Powertrain Optimization of an Autonomous Electric Vehicle

Thesis

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in
the Graduate School of The Ohio State University

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The Ohio State University
2018

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Abstract

In this thesis, a novel approach is presented for the powertrain optimization of electric autonomous transportation vehicles. Two applications of a Level 5 Autonomous Vehicle (AV) are investigated; pure Autonomous Driving (AD) and mixed Human and Autonomous Driving (HAD). The powertrain-system design process is demonstrated for both the applications. In addition, the tradeoffs in using a HAD optimized powertrain for autonomous driving, compared to an AD optimized powertrain is addressed.

A system level model is developed in MATLAB and Simulink to predict low-frequency dynamics. Two architectures of the electric powertrain, single (Front Wheel Drive) and double motor (All Wheel Drive) are considered. The optimization problem is set up, which includes defining the objective function, design space, static constraints and inputs for AD and HAD. Comfort requirements for AVs constrain the permissible acceleration while driving. Autonomous drive cycles are represented by optimal trajectories subject to constraints.

Optimal powertrains for both the applications are expressed as Pareto fronts. It is observed that there isn’t a particular trend between energy consumption and powertrain power, and even higher powered powertrains provide similar energy consumption values. The energy savings in driving autonomously is primarily attributed to the optimized trajectory, rather than optimized powertrain.
Dedication

To my family for their love and support.
Acknowledgments

Throughout my journey of pursuing graduate education at The Ohio State University, innumerable people have supported me in my academic as well as personal life. I would like to use this opportunity to acknowledge their support and to express my gratitude towards them.

I would like to thank my advisor Dr. Shawn Midlam-Mohler for his direction, support, and insights on technical details. He has always been there for any technical as well as personal difficulties. The knowledge that I have gained through my discussions with Dr. Punit Tulpule cannot be quantified. He has helped me immensely in building this body of work and I am sincerely grateful to him. A big shout out to the SIMCenter staff and my lab mates for making this experience thoroughly enjoyable. I would also like to thank the EcoCAR team of OSU, Dr. Krishnaswamy Srinivasan and Dr. Jason Dreyer for supporting me during the different phases of my journey here.

Finally, I would like to thank my sponsors, the MAE Department and The Ohio State University for giving me this opportunity to learn and work on such amazing projects.
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Publications


Fields of Study

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Chapter 1. Introduction

1.1. Background

Automated driving systems commonly known as self-driving or autonomous vehicles are claimed to be the next big step in the automotive industry, due to their promise of increased safety and transportation efficiency. These systems are being designed to drastically reduce the occurrence of accidents and vehicular related fatalities by eliminating the human error (which is the largest factor, causing 94% of all fatal crashes [1]) element from being introduced in vehicle operation. Enhanced system robustness and reliability, along with improved mobility and increased productivity is also a byproduct of connected and autonomous vehicles (CAV).

The work related to making autonomous vehicles a reality encompasses a wide array of multidisciplinary research areas. Currently, a lot of work is being done in developing the technology such as sensing methods, data processing algorithms, control algorithms, path planning, obstacle avoidance, telematics, V2X communications and improving active vehicle safety. In addition, there has been an emphasis on understanding the human interaction and interface with the vehicle, to assist in safe vehicle operation and productivity. The advent of autonomous vehicles has excited the entrepreneurial mind to come up with new business models, and the basis of vehicle ownership is itself being questioned. Transportation engineers are working on revamping the entire road
network for efficient transportation, reduced congestion and the connectivity infrastructure required for these automated vehicles. Governing agencies, along with the automotive industry, are working on developing the regulations, legislature and the liability aspects of autonomous vehicles (AV).

There has been a rising concern about climate change around the world. Road transportation accounts for around 10% of global greenhouse gas emissions, making it the single largest contributor [2]. To reduce the impact of vehicular transportation on climate change and fossil fuel consumption, the efficiency of vehicle operation is to be improved. The energy efficiency of the vehicle is affected by broadly two factors: usage-based and vehicle-based [2]. AVs are going to drastically improve the usage-based energy efficiency due to efficient driving, improved traffic flow, efficient routing, etc. This directly affects the powertrain operation, and to gain maximum benefits, the powertrain needs to be optimized for such operations.

This project investigates the powertrain optimization problem of a Level 5 autonomous vehicle, the various design requirements and constraints through an example of an electric powertrain. The vehicle driving scenario constraint due to user comfort factor such as motion sickness is considered. Optimal trajectory is used to define the vehicle operation in autonomous mode.

1.2. AD and HAD

NHTSA has adopted the Society of Automotive Engineers (SAE) 6 levels of driver assistance technology ranging from no automation (driver engagement required at all times) to full autonomy (no driver required, the vehicle operates independently) [1]. In
Level 5 Full Automation technology, the vehicle is capable of functioning autonomously, without driver assistance, in all conditions. The driver may have the option to control the vehicle. This results in a design choice for OEMs developing Level 5 automated vehicles.

Depending on the application and customer requirements, the vehicle can either be designed and optimized to operate purely autonomously with no driver control capability or with the option of human driving. This design choice affects the vehicle design and operation in terms of Human Machine Interface (HMI), customer expectation, legislature, etc. Powertrain design will also be one of the major factors as the performance requirements and driving pattern will be completely different for both the cases.

