Addis Ababa University

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Design and simulation of an energy-efficient model-predictive cruise controller for Three Wheel Electric Vehicle

A thesis submitted to Addis Ababa Institute of Technology, School of Graduate Studies, Addis Ababa University
In partial fulfillment of the requirement for the Degree of Master of Science in Electrical Engineering (Electrical control Engineering)

By: Mistere Getaneh

Advisor: Dr. Dereje Shiferaw

Addis Ababa

March 2025

DECLARATION

I declare that the work entitled "Design and simulation of an energy-efficient model-predictive cruise controller for electric Bajaj" is my original work and has not been presented for any degree in this university or any other university or colleges, as well as all sources of material, used for the thesis have been duly acknowledged.

Name	Signature	Date
Mistere Getaneh	…................................	....

Place: Addis Ababa Institute of Technology, Addis Ababa University, Ethiopia.

This thesis has been submitted for examination with my approval as the university advisor.

Advisor	Signature	Date
Dr. Dereje Shiferaw	…................................	....

Addis Ababa University

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Design and simulation of an energy-efficient model-predictive cruise controller for electric Bajaj

By: Mistere Getaneh

APPROVED BY BOARD OF EXAMINERS

Name	Signature	Date
………………………	……………………………	………………………
(School Dean Person)		
Dr.Dereje Shiferaw	……………………………	………………………
(Advisor)		
………………………	……………………………	………………………
(Internal Examiner)		
…………………………	……………………………	………………………
(External Examiner)		
…………………………	……………………………	………………………

ACKNOWLEDGMENT

First of all, I am grateful for the successful completion of this thesis, and I am bound to thank **God** first for everything He has blessed me with. Above all, I would like to acknowledge my thesis advisor, **Dr. Dereje Shiferaw**, whose tireless guidance and unfailing support were indispensable for every step in this process. His expertise and commitment were indeed instrumental in the realization of this work.

I would also like to extend my most profound appreciation to my **family**, who, through their endless love, prayers, and encouragement, supported me through my academic sojourn and the arduous process of researching and writing this thesis. Their support has been a source of strength at all times.

Lastly, I wish to thank all those who may have contributed, either directly or indirectly, toward this research work. Your support and assistance are highly appreciated.

ABSTRACT

As three-wheel electric vehicles (EVs) gain popularity in developing countries due to their affordability and environmental benefits, challenges related to energy efficiency and utilization remain critical. This research aims to enhance the energy efficiency and dynamic performance of these vehicles through advanced control techniques, specifically Model Predictive Control (MPC). The study identifies a significant research gap in the design of MPC controllers for three-wheel EVs, particularly due to the complexities of nonlinear vehicle dynamics and parameter uncertainties. To address this, we propose an energy-efficient MPC cruise controller for a Bajaj three-wheel EV, utilizing comprehensive mathematical models of vehicle dynamics, energy consumption, the Brushless Direct Current (BLDC) motor, and the inverter. Simulations conducted in MATLAB/Simulink demonstrate the effectiveness of the proposed controller in accurately tracking both constant and varying speed references. The results highlight the controller's ability to maintain a target speed of 35 km/h with minimal deviation, effectively responding to dynamic conditions. For instance, the vehicle accelerates from 0 to 25 km/h in just 10 seconds, reaches 35 km/h by 15 seconds, and decelerates smoothly to 25 km/h at the 30-second mark. This research not only contributes to the optimization of three-wheel EV performance but also lays the groundwork for future advancements in energy-efficient vehicle control systems.

Keywords: Electric Vehicle, Energy Efficiency, Model Predictive Control, BLDC Motor, PID, Vehicle Dynamics, Bajaj.

CONTENTS

LIST of FIGURES

LIST of TABLES

LIST OF ACRONYMS

ACC	Adaptive Cruise Control
BLDC	Brushless Direct Current
DC	Direct Current
DTC	Direct Torque Control
EV	Electric Vehicles
EMS	Energy Management Strategies
FOC	Field-Oriented Control
IM	Induction Motors
IRENA	International Renewable Energy Agency
IC engine	Internal Combustion Engine
MPC	Model Predictive Control
MPCC	Model Predictive Cruise Controller
NMPC	Nonlinear Model Predictive Control
PID	Proportional Integral Derivative
PI	Proportional Integral
PMSMs	Permanent Magnet Synchronous Motors
RHC	Receding Horizon Control
TVC	Torque Vectoring Control
3WEV	Three-Wheeled Electric Vehicles

CHAPTER 1: INTRODUCTION

1.1. Background of the thesis

The internal combustion engine has contributed a lot to the improvement of human life. Currently, being the major propulsion technology, internal combustion engines have become very essential in human life, especially for automobiles [1, 2]. In this context, the day-to-day increasing quantity of internal combustion engines is normally one of the main contributors to the emissions of greenhouse gases and other air pollution. In order to reduce air pollution, the automotive industry is working on sustainable mobility for the future [3, 4].

Electric vehicles have emerged as an advanced solution to deal with conventional fossil fuel-powered vehicles in the pursuit of sustainable transportation. Global dedication to reducing carbon emissions has been coupled with technological improvements, and this increases the circle of development and adoption of EVs across diverse transportation sectors.[5].

For nearly a century, scientists, engineers, and automakers have worked to design and enhance electric vehicles (EVs). The first electric car was created by Robert Anderson in 1839, followed by David Salomon's development of an electric car with a lightweight motor in 1870. However, the heavy batteries of that era resulted in poor performance. Today, advancements in battery technology have significantly improved the performance of EVs.

In addition to conventional cars, other types of vehicles have seen similar transitions toward electrification. For example, gasoline-powered three-wheelers, known locally as Bajaj in Ethiopia, have become a popular and cost-effective mode of transportation in both urban and rural areas. Bajaj Auto, the company responsible for manufacturing these vehicles, was established in India in 1945, and has since expanded its distribution to 16 countries, including Ethiopia[7, 8].

The Bajaj, a gasoline-powered three-wheeler, plays a critical role in Ethiopia’s transportation landscape, serving a range of purposes from passenger commutes to small-scale freight delivery[9]. As the demand for sustainable and energy-efficient transportation grows, there is a push to electrify vehicles like the Bajaj to further reduce emissions and improve fuel efficiency.

Electrifying three-wheelers, however, presents unique challenges. While the evolution of EVs has seen major advancements in battery technology, motor efficiency, and performance for cars, the application of these technologies to three-wheel EVs like the Bajaj requires tailored solutions. This is especially true in terms of energy efficiency and the need for operational effectiveness in diverse environments[10].

The electric motor is a critical component of any electric vehicle (EV), and among the various types available, the BLDC (Brushless DC) motor stands out as the most suitable due to its numerous advantages over brushed DC and induction motors [11, 12]. These advantages include:

- Minimal maintenance requirements
- Low electrical noise
- Reduced inertia, enhancing dynamic response
- Superior speed-to-torque characteristics
- Extended operational lifespan
- High efficiency and robust reliability
- High power density, lower cost, and reduced weight

BLDC motors are synchronous and commonly configured as three-phase systems, especially for medium- to high-power applications. Their operation relies on rotor position detection. However, the design of BLDC motor drives is complex due to challenges such as inverter switching and system instability arising from intricate speed and current regulation.

Optimizing battery power in EVs is crucial, particularly for precise torque control and fast-braking operations. Accurate modeling and simulation of BLDC motor drives, focusing on speed control, are essential. Researchers have proposed several techniques and algorithms for BLDC motor speed controllers [13-15], with PI, PID, fuzzy, and adaptive fuzzy PID controllers being widely utilized for this purpose.

This thesis aims to explore key strategies for improving the energy efficiency of electric Bajaj vehicles in Ethiopia. The research emphasizes gaining a comprehensive understanding of the vehicle's dynamics, designing advanced control systems, and accurately assessing energy consumption, all to promote sustainable and efficient operation.

The unique challenges in optimizing energy efficiency for Bajaj electric vehicles arise from the diverse operational environments in Ethiopia. Factors such as varying road conditions, traffic congestion, and irregular driving patterns significantly impact the energy utilization of these vehicles. Moreover, the reliance on a Brushless Direct Current (BLDC) motor presents both opportunities and challenges in designing control systems that maximize its efficiency while ensuring desired vehicle performance.

1.2. Statement of the problem

This thesis aims to enhance the energy efficiency and dynamic performance of these vehicles through advanced control techniques, specifically Model Predictive Control (MPC). The study identifies a significant research gap in the design of MPC controllers for three-wheel EVs, particularly due to the complexities of nonlinear vehicle dynamics and parameter uncertainties. To address this, we propose an energy-efficient MPC cruise controller for a Bajaj three-wheel EV speed optimization and to achieve a compromise between energy consumption and desired vehicle speed tracking. This includes to develop a comprehensive energy consumption model, integrate a BLDC motor, and predict future road conditions such as speed limits, slopes, and road curvature. The main objective is to develop a novel approach that maximizes the energy efficiency of three-wheel electric vehicles, notably the Bajaj, and consequently advances sustainable transportation in Ethiopia.

1.3. Objective of the thesis

1.3.1. General Objective

- ✓ The general objective of this thesis is to design and simulate of an energy-efficient model-predictive cruise controller for a three-wheel electric vehicle (Bajaj).

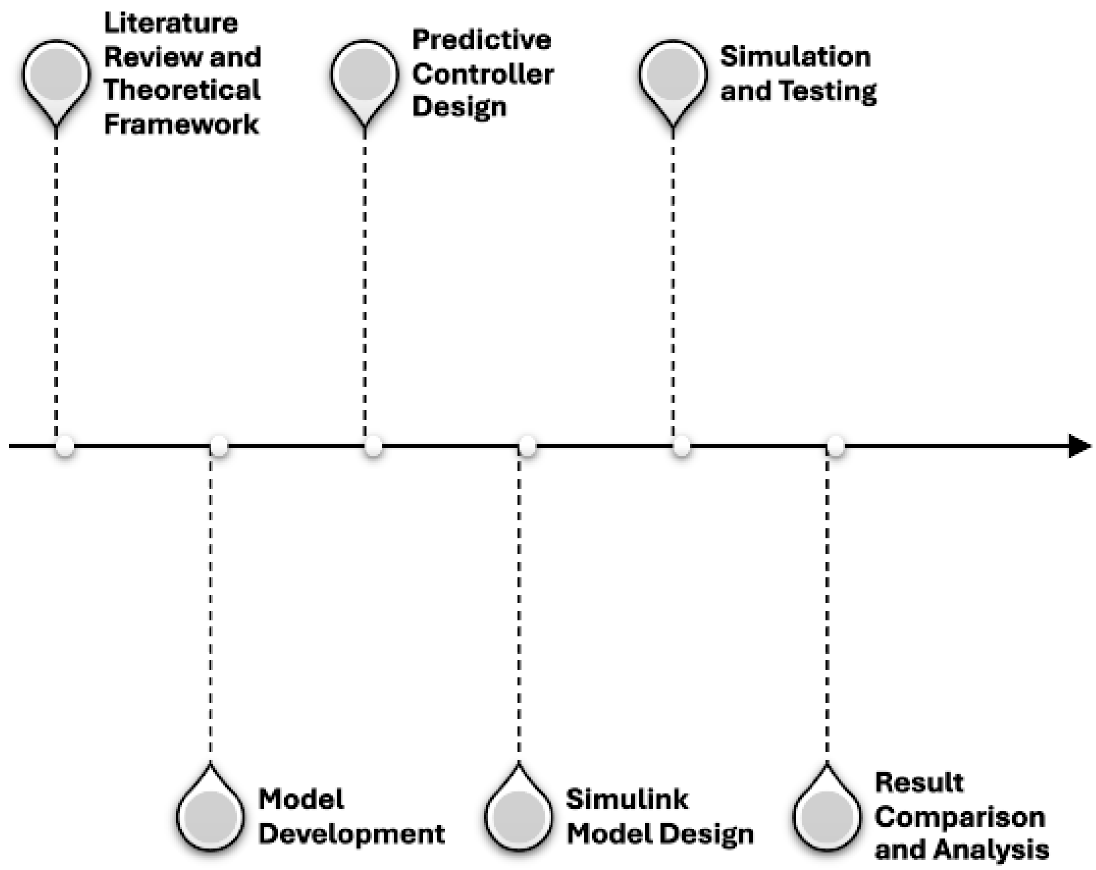
1.3.2. Specific Objectives of the thesis

The specific objective of this thesis is:

- ✓ To develop an energy consumption model.
- ✓ To adapt the motion dynamics models for three-wheel electric vehicles to improve energy efficiency under variable conditions.
- ✓ To Integrate the developed BLDC motor model into the vehicle system model.
- ✓ To design and optimize a Model Predictive Cruise Controller (MPCC) for energy-efficient speed regulation.
- ✓ To Validate the MPCC system and energy consumption model through MATLAB/Simulink simulations.

1.4. Methodology

To explore the proficiency of Design and simulation of an energy efficient model-predictive cruise controller for electric vehicles and to show their validity and effectiveness, the following tasks are achieved throughout the thesis:



1.5. Scope of the thesis

The thesis is organized into six chapters. Chapter 1 introduces the research topic, outlining the problem statement, objectives, scope, and methodology. Chapter 2 reviews literature on three-wheel electric vehicles, control strategies, and Brushless Direct Current (BLDC) motors, identifying key challenges and research gaps. Chapter 3 details the system modeling of the three-wheel electric vehicle, presenting mathematical models for vehicle dynamics, energy consumption, and the BLDC motor, along with block diagrams. Chapter 4 focuses on the design and optimization of the Model Predictive Cruise Controller (MPCC), discussing the MPC strategy and implementation in MATLAB/Simulink. Chapter 5 presents simulation results, evaluating the MPCC's performance in speed tracking and energy efficiency, and comparing planned versus actual outcomes. Finally, Chapter 6 summarizes the findings, draws conclusions, and suggests future research directions, highlighting the significance of the results and potential areas for further investigation.

1.6. Significance of the thesis

This Thesis holds significant implications for the improvement of electric vehicle technology, particularly in the context of three-wheel electric vehicles like the Bajaj. By developing detailed mathematical models and control strategies within MATLAB/Simulink, this research aims to offer an understanding of optimizing the performance and efficiency of such vehicles. The ability to accurately simulate vehicle dynamics, energy consumption, and motor control in a virtual environment allows for cost-effective testing and enhancement of design concepts. Furthermore, the implementation of a Model Predictive Cruise Controller (MPCC) offers potential benefits for energy-efficient speed regulation, contributing to the overall sustainability of electric transportation systems. Ultimately, the outcomes of this project have the potential to inform future developments in electric vehicle design, driving innovation towards more eco-friendly and reliable transportation solutions.

1.7. Outline of the thesis

The structure of the thesis is explained in more detail on a chapter-by-chapter basis. The paper is organized as follows:

Chapter one constitutes the introduction to the statement of the problem, objectives both in general and specifics, scope, and overall methodology of the thesis. It serves as a prelude to set the stage of the research and provides background and scope.

Chapter two, Theoretical Background and Literature Review, provides a comprehensive review of the literature related to three-wheel electric vehicles, electric vehicle control strategies, and Brushless Direct Current (BLDC) motors. It discusses the challenges and opportunities in three-wheel electric vehicles (Bajaj) and identifies gaps in current research, forming the theoretical framework guiding the simulation and analysis.

Chapter three describes the detailed system modeling of the three-wheel electric vehicle. It includes the development of mathematical models for vehicle dynamics, energy consumption, and the BLDC motor. This chapter explains the block diagram, vehicle dynamics modeling, and the mathematical modeling of the BLDC motor, providing a foundation for the control strategy design.

Chapter four is dedicated to designing and optimizing the MPCC. It talks about the MPC strategy, structure of the MPC controller, problem formulation, selection, and tuning of algorithms. The emphasis of this chapter will be on implementing the control strategy within the MATLAB/Simulink environment.

In Chapter five, the results obtained from the simulations are presented and discussed. The performance of the designed MPCC for speed tracking and energy efficiency is evaluated. Comparisons are made between the planned and actual outcomes, highlighting the effectiveness of the control strategies.

Chapter 6 summarizes the work done and the results obtained. This provides the conclusion derived from the research and states the directions for further work. At the end, this chapter closes the thesis with a reflection of findings and proposals of areas to investigate further.

CHAPTER 2: THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1. Introduction

In this chapter, various electric vehicle (EV) control strategies are reviewed, with a focus on their application to three-wheel electric vehicles (3W-EVs). The dynamics of 3W-EVs are evaluated, highlighting the unique challenges in stability and control due to their asymmetric design. The performance and efficiency of different control systems, including motor control, energy management, and torque distribution, are compared to optimize the vehicle's handling and stability.

Additionally, recent works related to control strategies for EVs are reviewed, focusing on their contributions to vehicle dynamics and overall performance improvement. The chapter examines key research on control mechanisms specifically for 3W-EVs, evaluating their merits and limitations. Relevant studies on regenerative braking, torque vectoring, and energy efficiency in electric vehicles are also discussed in detail.

2.2. Electric Vehicles

Electric vehicles (EVs) are gaining popularity as they have the potential to reduce noise and pollution and decrease transport's dependence on oil—if the electricity comes from non-oil-dependent generation. They are also essential in reducing greenhouse gas emissions. To achieve zero carbon dioxide emissions, EVs must be founded upon non-fossil fuel energy resources, such as nuclear and alternative energy.

Hybrid vehicles, having two or more power sources, offer flexibility in design. The most common type employs an internal combustion engine (IC engine) and a battery, electric motor, and generator [15].

While EVs are not new, advancements in technology and growing pollution concerns have brought them to the forefront as mobility for the future. Electric power is the main source of power in EVs, and electric motors use this power and transfer it into mechanical (rotational) power, which is directed to the wheels of the car via a transmission system. Four-wheelers tend to be the most superior in the EV category. EVs can run solely on electricity or use batteries augmented with gasoline engines to power the car. The battery, electric motor, and controller are some of the components that any EV requires.

In recent years, vehicle electrification has become a key strategy to tackle energy and climate change challenges. With the growing demand for automobiles, there is an increasing need for sustainable alternatives that minimize environmental impact and reduce reliance on fossil fuels. Electric vehicles have emerged as a promising solution for advancing sustainable transportation.

Governments, the automotive industry, and academia have all recognized the importance of transitioning to a green transportation system, and electric vehicles have been identified as a key component of this system[17]. The use of electric vehicles allows for a diversification of power sources in vehicle propulsion systems, as electricity can be generated from clean and renewable energy sources. Furthermore, electric vehicles offer numerous advantages over conventional vehicles. These include lower environmental impact, lower maintenance and operating costs, and the potential for zero emissions during the use process[18].

In contrast to the industrial models, electric vehicle motor drives have very different operational needs. EVs, in comparison to the industrial ones, experience more starts and stops and run within a huge range of conditions. Therefore, the EV motor drives should be formulated as a response to such needs. Their basic requirements include high torque generation for quick acceleration and high power density to keep the size and weight to maximum capacity.[19]

2.2.1. Three-wheel electric vehicle

Three-wheeled electric vehicles (3WEVs) are quickly transforming urban transportation, offering a unique blend of environmental sustainability, economic efficiency, and enhanced maneuverability. These cutting-edge vehicles are setting the stage for a greener and more streamlined future in urban mobility.

At the heart of their appeal lies their remarkable energy efficiency. Compared to their four-wheeled counterparts, 3WEVs boast several key characteristics that contribute to their impressive energy economy:

Lighter Weight: 3WEVs typically weigh significantly less than traditional cars, resulting in lower energy consumption and longer range. This is achieved through the use of lightweight materials like aluminum and composites, along with efficient design principles[20, 21].

Aerodynamic Design: By incorporating streamlined profiles and minimizing drag, 3WEVs optimize airflow and further reduce energy consumption[22].

Electric Powertrains: Unlike gasoline-powered vehicles, 3WEVs utilize electric motors that offer superior efficiency. These motors convert a larger percentage of stored energy into motion, significantly reducing energy waste.

Eco-Driving Techniques: By adopting practices like smooth acceleration, maintaining moderate speeds, and anticipating traffic flow, drivers can further maximize the energy efficiency of their 3WEV.

The benefits of these efficiency features extend beyond mere energy savings. By promoting cleaner air and reducing greenhouse gas emissions, 3WEVs contribute significantly to environmental sustainability. Additionally, their lower operating costs make them an economically attractive option for both individuals and businesses.

While 3WEVs hold immense potential, challenges remain on the path to widespread adoption. Battery cost and limited range are key concerns for many potential users.

