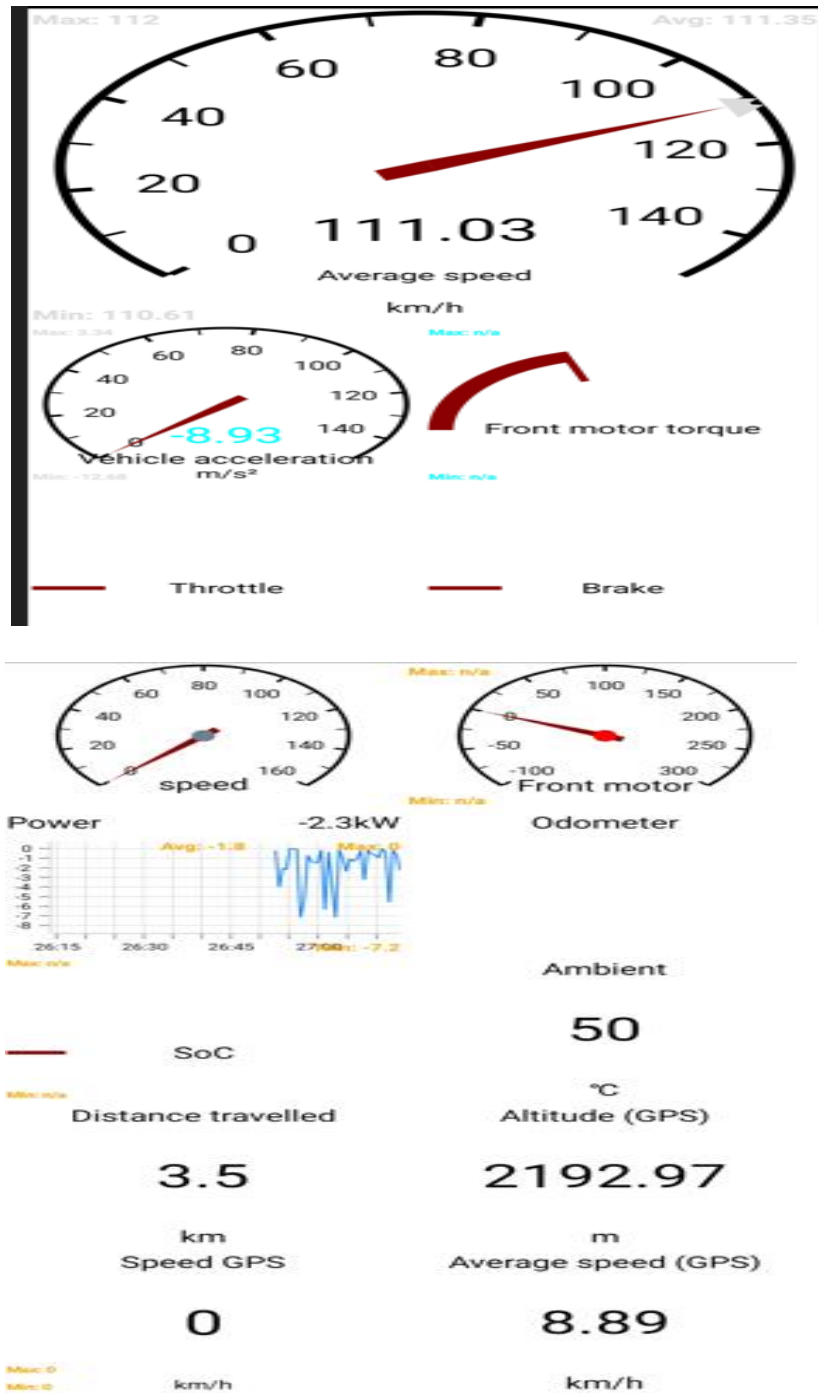


Figure 3. 6. Driving data samples



Figure 3. 7. Sample picture while collecting data

3.2.5. Data analysis

Data analysis in Excel identified variables impacting energy recovery and consumption, including vehicle speed, braking intensity, and road inclination during deceleration.

Vehicle speed

Vehicle speed was directly related to regenerative braking energy. Braking speed less than 10km/h was neglected due to the small EMF generated at very low speed not sufficient for the EV traction motor to act as a generator, regenerative braking at very low speed was not effective, so that braking was achieved only by conventional braking above 10km/h threshold (Szumska, 2025). The first route was characterized by frequent acceleration, braking, and stopping due to high traffic density. A total distance of 19.3km was selected to represent urban driving. Initial braking speed throughout the entire route was recorded. The average speed was in the range between 10 and 60 km/h. The second route had a total distance of 33.4km. The trip was characterized by intermittent braking due to a high percentage of speed limiters between 30-50 km/h and ring roads. An average speed of the vehicle was calculated from the entire dataset, and it was between 45-70km/h. The third route had a total distance of 29.4km/h with an average speed range between 90-120km/h, characterized minimum number of braking pedal usage.

Road condition

Ethiopian road condition was mixed terrain urban, rural roads and mountain having unique demand for braking and energy recovery. Efficiency of regenerative braking on flat road was 48% and on downhill 85%. 0 indicates flat road, positive was uphill and negative implies downhill. The road angle affected regenerative braking and energy usage. While downward (negative angles) could permit more regenerative braking, uphill (positive angles) would use more energy.

Braking and acceleration behavior

Energy recovery is prioritized over mechanical braking at the speed of 118.26 km/h, with braking intensity 0.116 and 92.15% regenerative braking usage. Only 22.49% regeneration occurs at 115.90 km/h, with braking intensity 0.9, for braking safety.

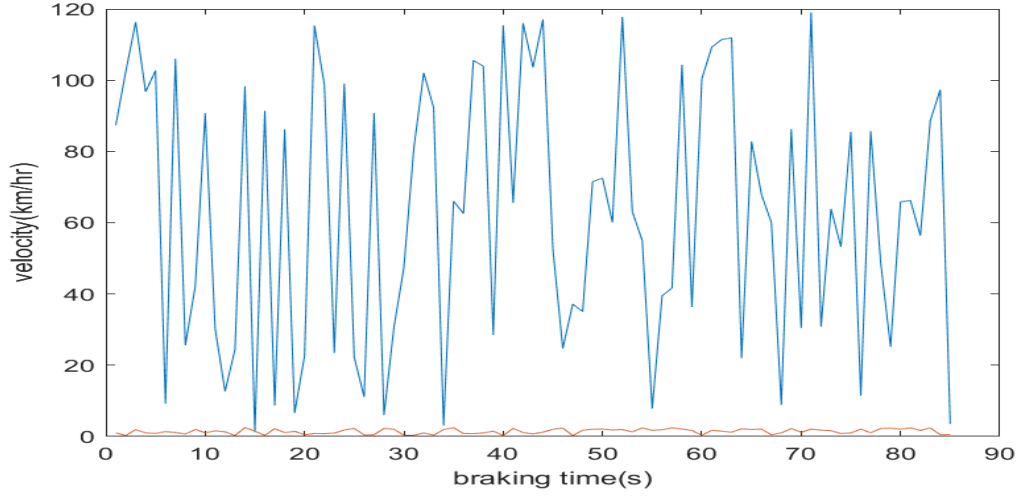


Figure 3. 8. Deceleration performance of the route

3.2.6. Vehicle mathematical modelling

In this section, vehicle dynamics, powertrain, and energy conversion mathematical modeling were presented.

Vehicle dynamics modelling

Vehicle dynamics was modeled to analyze the regenerative braking energy and components of traction power demand. Rolling resistance, aerodynamic drag, gradient resistance, and acceleration resistance were modeled mathematically to evaluate the total tractive force, power, and torque requirements of an electric vehicle for a specified test vehicle(Wager, 2017).

Rolling resistance force

$$F_{rr} = mg rrc \cos \alpha \quad \text{Eq. 3.1}$$

Where:

m, mass of the vehicle (kg); g, acceleration due to gravity (m/s^2); rrc, rolling resistance coefficient and α ; road angle (%).

Aerodynamic drag force

$$F_{ad} = 1/2 \rho_a c_d A_f V^2 \quad \text{Eq. 3.2}$$

Where:

ρ_a , density of air(kg/m^3); c_d , drag coefficient; A_f , frontal area of the vehicle(m^2) and v , speed of the vehicle(m/s).

Grading resistance force

$$F_{gr} = mg \sin \alpha \quad \text{Eq 3.3}$$

Where:

m , mass of the vehicle(kg); g , acceleration due to gravity(m/s^2) and α , road angle (radian).

Acceleration resistance force

$$F_a = \lambda m dv/dt \quad \text{Eq 3.4}$$

Where:

m , mass of vehicle(kg); v , vehicle speed(m/s) and λ , rotational inertia constant.

$$\sum F = ma \quad \text{Eq 3.5}$$

Total tractive effort (N)

$$F_t = F_{ad} + F_{rr} + F_g + F_a \quad \text{Eq 3.6}$$

Total power required (kW)

$$P_t = V \times F_t \quad \text{Eq 3.7}$$

Torque demand required

$$\tau = F_t \times r \quad \text{Eq 3.8}$$

Where:

τ , Torque (N.m); r , radius of the wheel (m) and F_t , total tractive effort (N).

Table 3. 3. Vehicle dynamics parameters

No	Parameters	value
1	Gross Mass of vehicle(m)	1160 kg
2	Gravitational acceleration(g)	9.81m/s ²
3	Rolling resistance coefficient(rrc)	0.02
4	Air density(rho)	1.25(kg/m ³)
5	Rotational inertia coefficient(lamda)	0.1
6	Drag coefficient (Cd)	0.2
7	Frontal area of vehicle (A f)	2.5(m ²)
8	Wheel radius(r)	19(m)

Source: Changan EV specification from EV database.

Energy conversion model

The amount of electricity utilized by the drive system was measured at the motor input. Similarly, the amount of electricity recovered during the braking operation was measured at the generator output. The difference between the energy used by the battery and that supplied by the braking process was noted. Following that, the results from the vehicle's onboard system were compared to the driving data. The selected driving route's energy consumption data was used directly to compute electricity use, and the equation was organized from (Kropiwnicki & Gawłtas, 2023).

Regenerative braking specific energy (Rbse)

$$Rbse = \frac{E_{reg}}{m \cdot S} \quad Eq 3.9$$

Where:

E_{reg} , total recovered energy (Wh/km); m, mass of the vehicle (kg) and S, travelled distance by vehicle (km).

The energy conversion efficiency of the regenerative braking system was

$$\rho = \eta_1 \eta_2 \eta_3 \quad Eq 3.10$$

Where:

η_1 , drivetrain efficiency (%); η_2 , motor generating efficiency (%) and η_3 , energy efficiency of wheel slip (%).

Regenerative braking efficiency was calculated using.

$$\eta_{regen} = \frac{E_{regen}}{E_{total}} * 100 \quad Eq 3.11$$

Where:

η_{regen} , efficiency of energy recovery (%); E_{total} , energy lost during braking(kWh) and E_{regen} , energy recovered through regenerative braking (kWh).

Power train modelling

An electric motor, an inverter, and an energy storage system were included in the power train modelling for RBS.

Table 3. 4. Power train specification

No	parameters	value
1	Motor type	Single PMSM motor
3	Gear box	Single-speed
4	Drive train	Front wheel drive

Source: Changan EV specification from EV database.

Battery modelling

Regenerative braking power influenced an amount of chemical energy accumulated in battery. The battery state of charge, internal resistance, and charging and discharging efficiency were all considered. SOC was high when the open-circuit voltage was high. When the SOC is high, the internal resistance of battery was low, and it also affected by temperature. Higher temperatures usually reduce the internal resistance of a lithium-ion battery (Garcia et al., 2009).

Table 3. 5. Lithium-ion battery parameters

No	Parameters	Value
1	Battery type	Lithium-ion battery
2	Battery Capacity	32.2 kWh
3	Usable capacity	31.86kWh
4	Nominal Voltage	403V
5	Battery Voltage	400 V
6	Rated capacity	5.4Ah
7	Internal resistance	100 Ω
8	Battery charge capacity	Finite

Source: Changan EV specification from EV database.