Therefore, there is a need to understand, first, the design requirements for a Level 5 autonomous vehicle powertrain, and second, to understand the tradeoffs between designing the powertrain of an autonomous vehicle with and without the human driving capability. The autonomous vehicle application without the human driving capability is henceforth referred to as Autonomous Driving (AD) and the one with the human driving functionality is referred to as Human & Autonomous Driving (HAD).

1.3. Thesis Objective

The objective of the thesis is to describe a framework for optimizing the powertrain design of a Level 5 autonomous vehicle, with and without human driving capability available in the vehicle. This is illustrated by using an example of a battery electric powertrain.
To analyze the vehicle response in terms of slower dynamics of vehicle speed, state of charge and energy consumption, which is necessary for system control and optimization, a vehicle system level forward model is developed.

Autonomous and electric vehicle operations, in terms of performance requirements and drive profiles, are analyzed. This is used to formulate the optimization constraints and inputs.

Finally, the two applications of a Level 5 autonomous vehicle, i.e. the one with the human driving capability (HAD), and the one without (AD) are compared and the tradeoffs in terms of energy consumption between the two design choices are analyzed.

1.4. Thesis Overview
The subsequent material of the thesis is segregated into five chapters as follows:

- Chapter 2 provides an overview of the literature on autonomous vehicle design considerations, comfort requirements, electric vehicle powertrain architecture, design requirements, and modeling practices.

- Chapter 3 details the modeling approach for the vehicle system. A brief on the subsystems along with their models is provided.

- Chapter 4 formulates the powertrain optimization problem, describing the objective, constraints, and procedure. A detailed description of the Autonomous Driving (AD) and Human & Autonomous Driving (HAD) is also provided.

- Chapter 5 provides the optimization results for the two cases (AD and HAD) and compares them against each other.

- Chapter 6 concludes the work and provides a direction for future work.
Chapter 2. Literature Review

Research available on autonomous vehicles is vast and multidisciplinary. For this project, research related to the electric powertrain, autonomous driving pattern, the effect on passenger comfort and optimal trajectory computations are focused on.

This background knowledge was important in understanding the powertrain design aspect for electric vehicles, performance requirements for an autonomous vehicle, and understanding how the autonomous driving would differ from conventional driving in light of improving user comfort, energy efficiency, and mobility efficiency.

2.1. Electric Powertrain Design

Electric vehicle architecture is fundamentally different from an internal combustion engine powertrain. Conventional systems such as clutches, torque converters, transmissions, intake and exhaust manifolds, and the auxiliary systems are not required. Components that are essential for electric powertrain operation are electric motors to provide propulsion, inverters to supply power and control the motors through variable frequency switching, and batteries to provide the electrical energy required to power the motor. These components are flexible in design and can be integrated with other drivetrain components at various levels. Numerous studies talk about the different architectures that can be achieved due to the flexible design of electric powertrains [3]–
Wu et al. [4] talk about general architectures for electrified powertrains, that include battery electric as well as hybrid architectures. Felden et al. [5] also introduce similar architectures using a combination of electric motors and transmissions.

These authors discuss the applications, advantages, and disadvantages of each of these powertrains.

Selection and sizing of electric machines are the next steps after architecture selection. Xue et al. [3] explain the basic electric motor operating characteristics and their effect on vehicle performance measures. The paper talks about the tradeoff between designing a motor to provide a wide constant power region, therefore high starting torque and designing the drivetrain to be able to sustain the heavy torque loads. Also, the tradeoff in achieving high motor speeds are highlighted in [7], along with defining the
performance metrics of an electric motor. The metrics are defined in terms of motor
torque, power capability and constant power speed ratio (CPSR), which is the ratio
between the maximum speed and the base speed where constant torque to constant power
mode switching takes place. The process of designing an electric propulsion system, to
meet the propulsion requirements, are detailed in [8]–[12]. The summary for motor sizing
from these sources [3], [8] are,

- the power required for achieving acceleration requirements decreases as constant
  power operation increases (CPSR increases), but this increases the motor torque,
  resulting in a larger motor,

- the gear ratio between the motor and drive shaft is determined by matching the
  motor and vehicle maximum speeds,

- the motor rated power requirement directly comes from the road load power at
  maximum cruising speeds and

- high-speed motors are generally favored for propulsion applications but increase
  the inverter cost due to higher frequency switching

In terms of model development, Rizzoni et al. [13], [14] provide a framework for
energy flow modeling of electrified drivetrain components. Also, Mahmoudi et al. [15]
details the analysis and modeling aspects of motor efficiency.

Finally, Grunditz and Thiringer [16] summarize the battery electric vehicle design
by comprehensively reviewing the vehicles produced by the industry.
2.2. Effect of Comfort Requirements on Driving Pattern

Owing to the passenger-centric design of an autonomous vehicle, comfort is one of the most important criteria. There are multiple factors that affect comfort, and especially, motion sickness [17]. One of the factors that affect it is the vehicle motion profile, i.e. acceleration, deceleration, and cornering. Therefore, the accelerations /decelerations need to be constrained to provide a comfortable experience.