2.2.2. Electric Vehicle Control Strategies

Electric Vehicle (EV) control strategies encompass a range of methods and technologies designed to optimize the performance, efficiency, and safety of electric vehicles. These strategies are critical in managing the powertrain components, including the battery, inverter, and electric motor, to ensure smooth and efficient operation. One of the well-known strategies is Model Predictive Control (MPC), in which a mathematical vehicle model is used for future state prediction and control input optimization in real time. MPC can handle multi-variable systems and constraints efficiently and therefore can be used in EVs for improving energy efficiency and battery life by optimizing power distribution and regenerative braking.

Another key control strategy for EVs is Torque Vectoring Control (TVC), which enhances vehicle handling and stability by distributing torque independently to each wheel. This technique is especially beneficial for electric vehicles with multiple motors, as it allows for precise control of each wheel's torque, improving traction and cornering performance. By adjusting the torque based on real-time driving conditions, TVC helps in reducing understeer and oversteer, thereby enhancing the safety and driving dynamics of the vehicle. Studies have shown that TVC can significantly improve the lateral stability and agility of EVs, making it a valuable control strategy for high-performance and autonomous electric vehicles.

Field-Oriented Control (FOC) is another advanced technique used in EVs to control the operation of the electric motor. FOC, or vector control, provides direct control of the motor magnetic field and current, enabling smooth and efficient operation. By enabling control of the motor in such a way as to decouple the torque and flux, FOC improves the dynamic response and efficiency of the motor. This method is highly effective in managing the torque and speed of Permanent Magnet Synchronous Motors (PMSMs) and Induction Motors, which are commonly used in EVs. Application of FOC in EVs leads to better acceleration ability, reduced energy consumption, and a general enhanced drive capability.

Another essential control strategy is the Direct Torque Control (DTC), which offers an alternative to FOC by directly controlling the motor's torque and flux without requiring complex transformations and coordinate systems. DTC provides a fast dynamic response and robust control performance, making it suitable for applications requiring high-speed and high-torque operations. This strategy simplifies the control architecture and reduces the computational load, which can be advantageous for real-time applications in EVs. DTC's ability to maintain efficient operation across a wide range of speeds and loads makes it a popular choice for various types of electric motors used in EVs.

Energy Management Strategies (EMS) are also crucial in optimizing the overall energy usage of EVs. EMS involves real-time decisions on how to allocate power between different vehicle subsystems, considering factors such as driving conditions, battery state, and driver inputs. One approach within EMS is the use of heuristic-based algorithms, such as rule-based control, which relies on predefined rules to manage power flow. Another approach is optimization-based EMS, which uses algorithms like dynamic programming and Pontryagin's Minimum Principle to find the optimal power distribution that minimizes energy consumption and maximizes vehicle range. These strategies are essential in enhancing the efficiency and sustainability of electric vehicles, particularly in hybrid and plug-in hybrid configurations where multiple power sources need to be managed effectively.

Furthermore, Adaptive Cruise Control (ACC) in EVs exemplifies the integration of control strategies to improve driving comfort and efficiency. ACC systems automatically change the vehicle speed to maintain a safe distance behind the front vehicle and employ sensors as well as control algorithms. In electric vehicles, ACC can be optimized to enhance energy efficiency by minimizing unnecessary acceleration and deceleration. By integrating ACC with other control systems, such as regenerative braking and torque control, EVs can achieve smoother and more efficient driving patterns, contributing to extended range and improved passenger comfort.

Collectively, thus, the application of these control strategies - including Model Predictive Control, Torque Vectoring Control, Field-Oriented Control, Direct Torque Control, Energy Management Strategies, and Adaptive Cruise Control - is at the very core of unlocking the performance potential of electric vehicles. Synergistically, all of these strategies complement one another, enhancing the EV's performance, efficiency, and safety, putting it on a more level playing field with traditional internal combustion engine vehicles, and putting it on a path towards a cleaner automotive future [23-27].

2.3. Summary and Gaps in Current Research on Three-Wheel EVs

2.3.1. Evaluation of Control Strategies and Vehicle Dynamics for Three-Wheel EVs

Recent research on three-wheel electric vehicles (EVs), including those by Bajaj, emphasizes the effectiveness of various control strategies and the importance of accurate vehicle dynamics modeling. Control strategies such as Model Predictive Control (MPC), Field-Oriented Control (FOC), and Direct Torque Control (DTC) have been shown to significantly enhance energy efficiency and vehicle performance. For instance, [28] highlight the advantages of MPC in providing real-time adjustments to driving conditions, ensuring optimal energy use and stability. These strategies facilitate efficient power distribution, which is crucial given the limited space for battery storage in three-wheel EVs. Additionally,[29] discuss how FOC improves motor performance, which is essential for handling the variable load conditions typical of these vehicles. Accurate vehicle dynamics modeling is also critical, as it allows for precise predictions and management of the unique operational challenges faced by three-wheel EVs, particularly under diverse and often harsh road conditions found in Ethiopia.

2.3.2. Recent Papers Reviewed

[28]Paper discusses the design challenges and control strategies for three-wheel EVs, it lacks a comprehensive real-time implementation framework for energy-efficient MPC. My thesis can address this gap by developing an energy-efficient model-predictive cruise controller specifically for three-wheel EVs, taking into account the limited battery storage space and variable load conditions.

[29]This research focus on improving motor efficiency using FOC, but it does not integrate MPC for energy management. My thesis will integrate MPC with advanced torque control techniques to optimize the energy efficiency and performance of three-wheel EVs under varying load conditions.

[30]This paper highlights infrastructure challenges but does not address how real-time predictive control strategies can be adapted to local conditions. My thesis will develop a MPC that can adapt to the specific road and traffic conditions in Ethiopia, enhancing the feasibility and efficiency of three-wheel EVs in this context.

[31]While this study emphasizes the need for accurate modeling of road and traffic conditions, it does not propose specific control strategies to address these challenges. My thesis will fill this gap by incorporating real-time road and traffic condition data into the MPC framework, optimizing energy consumption and performance in Ethiopian driving environments.

[32]although this report discusses the potential for integrating renewable energy with EV infrastructure, it does not focus on control strategies to enhance vehicle efficiency. My

thesis will explore the integration of renewable energy sources with an energy-efficient MPC for three-wheel EVs, promoting sustainable transportation solutions in Ethiopia.

By addressing these gaps and leveraging the identified opportunities, my thesis aims to significantly enhance the performance, efficiency, and adoption of three-wheel EVs in Ethiopia, contributing to a more sustainable and efficient transportation system.

2.3.3. Identified Gaps and Research Opportunities

Despite the significant advancements, there are a number of lacunas in the research on three-wheel EVs. There is a core lacuna in bringing predictive control schemes that can scale in real time to the substantially varying road and traffic conditions of Ethiopian roads. While MPC and other such alternatives promise much, their application should be tailored in line with the respective dynamics of the three-wheel EVs operating within Ethiopian conditions, as noted by [30]. Furthermore, there needs to be more precise real-time modeling of traffic and road conditions these vehicles encounter daily. Current models typically do not consider the full range of factors determining energy efficiency and performance in such conditions. [31] Stress the need for developing localized models considering Ethiopia's unique infrastructure and driving habits. Also, research needs to be carried out to adapt existing methodologies to the three-wheel EVs, with greatly different weight distribution, center of gravity, and load handling than four-wheelers. This adaptation is necessary to achieve the full potential of control strategies and to allow these vehicles to safely ride on the rough road conditions in Ethiopia.

Aside from this, the potential for substituting renewable power sources into charging infrastructure is another untapped ability. As [32] affirms, utilizing Ethiopia's renewable energy supplies can provide a clean and dependable source of electricity for charging three-wheel EVs, which will offset the inconsistency of an unreliably stable electric grid. Incorporating it can increase clean energy usage, reducing the transportation carbon footprint, and supporting the environmental goals of Ethiopia. Supplying charging infrastructure that is locally available and powered by renewable energy can ease the current lack of charging points and improve the viability of three-wheel EVs in Ethiopia. Socio-economic benefits are also possible through job creation in vehicle maintenance, installing charging infrastructure, and electric mobility services.

CHAPTER 3: SYSTEM MODELING

3.1. Introduction

These chapters focus on the use of Brushless Direct Current (BLDC) Motors in electric vehicles (EVs), particularly on three-wheel EVs such as the Bajaj. The chapters begin by exploring the BLDC motor construction and principles of operation, providing insight as to why BLDC motors are the preferred motors for EV applications, especially where efficiency, reliability, and minimum maintenance are of concern.

Next, we perform a performance comparison of various motor types commonly used in EVs, including induction motors, permanent magnet synchronous motors (PMSMs), and BLDC motors. This comparison highlights the key advantages and limitations of each motor type, offering a clear understanding of why BLDC motors are widely adopted in the EV industry, particularly in three-wheel vehicles.

This chapter focuses on system modeling for the MPC-based cruise control system developed for a Bajaj three-wheel EV. It emphasizes the creation of mathematical models that accurately depict the dynamics of the BLDC motor, traction motor, the three-wheel electric vehicle, and its energy consumption.

3.2. Brushless Direct Current (BLDC) Motors in EVs

3.2.1. Automotive BLDC Motor

3.2.1.1. *Choosing Traction Motor*

Automobiles, being both convenient and efficient, are an integral part of daily life. In developed countries, the automobile ownership rate is notably high. Modern automobiles often contain dozens, if not hundreds, of motors. As the industry shifts toward energy-saving and environmentally friendly technologies, high-efficiency permanent magnet motors, including BLDC motors, are becoming increasingly promising.

Performance indices commonly used to evaluate motors in electric vehicles are listed in Table 3.1. From Table 3.2, it is evident that BLDC motors, as a subset of permanent magnet motors, demonstrate significant technical advantages [33, 34].

Table 3. 1: Performance indexes of motors that are used to drive electric vehicles [34]

Performance indexes	Motor Type			
	DC motor	Induction motor	PM motor	Switched reluctance motor
Power density	Low	Intermediate	High	Very high
Peak efficiency (%)	<90	90–95	95–97	<90
Load efficiency (%)	80–87	90–92	85–97	78–86
Controllability	Simple	Complex	Hard for field weakening	Complex
Reliability	Normal	Good	Excellent	Good
Heat dissipation	Bad	Bad	Good	Good
Size & weight	Big, Heavy	Normal, Normal	Small, Light	Small, Light
High-speed performance	Poor	Excellent	Good	Excellent
Construction	Slightly worse	Better	Slightly better	Excellent
Combination property	Slightly	worse	Normal	Excellent Better

Table 3.2 lists various EV models from different manufacturers alongside the types of electric motors they use. As each company selects a motor drive tailored to its propulsion system, the table highlights that BLDC and induction motors are the most commonly chosen options by manufacturers.

Table 3. 2: Various electric vehicle models and their corresponding motors [34, 35]

No	Electric Vehicle	Manufacturer	Passenger Capacity	Motor Type	Country
1	Berlingo	PSA Peugrot-Citroen	5	DC	France
2	Nissan leaf	Nissan	5	BLDC	Japan
3	Mitsubishi-MiEV	Mitsubishi	4	BLDC	Japan
4	BYD E6	BYD Auto	5	BLDC	China
5	Morgan Pulse E	Morgan Motors	2	BLDC	UK
6	Toyota RAVA4	Toyota	4	BLDC	Japan
7	Tesla	Tesla Motors	5	BLDC/IM	USA

8	BMW/X5	BMW	4	IM	Germany
9	Renault	Renault/Kangoo	4	IM	France
10	Chevrolet	Chevrolet/Silverado	4	IM	USA
11	Nissan/Tino	Nissan	4	PMSM	Japan
12	Honda/Insight	Honda Motors	4	PMSM	Japan
13	Toyota/Prius	Toyota	4	PMSM	Japan
14	Holden	Holden/ECOmmodore	4	SR	Australia

Selecting an electric motor that best aligns with the technological requirements of EVs necessitates a thorough comparison based on key criteria. The most critical requirements for EV motors include:

- Fast dynamic torque and speed response
- Large low-speed torque for the capability to climb hills
- High torque-to-power ratio and size
- Smooth power release in a wide speed range
- High-precision electronic control
- Robustness and reliability of motor and drive system
- Low torque ripple and current harmonics
- Motor operation and gear transmission efficiency high
- Compact size and lightweight design suitable for the vehicle's load demands
- Reasonable initial and maintenance costs for both the motor and controller

Given the diversity of EV requirements, no single motor type can perfectly satisfy all these characteristics. The subsequent section explores various electric motors, analyzing their structures and performance attributes.

BLDC motors, in particular, are advancing toward greater energy efficiency and enhanced comfort. With continuous developments in power electronics, automation control, and computer science, BLDC motor speed regulation technologies are maturing, offering improved quality at lower costs. As a result, BLDC motors are poised for broader applications and are expected to remain a dominant choice in speed-regulation technologies.

3.2.1.2. Performance Comparison of Various Motor Types

3.2.1.3. BLDC vs Brushed DC

While brushed DC motors have served as the workhorses of electric applications for decades, BLDC motors offer distinct advantages:

Brushed DC motors utilize brushes for current commutation, a process that creates friction and sparking. This not only reduces efficiency but also necessitates regular brush replacement, adding to maintenance costs. BLDC motors eliminate these drawbacks entirely. The absence of brushes translates to lower friction, minimal sparking, and consequently, higher efficiency – a crucial factor for maximizing an EV's range.

The sparking and friction associated with brushed DC motors contribute to noticeable noise. BLDC motors, on the other hand, operate with remarkable silence. This translates to a more pleasant driving experience for passengers and a quieter environment for pedestrians.

3.2.1.4. The Induction Motors vs. BLDC Motors

Induction motors are another choice for electric vehicle applications. However, BLDC motors offer several key benefits for EVs:

Precise Control for a Smooth Ride: Induction motors rely on a rotating magnetic field induced in the rotor by the stator's current. This indirect approach makes precise speed control more challenging. BLDC motors, with their direct control over the stator's magnetic field via electronic controllers, deliver superior speed and torque control, leading to smoother acceleration and improved handling for EVs.

High Power Density: Packing a Punch in a Compact Design: BLDC motors excel in delivering high power output relative to their size. This compact design is ideal for space-constrained environments like EV motor compartments, allowing for efficient packaging and weight reduction, ultimately contributing to better vehicle performance.

A direct comparison of various machine parameters of BLDC motors and DC and IM motors indicates the superiority of BLDC motors over the latter two. A comparison reveals the extensive application of BLDC motors in EVs and other applications. It also shows that BLDC motors can be substituted for other motors due to their numerous advantages and their ability to be used in almost any application requiring a motor with a small drive system.

Table 3. 3 and Table 3. 4 below summarize the advantages of BLDC motors compared to DC and IM motors [34, 36].

Table 3. 3: Comparison between brushed DC and brushless DC motors

Feature	BLDC motor	Brushed DC motor	Electronic switches substitute mechanical devices for improved reliability.
Commutation	Electronic commutation based on rotor position information	Mechanical brushes commutato r	The voltage drop across electronic devices is less than that of brushes.
Efficiency	High	Moderate	Maintenance is minimized due to the absence of brushes and commutators.
Maintenance	Little/None	Periodic	Heat generation is confined to the stator, which is connected to the external casing, ensuring better heat dissipation than in brushed DC motors.
Thermal performance	Better	Poor	Modern permanent magnets eliminate rotor-related energy losses.
Output power/ Frame size (ratio)	High	Moderate/L ow	The absence of brush friction increases the motor's effective torque.
Speed/Torque characteristics	Flat	Moderately flat	Rotor inertia is reduced by using lightweight permanent magnets.
Dynamic response	Fast	Slow	Mechanical restrictions imposed by brushes and commutators are eliminated.
Speed range	High	Low	The lack of brush arcs prevents noise and mitigates EMI concerns.
Electric noise	Low	High	The absence of brushes and commutators simplifies the motor design.

Lifetime	Long	Short	Electronic switches substitute mechanical devices for improved reliability.

Table 3. 4: Comparison between AC induction and BLDC motors

Feature	BLDC motor	AC induction motor (IM)	Actual advantage
Torque /Speed characteristics	Flat	Nonlinear - lower torque at lower speeds	The permanent magnet design, combined with rotor position feedback, enables BLDC motors to achieve higher starting and low-speed torque.
Output power/ Frame size (ratio)	High	Moderate	Both the stator and rotor have windings for induction motor.
Dynamic response	Fast	Low	Less rotor inertia caused by the permanent magnet.
Slip between stator and rotor frequency	No	Yes	BLDC is synchronous motor; induction motor is an asynchronous motor.
Torque ripple	High	Less	Due to electronic commutation, BLDC motor has more torque ripple compared to induction motor

3.2.1.5. The BLDC Advantage for EVs:

BLDC motors stand out as a fascinating choice for powering EVs due to a winning combination of factors:

- **Superior Efficiency:** The absence of brushes and the use of permanent magnets lead to high efficiency, maximizing the range achievable on a single charge.
- **Minimal Maintenance:** Without brushes to wear out, BLDC motors require minimal maintenance, reducing operating costs for EVs.
- **Precise Controllability:** The electronic control system enables precise speed and torque control, translating to a smoother driving experience and improved handling.
- **Compact Design:** The high-power density of BLDC motors allows for space-saving packaging, contributing to efficient vehicle design.
- **Quiet Operation:** BLDC motors generate minimal noise, enhancing passenger comfort and contributing to a quieter environment.

3.2.2. Operation and Construction of BLDC Motor

3.2.2.1. Operation:

At the heart of a BLDC motor lies a captivating interplay of magnetism and electrical control. Unlike brushed DC motors that rely on physical brushes for current transfer, BLDC motors employ a permanent magnet rotor and a stator with strategically placed windings. The permanent magnets on the rotor generate a constant magnetic field. The magic unfolds in the stator windings. Here, an electronic controller orchestrates a carefully timed sequence of energizing these windings, creating a rotating magnetic field. This rotating magnetic field acts like an invisible hand, constantly pulling on the permanent magnets in the rotor, causing it to spin. Sensors, typically Hall effect sensors, precisely track the rotor's position. This information is fed back to the controller, ensuring the sequence of energized windings remains synchronized with the rotor's position, maintaining smooth and continuous rotation.

3.2.2.2. Basic Structure

The Brushless DC (BLDC) motor is a synchronous electric motor that operates without brushes. It is made up of several important parts:

The primary concept of a BLDC motor is to replace the mechanical commutator with an electrical switching circuit. In traditional DC motors, commutation is provided by employing brushes, which ensures that the stator and armature magnetic fields are always perpendicular during motor operation. That was until the "inverted DC motor" was invented, in which the magnet steel and armature winding are placed on the rotor and stator sides, eliminating mechanical brushes. In order to regulate the motor speed and direction, a rotor-position sensor, control circuit, and power inverter are required in a BLDC motor system. Figure 3. *1* illustrates the experimental system of a BLDC motor

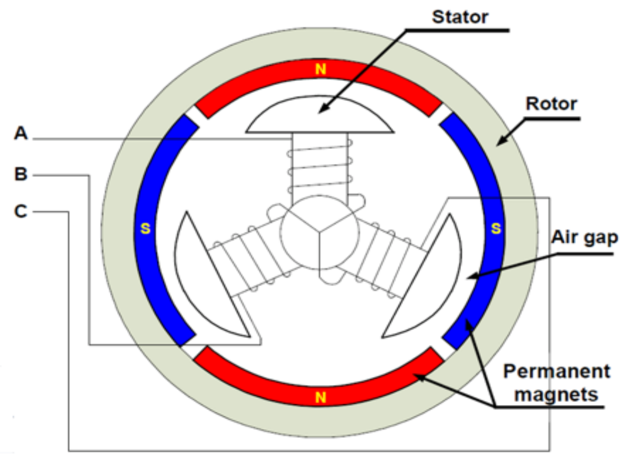


Figure 3. 1: BLDC motor's structure

The BLDC motor's structure contains a stator with armature winding and a rotor with a permanent magnet, which is similar to PMSM.

Permanent magnet rotor:

Stator Core:

The rotor of a BLDC motor consists of permanent magnets arranged in a specific pattern to generate a magnetic field that interacts with the stator's field, producing motion. It includes a shaft and a hub, with magnets configured in two to eight pole pairs, alternating between north and south poles. Figure 3.1 illustrates cross-sections of three different magnet arrangements in a rotor.

Various materials are used for these magnets, including ferrite mixtures and rare-earth alloys. While ferrite magnets are traditional and cost-effective, rare-earth alloys, such as NdFeB (neodymium-iron-boron), are becoming increasingly popular due to their higher magnetic density. This allows for smaller rotors while maintaining superior torque performance compared to ferrite magnets.

In BLDC motors, permanent magnets are either embedded within the iron core or mounted on the rotor's surface. These magnets exhibit high coercivity and remanence intensity, ensuring strong and consistent magnetic fields. Unlike brushed motors, where permanent magnets are positioned on the stator, BLDC motors have them installed on the rotor, distinguishing their structural and operational characteristics.