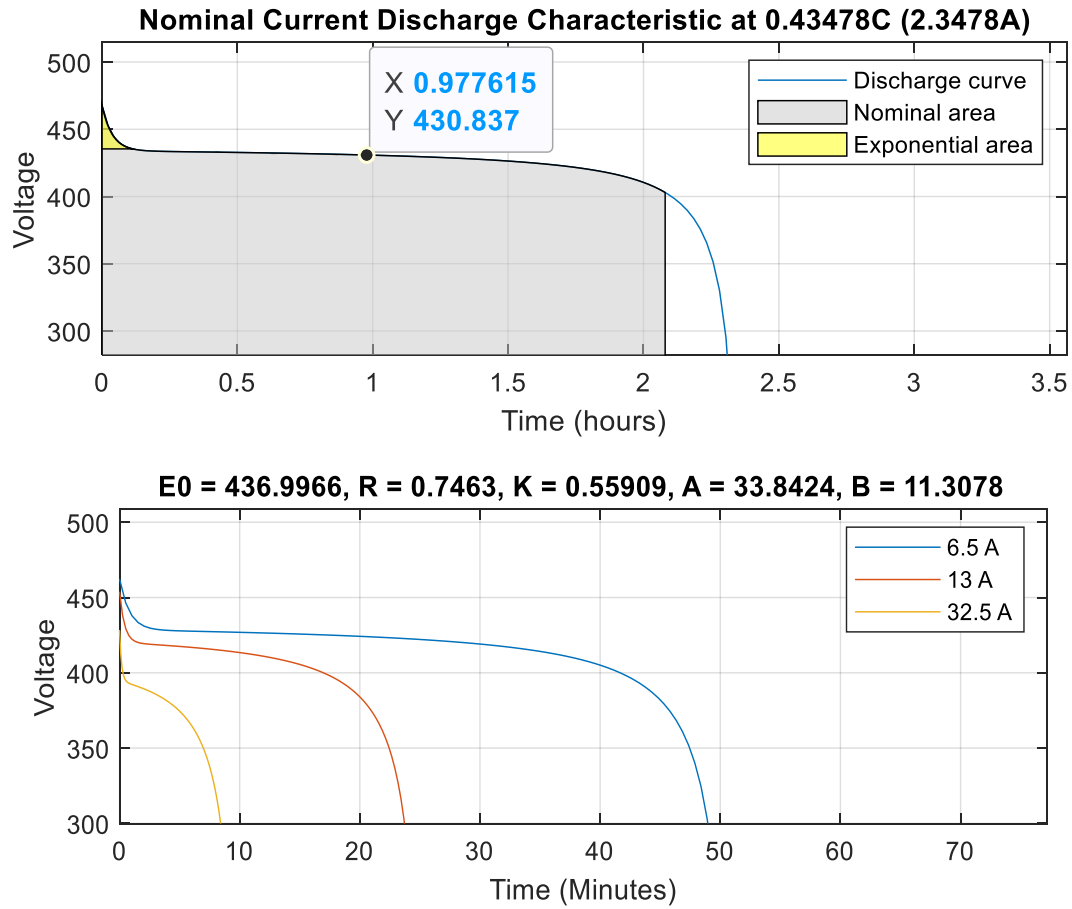


Figure 3. 9. Charging and discharging characteristics of the battery

Electric motor modelling

Permanent magnet synchronous motor was a better choice for light-duty electric vehicles due to its higher efficiency than the induction motor, being more compact and having a larger power density than the induction motor. Furthermore, it can regenerate energy at a very low speed (lower than 3 km/h) compared to an induction motor (Chen et al., 2020).

Table 3. 6. Specification of motor

No	Parameters	Value
1	Type of motor	Single PMSM
2	Maximum rated power	55 kw
3	Maximum rated torque	170 N*m
4	Maximum regen power	200kW

Source: Changan EV specification from EV database.

Back EMF is directly proportional to motor rotational speed (ω)

$$e = K_e \times \omega \quad \text{Eq 3.11}$$

Torque generated by the motor

$$\tau = k_t \times i \quad \text{Eq 3.12}$$

Electrical dynamics

$$V = L \times di/dt + R \times i + e \quad \text{Eq 3.13}$$

Where:

V, applied voltage; L, inductance of the motor; R, resistance (Ω); i, current(A) and e, back EMF.

Mechanical dynamics

$$J \times d\omega/dt = \tau - \tau_{Load} \quad \text{Eq 3.14}$$

Where:

J, moment of inertia of motor; $d\omega/dt$, motor speed and τ , external load torque.

3.2.7. Simulink model of RBS

Simulink model consists of vehicle dynamics, braking control, regenerative braking controller, and an inverter subsystem. The power and torque demand of the vehicle was determined by the vehicle dynamics subsystem, which is connected to the control and inverter subsystem. Regenerative braking control unit and inverter monitor the regeneration process and supply it to the battery. Brake control monitors, an amount of braking force applied, and motor status. The brake control was activated as magnitude of the applied braking strength was greater than zero. A brake pedal monitored the amount of braking force to simulate the effects of the applied braking intensity.

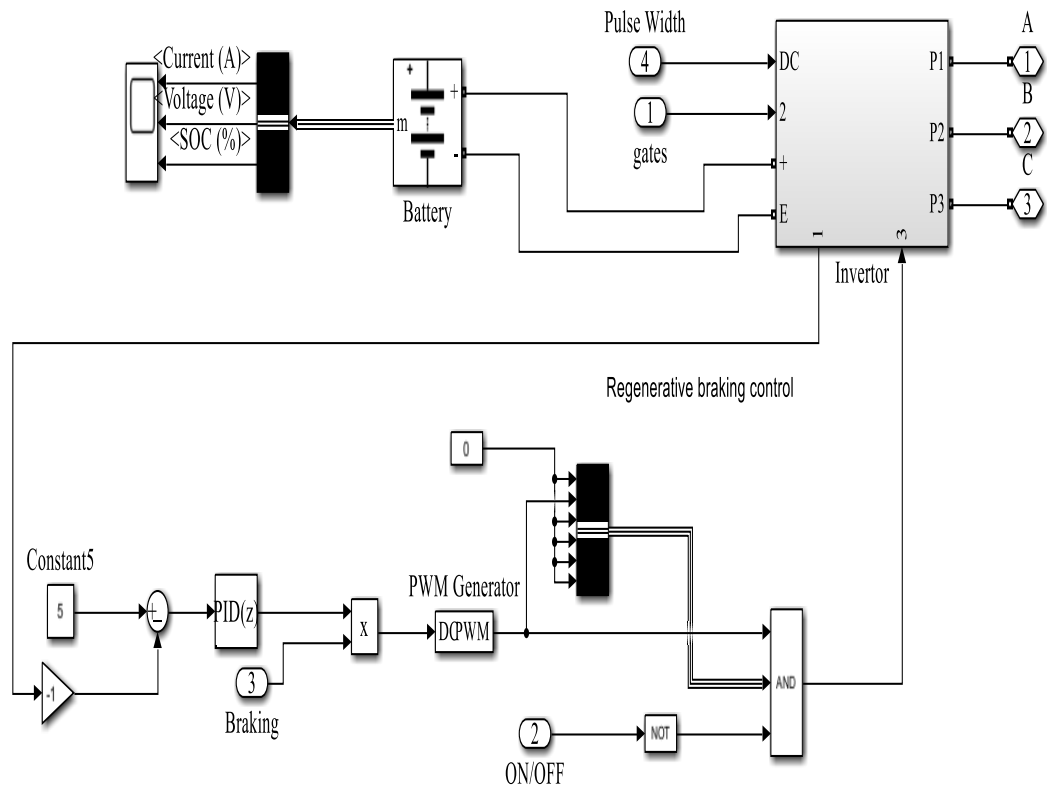


Figure 3. 11. Simulink model of regenerative braking controller and inverter

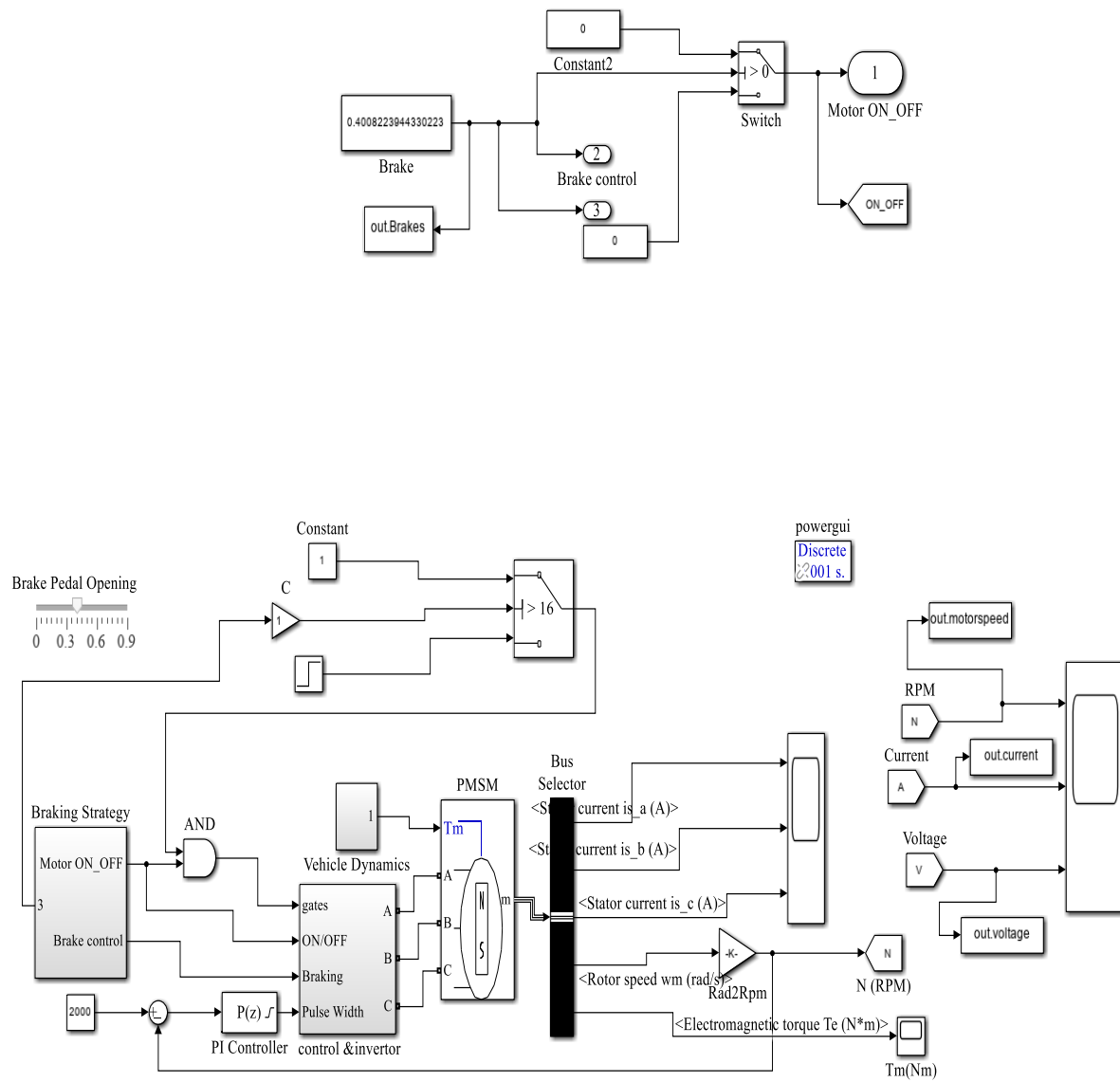


Figure 3. 12. Simulink model of RBS

Simulation test set-up

Simulation stop time was set to infinity to monitor fluctuation effect of initial braking speed, braking intensity, deceleration rate, and road angle on the regenerated energy. Input parameters were imported into the model from test vehicle driving data. Preset models were used from manufacturing specification data and standards. During the simulation run, the Minimum SOC was set to 20 % to protect the battery from discharging, and the maximum SOC was set to 80% to protect the battery from overcharging (Rezk & Abuzied, 2023). Driver demand request was monitored by brake pedal ranging from [0:0.90] with the time step size of 0.1%.