The study done by Jones et al., 2018 [18], limits the average longitudinal acceleration to 1-3 $m/s^2$. The main goal of the study was to develop an experimental procedure to study motion sickness in passengers. As per Hoberock, 1977 [19], it is difficult to come up with a specific comfortable drive profile due to the variability in the study, but does state that accelerations in the range of 0.11g to 0.15g (1.08 to 1.47 m/s2) experienced in public mass transportation are generally acceptable for the passenger. The acceleration constraint imposed due to acceptable levels of comfort characterized by the “coffee cup test” is set at 2 km/h/s (0.556 m/s2) [20]. Other authors also have used acceleration values derived from public transportation. Maximum acceleration experienced in Light Rail Transit (LRT) of $\pm 1.34 \, m/s^2$ is used by Karjanto et al., 2017 [21] to recreate autonomous driving styles experimentally in real time. This value is referred from Le Vine et al., 2015 [22], who consider the constraints for comfort driving as the accelerations/decelerations experienced in LRT and High Speed Rail (HSR) of $\pm 1.34 \, m/s^2$ and $+0.58, -0.54 \, m/s^2$ respectively. As LRT constraints itself are considered defensive by a large proportion of passengers [23], this study uses the LRT constraints instead of HSR for maximum accelerations and decelerations.
2.3. Autonomous Vehicle Operation

Effect of autonomous vehicles on energy efficiency is twofold. The benefits can be divided into usage-based and vehicle design based [2]. Due to the autonomous technology, vehicle driving can be significantly altered compared to conventional human driving. Driving, route finding and traffic flow will be significantly improved. Due to safer transportation, platooning and vehicle rightsizing, the overall design will also be improved in terms of weight reduction, optimized powertrains, optimized vehicle size, etc. [2].

A representative autonomous drive cycle was not found in the literature. Instead, different methods are proposed to simulate autonomous driving. Research suggests that AVs may smoothen the driving profile due to increased situational awareness, faster reaction times and sophisticated controls. Liu et al., 2017 [24] propose to simulate driving cycles for AVs by smoothing the EPA drive cycles using splined functions. The degree of smoothness depends on a smoothing factor. However, this method does not explicitly constrain the acceleration limits.

Mersky & Samaras, 2016 [25] have demonstrated the need for new procedures to evaluate the benefits of advanced driver assistance features and connected autonomous vehicle technology. Their proposed procedure is relevant for the near future, with conventional vehicles still predominant on the roads. They propose to use the vehicles car-following algorithm to generate the drive cycle, by making the AV follow a conventional vehicle driving an EPA standard cycle. This generated drive cycle would then be tested on the AV on a chassis dynamometer. However, this approach does not consider the complete benefits of connectivity due to a majority of autonomous vehicles
in the future. This will severely impact the traffic flow, and hence the typical drive scenario.

Tate et al. 2018 [2] propose autonomous driving for two different scenarios. For a fully autonomous scenario i.e. 100% autonomous vehicle penetration, the drive cycle is constrained using the distance based speed limits on the Read Driving Emissions (RDE) route. The distance-based speed limit vector is broken down into constant speed intervals and a trapezium profile is fitted for each interval, with the start and end ramp rates based on acceleration limits (imposed due to acceptable levels of comfort). A smoothing function is applied to this profile to simulate real driving. In addition, an isolated autonomous scenario is also considered which, along with speed constraints due to speed limits, considers speed constraints due to traffic too, in order to maintain a safe headway. This type of drive cycle is applicable for situations wherein autonomous vehicles are operating along with conventional vehicles.

To consider the best-case scenario of 100% AV penetration, optimal trajectory between two points is considered subject to constraints such as trip distance, time and driving dynamic constraints. Dynamic Programming (DP) is used to find the most optimal route between Point A and B. Mensing [26] provides a framework to compute the optimal speed trajectory for eco-driving using DP by converting the 3D problem with time, distance and speed to a 2D problem with distance and speed, and including time in the cost function with a penalty.
Chapter 3. Vehicle Model Development

Designing a vehicle is a complex systems engineering problem, having multiple requirements that need to be satisfied and many design choices to be made. Understanding and analyzing the effect of a design choice on the vehicle operation is not straightforward, due to the various levels of interaction between the multiple components of the vehicle. To accurately compute and analyze the effect of a particular design choice, physical testing on the vehicle needs to be done. But during the early design phase, iterating and testing for each design choice proves to be very time consuming and economically expensive.

An alternative to this design process is model-based design, i.e. developing a virtual vehicle and environment, on which the design choices can be tested out quickly. With the advent of high computing power and high fidelity mathematical models, this has become possible for complex engineering systems.

This chapter deals with the development of a vehicle system forward model which can predict the response of the vehicle to propulsion inputs and compute the energy consumption. The model is developed in MATLAB and Simulink [27]. These dynamic models to predict SOC and vehicle speed are based on the law of energy and power conservation. Wherever applicable, efficiency maps are used to develop quasi-static
models to reduce computation time. Various architectures, component models, their complexity and controls would be discussed further in the chapter.