The stator contains the motor windings, typically copper coils, which create an electromagnetic field when an electric current flows through them. The stator is fixed within the motor housing.

The stator design of a BLDC motor is similar to that of a standard synchronous motor or an induction motor. The windings, which can be single- or multi-phase, are embedded in an iron core and can be connected in a “Y” or “D” configuration. For better performance and cost-efficiency, the Y-type configuration is mostly used, where the three-phase windings are symmetrically connected without a neutral point. Unlike traditional brushed DC motors, where the armature winding is located in the rotor, the armature winding is installed in the stator of BLDC motors, reducing heat generation.

Position Sensor

Often included in BLDC motors, Hall sensors are used to detect the rotor's position. This information helps in controlling the commutation of the motor phases, improving efficiency and performance.

Commutation Electronics:

BLDC motors require advanced electronic commutation circuits to control the flow of current to the stator windings. This is typically accomplished through an electronic driver or controller that precisely controls the timing and sequence of current to the windings based on rotor position information.

3.3. Challenges and Opportunities in Three-Wheel EVs (Bajaj)

Three-wheel electric vehicles (EVs), such as those manufactured by Bajaj, face several specific challenges that can impact their adoption and performance, particularly in the Ethiopian context. One of the primary issues is the limited space available for battery storage. Unlike four-wheel EVs, three-wheelers have less room to accommodate large battery packs, which can restrict travel range, a key concern for potential users[37].

Additionally, 3-wheel EVs often experience variable load conditions. They may carry cargo in one trip and be empty the next, impacting battery efficiency. Traffic conditions and road quality can further affect energy consumption, making it difficult to predict range accurately.

Despite these challenges, there are opportunities to improve the efficiency of 3-wheel EVs. Research suggests that innovative control strategies can optimize motor and battery usage based on real-time conditions. Developing accurate models that take into account factors like variable loads and traffic patterns can also help predict energy consumption more precisely. Finally, tailoring solutions to address the specific operational challenges of 3-wheel EVs, such as designing efficient battery packs for limited space, can significantly enhance their overall efficiency.

3.4. Block Diagram Description

The block diagram comprises several key elements that communicate with one another to facilitate effective use of energy and optimal car performance. In the middle is the Model Predictive Cruise (MPC) Speed Controller that uses inputs like the desired speed trajectory, the state of the BLDC motors (i.e., three-phase current and angular velocity), and future states like speed limits, road slope, and road curvature to calculate the optimal compromise between energy consumption and speed for optimal running.

The inverter is also a very important block in the block diagram. It is used to convert the DC power from the vehicle's battery to AC power required by the BLDC motor. The inverter provides the motor with the appropriate voltage and frequency based on the control signals generated by the MPC controller.

The BLDC motor itself is the three-wheel electric vehicle's drive system. It converts the electrical energy received from the inverter into mechanical energy and provides the torque that propels the vehicle. The motor is regulated and monitored very closely by the MPC speed controller and PID current controller for optimum energy efficiency.

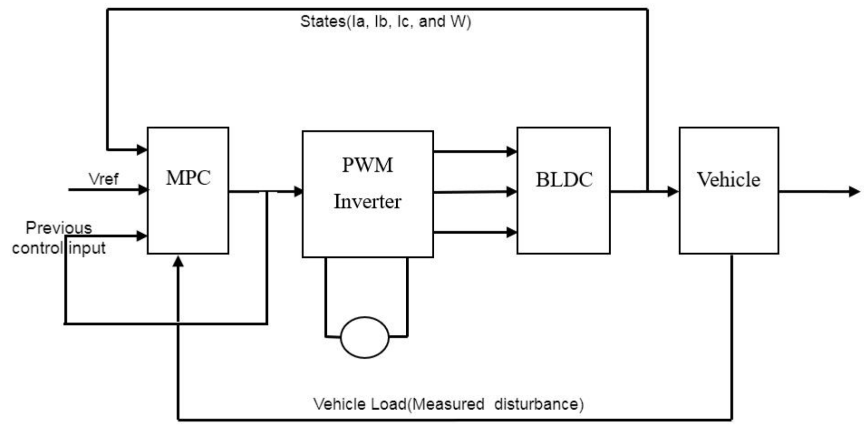


Figure 3. 2: Block Diagram Description

3.5. Three-wheel Electric Vehicle model

3.5.1. Three-wheel Electric Vehicle

Three-wheel electric vehicles (EVs) are a type of electric vehicle that has three wheels. They are typically smaller and more maneuverable than four-wheel EVs, and they are often used for urban transportation. Bajaj is a leading manufacturer of three-wheel EVs in India. The first three-wheel EV was developed in the early 1900s. However, it was not until the 1970s that three-wheel EVs began to gain popularity in India[38]. This was due to the high cost of gasoline and the lack of infrastructure for four-wheel vehicles. Bajaj began manufacturing three-wheel EVs in India in the 1980s, and they quickly became one of the most popular types of vehicles in the country.Three-wheel EVs are typically smaller and lighter than four-wheel EVs. This makes them more maneuverable and easier to park. They also have a lower center of gravity, which makes them more stable. Three-wheel EVs typically have a range of around 50-100 kilometers on a single charge. Three-wheel EVs are more maneuverable than four-wheel EVs[39]. This makes them easier to park and navigate in tight spaces. Three-wheel EVs are a good option for people who are looking for a fuel-efficient, low-cost, and environmentally friendly vehicle. They are particularly well-suited for urban transportation. Bajaj is a leading manufacturer of three-wheel EVs in India, and they offer a variety of models to choose from.

Three-wheel electric vehicles, particularly those manufactured by Bajaj, have gained significant popularity in recent years due to their numerous advantages. These vehicles, also known as auto-rickshaws or tuk-tuks, provide an efficient, cost-effective, and environmentally friendly mode of transportation in many urban areas, including Ethiopia. In this introduction, we will explore the features, benefits, and impact of three-wheel electric vehicles manufactured by Bajaj.

Bajaj, an Indian automotive company, has been a key player in the production of three-wheelers for several decades. Their electric variants offer a sustainable alternative to the traditional gasoline-powered auto-rickshaws. These vehicles are specifically designed to cater to the needs of urban commuters, providing an affordable and reliable transportation option[40, 41].

One of the significant advantages of Bajaj's three-wheel electric vehicles is their eco-friendliness. They produce zero tailpipe emissions, reducing air pollution and contributing to improved air quality in congested city areas. This aspect is particularly crucial for countries like Ethiopia that are striving to mitigate the environmental impact of transportation.

Furthermore, operating costs for three-wheel electric vehicles are considerably lower compared to their gasoline counterparts. With the rising fuel prices, the electric vehicles offer a cost-effective solution for both drivers and passengers. Electric charging is generally cheaper than refueling with gasoline, resulting in reduced operational expenses for drivers and potentially lower fares for passengers.

The compact size of Bajaj's three-wheel electric vehicles makes them well-suited for navigating through congested traffic and narrow streets, which are common in urban areas. Their maneuverability allows for efficient and quick transportation, making them an ideal choice for short-distance commuting within cities. Additionally, the vehicles offer a comfortable ride, with features such as spacious seating, improved suspension, and noise reduction technologies[42].

Bajaj's electric three-wheelers also contribute to job creation and socio-economic development. They provide employment opportunities for drivers, mechanics, and other related industries involved in the manufacturing and maintenance of these vehicles.

Moreover, the affordability and accessibility of these vehicles make them an attractive option for entrepreneurs, enabling them to establish small businesses and contribute to the local economy.

3.5.2. Three-wheel Electric Vehicle (Bajaj) Dynamics modeling

Vehicle dynamics is the study of the forces acting on a vehicle during its motion. Analyzing these forces provides valuable insights into the vehicle's stability, behavior, and overall performance [43].

When an electric vehicle travels on a slope under constant-speed cruise control, the required driving torque for longitudinal motion is an instantaneous parameter with changing driving conditions, i.e., road inclination angle of the vehicle and its longitudinal speed. The controller should adjust the driving and braking torques correspondingly for sustaining the target cruise speed. Throughout the movement of the vehicle, various elements affect its performance, such as rolling resistance, aerodynamic drag resistance, resistance to slope, and resistance to acceleration, as shown in Figure 3. 3 [43, 44].

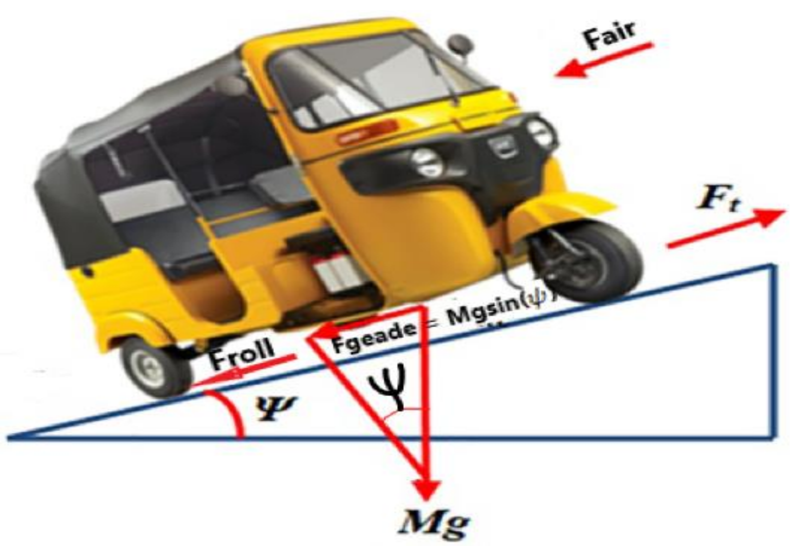


Figure 3. 3 Forces acting on three-wheel electric vehicle longitudinal motion.

The principles of vehicle dynamics applies to any moving mass whether it's electric or not. The summations of forces acting on a moving vehicle are[45, 46]:

$$\sum F = ma \quad (3.\ 1)$$

$$F_{tractive} - F_{air} - F_{roll} - F_{climb} = ma \quad (3.\ 2)$$

Let's explore the key forces involved in vehicle dynamics:

3.5.2.1. *Aerodynamic drag Resistance*

Drag is the resistance that a vehicle experiences as it moves through the air. It is in opposition to the motion direction of the vehicle and varies with the shape of the vehicle, velocity of the vehicle, and air density. Drag force impacts the speed of the vehicle at the peak and its efficiency in energy.

As a Bajaj vehicle is in motion, there is a high-pressure area in front of the vehicle and a low-pressure area behind it. The two areas resist the movement of the vehicle, and the force created as a result is called shape drag.[47]

The second component of aerodynamic drag is skin friction, which arises from the interaction between air molecules moving at different speeds. Air close to the vehicle's surface moves nearly at the same velocity as the vehicle, while air farther away moves at a different speed, generating friction. The aerodynamic drag force depends on the vehicle's linear velocity, V, and can be expressed as:[48]:

$$F_{air} = \frac{1}{2}\rho_a C_d A_V V^2 \quad (3.\ 3)$$

where A_v is the frontal area of the bajaj, C_d is the aerodynamic drag coefficient, ρ_a is density of air (1.22kg/m^3), V is the speed of Bajaj.

3.5.2.2. *Rolling Resistance Force*

Rolling resistance is the friction force that works against the movement of the vehicle as the wheels roll over the road. The force occurs because of the flattening of the tire at the point where it touches the road [49, 50]. The rolling resistance force is a conservative force, meaning it can be partially recovered. It depends on factors such as the type of tire, road conditions, and the vehicle's weight.

$$F_{roll} = mgC_r \cos(\psi) \quad (3.\ 4)$$

where m is the mass of the bajaj platform and cargo (kg), ψ is the gradient angle (rad), g is the acceleration due to gravity (m/s^2), and C_r is the rolling resistance coefficient.

Table 3. 5: Coefficient of friction for different type of surfaces [51, 52]

Contact surface	Coefficient of friction
Concrete surface (good/fair/poor)	0.010/0.015/0.02
Asphalt (good/fair/poor)	0.012/0.017/0.022
Macadam (good/fair/poor)	0.015/0.022/0.037
Snow/dirt	0.025/0.037
Mud (firm/medium/smooth)	0.037/0.09/0.15
Grass (firm/soft)	0.055/0.037
Sand (firm/soft/dune)	0.060/0.15/0.3

3.5.2.3. Climbing (Gradient) Resistance Force

As the vehicle platform is driving up or down the hill, the weight of the vehicle platform will create a hill-climbing resistance force in the direction downwards [52]. The force opposes or aids the movement. The force is the weight of the vehicle and is in a vertical direction downwards. It is dependent on the mass of the vehicle and the acceleration due to gravity. The gravity term in the travel direction is the hill-climbing resistance force and can be expressed by:

$$F_{climb} = mg\sin(\psi) \tag{3. 5}$$

Where, m is the mass of the vehicle platform and cargo (kg), g is the acceleration due to gravity (m/s2), ψ is the road or the hill-climbing angle, road slope (rad.).

Understanding and analyzing these forces play a crucial role in developing ADAS and autonomous driving technologies, as they help in predicting and controlling the vehicle's behavior in various driving conditions

The longitudinal motion of an electric vehicle refers to its motion along the forward and backward direction, commonly known as acceleration and deceleration. In this context, let's discuss the key aspects of the longitudinal motion of an electric vehicle:

3.5.3. The load torque

In EVs, the load torque is the torque required from the electric motor to overcome the various forces that oppose the vehicle's motion. This torque is essential for accelerating the vehicle, maintaining its speed on inclines, and overcoming aerodynamic drag and rolling resistance.

The load torque is influenced by several factors, including the vehicle's mass, acceleration rate, road grade, tire type, and aerodynamic design. Heavier vehicles require more load torque to accelerate, while steeper inclines demand greater torque to maintain speed. Similarly, vehicles with higher drag coefficients or poor tire designs experience increased rolling resistance, leading to higher load torque requirements.

Understanding the load torque is crucial for designing efficient and powerful EVs. By minimizing resistive forces and optimizing the load torque, engineers can improve the vehicle's range, acceleration, and overall performance.

3.5.3.1. Calculating Load Torque for Electric Vehicles (EVs)

To determine the load torque required for an electric vehicle (EV), the following formula can be utilized:

$$Load\ \text{Torque}(T_L) = \frac{\text{Resistive Forces*Wheel Radius}}{\text{Transmission Ratio}} = \frac{F_{\text{Resistive}} * R_{wheel}}{G} \qquad (3.\ 6)$$

Where,

Load Torque: The torque required at the motor to overcome resistive forces and propel the vehicle.

Resistive Forces: The cumulative forces acting against the vehicle's motion, which include:

- ✓ Rolling Resistance
- ✓ Aerodynamic Drag
- ✓ Climbing Resistance

Wheel Radius: The radius of the vehicle's wheels.

Transmission Ratio: The ratio of the motor's rotational speed to the wheels' rotational speed.

Combining Resistive Forces:

The total resistive forces can be expressed as:

$$F_{\text{Resistive}} = F_{roll} + F_{\text{climb}} + F_{air} \tag{3. 7}$$

Substitititing equation Eq.(3.3),Eq.(3.4), Eq.(3.5) and Eq.(3.7) into Eq. (3.6),

$$T_L = \frac{\left(\left(F_{roll} + F_{\text{climb}} + F_{air}\right) \times R_{\text{Wheel}}\right)}{G} \tag{3. 8}$$

Where: $F_{Resistive}$ is the Resistive force (Newtons)

T_L is the Load torque

G - Gear ratio is the ratio of the number of teeth on the driving gear to the driven gear in the transmission (dimensionless)

R_{wheel} - Wheel Radius is the radius of the vehicle's wheels (meters)

The equation effectively converts the resistive forces acting on the vehicle into load torque. The gear ratios and wheel radius function as mechanical advantages, amplifying the torque generated by the motor to overcome this resistive load and achieve the desired acceleration.

Table 3. 6: Different parameter value[53]

No	Parameter	symbol	Value
1	Frontal area of the bajaj (m^2)	A_v	2.223
2	Density of air (kg/m^{3})	ρ_a	1.22
3	Aerodynamic drag coefficient	C_d	0.44
4	Acceleration due to gravity (m/s^2)	g	9.81
5	Mass of the bajaj platform and cargo (kg)	M	678
6	Rolling resistance coefficient	C_r	0.015
7	Wheel Radius(m)	R_w	0.22

3.5.4. Driving/Tractive Force and Motor Torque relation:

In an electric vehicle, the driving force is generated by the electric motor. By controlling the motor's torque output, the vehicle can accelerate or decelerate. The driving force is responsible for propelling the vehicle forward and overcoming the resistive forces acting against it.

Driving/Tractive Force ($F_{tractive}$): This is the horizontal force acting at the point of contact between the tires and the road surface, propelling the vehicle forward. It overcomes rolling resistance (resistance due to tire deformation) and aerodynamic drag (air resistance).

Motor Torque (T_e): This is the twisting force generated by the engine (internal combustion engine) or electric motor. It acts on the crankshaft (engine) or motor shaft and is transmitted through the drivetrain to the wheels.

The relationship between motor torque and driving force can be expressed mathematically using the following equation:

$$F_{tractive} = \frac{G * T_e}{R_{wheel}} \tag{3. 9}$$

Where: $F_{tractive}$ is the driving/tractive force (Newtons)

T_e is the motor torque (Newton-meters)

G - Gear ratio is the ratio of the number of teeth on the driving gear to the driven gear in the transmission (dimensionless)

R_{wheel} - Wheel Radius is the radius of the vehicle's wheels (meters)

This equation essentially translates the rotational force (torque) generated by the motor into a linear force (driving force) that acts on the road surface to propel the vehicle. The gear ratios and wheel radius act as mechanical advantage, amplifying the torque to generate a sufficient driving force for overcoming resistance and achieving desired acceleration.

Substititing the force equation Eq.(3.3),Eq.(3.4),Eq.(3.5), and Eq.(3.6) into Eq.(3.2) yields

$$a = \frac{dv}{dt} = \left(\frac{GT_e}{mR_{wheel}} - \frac{1}{2m} \rho_a C_d A_V V^2 - gC_r \cos(\theta) - g \sin(\theta) \right) \tag{3. 10}$$

3.6. Energy Consumption Model

Electric three-wheeler vehicles, like those offered by Bajaj Auto, are gaining traction as eco-friendly and efficient transportation solutions. However, optimizing their energy consumption remains crucial for maximizing range and battery life. This is where energy consumption modeling comes into play.

Several factors significantly impact the energy consumption of a three-wheel electric vehicle. The primary factor is the driving force, which depends on the vehicle's weight, acceleration demands, road incline (uphill climbs require more energy), and aerodynamic drag (which increases with speed). Speed limits, road inclination, and even road curvature can all influence how much energy the vehicle expends. An efficient MPC system needs to consider these future possibilities.

Unfortunately, obtaining detailed real-world data on energy consumption specific to a Bajaj electric vehicle can be challenging. To overcome this, a physics-based model can be developed for use within a Model Predictive Control (MPC) system. This model focuses on the core factors like driving force and vehicle speed. The driving force is calculated based on Eq. (3.9) which considers factors like vehicle mass, acceleration, and anticipated road grade, while speed is obtained from sensors. By multiplying the driving force by the vehicle speed, the model estimates the instantaneous power consumption. Integrating this power consumption over time within the MPC framework allows for calculating the total energy consumed.

$$P = V * F_{tractive} \tag{3. 11}$$

$$P = V * \frac{GT_e}{R_{wheel}} \tag{3. 12}$$

$$E_{cons} = \int pdt \tag{3. 13}$$

$$E_{cons} = \int (V * F_{tractive})\, dt \tag{3. 14}$$

The benefits of incorporating an energy consumption model into the MPC control system are numerous. The MPC controller, with its ability to predict future conditions, can optimize motor control and driving force based on anticipated energy consumption. This leads to improved efficiency, resulting in a vehicle that travels further on a single battery charge. In turn, this translates to extended battery life and potentially lower operating costs.

3.7. Mathematical Model of BLDC

The mathematical model of the BLDC motor is required for the analysis of performance and the design of the control system. When developing the model, the structural properties of the motor and the working modes must be taken into account. The BLDC motor typically consists of three components: the motor body, the power driving circuit, and the position sensor. Various motor bodies and driving modes also exist. The differential equation model and the state-space model are the most widely used mathematical models.