3.2.8. Artificial neural network model (ANN) of RBS

ANN is the most powerful machine learning tool in engineering areas, handling complex tasks such as predictive modelling, adaptive control, and solving artificial intelligence problems (Iglesias-San Feliz Cubero et al., 2024). In this thesis work, ANN-based regenerative braking system was modelled using Non-linear auto regressive external output neural network (NARX) in MATLAB Simulink to control regenerative braking torque due to its suitability for non-linear dynamic systems to ensure optimal energy recovery and smooth deceleration. ANN was trained to predict the action of a driver and behavior of the vehicle in different driving scenarios.

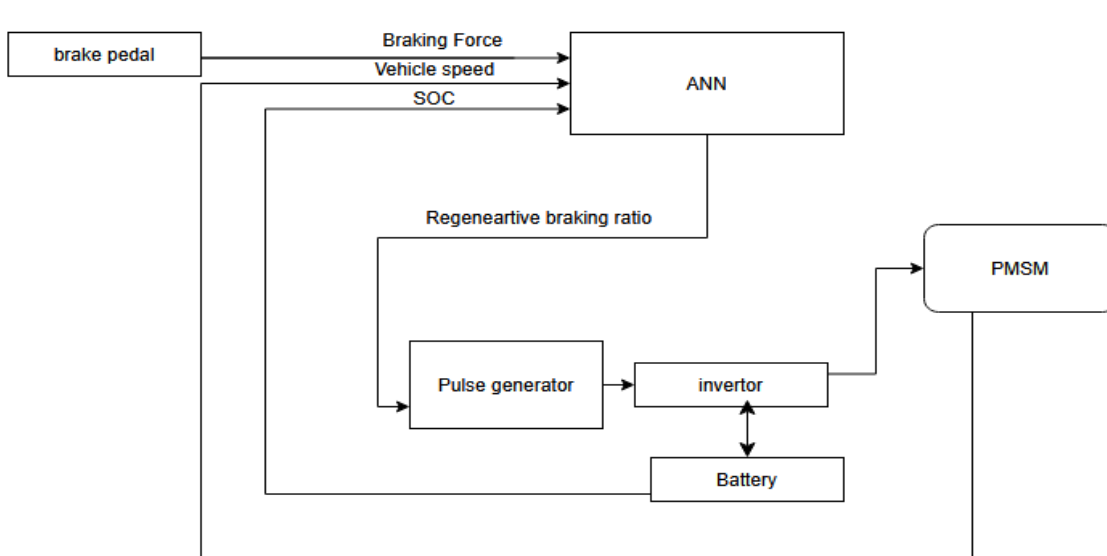


Figure 3. 13. ANN model of RBS block diagram

Defining equation for NARX model (organized from MATLAB 2024Rb Simulink documentation)

$$Y(t) = f(y(t-1), y(t-2) \dots y(t-n_y), u(t-1), u(t-2) \dots u(t-n_u)). \quad Eq\ 3.14$$

Where: the next value of output signal $y(t)$ from past values of dependent output signal $y(t)$ is regressed on measured value of output signal $y(t)$ regenerative braking torque and previous value of an independent input signal (vehicle speed of braking, braking pedal, deceleration rate and road angle).

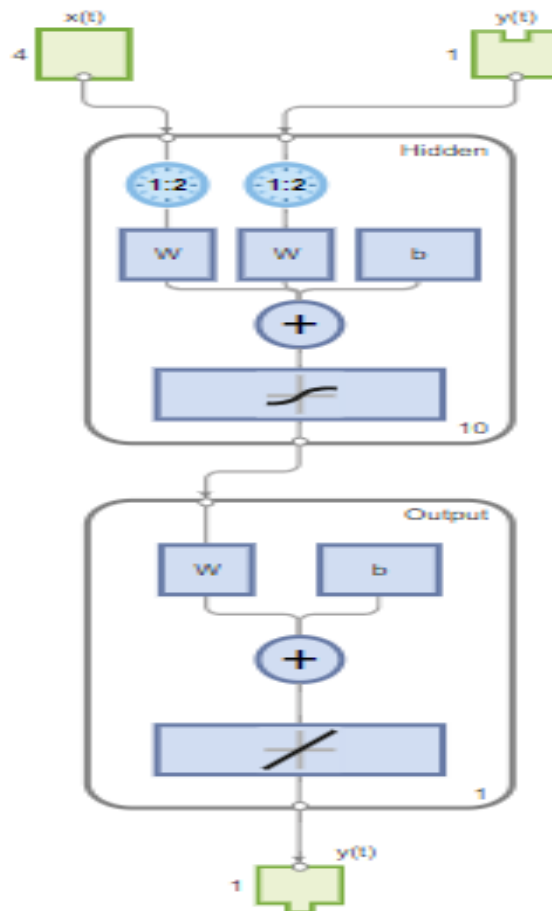


Figure 3. 14. NARX Neural Network

3.2.9. Optimization

The response surface method (RSM) joins together mathematical and statistical methods to model and optimize responses influenced by multiple variables. In this study, Box-Behnken Design (BBD), a three-level experimental design suitable for estimating first and second-order coefficients, was employed in Design-Expert software to analyze and optimize the system. The main effect factors (initial braking speed, braking intensity, deceleration rate, road angle) and response variables (regenerative braking energy) were derived from Simulink and ANN model outputs. The design comprised 24 experimental runs, each factor tested at three levels to balance efficiency and predictive accuracy.

Table 3. 7. Main factors for optimization

Factor	Name	Units	Minimum	Maximum	Mean	Std. Dev.
A	speed of the vehicle	m/s	20.69	118.26	57.00	29.11
B	braking intensity	%	0.1053	0.9726	0.6004	0.2993
C	deceleration rate	m/s ²	-3.00	2.99	0.2871	1.73
D	road angle	%	-1.96	1.89	-0.3984	1.07

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1. Results

Raw data collected

The thesis, data were collected from Ayertena to Bishoftu town using the Changan E-star EV by dividing a total study area into three main routes depending on different road conditions Table (4.1). While descending, the vehicle recovered 12% of its charge due to prolonged braking periods. However, during uphill braking, the discharge rate was 45%. In route three, the battery discharge rate was 35%. Energy Consumption was a maximum of 1.954 kWh during aggressive acceleration at 26.42 km/h and Lowest 0.104 kWh during coasting at 29.22 km/h with braking intensity of 0.722%. The maximum recovery of 98.47% was recorded at a 20.69 km/h steep downhill road angle of -1.80 in route 2. The lowest recovery of 0.79% was seen at 25.80 km/h, indicating minimal slowdown or system idleness in route 1.

Table 4. 1. Raw data collected from the test vehicle

Route	Total distance	Energy recovered (kWh)	Energy consumed(kWh)	Efficiency (%)
Route1	77.2km	2.2	7.69	28.6
Route 2	133.6km	3.04	12.936	23.34
Route 3	117.6 km	3.02	13.36	22.22

Simulink Model Results

As the simulation results showed in Figure (4.2), when vehicle speed remains constant during low acceleration starting from 0 to 0.25s, the battery SOC was remained constant. Energy recovery increased when the vehicle decelerated with increasing braking time (0.25s to 0.5s) as it received charge from the machine. Applying a medium braking force at 0.5s, the regenerated torque and current increased significantly. Conversely, during coasting steep downhill (0.5 to 0.75s) with lower braking force, the regeneration increased continuously. Applying medium braking at higher motor speed, when the vehicle's actual speed increases, also the braking time increased from 0.25s to 1.25s. during this time, the regenerated current increased optimally, which means the vehicle was running with regenerated energy, maintaining low consumption. Applying the higher braking force reduced the braking time, t value was 1.75 to 2s, which reduced the regenerated current.

Applying a medium braking force slowly from simulation time 1.25 to 2.5s increased braking time, with the optimum energy recovery observed from the simulation run Figure (4.2).

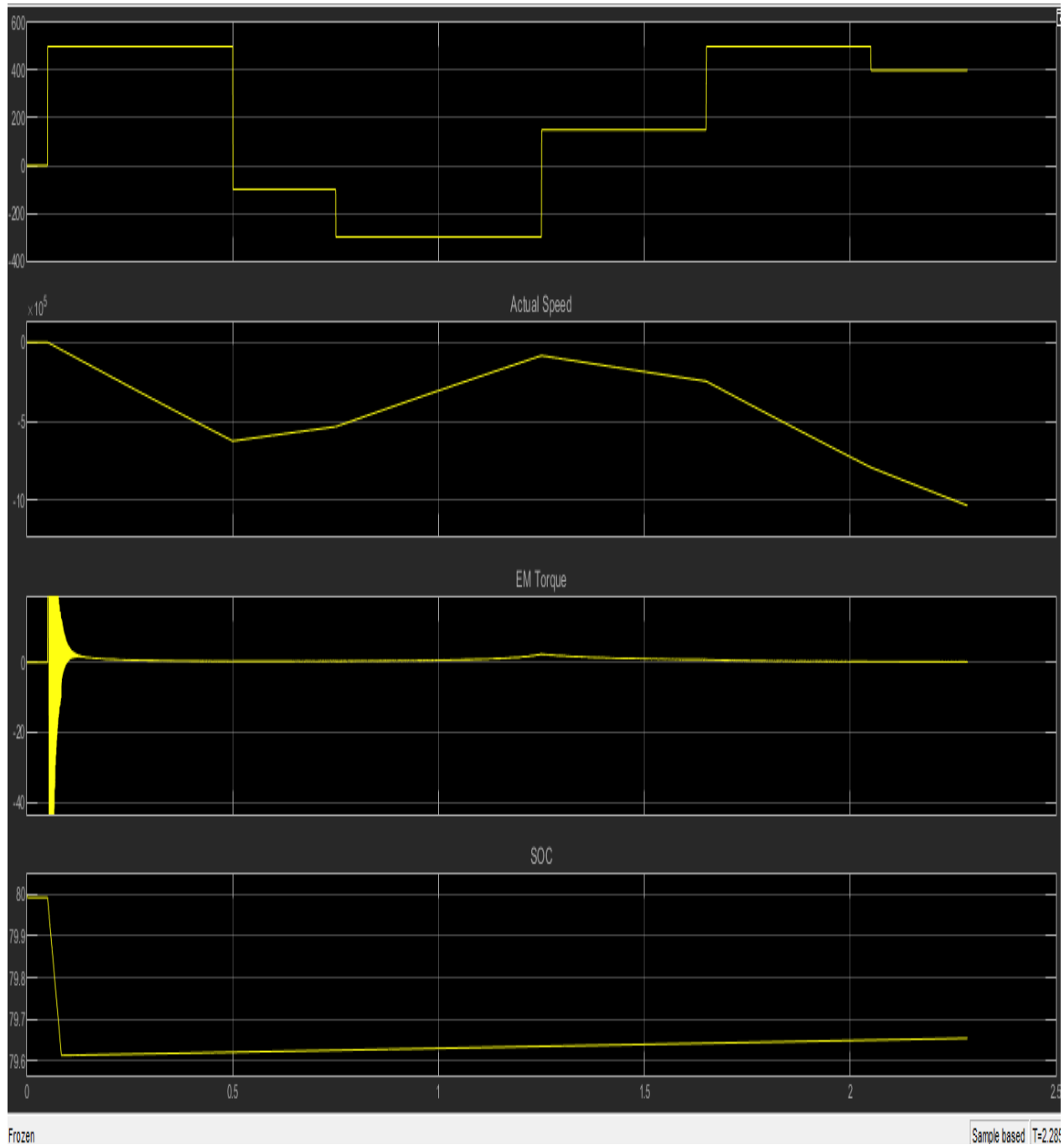


Figure 4. 1. Simulation graph

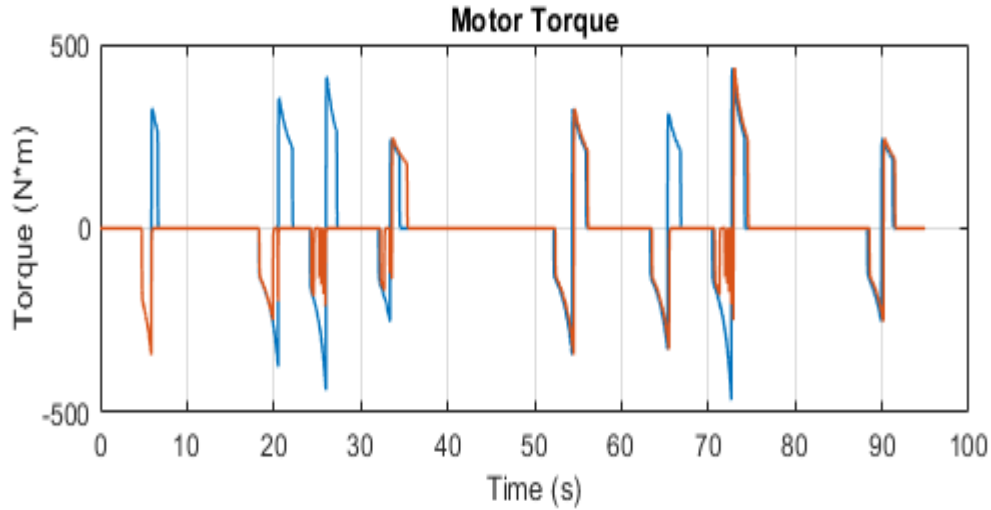


Figure 4. 2. Motor torque vs time

During regenerative braking, the motor speed decreases, converting the kinetic energy of the car into electricity. This reduction in speed correlates with the vehicle's deceleration and directly influenced the efficiency of energy regeneration through RBS. The regenerated torque values shown in Figure (4.2) range from -500 Nm during aggressive deceleration to -100 Nm during mild acceleration on route one. The braking torque applied by an electric motor during regenerative braking was indicated by negative values, which signify energy recovery.