3.1. Powertrain Architecture

Electric vehicle’s drivetrain differs from conventional IC engine vehicles, due to the different operating characteristics of an electric motor. Electric motors can be made in different shapes and sizes. They can be integrated with other drive components. They do not require auxiliary systems to operate efficiently. Since electric motors provide high torque at rest, there is no need for a clutch to disconnect the motor from the drivetrain and keep it idling like an IC engine. In addition, the motors can provide almost constant power for a large speed range, thereby mostly eliminating the need for a multi-speed transmission. The response of the vehicle to driver commands is significantly improved, owing to the fast dynamics of the electric machine. All these factors make developing an efficient, lighter and compact powertrain system possible [3]. The downside to electric vehicles is the increased cost, primarily due to the battery system, which is currently expensive and heavy.

These characteristics of an electric machine provide the freedom to have different options in terms of architecture [3]:

(a) Propulsion mode i.e. front-wheel drive, rear-wheel drive or all-wheel drive

(b) Number of electric motors

(c) Direct or indirect drive

(d) Number of transmission gear levels

(e) Position of the motors along the drivetrain
The different combinations can result in multiple architectures, some of which are as follows [3]:

(A) Conventional Type

An electric machine replaces the IC engine in the conventional drivetrain; all other components of the drivetrain are the same. It can be easily implemented in current fossil fuel based vehicles.

(B) Transmission-less architecture

It is similar to the conventional architecture, sans the clutch and transmission unit. This makes the architecture quite simple to produce and control compared to the conventional type.
(C) Cascade Type

The differential is removed from the above architecture, and two motors are installed on the body side with connected joints to provide power to the wheels with a function equal to the differential.
(D) In-wheel type with Reduction Gears

The transmission-less type is simplified by directly connecting two motors to the wheels with reductions gears.

![In-wheel type with reduction gears schematic](image)

Figure 5. In-wheel type with reduction gears schematic [3]

(E) In-wheel direct-drive type

The motors are integrated with the wheels (wheel hub motors), directly powering the wheels without any reduction gears. This is known as the in-wheel drivetrain system.

![In-wheel direct-drive schematic](image)

Figure 6. In-wheel direct-drive schematic [3]
(F) All-wheel direct-drive type

In this architecture, all four wheels are directly powered by individual in-wheel motors. The advantage of in-wheel motors is reduced transmission losses, improved response time and ability to torque steer. The main advantage of this architecture would be packaging, taking the least amount of space and hence providing more space for the cabin.

![All-wheel direct-drive schematic](image)

Figure 7. All-wheel direct-drive schematic [3]

As evident from the above architectures, there can be multiple combinations, which will result in a unique architecture with its own advantages, disadvantages, challenges, and applications. As the architecture progresses towards direct drive and reduced transmission losses, the motors need to be made lighter, compact but be able to operate at high speeds and torques, which increases cost. This results in a tradeoff and current capabilities result in an architecture with a single speed reduction [3].
This is also evident from the industry trend. A benchmark study done on existing electric vehicles converge to the industry standard architecture for passenger vehicles of either a transmission-less type, single gear reduction, Front Wheel Drive (FWD) system with a single electric machine or a transmission-less type, single gear reduction, All Wheel Drive (AWD) system with a front and a rear electric machine. Depending on packaging requirement and drive characteristic, the motor can also be connected to the rear wheels, resulting in Rear Wheel Drive architecture.

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<td>Front</td>
</tr>
<tr>
<td>Chevrolet</td>
<td>Bolt EV</td>
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<td>i3</td>
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</tr>
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<td>PMSM</td>
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<td>Front</td>
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<td>Front</td>
</tr>
<tr>
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<td>Fit EV</td>
<td>PMSM</td>
<td>1</td>
<td>Front</td>
</tr>
<tr>
<td>Kia</td>
<td>Soul EV</td>
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<td>AWD</td>
</tr>
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<td>IM</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Tesla</td>
<td>Model X</td>
<td>IM</td>
<td>2</td>
<td>AWD</td>
</tr>
</tbody>
</table>
Going with the industry trend, this study focuses on the common architectures of transmission-less type front-wheel drive and all-wheel drive (for performance applications) with single and double motors respectively.

### 3.1.1. FWD Architecture

The basic powertrain architecture considered is FWD with a single electric machine connected to the front axle via a single speed transmission. This architecture is very easy to implement.

![Figure 8. BEV FWD architecture [28]](image)

The controls are also simple and robust due to fewer components. The motor is in the front bay along with the inverter and cooling circuit. It is connected to the drive shafts via a transaxle that has a reduction gear and differential integrated into it. The schematic for this architecture is shown below in Figure 9.
The propulsion components modeled are: electric machine, inverter, transaxle (gear reduction plus differential gear), battery system, DC-DC converter, accessory load, supervisory controller and the vehicle drivetrain that consists of axles, wheels, brakes and the longitudinal vehicle dynamics model.

3.1.2. AWD Architecture

Figure 9. Schematic of FWD transmission-less architecture

Figure 10. Tesla Model S architecture [29]
The other architecture considered is AWD with each of its axle being powered by an electric machine. Tesla Model S and X and the upcoming Model 3 (select variants) use this architecture. This architecture is generally used for high-performance vehicles. The main difference between this and the previous architecture is the addition of another electric machine along with an inverter and a transaxle. The addition of an electric motor adds a degree of freedom to the control problem. The schematic for the architecture is shown below in Figure 11.