3.7.1. Mathematical Derivation

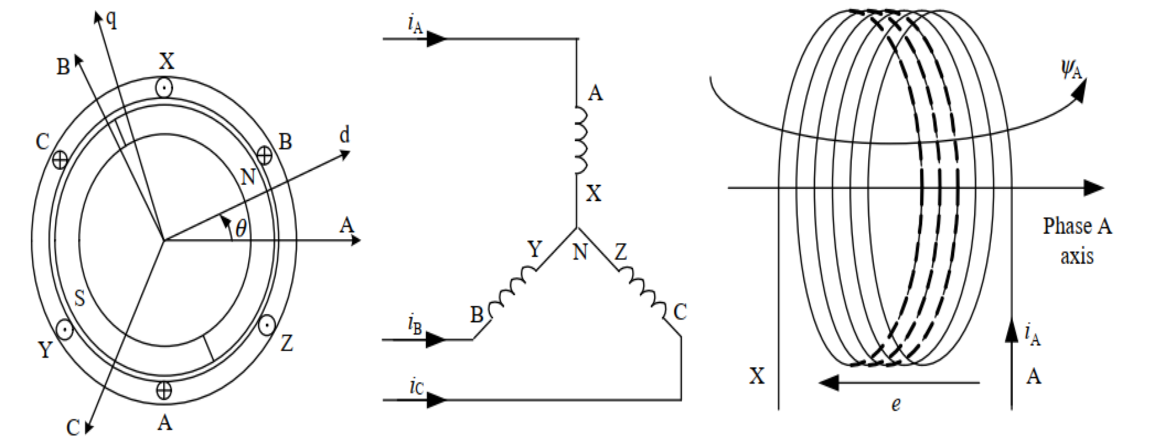
3.7.1.1. *Electromagnetic Equations*

Electromagnetic equations define the motor's behavior by linking electrical quantities (voltage, current) to mechanical properties (torque, speed) through principles such as Faraday's law and motor equations.

Here, the model of a three-phase, two-pole BLDC motor is formulated based on a differential equation. A Y-connected full-pitch winding concentrated in the stator is employed, while the rotor includes a nonsalient pole arrangement. Three symmetrically spaced 120° interval Hall sensors are placed. Based on the above, the assumptions to derive the differential equation of the BLDC motor are given as [35]:

- Core saturation, eddy current losses, and hysteresis losses are neglected.
- The armature reaction is ignored, and the air-gap magnetic field distribution is assumed to be a trapezoidal wave with a flat top over 120° electrical angle.

- The cogging effect is neglected, and it is assumed that the conductors are continuously and uniformly distributed over the armature surface.
- The power switches and flywheel diodes of the inverter circuit are presumed to have ideal switch characteristics.



(a) Structure of BLDC motor (b) Connecting type of winding (c) Provision of positive direction (Phase A)

Figure 3. 4: BLDC Motor structure, connection type, and phase direction

In accordance with the indicated positive direction illustrated in Figure 3. 4 the phase voltage of each winding, encompassing both the resistance voltage drop and the induced EMF, can be expressed as follows:

$$U_x = R_x i_x + e_x \tag{3. 15}$$

U_x — phase voltage, in which subscript x denotes phase A, B and C;

i_x — phase current;

e_x — phase-induced EMF;

R_x — phase resistance. For three-phase symmetrical winding, there exists $R_A = R_B = R_C = R$

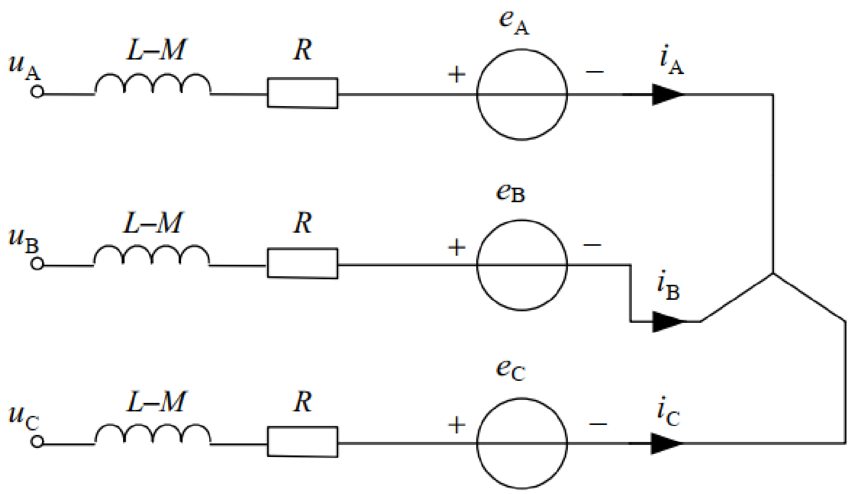


Figure 3. 5: Modeling of BLDC motor

$$
\begin{aligned}
u_A &= Ri_A + d/dt(L_A i_A + M_A B i_B + M_A C i_C + \varphi_{pm}) \\
&= Ri_A + d/dt(L_A i_A + M_A B i_B + M_A C i_C) + d/dt[NS\int_{-\frac{\Pi}{2}+\theta}^{\frac{\Pi}{2}+\theta} B(x)dx] \qquad (3.\ 16) \\
&= Ri_A + d/dt(L_A i_A + M_A B i_B + M_A C i_C) + e_A)
\end{aligned}
$$

Usually, the salient-pole rotor is installed on the surface for BLDC motors. The winding inductance in this situation will be constant with respect to time. Also, since the three-phase stator windings are symmetric, the self-inductances will be identical, and therefore the mutual inductance. That is $L_A = L_B = L_C = L$, $M_{AB} = M_{BA} = M_{BC} = M_{CB} = M_{AC} = M_{CA} = M$. Substituting them into Eq. (3.11), we can get

$$u_A = Ri_A + L\frac{di_A}{dt} + M\frac{di_B}{dt} + M\frac{di_C}{dt} + e_A \qquad (3.\ 17)$$

Then, the θ-dependent back-EMF wave of phase A is $\pi/2$ ahead of the distribution of the magnetic density in air gap, and e_A can be expressed as

$$e_A = \omega\psi_m f_A(\theta) \qquad (3.\ 18)$$

B_m - maximum value of PM density distribution in air gap;

ψ_m - maximum value of PM flux linkage of each winding,

$f_A(\theta)$ - back-EMF waveform function of phase A.

Note that the $f_A(\theta)$ has a trapezoidal distribution with the rotor position, and its maximum and minimum values are, respectively, +1 and -1. The corresponding waveform and its phase relationship with $B(\theta)$ and e_A are shown in Figure 3. 6. As for the three-phase symmetrical windings, there also exist $f_B(\theta) = f_A(\theta - 2\pi/3)$ and $f_C(\theta) = f_A(\theta + 2\pi/3)$

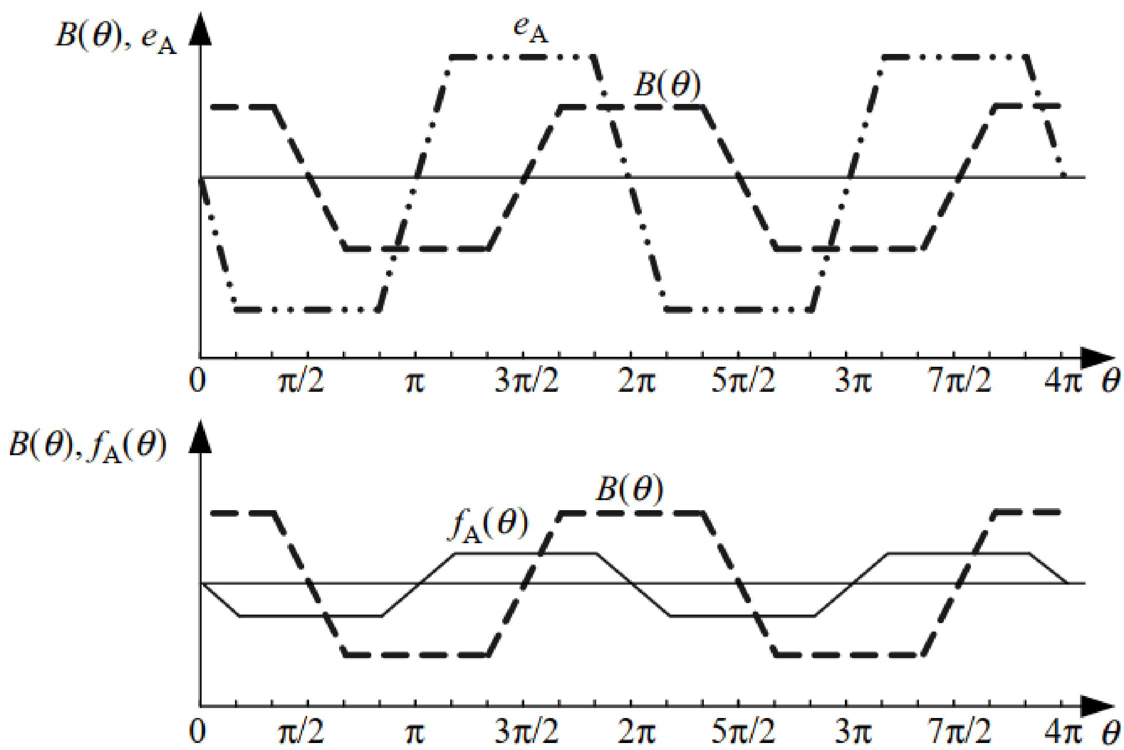


Figure 3. 6: Phase relationship between B (θ),e_A and $f_A(\theta)$

Since the current equation satisfying

$$i_A + i_B + i_C = 0 \tag{3. 19}$$

Based on Eq. (3.14). Eq. (3.12) can be further simplified as:

$$\begin{cases} u_A = Ri_A + (L-M)\dfrac{di_A}{dt} + e_A \\ u_B = Ri_B + (L-M)\dfrac{di_B}{dt} + e_B \\ u_C = Ri_C + (L-M)\dfrac{di_C}{dt} + e_C \end{cases} \tag{3. 20}$$

Then, the matrix form of the phase voltage equation of the BLDC motor can be expressed as:

$$\begin{bmatrix} u_A \\ u_B \\ u_C \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} + \begin{bmatrix} e_A \\ e_B \\ e_C \end{bmatrix} \tag{3. 21}$$

Rearranging Eq. (3.15) gives the two phases of current differential equations as follows:

$$\begin{aligned} \frac{di_A}{dt} &= \frac{u_A}{L-M} - \frac{Ri_A}{L-M} - \frac{e_A}{L-M} \\ \frac{di_B}{dt} &= \frac{u_B}{L-M} - \frac{Ri_B}{L-M} - \frac{e_B}{L-M} \\ \frac{di_C}{dt} &= \frac{u_C}{L-M} - \frac{Ri_C}{L-M} - \frac{e_C}{L-M} \end{aligned} \tag{3. 22}$$

Eq. (3.17) can be represented in the form of a matrix as:

$$\frac{d}{dt}\begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} = \begin{bmatrix} -\frac{R}{L-M} & 0 & 0 \\ 0 & -\frac{R}{L-M} & 0 \\ 0 & 0 & -\frac{R}{L-M} \end{bmatrix} \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} + \frac{1}{L-M}\begin{bmatrix} u_A \\ u_B \\ u_C \end{bmatrix} - \frac{1}{L-M}\begin{bmatrix} e_A \\ e_B \\ e_C \end{bmatrix} \tag{3. 23}$$

Hence, the state space equation form is

$$\begin{cases} \dfrac{dx}{dt} = Ax + B(U-e) \\ x = \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix}, A = \begin{bmatrix} -\frac{R}{L-M} & 0 & 0 \\ 0 & -\frac{R}{L-M} & 0 \\ 0 & 0 & -\frac{R}{L-M} \end{bmatrix}, U = \begin{bmatrix} u_A \\ u_B \\ u_C \end{bmatrix}, B = \frac{1}{L-M}, e = \begin{bmatrix} e_A \\ e_B \\ e_C \end{bmatrix} \end{cases} \tag{3. 24}$$

3.7.1.2. *Torque-Speed Characteristics of BLDC motor – Dynamic modeling*

The analysis of power and torque in BLDC motors draws parallels to that of DC motors. Both rely on the fundamental principle of energy transfer. During operation, the BLDC motor absorbs electrical power from the source. A minor portion of this power is dissipated as copper and iron losses within the motor windings and core, respectively. However, the majority of the power is converted into mechanical energy and transferred to the rotor through the air gap via the motor's torque generation capability.

This transferred power, referred to as electromagnetic power (P_e), represents the combined product of the current (I) and back-electromotive force (EMF, also denoted as E) in each of the three motor phases. Mathematically, this relationship can be expressed as:

$$P_e = e_A I_A + e_B I_B + e_C I_C \tag{3. 25}$$

Ignoring the mechanical loss and stray loss, the electromagnetic power is totally turned into kinetic energy, so

$$P_e = \tau_e \Omega \tag{3. 26}$$

$$\tau_e = \frac{e_A I_A + e_B I_B + e_C I_C}{\Omega} \tag{3. 27}$$

$$\begin{cases} e_A = \omega \psi_m f_A(\theta) \\ e_B = \omega \psi_m f_B(\theta) \\ e_C = \omega \psi_m f_C(\theta) \end{cases} \tag{3. 28}$$

$$\begin{cases} \tau_e = \dfrac{\omega \psi_m f_A(\theta) I_A + \omega \psi_m f_B(\theta) I_B + \omega \psi_m f_C(\theta) I_C}{\Omega} \\ \tau_e = p\left[\psi_m f_A(\theta) I_A + \psi_m f_B(\theta) I_B + \psi_m f_C(\theta) I_C\right] \end{cases} \tag{3. 29}$$

Where, p is the number of pole pairs

When the BLDC motor operates in the 120° conduction mode and the transient commutation process is neglected, the currents flowing through the Y-connected motor windings have the same amplitude but opposite directions, and these currents are confined to only two of the three-phase windings at any given time. It should be noted that the symbols for f(y)f(y)f(y) at the flat-top position are opposite to each other for different windings. This allows Eq. (3.24) to be simplified further as follows:

$$\tau_e = 2p\psi_m I_A = K_t I \tag{3. 30}$$

Where,

K_T — the torque coefficient;

I — the steady phase current

With the Newton's second law of motion, the angular motion of the rotor can be written as follows:

$$\frac{d\omega}{dt} = T_e - T_L - \beta\omega \tag{3. 31}$$

Combining the current Eq. (3.20) and the dynamic Eq (3.29) results in:

$$\begin{cases} \frac{di_A}{dt} = \frac{u_A}{L-M} - \frac{Ri_A}{L-M} - \frac{e_A}{L-M} \\ \frac{di_B}{dt} = \frac{u_B}{L-M} - \frac{Ri_B}{L-M} - \frac{e_B}{L-M} \\ \frac{di_C}{dt} = \frac{u_C}{L-M} - \frac{Ri_C}{L-M} - \frac{e_C}{L-M} \\ \frac{d\omega}{dt} = T_e - T_L - \beta\omega \end{cases} \tag{3. 32}$$

Hence, the states are,

$$\begin{gathered} x = \begin{bmatrix} i_A & i_B & i_c & \omega \end{bmatrix}^T \\ u = \begin{bmatrix} u_A & u_B & u_c & T_L \end{bmatrix}^T \end{gathered} \tag{3. 33}$$

Becomes,

$$\begin{cases} \dot{x}_1 = -\frac{Rx_1}{L} + \frac{u_1}{L} - \frac{e_A}{L} \\ \dot{x}_2 = -\frac{Rx_2}{L} + \frac{u_2}{L} - \frac{e_B}{L} \\ \dot{x}_3 = -\frac{Rx_3}{L} + \frac{u_3}{L} - \frac{e_C}{L} \\ \dot{x}_4 = T_e - T_L - \beta\omega \end{cases} \tag{3. 34}$$

$$y = \frac{3.6 * G * x(4)}{R} \tag{3. 35}$$

where as, G-GearRatio and R-wheel Radius

Rearranging Eq. (3.32) and Eq. (3.33) provides the nonlinear equation of the system as:

$$\begin{cases} \dot{x} = f\left(x, u, \psi_m, f_A(\theta)\right) \\ y = f(x) \end{cases} \tag{3. 36}$$

3.8. Speed Generation

The system prioritizes safety through the intelligent reference speed generator block. This block acts as the mastermind behind the vehicle's speed, accurately evaluating data from various sources. It factors in the posted road traffic limit, a crucial benchmark for legal and safe operation. Additionally, a radar sensor keeps the system informed about the real-time situation on the road. This includes detecting vehicles ahead and measuring their speed. By analyzing the relative distance and speed of nearby vehicles, the radar can determine a safe following distance to maintain.

But the reference speed generator goes beyond just following the car in front. The radar also plays a vital role in understanding the upcoming road itself. By analyzing the curvature of the road ahead, the radar can estimate a safe speed for navigating the bend. This takes into account factors like centrifugal force and maintaining vehicle control. The reference speed generator then takes the most restrictive value from all this data. This ensures the system obeys to the speed limit, maintains a safe distance from preceding vehicles, and adjusts speed for upcoming curves. This comprehensive approach promotes a smooth, safe, and controlled driving experience, anticipating potential hazards and adapting accordingly.

CHAPTER 4: Model Predictive Controller Design

4.1. Introduction:

This chapter focuses on developing a Model Predictive Control (MPC) system to optimize energy efficiency for a Bajaj three-wheeler electric vehicle's cruise control. Unlike traditional cruise control that simply maintains a reference speed, MPC offers a more sophisticated approach. It leverages its ability to predict future driving conditions – such as upcoming changes in speed limits, elevation variations, and road curvature – to proactively optimize control actions throughout the cruise. This foresight allows the MPC controller to make informed decisions that minimize energy consumption. This ability to predict and optimize control actions based on future scenarios sets MPC apart from conventional approaches and unlocks significant energy savings in cruise control operation.

The MPC controller of the three-wheel EV(Bajaj) directly controls the Brushless Direct Current (BLDC) motor, an essential part of electric vehicles. By dynamically adjusting the motor's operation based on predictive modeling of vehicle dynamics and energy consumption, the MPC controller can efficiently regulate speed while minimizing energy consumption[54, 55].

Moreover, the MPC strategy enables real-time adjustments to account for uncertainties in parameters and nonlinear dynamics inherent in three-wheel EVs. This adaptability enhances the controller's ability to maintain optimal energy efficiency across various driving conditions.

Model Predictive Control (MPC) is a highly promising optimal control technique based on models. It is effective by incorporating constraints on outputs and inputs and directly integrating an objective function into the control algorithm. Additionally, MPC is distinctive in being able to consider future information about the system and the environment. This characteristic of MPC makes it highly effective in handling time delays, non-minimum phase behavior, and previewing future events. Therefore, MPC provides a simple way to directly include technical specifications, safety requirements, and performance limitations in the design of the control system, e.g., for helicopters. MPC is able to calculate the optimal control input with regard to a customized objective function and the predicted future dynamics and flight situations.

This burden is indeed heavy. Despite the fact that the optimization approach and the amount of work that can be done is changing for the better, the practical use of MPC on dynamically active systems like helicopters and EVs is still a work in progress. In addition, non-applicable or idealized Lyapunov stability changes not being used in conjunction with the MPC problem means that tuning, which is infamously regarded as a black art, must perform the stabilization, which is highly unstructured for people conversant with system administration. This problem is even more severe for nonlinear MPC, because both the computational complexity and stability issues are problematic.

First used in the 1980s in industrial applications for refining, petrochemicals, and pulp and paper, MPC is now being applied in numerous other industries such as electronics, medicine, energy, environment, and aerospace and automotive industries. As MPC gains popularity, there are more opportunities in improving speed monitoring in vehicles. Research on MPC for autonomous aircraft has been ongoing since the 1900s, including activities like tracking, formation flight, obstacle avoidance, autorotation flight, and finding control limits equivalent to the flight envelope or load limits.

4.2. Working principle of MPC

Model Predictive Control (MPC) is a model-based, optimal control strategy where, at each time step k, an optimal control input sequence $u_k = [u_k; u_{k+1}; : : : ; u_{k+N-1}]$ is computed online over a future time horizon N. This is achieved by solving an open-loop optimization problem that incorporates knowledge of the system model. The optimization process begins by using the current system state as the initial state, along with the system's model, to predict future states along the prediction horizon. The goal is to optimize a predefined objective function. Once the optimal control sequence is calculated, only the first control input, uk, is applied to the system. In the next time step, the prediction horizon is shifted forward to k+1, and a new optimal control sequence $uk+1 = [uk+1; uk+2; : : : ; uk+N\ ]$ is computed.

In Figure 4.1, the concept of MPC is illustrated for a reference tracking problem in discrete time. In this type of problem, the objective function of the optimization is to minimize the error $\bar{e} = [e_{k+1}; \dots; e_{k+N}]$, which is the difference between the reference trajectory $\bar{r} = [r_{k+1}; \dots; r_{k+N}]$ and the predicted output trajectory $\bar{x} = [x_{k+1}; \dots; x_{k+N}]$. The optimization problem seeks to determine the optimal control input over the prediction horizon, minimizing tracking error while ensuring compliance with system constraints.