Artificial neural network result

The ANN training successfully met the validation criteria, achieving a mean squared error (MSE) of less than 1 in training, validation, and test datasets. Additionally, regression correlation coefficient of 0.99662 confirmed the model's high efficiency. To further validate the model's performance, the trained network was exported to the MATLAB workspace. The training process utilized the Levenberg-Marquardt algorithm with an average error (MSE) as the performance metric. The training conducted on a dataset composed of 70% training, 15% validation, and 15% test data obtained from raw data, completing at 12 epochs. The best validation performance of 0.345 was achieved at 12 epochs.

Vehicle_speed,braking intensity,SOC,decc,rate

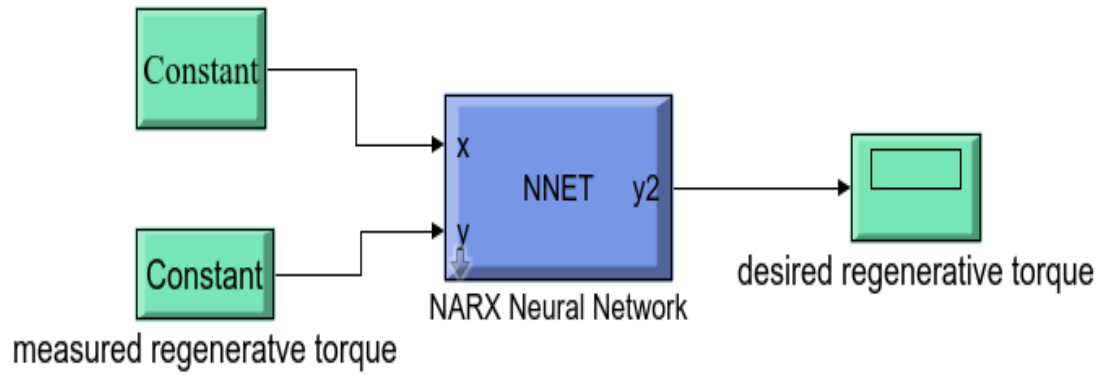
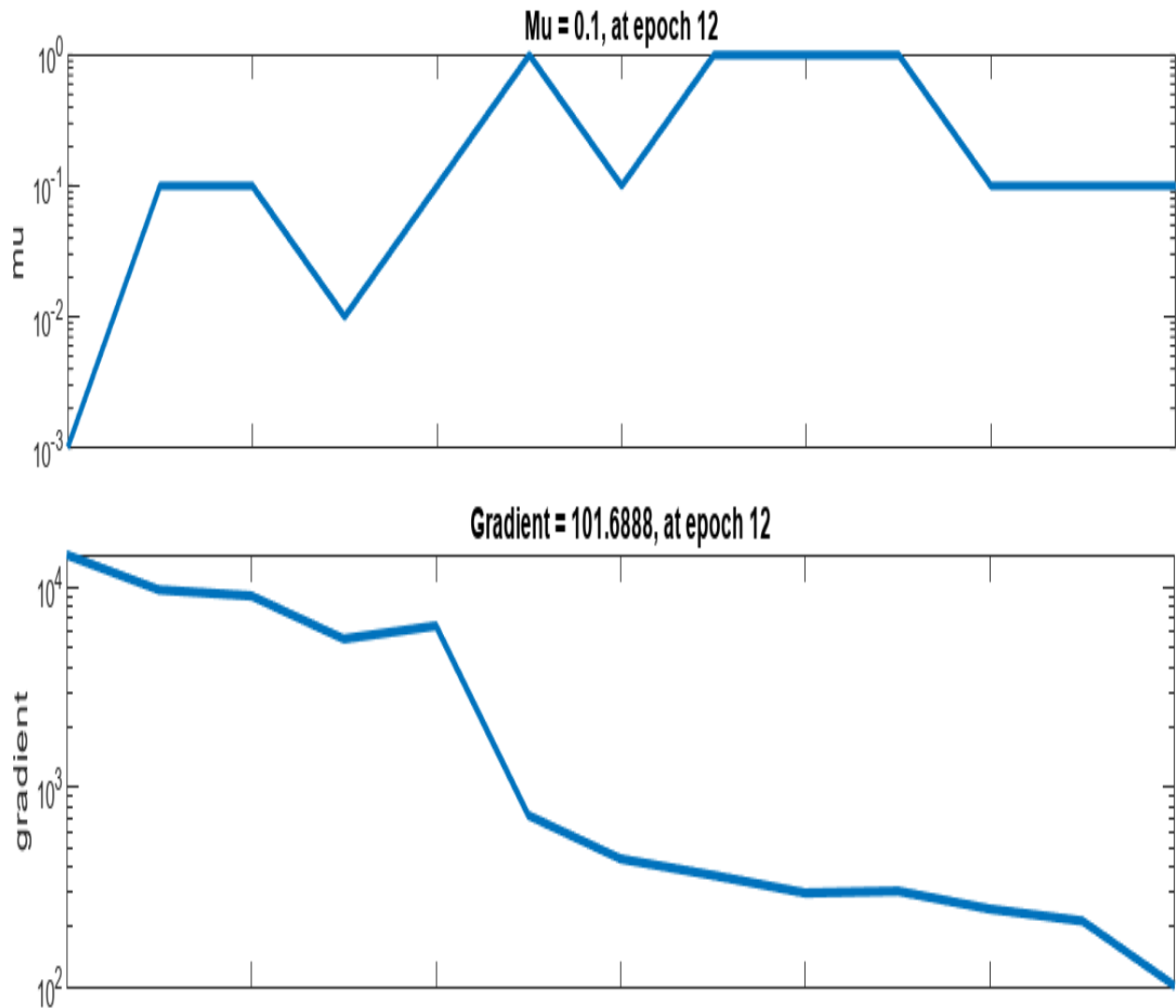