![Figure 11. Schematic of AWD transmission-less architecture](image)

### 3.2. Component Models

The model-based design approach is used in this study to analyze the vehicle design choices. This deals with breaking down the vehicle system into its subsystem component level and creating models for each of its component. These component models are integrated together to make the complete vehicle drivetrain model. The supervisory controller of the vehicle is also modeled, to generate appropriate command
signals for the powertrain. Inputs to the controller come from the driver, via the accelerator and brake commands, which is provided by the driver modeled by a feedback PID controller.

The models are designed to be modular, enabling the ability to simulate different architectures using the same models. While the driver model does not change with the architecture, the controller model needs to be modified to incorporate the various control signals.

This subsection details the basic working of the components and the modeling approach considered.

3.2.1. Electric Motor

![Parker Electric motor](image)

Figure 12. Parker Electric motor [30]
An electric motor (EM) is fundamentally a rotary electromagnetic two-way energy conversion device that can convert electrical energy to mechanical (motoring) or convert mechanical energy to electric (generating). Even though the basic principles are the same, there are multiple ways to achieve this energy conversion. Induction motors, Permanent Magnet Synchronous Machine (PMSM), switched reluctance, DC machines, etc. are some of the types of EMs used in automotive traction applications. PMSM have a very high efficiency and power density but cannot operate at high speed [31, p. 46]. This leads to a shorter constant power range [6]. Induction motors have low cost, are very simple to design and construct, robust and have a wide speed range. But they are less efficient than PM motors, have low power density and have a high thermal problem at high speed [6], [31, p. 46]. Switched reluctance motors are capable of very high speeds but are currently expensive [6]. The industry trend is to use AC PMSM motors (Table 1). Tesla models and currently discontinued Toyota Rav4 EV use induction motors. In this study, PMSM motors are considered.
Figure 13: Cross-sections of electric motor types [32]

Figure 14. Typical electric motor operating characteristic
A typical motor torque/power vs speed characteristic is shown in Figure 14.

There are two distinct operating regions: constant torque region and constant power region. The speed at which this transition takes place is the base speed. In constant torque region, due to lower speeds, the motor back emf is small enough to allow the desired current (armature control). When the motor speed increases beyond the base speed, the motor induced back emf becomes high enough requiring flux-weakening control to operate at constant power [7, p. 34]. However, the power output of some motors reduces at high speeds (natural mode) [8]. This reduction in power at higher speeds is neglected for the study. In addition, the motor can only operate continuously with rated power/torque characteristics and intermittently with peak power/torque characteristics due to overheating issues.

Figure 15. EM continuous and intermittent operating regions
A typical efficiency map of a PM motor is shown above. Such maps are used to generate quasi-static models of the electric motor. The motor efficiency is modeled as a function of motor torque output and speed. Based on the desired motor torque and current motor speed, efficiency is computed and used to calculate the electric power required to operate the motor. This depends on whether the machine is motoring or generating.

Inputs to the model are requested torque and speed of rotation of the motor. Outputs are torque provided by the motor and the electric power associated with it. Data required for the model are the motor operating characteristics (peak and rated), efficiency/loss map for motoring and generating and motor design data like rotor inertia. The basic representation of EM model is shown in Figure 17.
Equations used to model the electric motor are,

\[
\eta_{em} = f(\omega_{em}, T_{em}) \quad (1)
\]

\[
P_{em,elec} = \frac{T_{em}\omega_{em}}{\psi} \eta_{em} \quad (2)
\]

\[
\psi = 1 \text{ for } T_{em}\omega_{em} > 0 \quad \psi = -1 \text{ for } T_{em}\omega_{em} < 0 \quad (3)
\]

\[
J_{em}\dot{\omega}_{em} = T_{em} - T_{load} \quad (4)
\]

The electric power through the motor is \( P_{em,elec} \), which depends on the motor efficiency \( \eta_{em} \). The exponent of efficiency depends on whether the motor is motoring (\( \psi = 1 \)) or generating (\( \psi = -1 \)).

These equations are modeled in Simulink. The torque request is capped by the maximum torque limits to simulate dynamic constraints and to not allow the motor model
to produce torques above the limit. Also, the rate of change in torque output is limited to simulate real dynamics.

The efficiency maps are produced by scaling a typical PM efficiency map based on the max torque and rated speed. Generally, peak intermittent specifications are 1.5 times the continuous specifications [7, p. 34]. For the motor options considered in the study, not all have rated specifications specified. The above generalization is used to create the missing data for such cases.

The number of electric motor options considered is 10 and the data was sourced from publically available catalogs [30], [33]. The motor parameters data used is tabulated and graphically represented below.