4.2.1. Objective and Mathematical Representation of MPC

MPC is an optimal controller utilized when we have a model (available) of the system controlled. In other words, the design of the MPC is geared towards minimizing a predetermined cost function under constraints such as system dynamics, actuator limitations, etc. At each time step, we calculate the best set of control actions that minimize the cost function over a particular time horizon and apply the one corresponding to the first time-step — and repeat for the next time-step. This is illustrated in the Figure 4. 1 below.

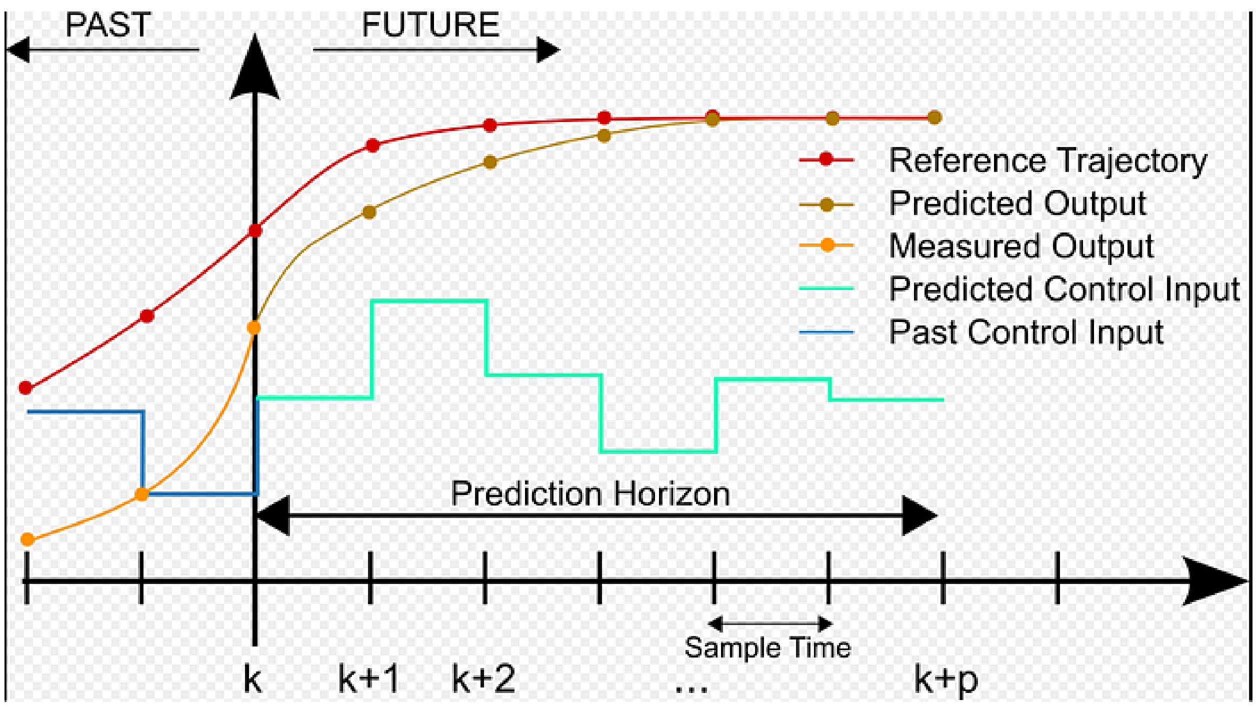


Figure 4. 1: MPC Controller Receding horizon principle

As stated above, in MPC the objective is to minimize the cost function while satisfying system dynamics and actuator constraints. This is mathematically represented as follows:

$Given: \overline{x}_0$
for t=0,1,2,...,T
solve

$$\min_{x,u} \sum_{k=t}^{T} c_k(x_k, u_k) \tag{4. 1}$$
$$\text{s.t } x_{k+1} = f(x_k, u_k), \quad \forall k \in \{t, t+1, ..., T-1\}$$
$$x_t = \overline{x}_t$$

- Execute U_t
- Observe resulting state, $\overline{x}_{t+1}$

Where, x is the system state, u is the control input or actuation, c is the cost function, and f is the system dynamics model. There are additional constraints, such as (1) the initial state for optimization equaling the current observed state, and (2) actuation constraints, because the actuator cannot be controlled arbitrarily — though this is not indicated in the figure above.

While the figure above computes the cost function and system constraints over the entire time period T (i.e., at each time step, the entire trajectory is replanned), this is often impractical because TTT can be very long. A more practical approach involves replanning the trajectory at each time step over a fixed time horizon HHH, where the cost summation and constraints are evaluated from k=t to k=t+H. This method is why MPC is also known as receding horizon control.

Model Predictive Control (MPC), also called moving horizon control or receding horizon control, is one of the most successful and widely used advanced control techniques. The fundamental idea of MPC is to predict the future behavior of the controlled system over a finite time horizon and compute an optimal control input that minimizes a predefined cost function while ensuring that system constraints are satisfied. More specifically, the control input is determined by solving an open-loop optimal control problem over a finite horizon at each sampling instant. The first portion of the resulting optimal input trajectory is applied to the system until the next sampling instant, at which the horizon is shifted, and the process is repeated. MPC's success is largely due to its ability to explicitly incorporate both state and input constraints, as well as a suitable performance criterion, into the controller design.

4.2.1. Linear vs. Nonlinear MPC

A distinction is made between linear and nonlinear model predictive control (MPC) based on the type of objective function, constraints, and prediction model used. If any of these elements are nonlinear, the controller is classified as a nonlinear MPC controller [61, 62, 64].

Nonlinearity often introduces non-convexity, which can lead to multiple local optima in the optimization problem. This increases the complexity of solving the optimization and may cause the optimization solution to be suboptimal. Consequently, nonlinear MPC (NLMPC) generally requires more computational time and resources. Additionally, due to the increased complexity, the algorithm may fail to find the global optimum, resulting in suboptimal solutions.

The model fidelity also plays a significant role in the closed-loop performance. Since the algorithm optimizes the error between the predicted state and the reference state over the prediction horizon, the quality of the model directly impacts the system's performance. When a linear MPC is applied to a highly nonlinear system, the prediction accuracy may degrade, as linear models cannot accurately capture the complexities of the nonlinear dynamics. This can reduce the effectiveness of the control strategy, leading to poor performance, especially in systems where nonlinearities are significant.

In contrast, a nonlinear prediction model in NLMPC is better suited for capturing such complexities, but it increases the computational burden and may introduce challenges related to finding a globally optimal solution.

4.3. Mathematical Formulation and Properties of Nonlinear Model Predictive Control

Model Predictive Control (MPC), or moving horizon control and receding horizon control, is a feedback technique that has gained popularity, particularly in linear processes. Linear MPC describes system dynamics using linear models, even though the closed-loop system is potentially nonlinear due to constraints. Linear MPC has been widely utilized, particularly in the process industries, and the theory is robust. Major issues such as computation on line, control relationship/identification and modeling, and stability of the system have been discussed extensively.

But most real systems are nonlinear. In industrial processes where product quality, productivity, environment regulation, and economy are of top concern, systems must be operated near the edge of their admissible operating envelope. Under such scenarios, linear models often fail to describe the system dynamics fairly well, and nonlinear models must be used. That has generated interest in Nonlinear Model Predictive Control (NMPC).

NMPC applies the principles of MPC but incorporates nonlinear models to capture the more complex dynamics of systems that cannot be adequately described by linear models. This approach enables more accurate predictions and better control of nonlinear systems, especially when they are operating near their boundaries or under varying conditions.

This paper reviews the key principles behind NMPC, highlighting its advantages and disadvantages. It also discusses some theoretical, computational, and implementation challenges associated with NMPC. However, it is not intended as a comprehensive review of all existing NMPC techniques, but rather as an overview of the essential aspects that define the application of MPC in nonlinear systems.

4.4. MPC strategy

A Model Predictive Control (MPC) strategy, as illustrated in Figure 4. 2[65], proposes a sequence of candidate future control inputs, $u(t + k|t)$, that are expected to optimize a predefined performance index(objective). This performance index typically balances desired system behavior with control effort.

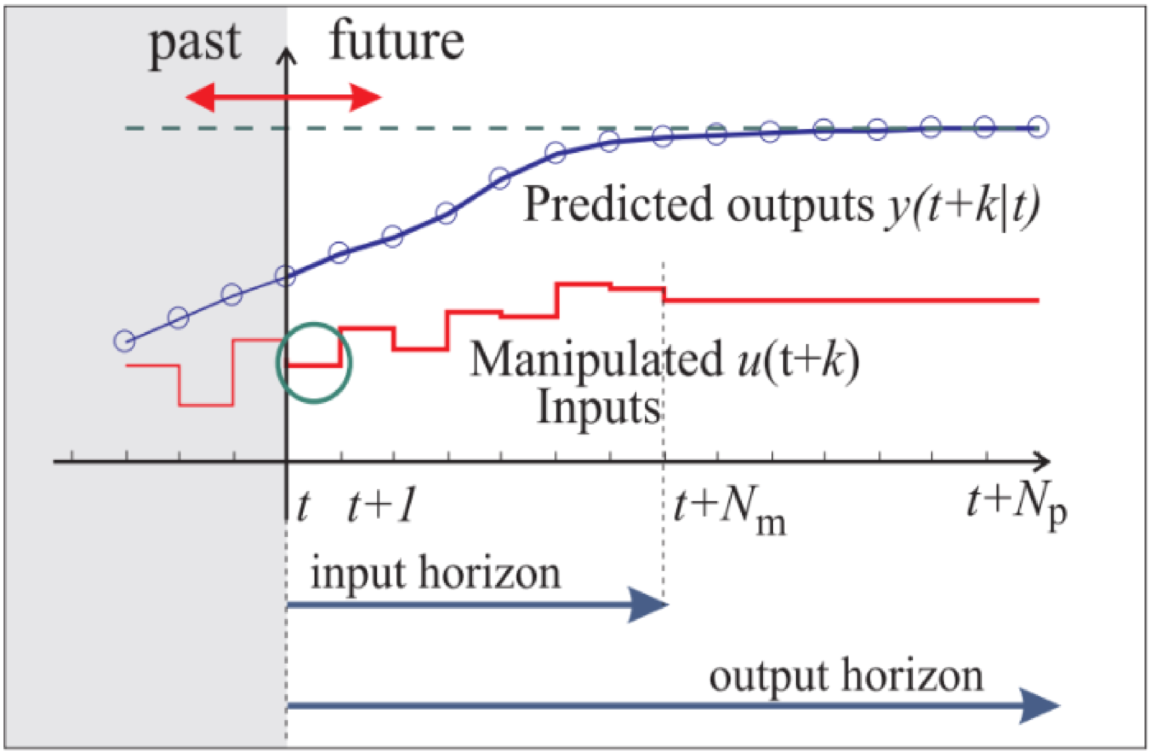


Figure 4. 2: MPC Strategy

The figure depicts the prediction horizon (Np) and the input horizon (Nm). Np represents the number of future time steps for which the controlled process outputs, $y(t + k|t)$, are predicted based on a mathematical model of the system. The control horizon, Nm (typically shorter than Np), defines the timeframe over which the control inputs are optimized or applied.

Within the input horizon, the MPC strategy solves an optimization problem that minimizes the performance index while considering system constraints. The optimization problem typically involves:

Objective function: This function incorporates the desired system behavior and control effort penalty. Common formulations include minimizing the deviation of the predicted outputs, $y(t + k|t)$, from a reference trajectory and penalizing large control input changes, $u(t + k|t) - u(t - 1)$.

Constraints: These represent limitations on the manipulated inputs, $u(t + k|t)$, and predicted outputs, $y(t + k|t)$. Constraints can ensure safety, prevent actuator saturation, or enforce physical limitations.

The key concept of MPC lies in utilizing only the first control input, $u(t)$, from the optimized sequence for actual control. The remaining control inputs, $u(t + k|t) \mid k > 0$, serve for planning purposes. At the next time step $(t + 1)$, a new measurement of the system state is obtained. This updated information is used to refine the model prediction and re-solve the optimization problem for a new control sequence over the receding horizon. This iterative approach, where the optimization window continuously moves forward in time, is known as receding horizon control (RHC). RHC allows MPC to adapt to process disturbances and model uncertainties while maintaining optimal control over a finite, yet adaptable, planning horizon.

In control engineering, the goal is to design a controller that will cause the system, or plant, to behave a particular manner. This desired behavior is defined by a reference trajectory, which shows the ideal output over time. Traditional control methods typically use feedback. They monitor the difference between the actual output and the reference, then adjust the input accordingly. Model Predictive Control (MPC) takes a more advanced approach.

MPC uses a mathematical model of the plant to predict its future behavior over a defined prediction horizon. This model encapsulates the system's dynamics and allows the MPC to anticipate how the plant will respond to various control inputs. By incorporating this predictive capability, MPC surpasses the limitations of solely relying on past and current information. It can proactively consider upcoming disturbances or changes in the reference trajectory, leading to improved control performance.

After predicting future behavior, MPC uses an optimization algorithm to find the best control plan. This algorithm considers many possible control actions over a set time horizon. Each option is scored based on a cost function. This function reflects the desired outcomes for the system, often balancing factors like:

- Minimizing tracking error (the difference between desired and actual output)
- Ensuring efficient operation (e.g., minimizing energy use)

- Maintaining system stability

By adjusting the weights in the cost function, engineers can fine-tune the MPC strategy to prioritize specific goals for the system under control.

Ultimately, the MPC algorithm selects the control sequence that minimizes the overall cost over the prediction horizon. However, only the first control input from this sequence is actually implemented on the plant. This approach, often referred to as receding horizon control, allows for continuous adaptation and optimization throughout the control process. As new sensor measurements become available, the prediction horizon is continually rolled forward, and the MPC process is repeated at each sampling instant. This ensures responsiveness to changing conditions and enables the MPC to maintain optimal control performance over extended periods.

4.5. Structure of MPC controller

Model Predictive Control (MPC) has become a cornerstone technique in control engineering, particularly for regulating complex systems. Its effectiveness lies in its ability to anticipate future system behavior and optimize control actions based on that prediction. This optimization capability allows MPC to achieve superior control performance compared to traditional approaches. The core functionality of MPC is encapsulated within a specific block diagram structure, as shown in the figure. This structure facilitates a systematic approach to determining the optimal control input for the system being controlled. By understanding the function of each block within this structure, we gain valuable insights into the inner workings of the MPC controller.

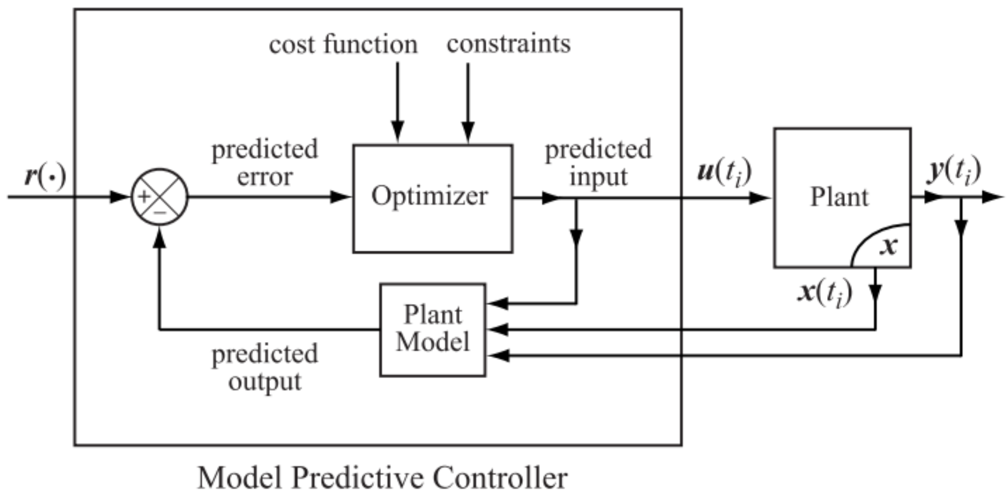


Figure 4. 3: Block diagram of a Model Predictive Controller

The Figure 4. 3 illustrates a block diagram of a Model Predictive Controller (MPC. The MPC receives a **reference signal**, r(t), which defines the desired output trajectory for the controlled process.

At the heart of the MPC lies a **mathematical model of the plant**. This model acts as a virtual replica, allowing the MPC to predict future outputs based on different **control inputs**, u(t). These predictions are then compared to the reference signal, generating a prediction error. This error signifies the deviation between the desired and actual outputs.

Leveraging this information, the MPC employs an **optimizer**. This sophisticated algorithm analyzes a cost function, aiming to minimize the difference between the predicted outputs and the reference signal. Additionally, the optimizer factors in constraints, ensuring the control inputs and plant outputs stay within acceptable limits. By considering both cost and constraints, the MPC finds the optimal control input that steers the process towards the desired behavior while respecting operational limitations.

The identified control input, u(t), is then applied to the actual plant. The plant's response is measured as the actual output, y(t). This measured output serves a critical role by being fed back into the MPC. This feedback loop is essential for continuous improvement. By incorporating the actual plant behavior, the MPC can refine its internal model, leading to more accurate predictions and ultimately, better control performance in subsequent cycles.

In essence, the MPC operates in a closed-loop fashion, constantly analyzing, predicting, and optimizing to ensure the controlled process adheres to the desired trajectory. This systematic approach makes MPC a valuable tool in various applications where precise control and performance are crucial.

4.6. Model predictive controller problem formulation

4.6.1. The performance index (Objective function)

For the majority of MPC algorithms, the control law is obtained based on the optimization of the predicted performance in terms of a performance index (Objective function). Throughout this thesis, the three terms performance index, Objective function and cost function are employed interchangeably.

4.6.1.1. Typical cost functions

A typical common performance index penalizes the weighted squares of both predicted tracking errors and the control increments/deviations[66, 67]; that is:

$$J = \sum_{i=1}^{n_y} \left\| r_{k+i} - y_{k+i} \right\|_2^2 + \sum_{i=0}^{n_{u-1}} \left\| W(u_k - u_{ss}) \right\|_2^2 + \left\| W_d \Delta u_k \right\|_2^2 \tag{4. 2}$$

Here, u_{ss} represents the expected steady-state input, which ensures that r_{k+i} asymptotically approaches $y_{k+i,}$ the estimated true output target. However, due to the treatment of tracking, there are minor modifications to this popular index. When the horizons n_y and n_u are large (or infinite), it may be impossible for the output prediction to reach the desired target while satisfying constraints, potentially causing J to become unbounded. A typical performance index can also be defined over the infinite horizon; for example,

$$J = \sum_{i=0}^{\infty} \left\{ x_{k+i+1}^T Q x_{k+i+1} + u_{k+i}^T R u_{k+i} \right\} \tag{4. 3}$$

This objective function provides a sensible definition of the optimum solutions for linear systems. The design of cost function for energy efficient cruise control for three-wheel electric vehicle speed control consider:

- Energy consumption term (e.g., minimize battery power usage)
- Tracking error term (minimize difference between desired and actual speed)

- Actuator effort term (penalize aggressive acceleration/deceleration)

Based on these factors the cost function for the control:

$$J = \sum W_1 (V_r ef - V)^2 + W_2 U^2 + W_3 E_p redicted \tag{4. 4}$$

4.7. Optimization Problem Formulation

4.7.1. Mathematical Formulation

4.7.1.1. Objective Function:

- The objective function (J) is formulated as a minimization problem considering both speed tracking accuracy and energy efficiency:

$$J = \sum \left[W_1 (V_r ef - V)^2 + W_2 U^2 + W_3 E_p redicted \right] \tag{4. 5}$$

where:

Σ represents the summation over the prediction horizon (number of future time steps considered by the MPC).

$V_{ref}(t)$ is the desired speed at time step t.

V(t) is the predicted motor speed at time step t.

u(t) is the motor voltage at time step t.

$E_{predicted\_horizon}(t)$ is the estimated energy consumption over the prediction horizon at time step t.

w_1, w_2, and w_3 are weighting factors.

Tracking Error:

- The first term ($w_1 \left(V_{ref}(t) - V(t) \right)^2$) penalizes the difference between the desired speed ($V_{ref}(t)$) and the predicted motor speed (V(t)). A higher weight (w_1) prioritizes accurate speed tracking.

Energy Efficiency:

- The second term (w_2u^2) penalizes the squared motor voltage (u^2). Since voltage is proportional to power, this term discourages excessive energy consumption by penalizing high voltage applications.