Figure 4. 3. NARX model



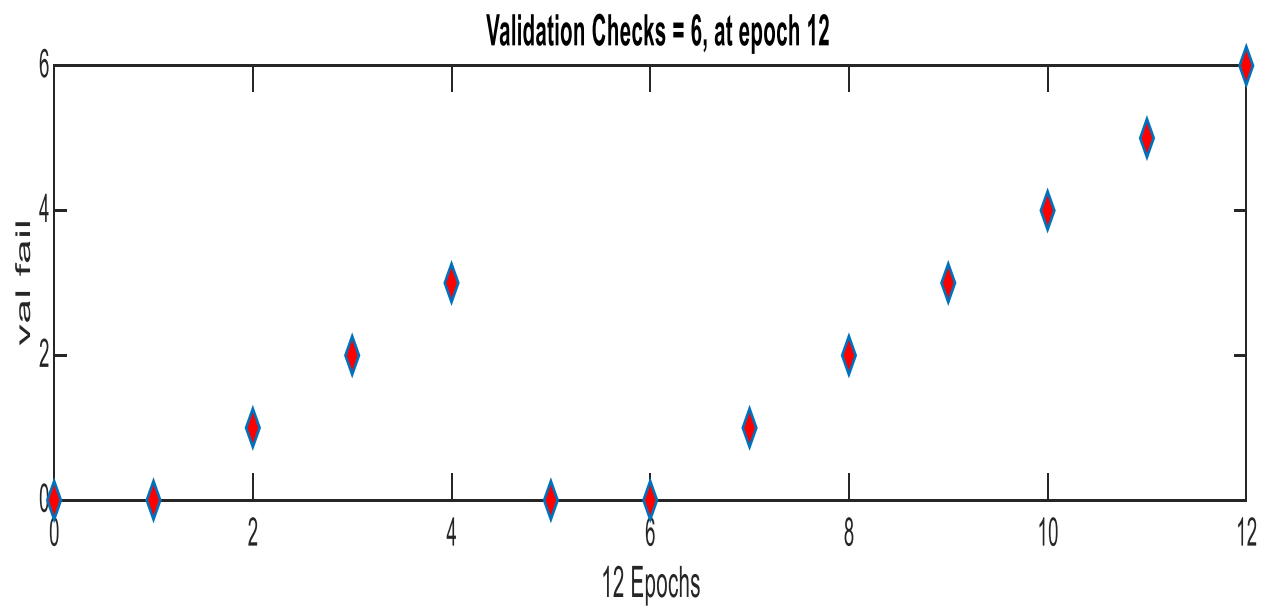


Figure 4. 4. Training state

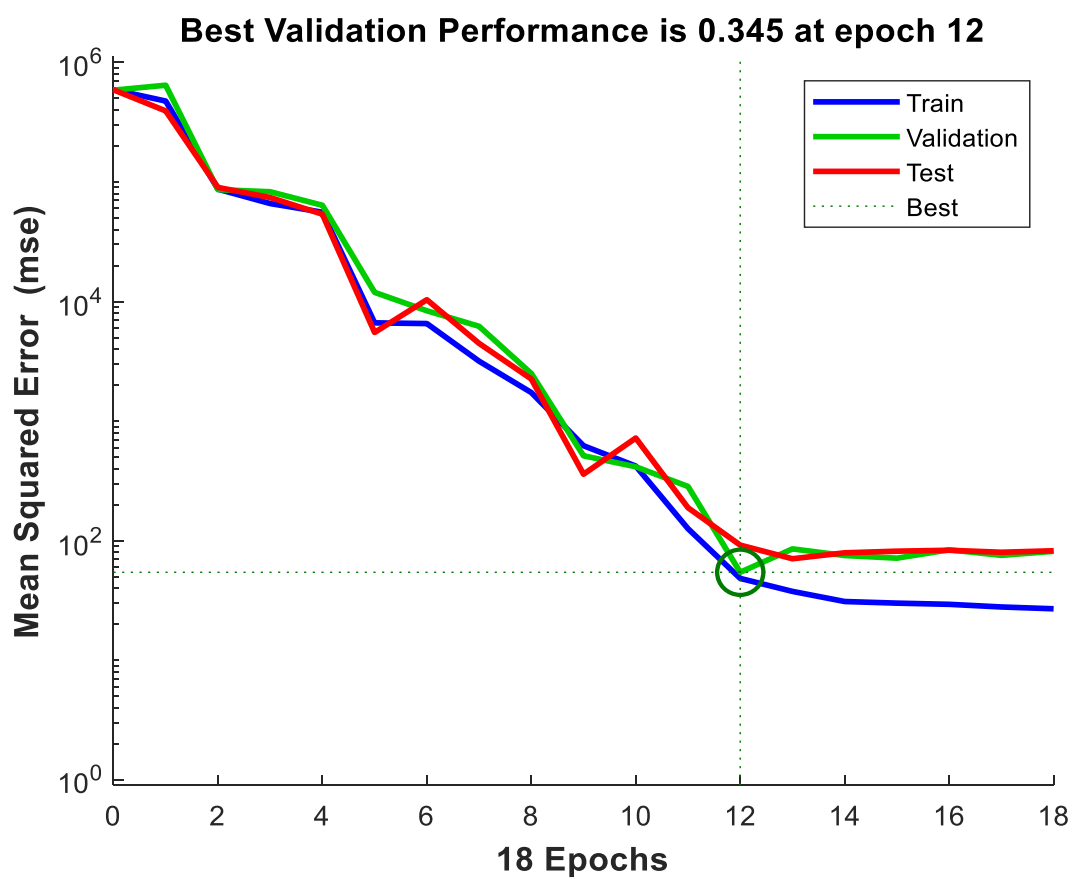


Figure 4. 5. Best validation performance

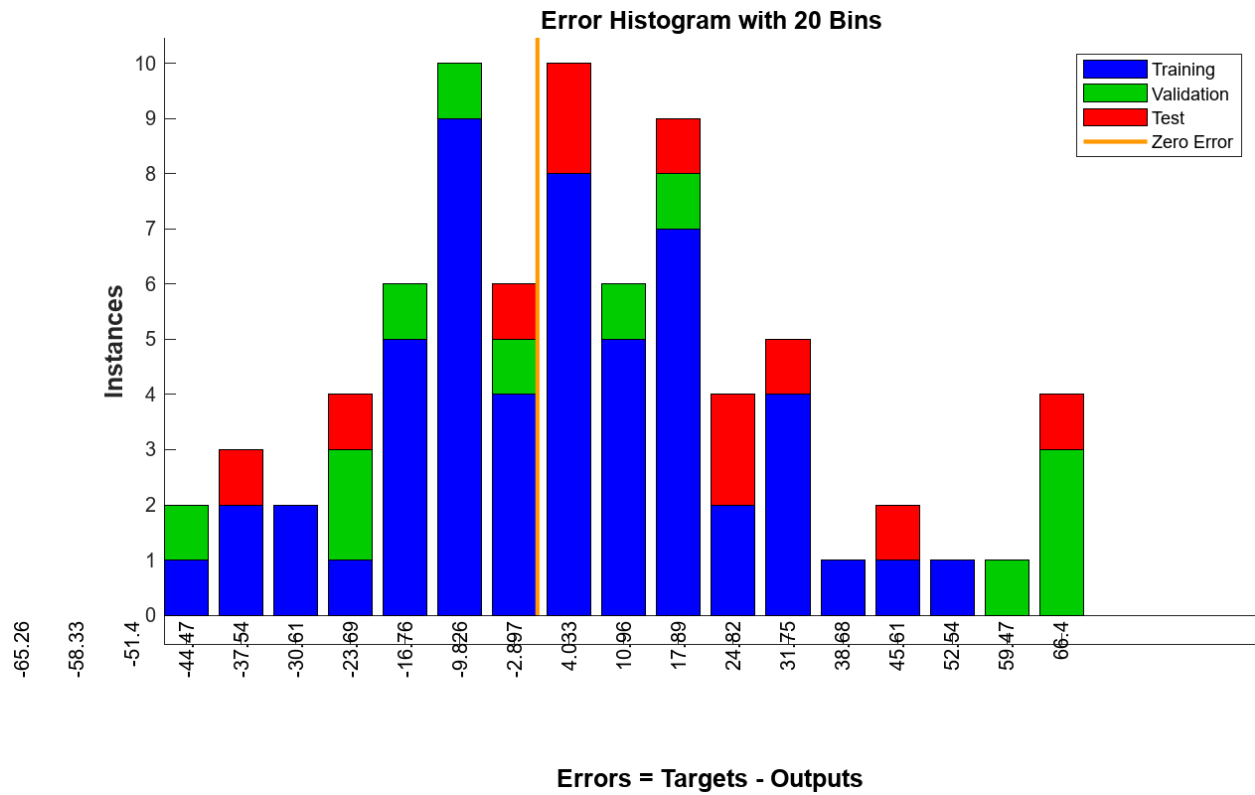
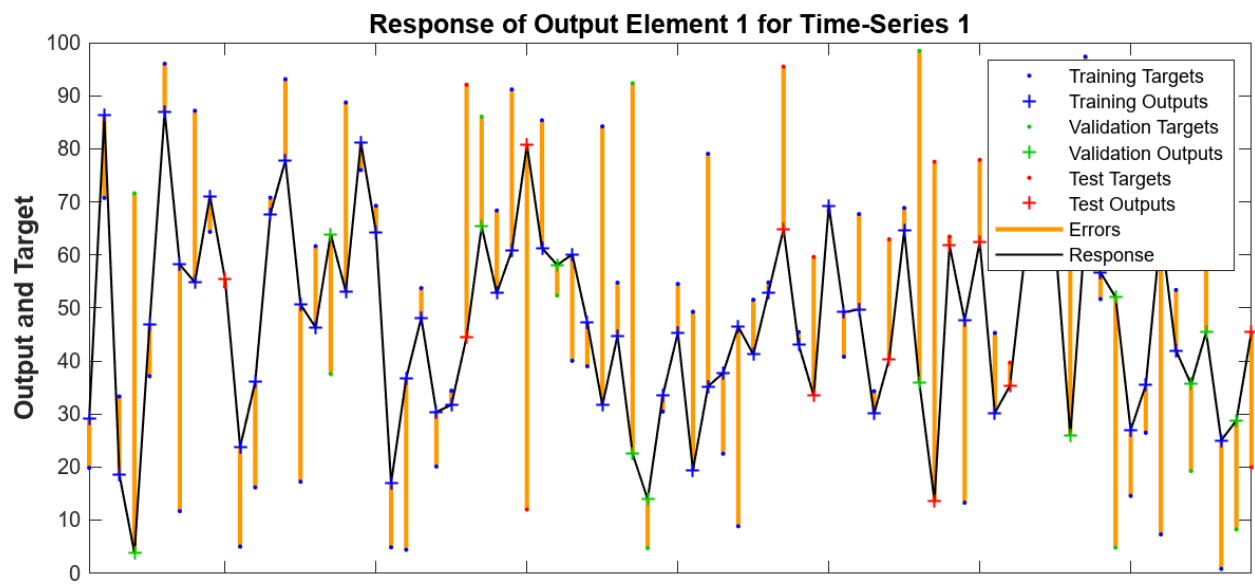