Table 2. Electric motor data - 1

<table>
<thead>
<tr>
<th>Motor</th>
<th>#1</th>
<th>#2</th>
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<th>#4</th>
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<tr>
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<td>350</td>
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<td>260</td>
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<td>1573</td>
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<td>53</td>
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<td>10500</td>
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<td>0.02825</td>
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<td>8000</td>
<td>8000</td>
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<tr>
<td>Rotor Inertia [kg-m²]</td>
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<td>0.02825</td>
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<tr>
<td>Motor Weight [kg]</td>
<td>58</td>
<td>58</td>
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</tbody>
</table>
Figure 18. Torque – Speed characteristics for electric motor options

Figure 19. Power – Speed characteristics for electric motor options
3.2.2. Energy Storage System

Automotive battery packs comprise of many modules (each comprising of multiple cells) connected in series to get the desired voltage and in parallel to get the desired capacity. Battery management systems are connected to the cells to monitor their voltage, temperature, health, etc. These cells along with the connectors, relays, wiring harness, electronics, and controls make up the Energy Storage System (ESS) [35].

Electrochemical cells through internal chemical reactions provide the electrical energy required to power the traction electric machines and other electrical systems. The different types of secondary cells available in the market for automotive application are Lead Acid (PbA), Lithium-ion (Li-ion), Nickel Metal Hydride (NiMH), etc. High specific energy and power, along with high Open Circuit Voltage (OCV) that leads to lighter and
compact battery packs have made the Lithium-ion cell the most common battery technology in today’s automotive industry.

A wide array of models is available ranging from empirical to first principle models to describe the performance and the dynamic response of a cell. For this study, Equivalent Circuit Model (ECM) of 0\textsuperscript{th} order (Static model) is considered. It is one of the quickest methods to predict the cell voltage based on the current and/or temperature input. The 0\textsuperscript{th} order ECM models the cell as a constant voltage source (OCV of the cell) coupled with an internal resistance. The schematic and the equations are shown below.
The OCV ($V_{oc}$) and the internal resistance ($R_0$) values are characterized as functions of cell State of Charge (SOC). The coulombic efficiency ($\eta_c$) is assumed to be 1. The output voltage ($V_{out}$) depends on the cell current ($I_b$) and OCV. SOC is based on the initial SOC ($SOC_0$), cell current and cell nominal capacity ($C_{nom}$).

$$V_{out}(t) = V_{oc} - R_0 I_b(t) \quad (5)$$

$$[V_{oc}, R_0] = f(SOC) \quad (6)$$

$$SOC(t) = SOC_0 - \frac{1}{C_{nom}} \int_{t_0}^{t} \eta_c(t) I_b(t) \, dt \quad (7)$$
The functions are specified as maps based on the experimental data. The study does not focus on optimizing the battery system, therefore a standard Li-ion cell is considered [37]. A typical variation of OCV and resistance with SOC for LFP (Lithium Iron Phosphate) cell are shown below.

Figure 24. Typical $V_{oc}$ vs SOC profile

Figure 25. Charging and discharging internal resistance as a function of cell SOC
These formulations are applicable for a cell. In a battery pack, number of cells are connected in series \( (n_s) \) and parallel \( (n_p) \) to provide the pack voltage and current. The battery pack voltage \( (V_{pack}) \) and current \( (I_{pack}) \) are given by,

\[
V_{pack} = n_s \times V_{out}
\]
\[
I_{pack} = n_p \times I_b
\]

All the cells in the pack are assumed to be perfectly balanced, having the same SOC and providing the same voltage and current.

The battery pack size i.e. the number of cells in series and parallel is based on the cell parameters, desired battery pack voltage and capacity. A general Lithium Iron Phosphate cell is considered. Cell nominal voltage of 3.3V and a nominal capacity of 25Ah is considered. The battery pack voltage and capacity is selected to be 350V and 175Ah (61 kWh) respectively. This is based on the desired range of 180 miles. Preliminary analysis of the vehicle results in energy consumption of 34 kWh/100 miles. This results in the selected pack size of 61 kWh.

Battery nominal capacity,

\[
C_{pack,nom} = \frac{61kWh}{350V} = 175Ah
\]
The nominal battery pack capacity \( C_{\text{pack,nom}} \) is related to the cell nominal capacity \( C_{\text{nom}} \) as follows,

\[
C_{\text{pack,nom}} = n_p \times C_{\text{nom}} \tag{11}
\]

\[
n_p = \frac{175}{25} = 7 \tag{12}
\]

To provide 350V pack voltage, the number of cells in series is,

\[
n_s = \frac{350}{3.3} \approx 106 \tag{13}
\]

Therefore, the battery pack consists of 106 cells in series and 7 in parallel \((106s7p)\), with a total of 742 cells. These cells can be arranged in modules to make the system more modular, which will aid in production, installation, control, and maintenance.

While designing the pack, the current limitations of the cell also need to be considered. The motor and electrical accessories should never draw currents above the limits, for the specified duration. This is checked while selecting the pack and the maximum current drawn is well below the pack current limits. These dynamic constraints are also modeled in Simulink as charge and discharge buffers so that the torque request is limited.
3.2.3. Transmission

Due to electric motors ability to produce high torque even at zero speed, a clutch is not required to keep the motor idle like an IC engine. In addition, the motors can provide maximum constant power for a broad speed range, thereby eliminating the need for a multi-speed transmission. A single reduction gear might be required to match the motor characteristics with desired vehicle response. This single gear ratio is optimized based on either higher acceleration (higher gear ratios) or higher top speed (lower gear ratios). Due to no clutches, the motor is directly connected to the wheels all the time, and with fewer moving parts, the efficiency and reliability of the transmission are greatly improved.