Energy Consumption Over Prediction Horizon:

- The third term ($w_3E_{predicted\_horizon}$) incorporates the estimated total energy consumption ($E_{predicted\_horizon}$) over the prediction horizon, considering future control actions. A higher weight (w_3) emphasizes energy efficiency in the control decisions.

4.7.1.2. State Space prediction model

- A dynamic model relating motor speed (ω) to motor voltages (u) and motor currents is required for prediction within the MPC framework. This model is given as:

$$\begin{aligned} \dot{x} &= f\left(x, u, \psi_m, f_A(\theta)\right) \\ y &= f(x) \end{aligned} \tag{4. 6}$$

4.7.1.3. Constraints:

A key benefit of Model Predictive Control (MPC) is its ability to integrate both soft and hard constraints on inputs and system states directly within the controller. As a result, physical limitations on input values and their rates of change are enforced due to actuator restrictions. Below are some of these constraints.

Input Constraints (Motor Control Signals):

The motor voltage (u) will have upper and lower bounds due to physical limitations and safety considerations: u_min ≤ u(t) ≤ u_max (Eq. 4.5)

$$u_{\min} \le u(t) \le u_{\max} \tag{4. 7}$$

Output Constraints (Motor Speed and Derived):

Maximum Speed Limit: This is the absolute maximum speed the motor can safely reach due to mechanical constraints like centrifugal forces on the rotor. For the three-wheel electric vehicle operating in Ethiopian the maximum allowable speed is about 50kmph.

$$V(t) \le 50\,\text{kmph} \tag{4.8}$$

Rate of Change of speed Constraints:

Ensuring passenger safety is of utmost importance, encompassing more than merely regulating the vehicle's final speed. The rate of change of the vehicle's speed, or acceleration, must be meticulously controlled within the Model Predictive Control (MPC) strategy. Excessive acceleration can lead to passenger discomfort and disorientation, and may result in injuries due to abrupt movements within the cabin during aggressive maneuvers. By imposing constraints on the vehicle's acceleration, represented as v_{min} and v_{max} the MPC controller can effectively manage these changes, thereby guaranteeing a smooth and comfortable ride for passengers.

$$V_{\min} \le \frac{dV(t)}{dt} \le V_{\max} \tag{4.9}$$

4.7.1.4. Complete MPC Mathematical Formulation:

To summarize the MPC controller design used for the simulation analysis of energy-efficient eco-cruise control for the three-wheel electric vehicle (Bajaj), the complete MPC optimization problem is outlined in Equation 4.10. This optimization problem will be solved in MATLAB 2020a using the fmincon function, with sequential quadratic programming as the optimization algorithm, which is a smooth nonlinear optimization method. It is important to note that for each simulation, individual components may change, such as the model (when using NLMPC), the implementation of error from sensitivity analysis, or the weight Q when testing a different cross-coupling case.

$$\text{minimize} \quad J = \sum \left[w_1 \left(V_{ref}(t) - V(t) \right)^2 + w_2 u^2 + w_3 E_{predicted\_horizon} \right] \tag{4.10}$$

Subjected to:

$$\begin{cases} \dot{x} = f(x, u, \psi_m, f_A(\theta)) \\ \quad y = \mathrm{f(x)} \\ \quad u_{min} \le u(t) \le u_{max} \\ \quad V(t) \le 50 \\ \quad v_{min} \le \dfrac{dV(t)}{dt} \le v_{max} \end{cases} \tag{4. 11}$$

4.7.2. Algorithm Selection and Tuning:

4.7.2.1. Solution Algorithm:

The MPC problem at each control step is resolved by optimizing the objective function (Eq. 4.8) subject to the provided constraints (Eq. 4.9) using an optimization algorithm. The first three control input (voltage) from the optimized sequence is applied to the motor. The process is continued at the next time step with fresh state information for continuous control.

Tuning Parameters:

After extensive trial and error and to reduce energy consumption, the tuning parameters of the simulation of energy-efficient model predictive cruise control have been selected. The parameters include control horizon (C), prediction horizon (P), weighting matrices for forecasted errors (W1), control movements (W2), energy consumption (W3), and sampling time (Ts).

First, the controller will have a sampling time of 0.03 s. With a simulation sampling time of 0.01 s, this means the controller calculates a new control input every 3 simulation time steps. During the remaining steps, the control input is maintained as the previously calculated input.

The prediction horizon, P, is a tuning parameter in optimization computations. As P increases, the control action is more conservative but with increased computational effort. Hence, a fixed prediction horizon P of 15 control time steps (0.45 s) is used.

The control horizon, C, in optimization calculations, is used to minimize predicted errors. If the value of C is too large, too much control action is the result, whereas smaller values of C result in a robust controller that is insensitive to modeling errors. To save computation time, a control horizon C equal to 3 control steps (0.09 s) was selected. Thus, after 3 control time steps, the control input in the last step is held constant for the remaining steps in the prediction horizon.

The weighting matrix of predicted errors W1 is usually set to the identity matrix, I. The weighting matrix of control moves is set to f × I, where f is a scalar design parameter. Larger values of f punish control actions more, leading to less aggressive control. On the other hand, when the value of f is zero, the controller gains are very sensitive to the control horizon C. To obtain significant dynamic information, the sampling interval (Δt) should be small. If the sampling interval is too small, however, it will cause other issues[68].

The weights for energy consumption are critical in balancing the trade-off between maintaining the desired speed and minimizing energy use. By adjusting the weighting matrix for energy consumption W3, the controller can be tuned to prioritize efficiency. For the given scenario, we select the following values for the weights:

- W1 (weight for Speed tracking): 1.0
- W2 (weight for control moves): 0.5
- W3 (weight for energy consumption): 1.0

These values ensure that energy consumption is adequately prioritized without compromising the vehicle’s ability to maintain the desired cruise speed.

CHAPTER 5: RESULT AND DISCUSSIONS

5.1. Introduction

This chapter presents the simulation results obtained for the Model Predictive Control (MPC) strategy designed to control the speed of a three-wheeled electric vehicle (Bajaj) while prioritizing energy efficiency.

This chapter describes the results obtained from investigating the complete MPC-based control model for optimizing the energy efficiency of a Bajaj three-wheeler electric vehicle's cruise control. The discussion begins with an analysis of speed performance and characteristics, and control voltages under different load and no-load operating conditions. The evaluation considers various scenarios to understand how the MPC controller manages speed regulation when the vehicle is subjected to changes in load. Additionally, the controller's response to disturbances, such as sudden changes in road conditions. This part of the investigation demonstrates the MPC controller's ability to adapt to real-time changes and maintain optimal speed performance, ensuring energy efficiency is maximized regardless of external conditions.

Following the speed tracking analysis, the evaluation of the MPC controller's effectiveness in maintaining energy-efficient operation under various driving conditions and weights is provided. The focus is on how the MPC controller dynamically adjusts the Brushless Direct Current (BLDC) motor's operation, leveraging predictive modeling to anticipate changes in vehicle dynamics and energy consumption. The results highlight the MPC's capability to minimize energy usage while maintaining the desired speed. The adaptability of the MPC strategy in real-time adjustments to account for uncertainties in parameters and nonlinear dynamics inherent in three-wheel EVs is a key point of discussion, illustrating how this advanced control method enhances the vehicle's overall performance.

5.2. Speed Tracking Performance

The detailed MATLAB/Simulink simulation diagram used for the energy-efficient model predictive cruise control of three-wheel electric vehicles, which illustrates the various components and their interactions within the system, is presented in the Figure 5. 1 for a comprehensive understanding of the setup and its operational flow.

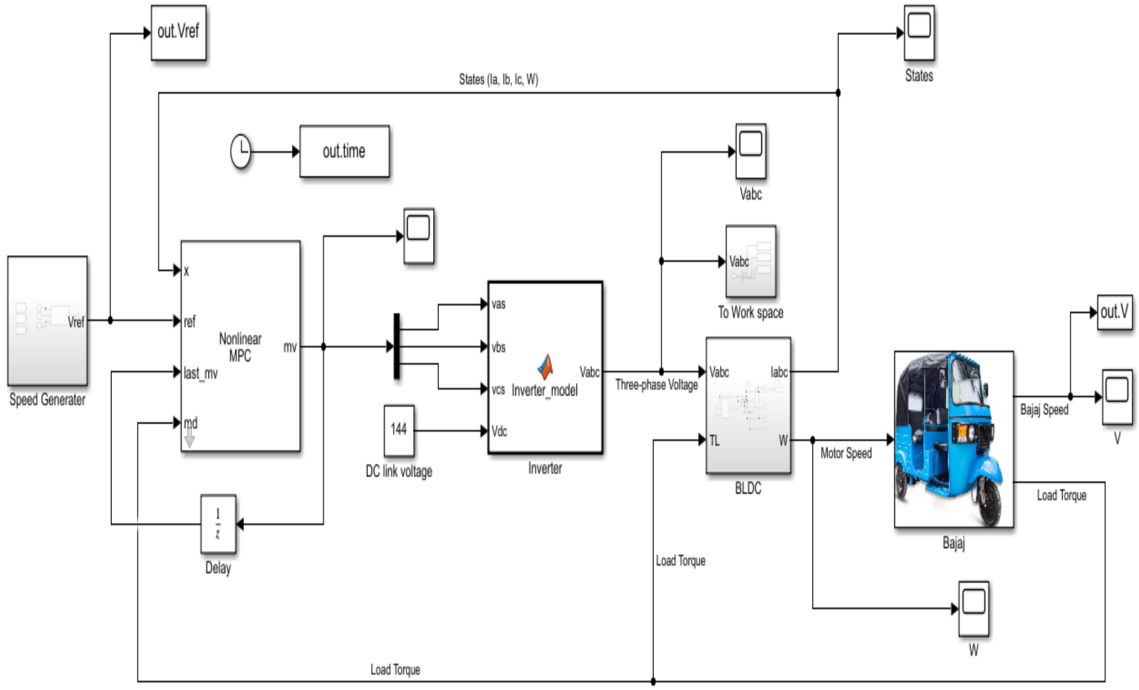


Figure 5. 1: MATLAB Simulation Diagram

5.2.1. Constant Speed Tracking Performance:

The plot below illustrates the constant speed-tracking performance of the vehicle. The desired speed profile, represented by the red dashed line, is set at 35 km/hr. The actual speed of the vehicle, shown by the blue solid line, is tracked over 25 seconds. Initially, the vehicle accelerates rapidly and approaches the desired speed within the first 10 seconds. (Include the rise and sampling time). After reaching approximately 35 km/hr, the actual speed stabilizes and closely follows the desired speed with minimal deviation. This indicates that the control system is effective in achieving and maintaining the target speed, demonstrating robust performance in constant speed tracking.

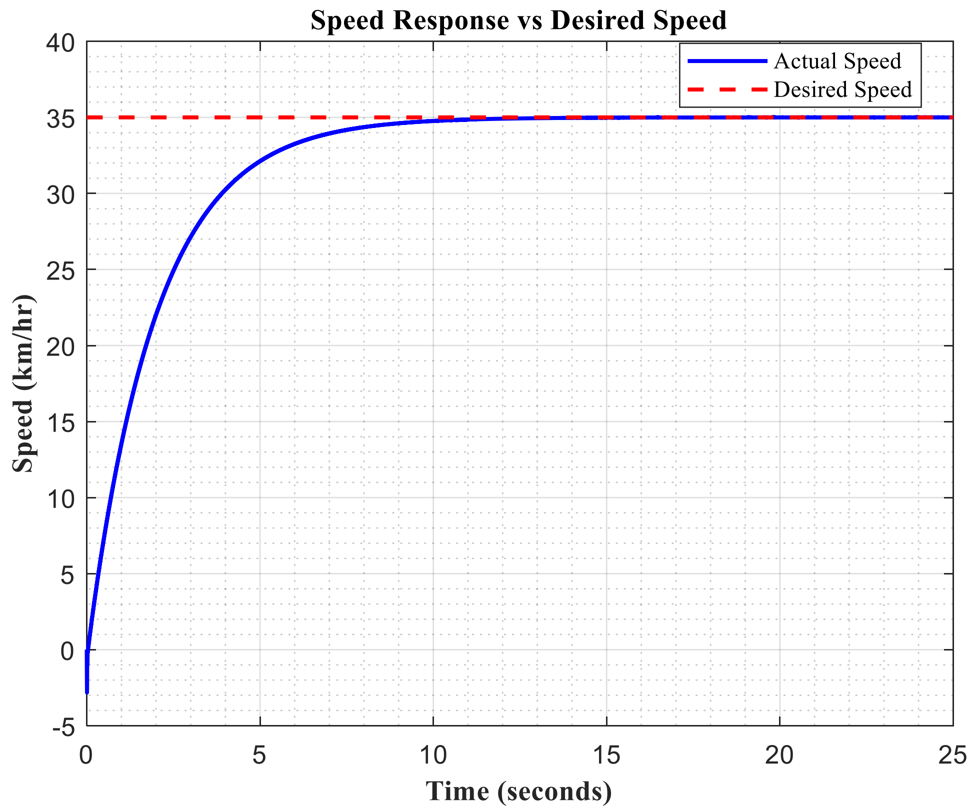


Figure 5. 2: Constant Speed tracking

5.2.2. Varying reference speed tracking performance

The plot below, Figure 5. 3 illustrates the varying speed reference tracking performance of the vehicle. The desired speed profile, represented by the red dashed line, changes at specific intervals, providing a more dynamic and challenging scenario for the control system. The actual speed of the vehicle, shown by the blue solid line, attempts to follow this varying reference speed.

Initially, the vehicle accelerates to reach the first desired speed of 25 km/hr and maintains it until around the 15-second mark. At this point, the desired speed increases to 35 km/hr. The vehicle responds by accelerating and closely follows the new speed reference, stabilizing at approximately 35 km/hr. Subsequently, at the 30-second mark, the desired speed drops back to 25 km/hr. The vehicle decelerates accordingly and aligns with the new target speed, maintaining it for the remainder of the time.

This plot demonstrates the controller's ability to adjust its speed promptly in response to changes in the desired speed profile, showcasing the effectiveness and adaptability of the control system in varying speed conditions.

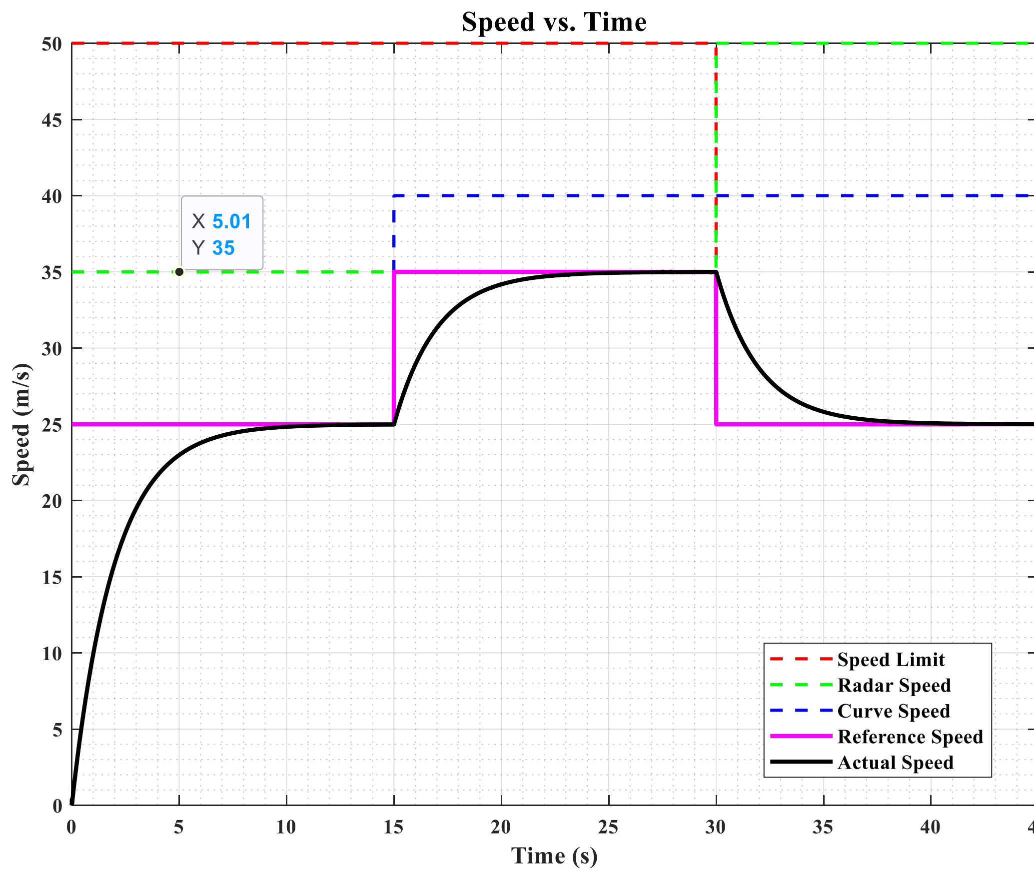


Figure 5. 3: Varying reference speed tracking

5.3. Control Input Analysis:

The voltage and current responses in the results indicate that the Model Predictive Control (MPC) system is effectively managing the electric motor for speed tracking at 35 km/h. The voltage graphs show a sharp initial increase, followed by a stabilization phase, typical of step responses where the controller applies high initial voltage to quickly reach the target speed. The voltage then plateaus, indicating steady-state operation. Similarly, the current graphs display an initial spike as the motor accelerates, followed by a gradual settling to stable values, reflecting that the system has reached the desired speed with minimal variations in current. The fast settling times, minimal overshoot, and stable steady-state behavior in both voltage and current suggest that the MPC is well-tuned and efficiently controlling the motor's performance. This ensures that the motor reaches the target speed quickly and maintains it with minimal control effort after the initial transients. Overall, the system demonstrates good control performance and efficiency.

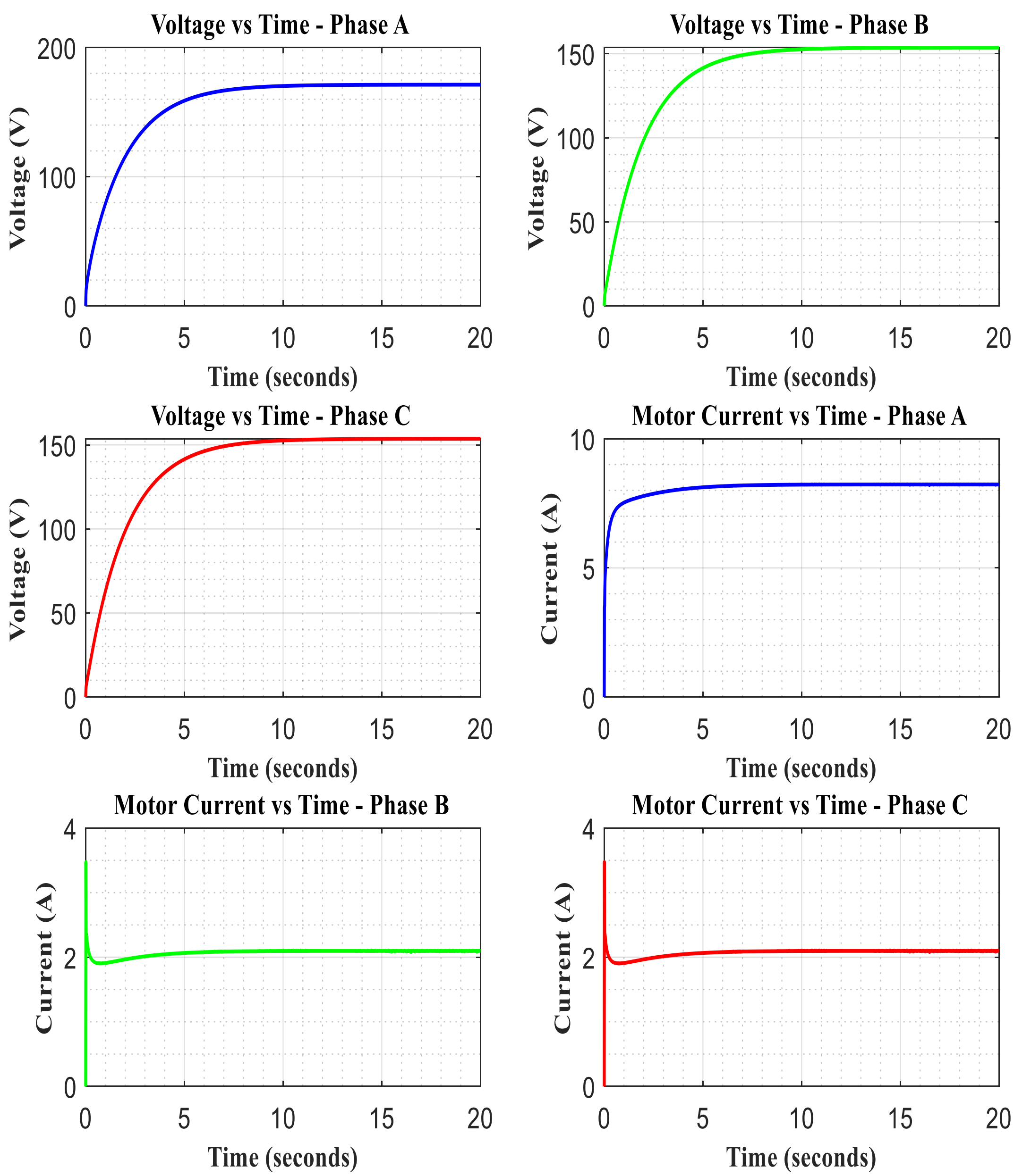


Figure 5. 4: Control Voltage and Motor current response

The Figure 5. 5 below shows the voltage and current responses for the varying speed reference case of the electric motor. Initially, the voltage rapidly increases to reach the first target speed of 25 km/h, stabilizing around 100 V within the first 10 seconds. As the desired speed increases to 35 km/h at the 15-second mark, the voltage rises again, peaking near 150 V as the system accelerates to match the new speed. Around the 30-second mark, the desired speed drops back to 25 km/h, and the voltage decreases accordingly, stabilizing at a lower value to maintain the reduced speed.