Figure 4. 6. Error histogram



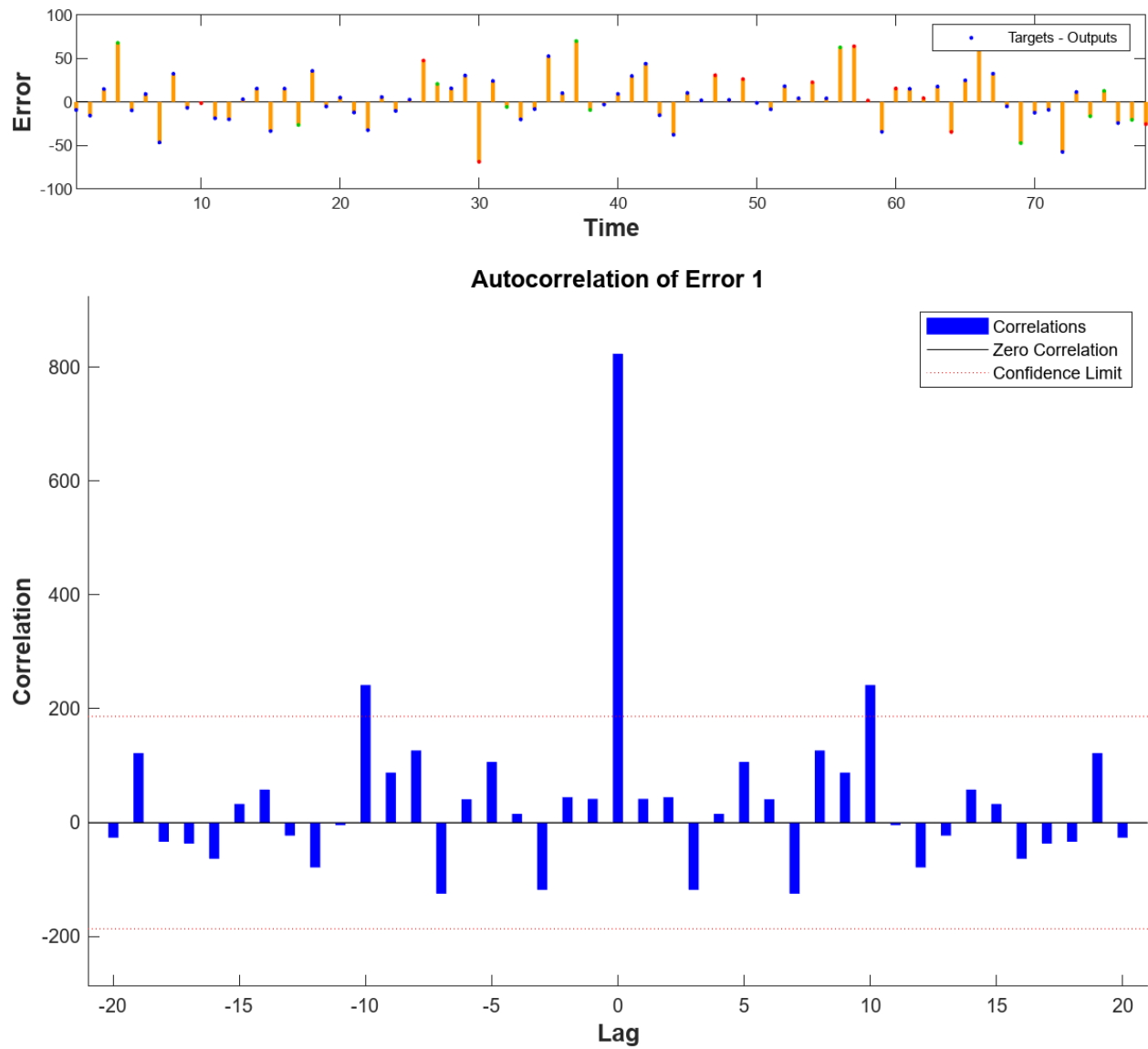


Figure 4. 7. Regression correlation coefficient

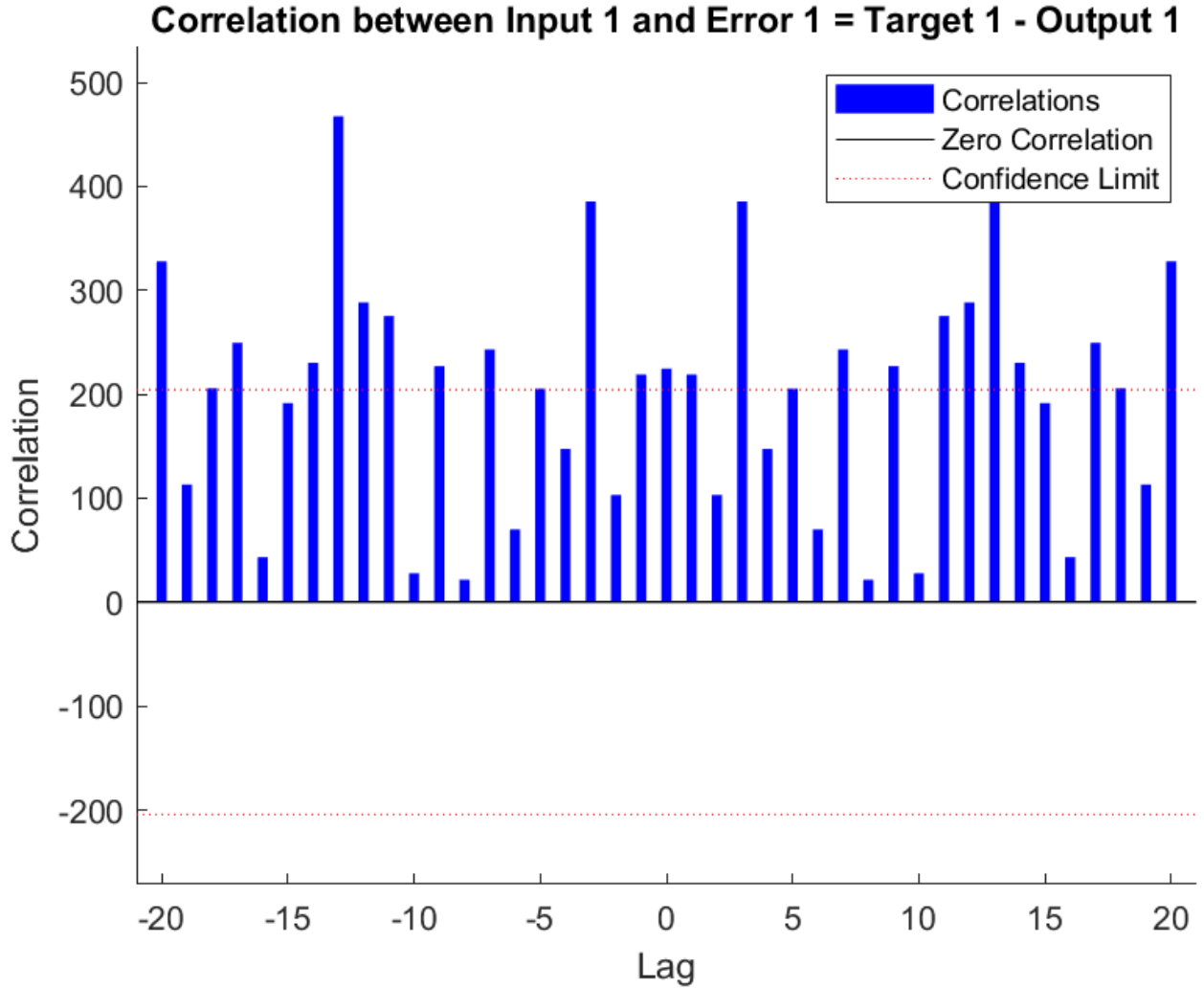


Figure 4. 8. Correlation between input and output

World light-duty test cycle performance test

The proposed Simulink and ANN models were tested under the WLTC drive cycle to evaluate energy recovery and consumption. Energy consumption calculations utilized the WLTC Class 3a driving cycle because the vehicle's power-to-weight ratio (PWR) of 44.35, calculated as the ratio of curb weight [1160 kg] to rated power [50 kW], exceeds the 34 thresholds. As shown in Figure (2.6), the WLTC Class 3a cycle comprises four speed phases: low (≤ 56.5 km/h), medium (≤ 76.6 km/h), high (≤ 97.4 km/h), and extra-high speed (≤ 131.3 km/h). Comparative analysis demonstrated that the ANN model outperformed the Simulink model in maintaining higher state-of-charge (SOC) levels and achieved superior energy recovery throughout the WLTP cycles.

Table 4. 2. WLTC performance test

Parameter	ANN Model	Simulink Model
Recovered current	300.4 A	295.5 A
Error	3%	5%
Energy recovery rate	45.8%	58.2%
Total Energy Consumption	4.375wh	4.375wh

4.2. Analysis

Proposed model analyzed using ANOVA was statistically significant ($p < 0.05$), with initial braking speed and braking force emerging as the most influential factors across all three test routes. Road gradient was found to predominantly affect the electric vehicle's energy consumption. For the Reduced Cubic model predicting regenerated energy, the overall model demonstrated statistical significance (F-value = 4.93, $p = 0.008$) and explained a substantial portion of the response variance. However, only three interaction terms showed significance at $\alpha = 0.05$: ACD ($p = 0.017$), AC^2 ($p = 0.003$), and C^2D ($p = 0.001$), indicating that energy regeneration is governed by complex non-linear and multifactorial relationships. Consequently, vehicle speed was identified as the most critical factor, with optimal energy recovery occurring within the 60-90 km/h range when combined with moderate braking intensity.

Factor Coding: Actual

3D Surface

regenerated torque (Nm)

11.9818  98.467

X1 = A

X2 = B

Actual Factors

C = 0

D = 0

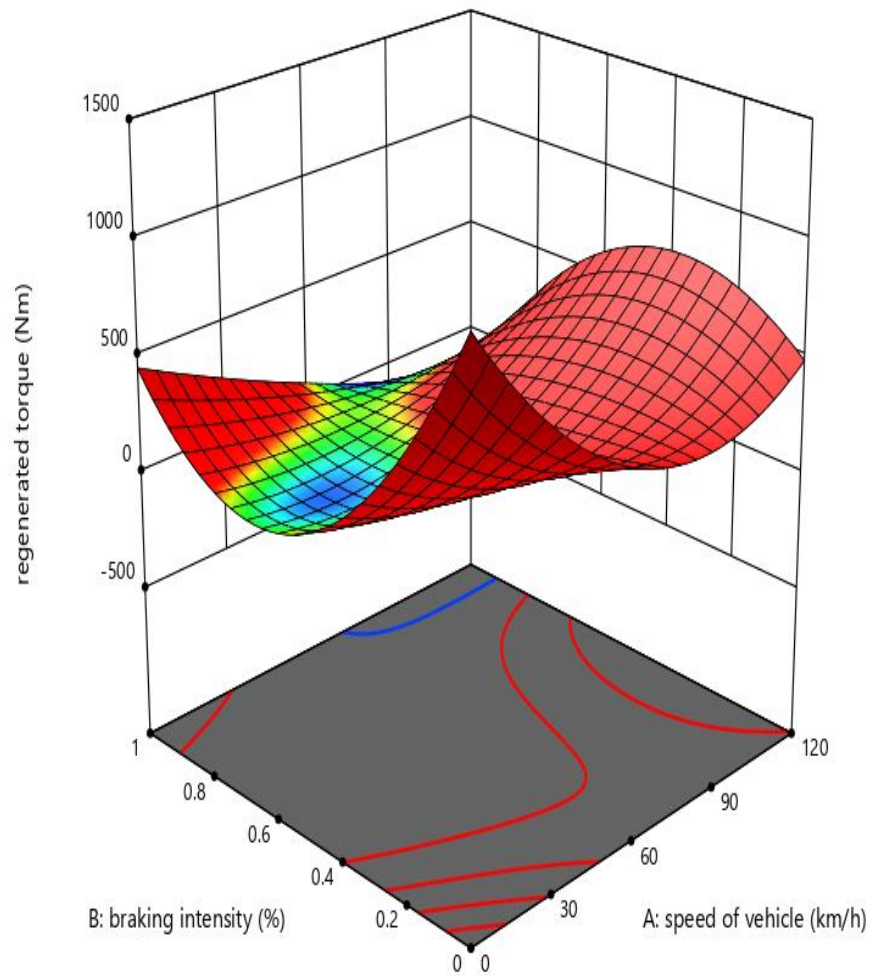


Figure 4. 9. Speed of the vehicle and braking intensity effects on regenerated energy

Factor Coding: Actual

3D Surface

regenerated energy (Wh)

11.9818 98.467

X1 = A

X2 = C

Actual Factors

B = 0.5

D = 0

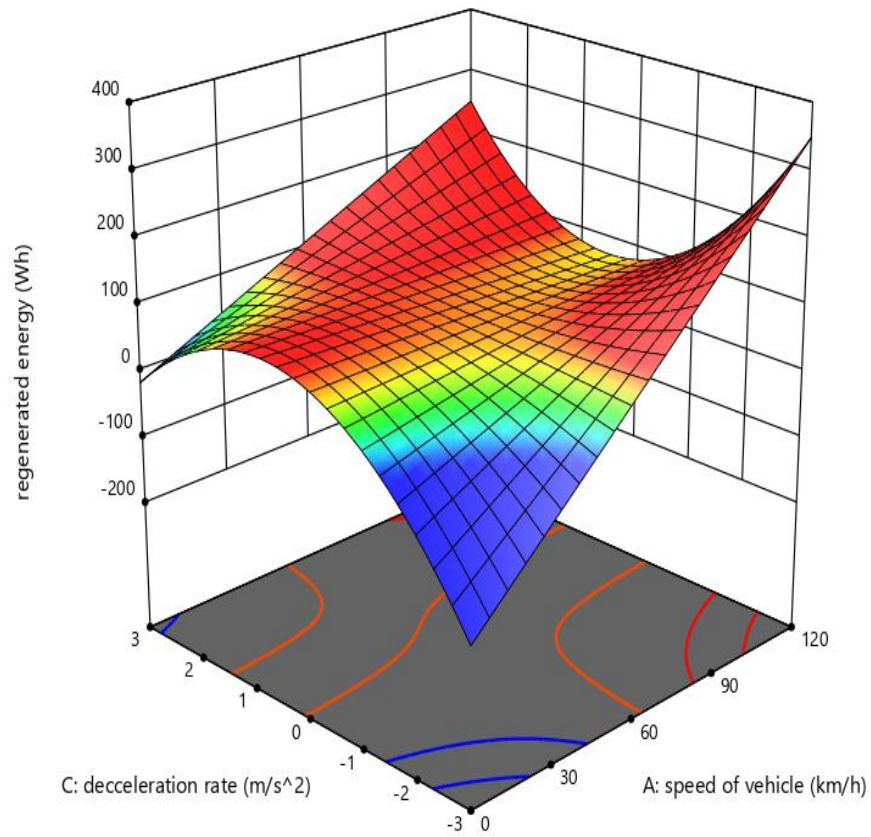


Figure 4. 10. Vehicle speed and deceleration rate effects on regenerated energy

Factor Coding: Actual

3D Surface

energy consumption (wh)