To save space, cost and improve packaging, the differential gear is combined with the transmission, just like a transaxle. These are called electric drive transmissions
Some manufacturers also provide a parking lock integrated with the transmission. Since it is a single component, only the final gear reduction between the motor and the driveshafts need to be specified.

The transmission is modeled as a simple gear reduction with constant efficiency and negligible inertia.

\[ T_{out} = \eta_t \lambda T_{in} \]  
\[ \omega_{out} = \omega_{in}/\lambda \]  

Figure 27. Model flow diagram of an electric drive transmission

The transmission efficiency is assumed to be a constant (\( \eta_t = 0.95 \)) [33]. \( \lambda \) is the gear ratio between the motor and the wheels (transmission & differential gear ratio).

In this study, to maximize performance and acceleration from a selected motor, the gear ratio selected is as high as possible without physically violating the top speed.
constraint. Based on the wheel rolling radius ($R_w$), the gear ratio is selected to match the vehicle top speed ($v_{veh,\text{max}}$) with the electric machine maximum speed ($\omega_{em,\text{max}}$).

$$\lambda = \omega_{em,\text{max}} \times \frac{R_w}{v_{veh,\text{max}}}$$ \hspace{1cm} (16)

### 3.2.4. Other Components

Inverter, DC/DC converter, accessory load, drive away chassis and vehicle body models are described in this section. This model does not simulate the thermal response and hence, does not have a cooling circuit model.

![Figure 28. Rinehart Motion Systems inverter [38]](image)

Inverters control the electric machines by converting DC power from the battery into AC power with desired frequency. Control commands for the motors are converted into appropriate phase voltages and frequencies by the inverter. They operate with a very
high efficiency (~97% [39]). For this study, inverters are just considered as an efficiency drop mechanism, with their efficiency combined with the electric machine efficiency.

![Image of Bel Power Solutions DCDC converter](image)

Figure 29. Bel Power Solutions DCDC converter [40]

DC/DC converter is required to convert the high voltage source of the battery system into a low voltage source to power the accessories like HVAC system, controllers, lights, charge the 12V lead-acid battery etc. It is also modeled as a constant efficiency (~93%) [40] drop between the ESS and the accessory load.

The energy required to drive the HVAC system, various on-board controllers, brake vacuum pump, lights, power electronics cooling system, heated seats, touchscreen, etc. need to be provided by the ESS [41]. This extra electric load on the battery are combined as accessory loads. Some of the loads are essential for safe vehicle operation whereas others are for customer comfort and acceptability. Since some of the loads like HVAC, heated seats are not constant throughout the vehicle operation, an average constant value of accessory load of (1kW+400W) [42, p. 903], [43, p. 3] is considered in the model.
The Drive-Away-Chassis system includes the suspension systems, vehicle chassis, driveshafts/axles, wheels, and brakes. Since this study deals with longitudinal propulsion, only drive shafts, wheels and brakes are considered. Drive shafts are modeled using Simscape Simulink connections and are assumed to be rigid shafts. For wheels and tires, Simscape Tire (Magic Formula) [27] blocks are used with appropriate values for rolling radius, tire inertia and rolling resistance constant and default values for other parameters. Similarly, for brakes, disc brakes are considered on all four wheels and are modeled using the Simscape Disk Brake block. Default values are considered.

The longitudinal dynamics of the vehicle body is simulated by using the Vehicle Body block in Simscape. It is basically a mask for the force balance equation applied to the vehicle. All the major vehicle design parameters like vehicle mass, drag coefficient, frontal area, etc. are initialized here.

\[
M_{eff} \frac{dv_{veh}}{dt} = F_w - (F_{aero} + F_{roll} + F_{grade})
\]  

(17)

### 3.3. Vehicle System

All the components discussed above along with the control logic are combined in Simulink and MATLAB by using equations, existing blocks and state flow charts, to form the entire vehicle system. Driver model is required to provide the appropriate accelerator and brake pedal commands to make the vehicle follow a predetermined drive profile. A supervisory controller is required to convert these signals into the torque request signals for the propulsion system and the brake command for the vehicle brakes.
The details of the vehicle plant/powertrain, driver, and controller model are described in this section. These three models are connected in a loop to form a feedback system (Figure 30).

![Figure 30. Vehicle system schematic](image)

### 3.3.1. Vehicle Plant Model

Plant models are defined by the powertrain architecture of the vehicle. Since this study deals with two distinct powertrain architectures, there are two models, one for FWD and one for AWD. Simulink and Simscape blocks are used to model the individual components and connect them to each other.