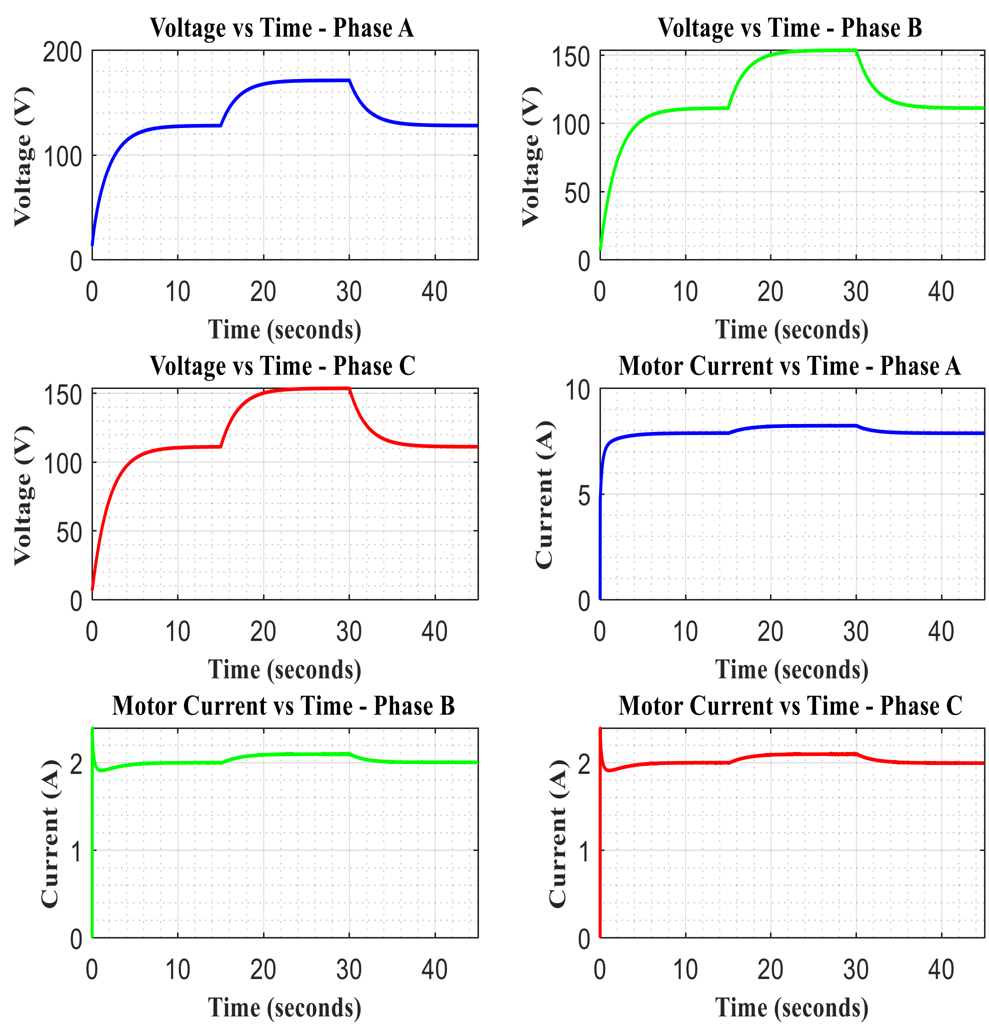


Figure 5. 5: Control Voltage and Motor current response for varying reference speed tracking

The current follows a similar pattern, with an initial rise during the acceleration phase, followed by stabilization as the voltage levels off. When the speed increases to 35 km/h, the current rises slightly to provide the necessary power for higher speed operation. After the speed drops to 25 km/h at 30 seconds, the current decreases, reflecting the reduced energy demand. This behavior highlights the system's ability to adjust voltage and current in response to changing speed targets, ensuring smooth transitions and stable performance throughout.

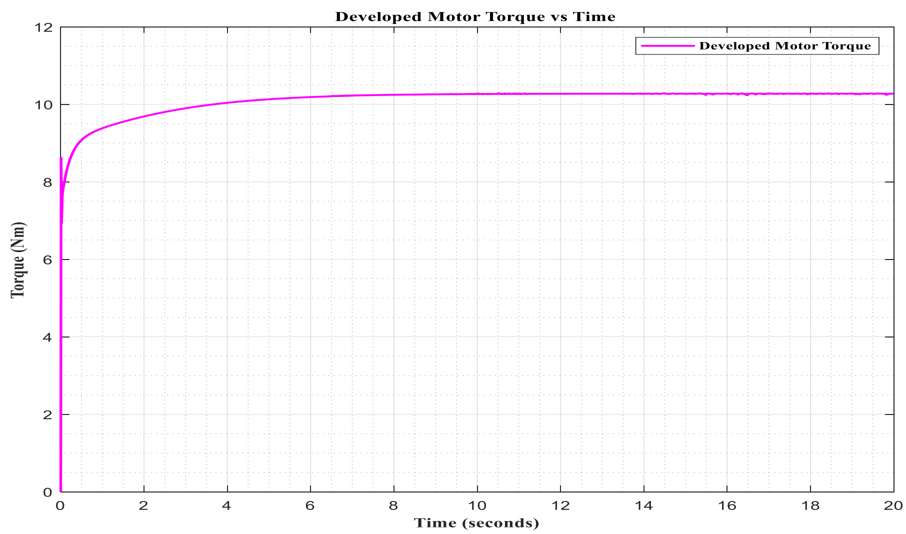


Figure 5. 6: Generated torque

5.4. Energy Consumption Analysis:

This section analyzes how the vehicle's energy consumption varies in response to different control strategies. Energy consumption is a critical factor in evaluating the efficiency of the vehicle's performance, particularly under varying road conditions. The effectiveness of control strategies in minimizing energy usage while maintaining the desired speed profiles is assessed.

The analysis compares the vehicle's energy consumption in two scenarios: one where energy consumption is explicitly included in the objective function, and another where only speed tracking is considered in the objective function. The total energy consumed over the simulation period provides valuable insights into the trade-offs between maintaining speed accuracy and optimizing energy usage. This analysis, conducted over the first 50 seconds of operation, highlights the effectiveness of each strategy in optimizing the vehicle's performance.

The objective function is a critical component of the control strategy, as it determines the criteria by which the controller optimizes system performance. In this analysis, two scenarios are considered to evaluate the energy efficiency of the vehicle.

Equation 5.1 represents the objective function where only speed tracking is included. In this case, the control strategy focuses solely on minimizing the error between the reference velocity, Vref(t) and the actual velocity, V(t). This can be mathematically expressed as:

minimize

$$J = \sum \left[w_1 \left(V_{ref}(t) - V(t) \right)^2 \right] \tag{5. 1}$$

Here, w1w_1w1 is the weight associated with the speed tracking objective, emphasizing the importance of maintaining the desired speed profile.

On the other hand, Equation 5.2 incorporates energy consumption into the objective function. In this scenario, the control strategy optimizes not only speed tracking but also minimizes control effort (u^2) and energy usage ($E_{predicted\_horizon}$). This is expressed as:

minimize

$$J = \sum \left[w_1 \left(V_{ref}(t) - V(t) \right)^2 + w_2 u^2 + w_3 E_{predicted\_horizon} \right] \tag{5.2}$$

In this equation:

- w_2 is the weight associated with minimizing the control input effort (u^2).
- W_3 is the weight assigned to minimizing the predicted energy consumption over the control horizon, Epredicted_horizon.

The fig

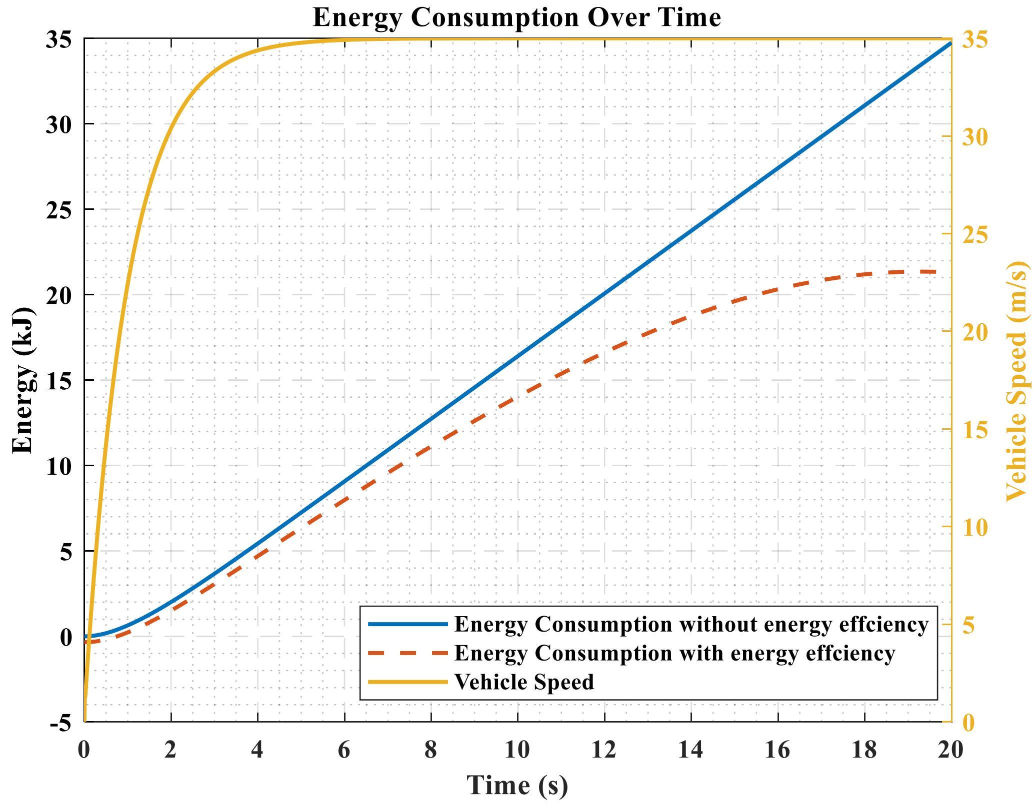


Figure 5.6: Energy Consumption Over Time with and without inclusion of energy consumption in the objective function

The figure demonstrates the impact of including energy consumption in the objective function. The energy consumption without energy optimization (solid blue line) is higher compared to the scenario with energy optimization (dashed orange line). This result highlights that incorporating an energy consumption model into the objective function effectively minimizes energy utilization while maintaining vehicle speed performance (yellow line, right axis).

5.4. Disturbance Rejection and Parameter Variation

5.4.1. Road Slope or Gradient

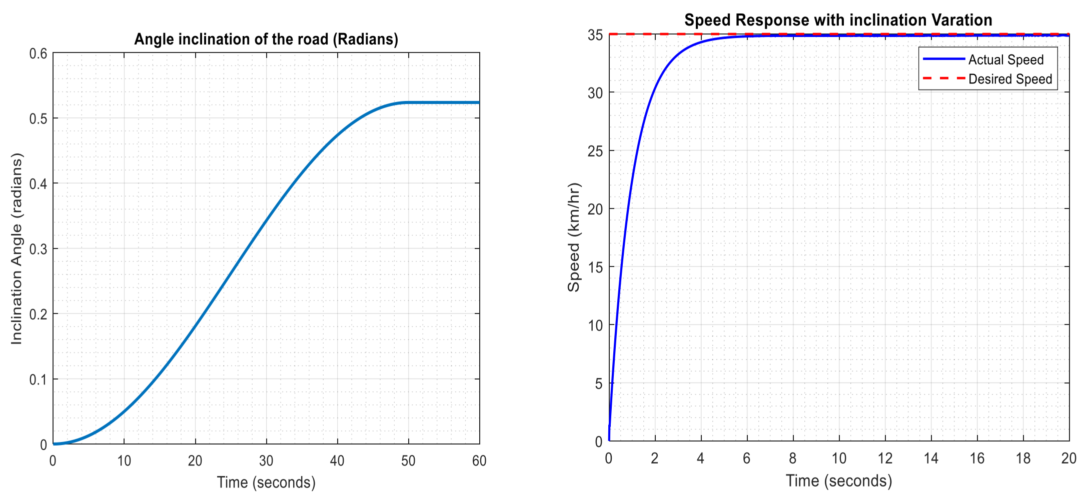
The speed variation of the system is considered by varying the road inclination angle. This variation is modeled using a sigmoid-shaped function given by:

$$\theta(t) = \frac{\pi}{6} * \frac{1}{1 + e^{-K(t - t_0)}}$$

Where:

- θ(t): Inclination angle at time t (radians)
- π/6: Final inclination angle (approximately 0.524 radians)
- k: Slope rate constant that determines how quickly the angle changes
- t: Time (seconds)

The inclination angle starts at 0 radians, increases gradually in the middle phase, and then transitions smoothly to a final steady value of π/6 radians (approximately 0.524 radians). The figure in **Fig. 5.7a** shows this smooth variation of the inclination angle, ensuring a realistic and gradual representation of varying road conditions, without abrupt changes or unrealistic disturbances.



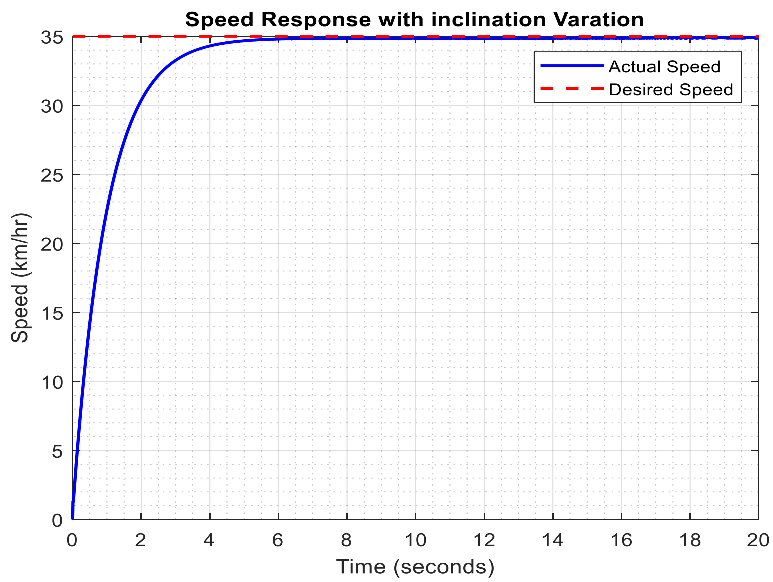
a *b*

Figure 5.7: Angle inclination(a) and speed response(b) when an inclination angle of 30 degree is applied

The figure in 5.7b depicts the speed response of the vehicle when the varying inclination angle is applied. The blue line represents the actual speed, while the red dashed line indicates the desired speed of 35 km/h. Despite the increasing inclination, the controller effectively maintains stability, with the actual speed converging to the desired value with minimal steady-state error. This demonstrates the capability of the controller to handle dynamic conditions while ensuring smooth and efficient performance.

5.4.2. Load Change

Load change refers to the alteration of a vehicle's mass due to factors like added passengers or cargo, affecting acceleration, energy consumption, and overall performance. In this analysis, a **50 kg** mass was added to simulate realistic loading conditions. The increased mass reduces acceleration and speed while raising energy demands, as the system adjusts to the new load. This highlights the importance of designing control systems that can effectively compensate for dynamic load changes to maintain stability and efficiency.



CHAPTER 6: Conclusion and Future Work:

6.1. Conclusion

In this thesis, the modeling and design of a Model Predictive Cruise Controller to optimize the energy consumption of a three-wheel electric vehicles (Bajaj) were presented using MATLAB software. Unlike traditional cruise control systems that maintain a reference speed, the MPC controller leverages predictive capabilities to optimize control actions based on anticipated driving conditions, such as changes in speed limits, elevation variations, and road curvature. This approach has been shown to significantly enhance energy efficiency. A detailed literature review identified gaps in existing research, motivating the implementation of the MPC controller with a focus on minimizing energy consumption while maintaining optimal speed performance. The MPC strategy was thoroughly modeled and simulated in MATLAB/SIMULINK, incorporating various sub-blocks like the reference speed generator, vehicle dynamics, and the BLDC motor controller.

The design of the MPC controller necessitated the development of a state-space model derived from the BLDC motor and vehicle dynamics. The model is used to predict future states and optimize the control inputs accordingly. The simulation results, discussed in chapter five, revealed that the MPC controller significantly outperformed, particularly in minimizing energy consumption while tracking the desired speed. The no-load and load tests highlighted the MPC controller's capability to maintain a steady-state speed error well within acceptable limits, even under varying road conditions.

6.2. Future Works

Future work will focus on enhancing the motor speed-torque characteristics over a wider range of speeds using techniques such as flux weakening. For the BLDC motor to be effectively used in traction drives for electric vehicles, further optimization research should address power and torque ratings to ensure compatibility with various vehicle dynamics and load conditions. Additionally, future studies will aim to integrate the vehicle and BLDC motor modeling into hardware implementations to validate the simulation results through experimental testing. This hardware implementation will provide deeper insights into the real-world performance of the MPC controller and its potential for broader application in electric vehicle technologies.

References

1. Taylor, A.M.K.P., *Science review of internal combustion engines.* Energy policy, 2008. **36**(12): p. 4657-4667 %@ 0301-4215.
2. Faiz, A., C.S. Weaver, and M.P. Walsh, *Air pollution from motor vehicles: standards and technologies for controlling emissions*. 1996: World Bank Publications.
3. Dominković, D.F., et al., *The future of transportation in sustainable energy systems: Opportunities and barriers in a clean energy transition.* Renewable and Sustainable Energy Reviews, 2018. **82**: p. 1823-1838 %@ 1364-0321.
4. Høyer, K.G., *The history of alternative fuels in transportation: The case of electric and hybrid cars.* Utilities policy, 2008. **16**(2): p. 63-71 %@ 0957-1787.
5. Chan, C.C. *The past, present and future of electric vehicle development*. 1999. IEEE.
6. Weinert, J., C. Ma, and C. Cherry, *The transition to electric bikes in China: history and key reasons for rapid growth.* Transportation, 2007. **34**: p. 301-318 %@ 0049-4488.
7. Vira, D., *The History Of Bajaj Auto.* 2012, July 22.
8. Wikipedia, t.f.e. *Bajaj Auto.* . (2024, June 5); Available from: https://en.wikipedia.org/wiki/Bajaj_Auto.
9. Anbalagan, C. and K. Kanagaraj, *A Study on Problems and Prospects of Transport in Ethiopia: Special Reference with Auto Rickshaw's (Bajaj) in Hawassa City, SNNPRS, East Africa.* African International Journal of Research in Management, 2014. **2**(03): p. 2308-3034.
10. Alanazi, F., *Electric vehicles: benefits, challenges, and potential solutions for widespread adaptation.* Applied Sciences, 2023. **13**(10): p. 6016 %@ 2076-3417.
11. Patel, V.K.S. and A. Pandey, *Modeling and performance analysis of PID controlled BLDC motor and different schemes of PWM controlled BLDC motor.* International Journal of Scientific and Research Publications, 2013. **3**(4): p. 1-14.
12. Mohanraj, D., et al., *A review of BLDC motor: state of art, advanced control techniques, and applications.* Ieee Access, 2022. **10**: p. 54833-54869 %@ 2169-3536.