0.104586  1.99568

X1 = A

X2 = B

Actual Factors

C = 0

D = 0

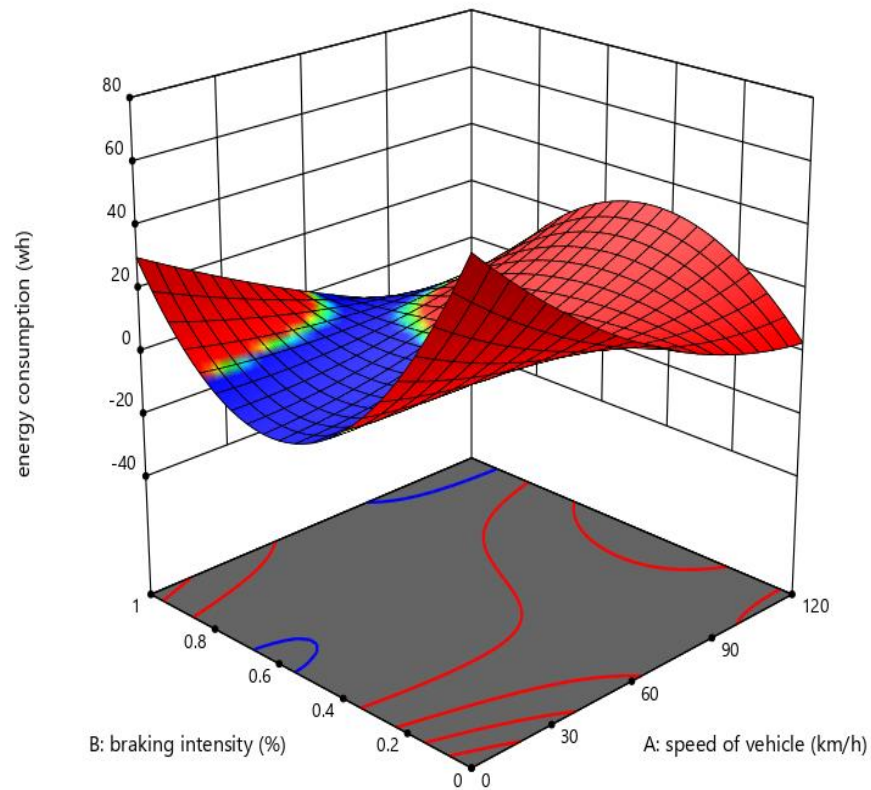


Figure 4. 11. Vehicle speed and braking intensity effects on energy consumption

4.3. Discussion

In this study, data were collected from Ayertena to Bishoftu town, dividing the test area into three basic categories. As indicated in the table (4.1), the recovered energy across routes one, two, and three was 2.3 kWh/77.2km, 3.04 kWh/133.6km, and 3.02 kWh/117.6km, respectively, which verified that energy recovery was greater in route one compared with route two and route three. This is because the amount of braking pedal usage was greater due to an increased number of traffic conditions, and minimum energy recovery was obtained at route three due to low braking times, and the vehicle used more power compared to routes two and one. Experimental results identified braking velocity and braking force as the most significant factors affecting energy recovery efficiency, and optimal energy recovery of 71.62% was achieved at mid-speed ranges of 60–90 km/h. The results were acceptable and significant when compared with (Valladolid et al., 2023). In this study, the raw data obtained from experimental tests were simulated in a MATLAB Simulink model, and the Simulation output showed that the effect of initial braking speed was significant on the amount of regenerated energy, whereas the braking intensity affected the braking time. Additionally, the battery discharge was affected by road angle, and the result was consistent when compared with real driving data. Artificial neural network (ANN) training was carried out to reduce prediction error and validate simulation results from 70% training, 15% validation and 15 % of raw data collected and mean square error (MSE) between actual and predicted regenerative braking torque was less than 1 and regression correlation coefficient of 0.996 for all training, validation and test results. Compared to conventional Simulink models, the ANN model more effectively managed the dynamic complexity of regenerative braking ratios, reducing prediction errors by 3%. The result obtained indicated similar results to (Rezk & Abuzied, 2023) Which enhanced driving range by 15-20%, confirming its particular suitability for Ethiopian road conditions and driving patterns. Testing under WLTC drive cycles showed the ANN model achieved 22% greater energy recovery in urban settings and 18% improvement in suburban areas compared to conventional systems. Optimization of study significances analyzed using response surface method (RSM) by using initial braking speed, braking force, road angle and deceleration rate as main parameters to validate the simulation results and the result was significant ($P < 0.05$) and vehicle speed was identified as critical factor in all three routes which was consistent with ANN training and MATLAB Simulink output.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

Ethiopia's transportation sector relies primarily on fuel-dependent vehicles (ICEVs) and battery powered vehicles (EVs), with ICEVs facing problems of rising fuel costs, limited availability, and harmful emissions that have spurred EV adoption. However, EV growth remains constrained by limited driving range, inadequate charging infrastructure, and battery dependency. This study addressed these limitations by designing, simulating, and optimizing an artificial neural network (ANN) based regenerative braking system (RBS) for light-duty EVs under Ethiopian road conditions using MATLAB/Simulink modeling validated with experimental data from Changan E-star vehicle tests. The research developed comprehensive models of vehicle dynamics, powertrain systems, and energy consumption, incorporating Response Surface Methodology optimization that demonstrated the ANN RBS's superior energy recovery capability compared to conventional systems, particularly effective in urban stop-and-go conditions characteristic of Ethiopian cities. The optimized system not only enhances EV range by recovering braking energy but also simplifies EV architecture and increases production viability, offering particular benefits for developing countries where heavy urban vehicles dominate transportation. These findings suggest ANN ANN-based RBS technology could significantly support Ethiopia's transition to sustainable transportation when combined with supporting charging infrastructure development and policy incentives for EV adoption. In general, the study used four parameters on three types of road conditions, which included Ayertena to Bishoftu, to analyze energy recovered from a light-duty electric vehicle, and an optimum operating point of energy recovery was identified. The study verified that to maximize energy regeneration, it is recommended that the vehicle operates above its average speed, with the driver applying medium braking force for an extended duration.

5.2. Recommendation

I recommend that future researchers add any ideas that were not addressed here, which are listed in the following

- ✓ The present work used only a single electric vehicle to design, analyze, simulate, and optimize RBS, but any researcher or student who will need to work on RBS if he/she works on different models of vehicles will be more appreciable and significant.
- ✓ I recommend designing and simulating a regenerative braking system in all road conditions, like paved or unpaved roads, uphill climbing, and downhill coasting, as Ethiopian road conditions include varied road geography.
- ✓ The present study used a light-duty electric vehicle for design, analyze, simulate, and optimize RBS, but in future work, if any researchers have used it on heavy-duty EVs, city buses, motorcycles, and three-wheelers can add value to the country and individual income.
- ✓ The government should encourage EV-related research to adopt efficient electric vehicles according to Ethiopian driving conditions and demands.
- ✓ I recommend that the Ethiopian Ministry of Transportation implement and manipulate policy related to Electric vehicle standards, predesign analysis, standard drive cycle, and measurement procedure before importing into the Ethiopian market.

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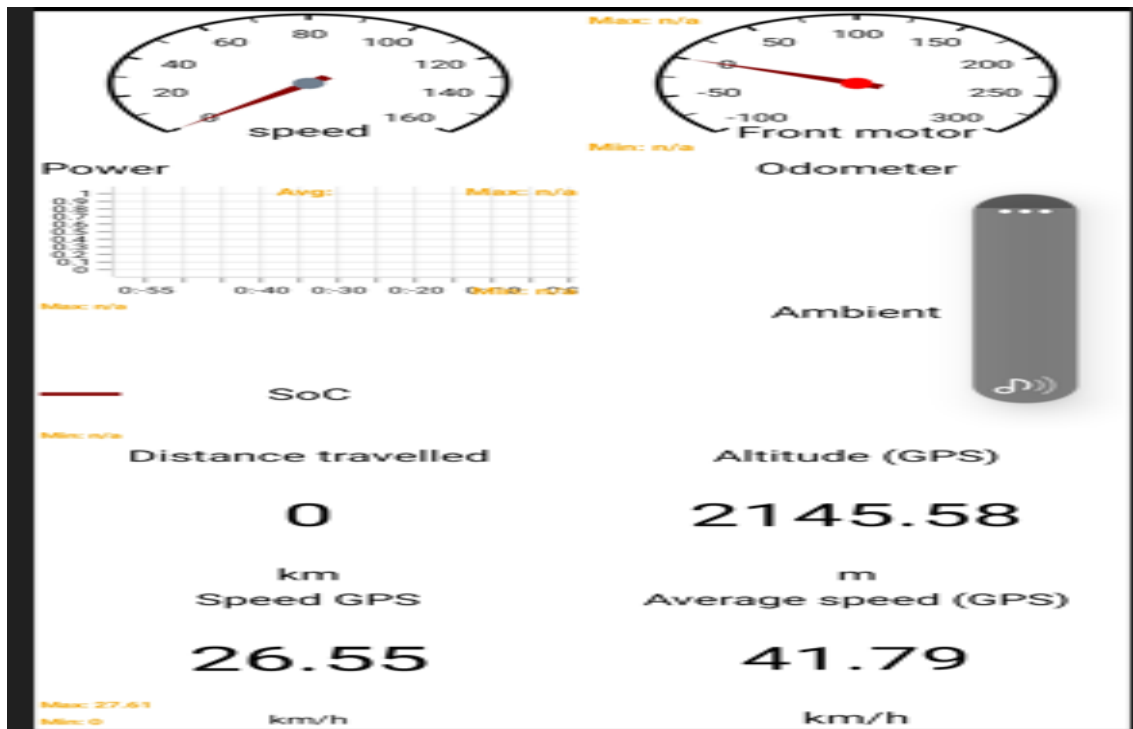
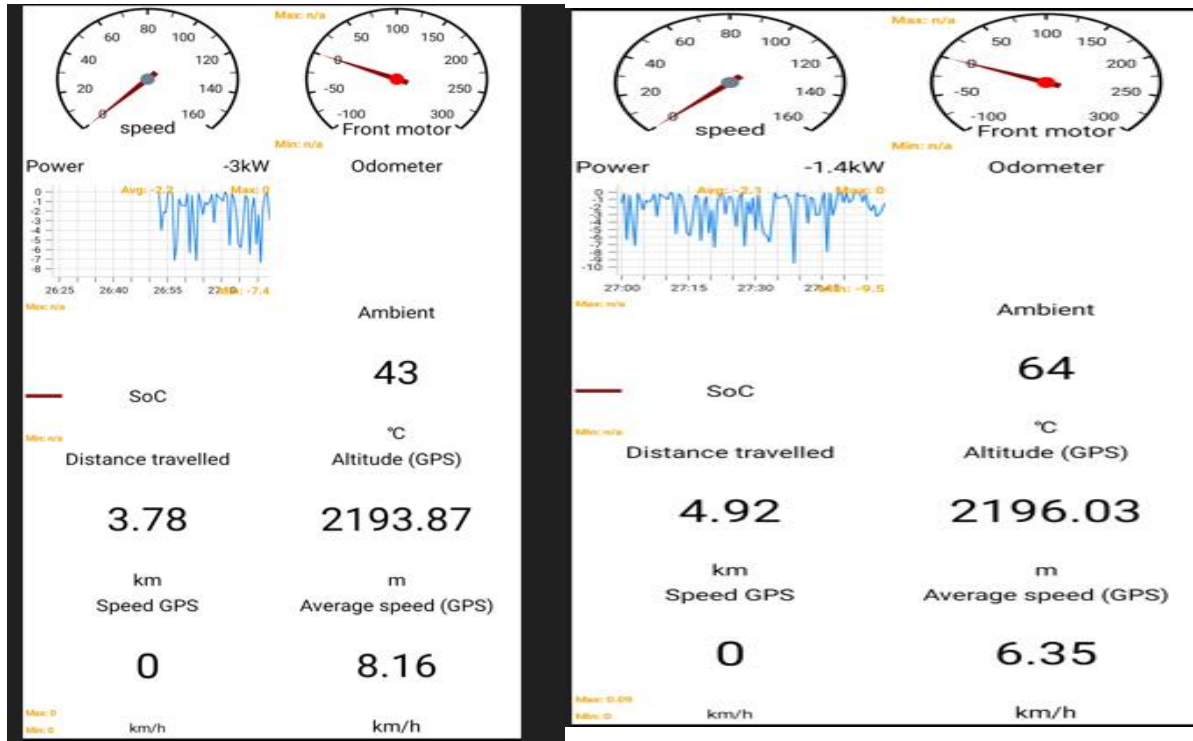
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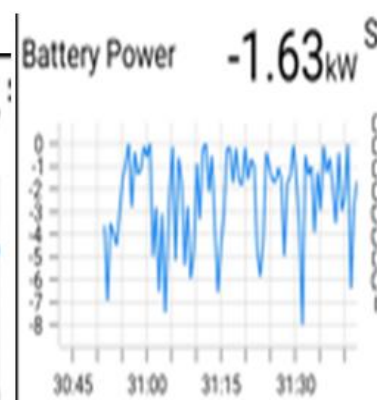
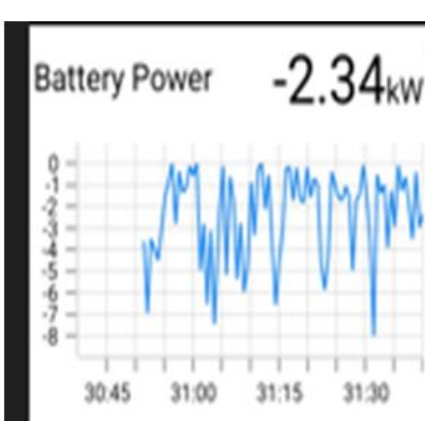
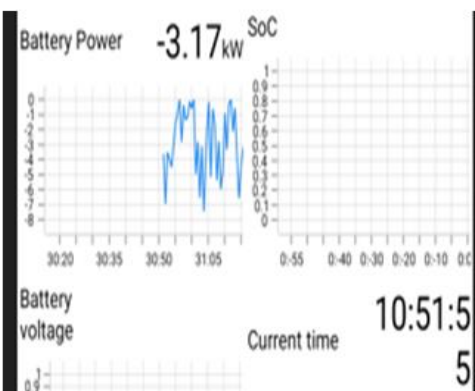
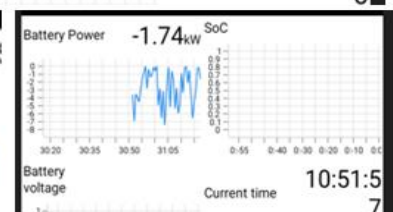
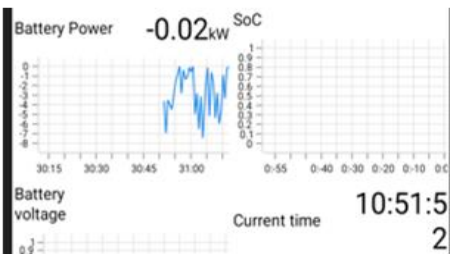
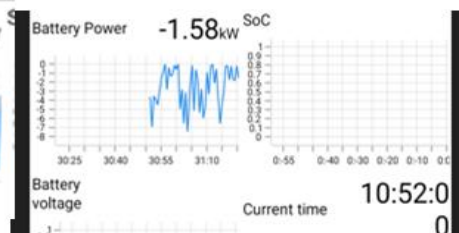
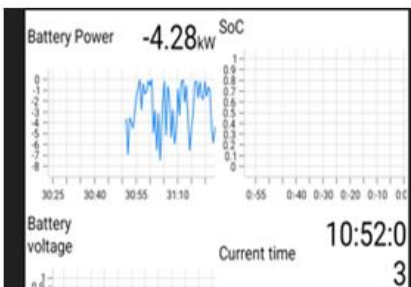
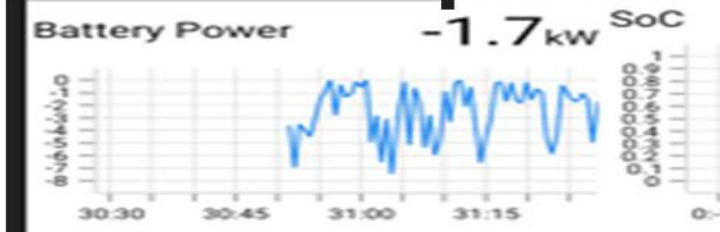
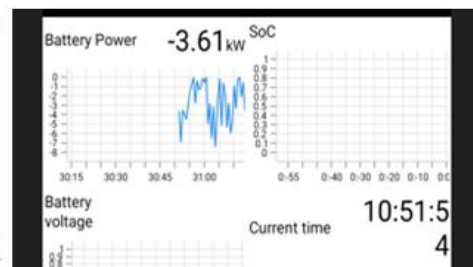
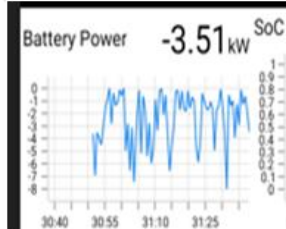
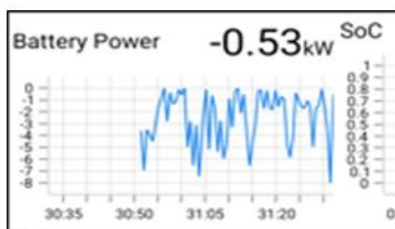
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APPENDIX A

Sample collected data





APPENDIX B

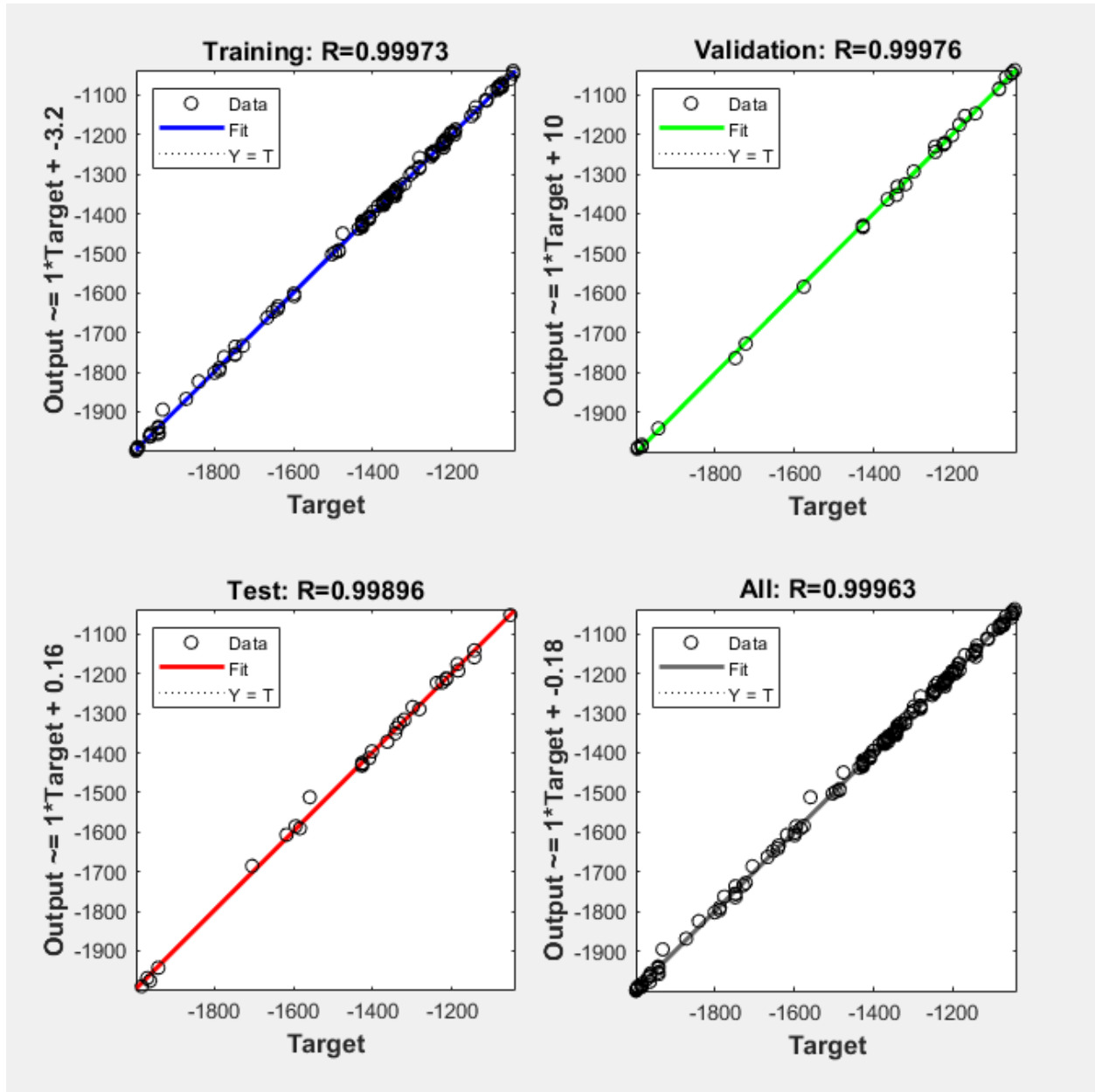
MATLAB Simulink

Vehicle dynamics parameters used in MATLAB

```
1      m=1160;           %massof vehicle (kg)
2      g=9.81;           %acceleration due to gravity(m/s^2)
3      rrc=0.02;         %rolling resistance coefficient
4      rho=1.25;         %density of air(kg/m^3)
5      lamda=0.1;        % rotational inertia coefficient
6      cd=0.2;           %drag coefficient
7      Af=2.5;           %vehicle frontalarea(m^2)
8      r=19;             %radiusof wheel(m)
```

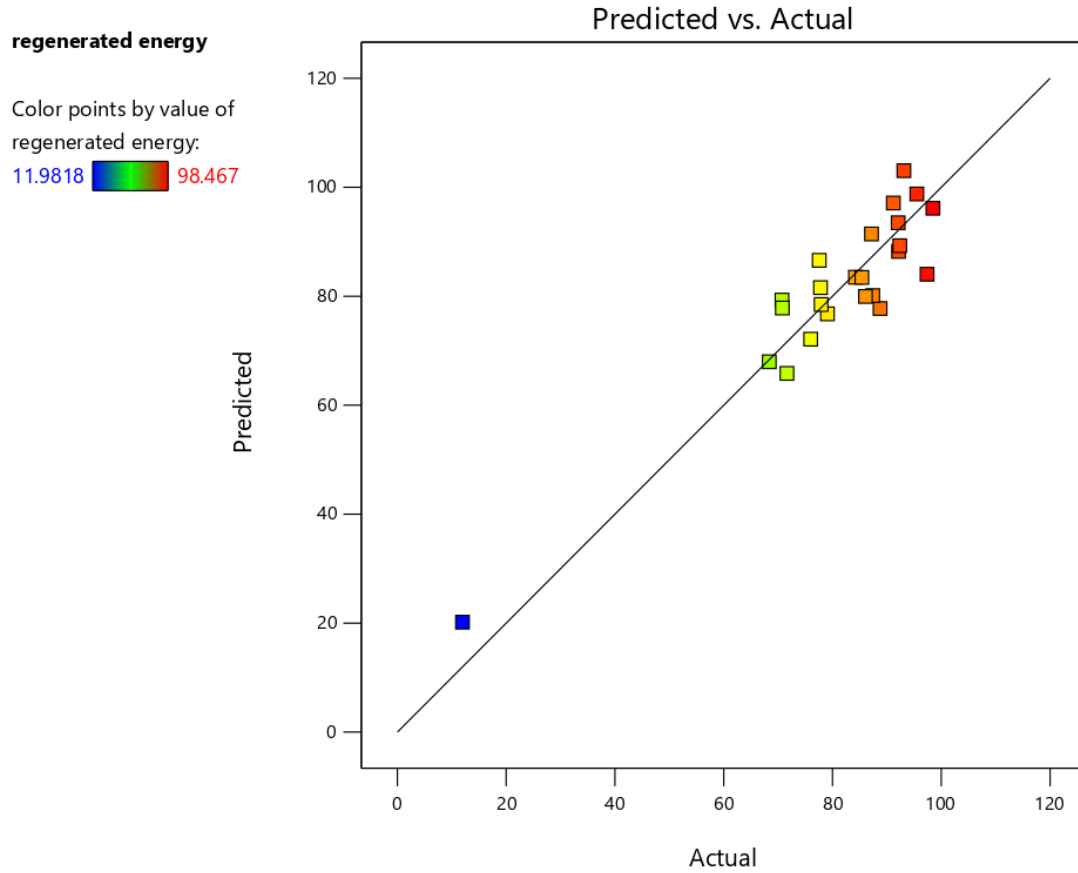
APPENDIX C

ANN training data



APPENDIX D

Response surface methodology



Final Equation in Terms of Coded Factors

Regenerated braking torque	=
+88.01	
-7.36	A
-9.67	B
+13.10	C
+36.50	D
-61.48	AC
+35.90	AD
+6.77	BD
-63.66	CD
-5.92	B ²
+17.55	C ²
-293.97	ACD
+202.17	AC ²
-252.90	C ² D

Final Equation in Terms of Actual Factors

Regenerated braking torque	=
+99.11657	
-0.122636	speed of the vehicle
+4.35024	braking intensity
+24.86014	deceleration rate
-1.54289	road angle
-0.341565	speed of vehicle * deceleration rate
+0.149565	speed of vehicle * road angle
+3.38545	braking intensity * road angle
+19.19246	deceleration rate * road angle
-23.69338	braking intensity ²
-20.51277	deceleration rate ²
-0.408285	speed of vehicle * deceleration rate * road angle
+0.374381	speed of vehicle * deceleration rate ²
-7.02507	deceleration rate ² * road angle

APPENDIX E

Standard coefficients

rolling resistance coefficient	Real-world loads
0.002 - 0.005	low resistance tubeless tires
0.006 - 0.01	truck tire on asphalt
0.01 - 0.015	ordinary car tires on concrete new asphalt, cobbles small new
0.02	car tires on tar or asphalt
0.02	car tires on gravel - rolled new
0.03	car tires on cobbles - large worn
0.04 - 0.08	car tire on solid sand, gravel loose worn, soil medium hard
0.2 - 0.4	Car tire on loose sand