13. Singh, S., et al., *A Review on control of a brushless DC motor drive.* Int. J. Future Revolution Comput. Sci. Commun. Eng, 2018. **4**: p. 82-97.
14. Worawalai, W.K.-N.W.K.N.C.P.S.P.M.P., *High Performance BLDC Motor Control for Electric Vehicle.* IEEE Transactions on control systems technology, 2018.
15. K. Poornesh, R.M., J. S. R. V and G. R. N, *Speed Control of BLDC motor using Fuzzy Logic Algorithm for Low Cost Electric Vehicle.* International Conference on Innovations in Science and Technology for Sustainable Development (ICISTSD), 2022.
16. Mo, T., et al., *Trends and emerging technologies for the development of electric vehicles.* Energies, 2022. **15**(17): p. 6271.
17. Lutsey, N., et al. *Power play: How governments are spurring the electric vehicle industry*. 2018. ICCT Washington, DC, USA.
18. Sanguesa, J.A., et al., *A review on electric vehicles: Technologies and challenges.* Smart Cities, 2021. **4**(1): p. 372-404.
19. Guo, Y., et al., *Designing high-power-density electric motors for electric vehicles with advanced magnetic materials.* World Electric Vehicle Journal, 2023. **14**(4): p. 114.
20. Honorati, O., et al. *Lightweight, compact, three-wheel electric vehicle for urban mobility*. in *1998 International Conference on Power Electronic Drives and Energy Systems for Industrial Growth, 1998. Proceedings.* 1998. IEEE.
21. Weiss, M., K.C. Cloos, and E. Helmers, *Energy efficiency trade-offs in small to large electric vehicles.* Environmental Sciences Europe, 2020. **32**: p. 1-17.
22. Selvan, V.A.M., et al., *Aerodynamic Design Optimization of Electric Vehicles Using Computational Fluid Dynamics*. 2022, SAE Technical Paper.
23. Görges, Y.J.R.J.D., *Energy-Optimal Adaptive Cruise Control for Electric Vehicles Based on Linear and Nonlinear Model Predictive Control.* IEEE Transactions on Vehicular Technology, 2020. **69**(12).
24. G. De Filippis, B.L., A. Sorniotti, P. Gruber and W. De Nijs, *Energy-Efficient Torque-Vectoring Control of Electric Vehicles With Multiple Drivetrains.* IEEE Transactions on Vehicular Technology, 2018. **67**(6).

25. M. Syazmie Sepeeh, S.A.Z., S. Yi Sim, E. Pathan, *A Comprehensive Review of Field-Oriented Control in Sensorless Control Techniques for Electric Vehicle.* International Review of Electrical Engineering (I.R.E.E.), 2018. **13**(6).
26. Mustafa Aktas , K.A., Mehrdad Ehsani , Aydemir Arisoy, *Direct torque control versus indirect field-oriented control of induction motors for electric vehicle applications.* Engineering Science and Technology, an International Journal, 2020. **23**(5).
27. Lorenzo Bertoni , J.G., Maria Basso , Marco Masoero , Sabri Cetinkunt , Francesco Borrelli *An adaptive cruise control for connected energy-saving electric vehicles.* IFAC-PapersOnLine, 2017. **50**(1).
28. Sharma, R.K., & Goel, R. , *Design and Development Challenges in Three-Wheel Electric Vehicles.* International Journal of Automotive Technology, 2021. **22**(4): p. 923-936.
29. Lee, S., & Ehsani, M, *Advanced Torque Control of the Induction Motor Drive for Electric Vehicles.* IEEE Transactions on Vehicular Technology, 2023. **72**(2): p. 1415-1425.
30. Yilma, A.D., & Mesfin, D, *Electric Vehicle Adoption in Ethiopia: Infrastructure and Market Perspectives.* Ethiopian Journal of Energy and Environment, 2020. **15**(2): p. 45-58.
31. Mulugeta, Y., & Assefa, G. , *Road Quality and Traffic Dynamics Impact on Electric Vehicles in Ethiopia.* Ethiopian Journal of Transportation and Logistics, 2019. **14**(3): p. 109-125.
32. (IRENA)., I.R.E.A., *Renewable Energy Potential in Ethiopia: Opportunities for Electric Mobility*. 2021: Abu Dhabi: IRENA.
33. Krishnan, R., *Permanent magnet synchronous and brushless DC motor drives*. 2017: CRC press.
34. Luthra, G., *Comparison of characteristics of various motor drives currently used in electric vehicle propulsion system.* International Journal of Mechanical and Production Engineering, 2017. **5**(6): p. 2.

35. Bello, A., et al., *Comparative Review Of PMSM And BLDCM Based On Direct Torque Control Method.* International Journal of scientific & technology research, 2014. **3**(3): p. 195-199.

36. Jape, S.R. and A. Thosar, *Comparison of electric motors for electric vehicle application.* international Journal of Research in Engineering and Technology, 2017. **6**(09): p. 12-17.

37. *Electric Tuk-tuks Market : Industry Analysis, Trends, and Forecast*. 2024, MAXIMIZE MARKET RESEARCH.

38. M.A. Majid, C.R.K.J., Arbaz Ahmed, *Advances in electric vehicles for a self-reliant energy ecosystem and powering a sustainable future in India.* Advances in Electrical Engineering, Electronics and Energy, 2024. **10**.

39. Sriram, V. and V. Sriram, *The Story.*

40. Vijayakumar, A. and S. Sridevi, *Analysis of operating efficiency of two and three wheeler sector of Indian automobile industry.* International Journal of Managment, IT and Engineering, 2013. **3**(10): p. 434-450.

41. Harish, R., *Bajaj Auto: From Chetak to Pulsar and Beyond.* IUP Journal of Marketing Management, 2011. **10**(1).

42. Jhunjhunwala, A., P. Kaur, and S. Mutagekar, *Electric vehicles in India: A novel approach to scale electrification.* IEEE Electrification magazine, 2018. **6**(4): p. 40-47.

43. Milliken, W.F., D.L. Milliken, and L.D. Metz, *Race car vehicle dynamics*. Vol. 400. 1995: SAE international Warrendale.

44. Husain, I., *Electric and hybrid vehicles: design fundamentals*. 2021: CRC press.

45. Gillespie, T., *Fundamentals of vehicle dynamics*. 2021: SAE international.

46. Rajamani, R., *Vehicle dynamics and control*. 2011: Springer Science & Business Media.

47. Hucho, W.-H., *Aerodynamics of road vehicles: from fluid mechanics to vehicle engineering*. 2013: Elsevier.

48. Anderson Jr, J.D., *Fundamentals of Aerodynamics, McGraw-Hill.* New York, 1991.

49. LaClair, T., *Rolling resistance.* The pneumatic tire, 2006: p. 475.

50. Sandberg, U., et al., *Rolling resistance: basic information and state-of-the-art on measurement methods. Final version*. 2011, Statens väg-och transportforskningsinstitut.
51. Grunditz, E.A., *BEV Powertrain Component Sizing With Respect to Performance, Energy Consumption and Driving Patterns,*, G. Chalmers University of Technology, Sweden, Editor. 2014.
52. M. J. Akhtar, R.K.B.a.S.K.P., *Propulsion System Design of Electric Vehicle.* 2015.
53. Balaj, S.a.M., *Modelling, design and control of a light electric vehicle with hybrid energy storage system for Indian driving cycle.* Measurement and Control, 2019. **52**(9).
54. Vahidi, A. and A. Sciarretta, *Energy saving potentials of connected and automated vehicles.* Transportation Research Part C: Emerging Technologies, 2018. **95**: p. 822-843.
55. Falcone, P., et al., *Predictive active steering control for autonomous vehicle systems.* IEEE Transactions on control systems technology, 2007. **15**(3): p. 566-580.
56. Rawlings, J.B. and D.Q. Mayne, *Model predictive control: theory and design, Nob Hill Pub.* Madison, Wisconsin, 2009. **825**.
57. Qin, S.J. and T.A. Badgwell, *A survey of industrial model predictive control technology.* Control engineering practice, 2003. **11**(7): p. 733-764.
58. Rawlings, J.B., D.Q. Mayne, and M. Diehl, *Model predictive control: theory, computation, and design*. Vol. 2. 2017: Nob Hill Publishing Madison, WI.
59. Garcia, C.E., D.M. Prett, and M. Morari, *Model predictive control: Theory and practice—A survey.* Automatica, 1989. **25**(3): p. 335-348.
60. Wellens, L., *Model Predictive Control for Helicopter Flight Control: Evaluating Linear and Nonlinear Model Predictive Control for Reducing Cross-coupling Effects in Helicopter Flight.* 2021.
61. Bordons, C., et al., *Model predictive control fundamentals.* Model Predictive Control of Microgrids, 2020: p. 25-44.

62. Hrovat, D., et al. *The development of model predictive control in automotive industry: A survey*. in *2012 IEEE International Conference on Control Applications*. 2012. IEEE.
63. Eren, U., et al., *Model predictive control in aerospace systems: Current state and opportunities.* Journal of Guidance, Control, and Dynamics, 2017. **40**(7): p. 1541-1566.
64. Dalamagkidis, K., K.P. Valavanis, and L.A. Piegl, *Nonlinear model predictive control with neural network optimization for autonomous autorotation of small unmanned helicopters.* IEEE Transactions on Control Systems Technology, 2010. **19**(4): p. 818-831.
65. Stefan Misik, Z.B., Cela Arben, *Reducing usage of the computational resources by event driven approach to model predictive control.* Journal of Electrical Engineering 2017. **68**(4).
66. Dughman, S., *Improving Tracking in Optimal Model Predictive Control*. 2019, University of Sheffield.
67. Rossiter, J.A., *Model-based predictive control: a practical approach*. 2017: CRC press.
68. Seborg, D.E., et al., *Process dynamics and control*. 2016: John Wiley & Sons.

Appendix

Appendix A. Nonlinear Model Predictive Control (MPC) Parameter Definitions and Function Implementations

In this appendix, we detail the parameters and functions used in the model predictive control (MPC) framework for vehicle cruise control. The following MATLAB/Simulink code snippets define the various parameters, state and output functions, cost function, and constraints essential for the MPC implementation.

MPC Parameter Definitions and Function Implementations

The provided code defines a nonlinear MPC object and includes all necessary parameters, cost functions, state functions, and constraints. These are crucial for creating a robust and efficient MPC controller for vehicle cruise control.

Thhe code defines the necessary components for the MPC setup, including the system parameters, state and output functions, custom cost and constraint functions, and the state equations for the vehicle's motion. These elements are critical for implementing and simulating the MPC controller to achieve energy-efficient vehicle cruise control.

```
% Define parameters
nx = 4; % Number of states
ny = 1; % Number of outputs
nu = 3; % Number of inputs (u1, u2, u3)
Ts = 0.1; % Sampling time
PredictionHorizon = 15; % Prediction horizon
ControlHorizon = 2; % Control horizon

% Weights for the cost function
w1 = 1; % Weight for the reference tracking error
w2 = 1; % Weight for the control effort
w3 = 1; % Weight for the predicted horizon energy

% state space function
function dxdt = VehicleCruiseControlStateFcn(x, u)
      % State equations of the vehicle.
      %
      % States:
```

```
    %  x(1)  Ia current to phase a
    %  x(2)  Ib current to phase b
    %  x(3)  Ic current to phase c
    %  x(4)  W angula veloity of the motor

    % Inputs:
    %   u(1): Vas voltage
    %   u(2): Vbs voltage
    %   u(1): Vcs voltage
    %   u(4): Load torque

    % Parameters
    %saw = 0.1378;
    Ke = 0.8268;
    L = 0.0085;
    R = 2.875;
    J = 0.0089;
    B = 0.001;

    Vdc = 144;
    uabc = Inverter_model(u(1), u(2), u(3), Vdc);

    % State equations
    dxdt = zeros(4,1);
    dxdt(1) = (uabc(1) - R*x(1) - Ke * x(4)) / L;
    dxdt(2) = (uabc(2) - R*x(2) - Ke * x(4)) / L;
    dxdt(3) = (uabc(3) - R*x(3) - Ke * x(4)) / L;
    dxdt(4) = (Ke*(x(1)*x(2)*x(3)) - u(4) - B * x(4)) / J;
end

% Output functions

function y = VehicleCruiseControlOutputFcn(x, u)
  % Extract the desired output (velocity) from the state vector
  G = 4.04;
  R = 0.22;
  y = (3.6 * R * x(4)) / G;  % velocity is the first state
end

% Create nlmpc object

%

nlobj = nlmpc(nx,ny,'MV',[1, 2, 3], 'MD',4);

nlobj.Ts = Ts;

nlobj.PredictionHorizon = PredictionHorizon;

nlobj.ControlHorizon = ControlHorizon;

% Specify the state function

nlobj.Model.StateFcn = VehicleCruiseControlStateFcn;
```

```
% Specify the output function
nlobj.Model.OutputFcn = VehicleCruiseControlOutputFcn;

% Define custom cost function
nlobj.Optimization.CustomCostFcn = @(X, U, e, data) customCostFunction(X,
U, w1, w2, w3);

% Custom constraints function
nlobj.Optimization.CustomIneqConFcn = @(X, U, data) customConstraints(X,
U, v_min, v_max, V_max);

% Specify constraints on the inputs
nlobj.MV(1).Min = u_min;
nlobj.MV(1).Max = u_max;
nlobj.MV(2).Min = u_min;
nlobj.MV(2).Max = u_max;
nlobj.MV(3).Min = u_min;
nlobj.MV(3).Max = u_max;

% Validate functions (optional but recommended)
validateFcns(nlobj, rand(nx,1), rand(nu,1));

function J = customCostFunction(X, U, w1, w2, w3)
    % Extract V and reference V_ref
    V = X(:,4); % Assuming V is the fourth state
    V_ref = 0; % Define the reference signal for V here
    u = U(:,1:3);
    E_predicted_horizon = sum(U.^2, 'all'); % Example energy calculation
over the predicted horizon

    % Calculate the cost
    J = sum(w1*(V_ref - V).^2 + w2*sum(u.^2, 2) + w3*E_predicted_horizon);
end

function [cineq, ceq] = customConstraints(X, U, v_min, v_max, V_max)
    % Extract V and dV/dt
    V = X(:,4); % Assuming V is the fourth state
    dV_dt = gradient(V); % Compute the derivative of V
```

```
    % Inequality constraints
    cineq = [V - V_max; % Ensure V(t) <= V_max
             dV_dt - v_max; % Ensure dV/dt <= v_max
             v_min - dV_dt]; % Ensure dV/dt >= v_min

    % Equality constraints (none in this case)
    ceq = [];
end
```

Appendix B. MATLAB/Simulink blocks

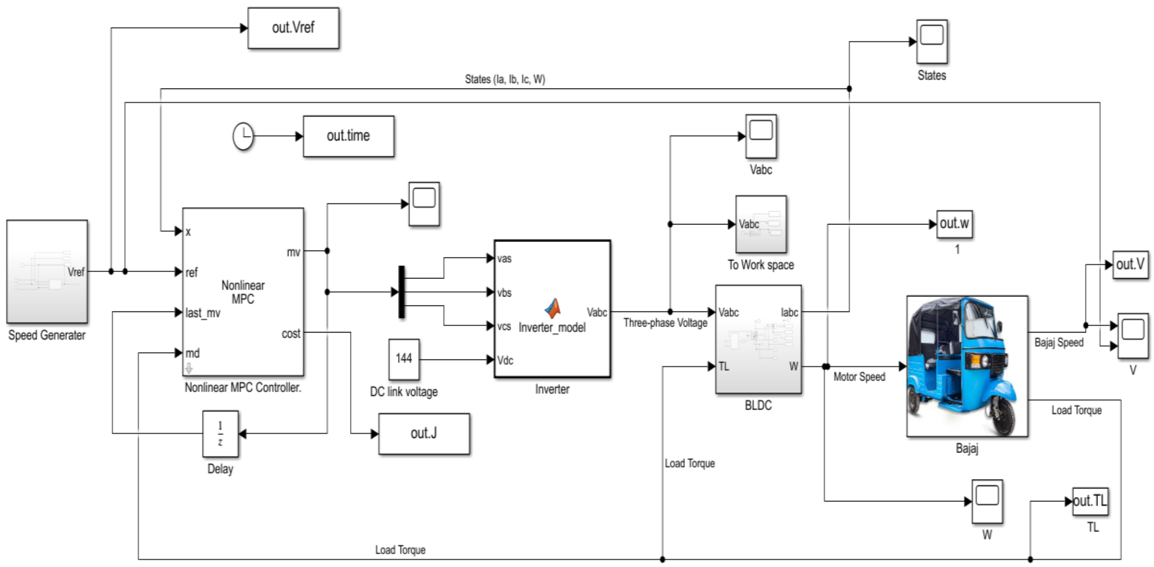


Figure A. 1: MATLAB simulation setups

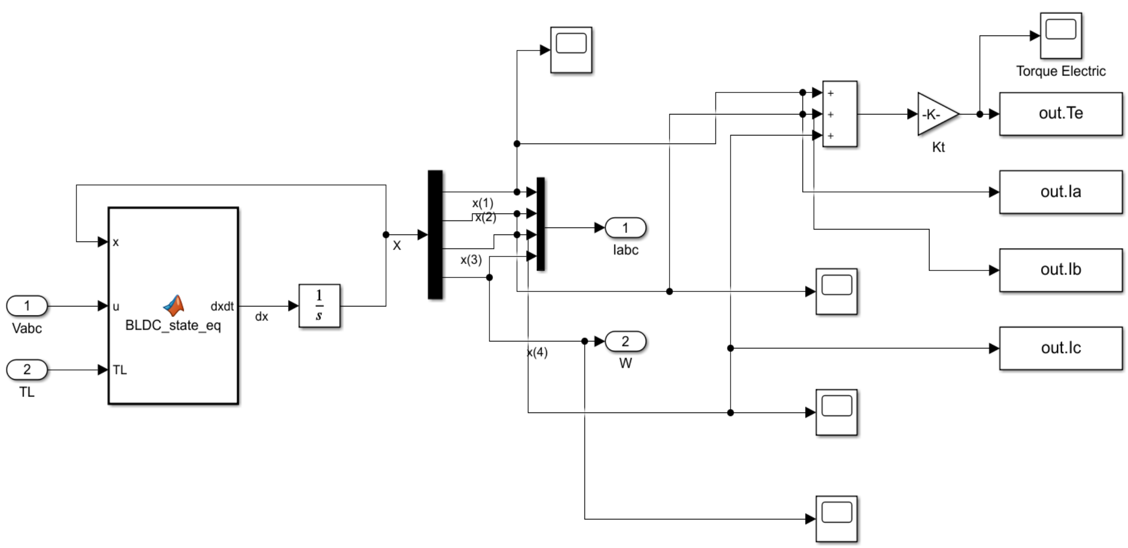


Figure A. 2: Motor mathematical modeling

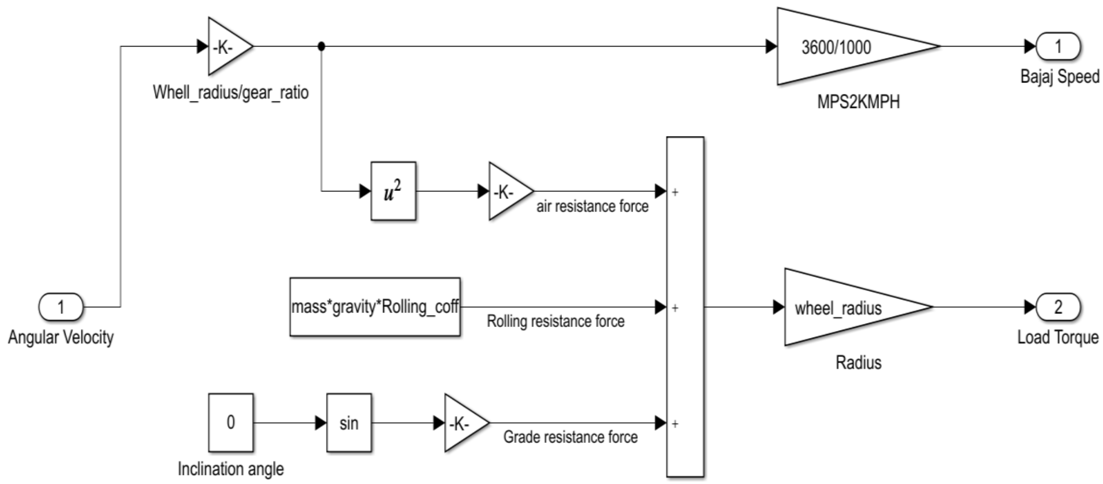


Figure A. 3: Forces acting on the Bajaj and load torque calculations