The inputs to this system are the torque request signals and brake command from the controller and the outputs are the vehicle states i.e. vehicle speed and position, along with each component state and their respective variables, like the ESS state of charge (SOC), battery power, motor torque, and power, etc.
The schematics for the architectures are shown in Figure 31 and Figure 32. FWD vehicle contains one EM connected to the front axle via a transmission/differential, an ESS to provide the voltage source for the EM and the accessories. The front and rear
axles are connected to the wheels and brakes. The input command from the controller determines the torque that needs to be produced by the EM. This torque can be either positive (motoring) or negative (generating). Based on the EM maximum power limits and inertia, the EM provides a torque to the differential. Depending on the motor speed (which is directly linked to the vehicle speed since the EM is directly coupled) and the torque out, the efficiency of the motor is computed. This is used to compute the power flow through the EM, i.e. either the power in or out to the drivetrain and the power out or in to the ESS from the electric machine. Based on the power drawn or provided to the ESS by the electric machine, and the ESS voltage, the current flowing through the machine is computed. This current, along with the current drawn by the accessories, needs to be provided by the battery system. This current flow results in the voltage drop in the battery and the change in the State of Charge.

The torque out from the motor is multiplied due to the gear ratio of the transmission/differential and is distributed amongst the two front wheels. The brakes are connected to the wheels to provide the friction braking torque when needed. The torque acting on the wheels generates a longitudinal force on the body through the tire-road friction. This force along with the aerodynamic drag, rolling resistance and the force due to gravity provide a net force on the vehicle which accelerates or decelerates the vehicle. Integrating this acceleration results in the vehicle speed and integrating the speed results in the vehicle position based on the initial conditions. This speed and position value are sent to the driver model.

For AWD, the model is very similar, with an added EM which powers the rear differential, axle, and wheels. The extra current draw is added to the ESS. New control
signals are generated to control the second electric motor. The control strategy is discussed later.

3.3.2. Driver Model

The driver model generates the accelerator and brake pedal command based on the current vehicle state and desired state. There are various models with varied fidelity, either modeling the human behavior or modeling an autonomous system. Few of the proposed models are mentioned in [44]. In this study, the driver is simply modeled by a PI controller, which based on the error between the desired and actual (feedback) speed profile, generates the control signal. The Powertrain Blockset block of Longitudinal Driver in Simulink [27] is used to model the driver. The parameters of the block are tuned to achieve desirable results. Also, a feedforward model, with custom accelerator and brake commands is implemented to simulate the acceleration 0-60 mph test for the vehicle.

![Driver Model Diagram]

Figure 33. Driver PI model
3.3.3. Supervisory Controller Model

A vehicle supervisory controller is required to send out the control commands to the sub-system controllers. This controller decides the simultaneous operation of the system components. The control actions are dependent on the driver commands and the states of the vehicle and the subsystems.

![Supervisory Controller schematic](Image)

The controller is divided into 2 parts: Mode Selection and Mode Operation. In Mode Selection, based on the driver commands and the vehicle state, the vehicle can be either in Rest (stationary), Propulsion or Coasting /Regenerative Braking mode. Based on the operating mode, the command signals for the propulsion unit vary. The command signals are throttle and brake commands to the Mode Operation block.

The Mode Operation converts these command signals into the traction motor torque request and the brake line pressure command. The motor torque request can be either positive or negative based on the throttle and brake commands.
Figure 35. Mode Selection flowchart

Figure 36. Mode Operation flowchart
When the throttle command is applied, a positive torque request is generated, which is a fraction (determined by the throttle command) of the maximum possible propulsion torque value at that speed. The torque request is further multiplied by a discharge limiting value based on the SOC to limit excessive ESS discharge at lower SOCs [27]. The negative torque request is computed in a different way, as the vehicle can apply the friction brakes too along with regenerative braking. Based on the brake command, the fraction of maximum possible brake torque ( summation of maximum friction brake torque and the maximum EM regenerative torque) requested is computed, which is the braking torque requested by the Driver. This value is compared against the maximum EM regenerative torque and the lower of the two values gives the negative motor torque request. This value is multiplied with the charge limiting value to prevent overcharge of the battery and a regen-braking cutoff value to limit regenerative braking at lower vehicular speeds. If the requested braking torque is below the maximum EM braking limit, then all the braking torque is provided by the electric machine in the form of regenerative braking. Whereas if it is the other way around, the maximum possible EM regenerative torque is applied and the remaining brake torque is provided by the friction brakes by providing the necessary brake line pressure [27].

The above detailed procedure is valid for the FWD architecture with only one motor. When two motors are considered, the torque split between the motors needs to be considered. For AWD architecture, the motor capability for propulsion and regen-braking is the summation of the individual motors. The procedure is similar; the only difference is that the motor torque request now computed is composed of the individual motor request.
The split between the two motors is dependent on the total torque requested and the vehicle speed. This split is an optimal one found by selecting the split that uses the least power (or generates the maximum power) for a given total torque request and vehicle speed.

The total torque request is a summation of individual motor torques. The individual motor speeds depend on the vehicle speed and their gear ratios,

\[ T_w = \eta_t \lambda_1 T_{em,1} + \eta_t \lambda_2 T_{em,2} \tag{18} \]

\[ \omega_{em,1} = \lambda_1 \frac{v_{veh}}{R_w} \quad \omega_{em,2} = \lambda_2 \frac{v_{veh}}{R_w} \tag{19} \]

The torque split $\gamma$ varies from 0 to 1 and determines the torque provided by the individual motors,

\[ \eta_t \lambda_1 T_{em,1} = \gamma T_w \tag{20} \]
\[ \eta_t \lambda_2 T_{em,2} = (1 - \gamma) T_w \tag{21} \]

Based on the individual motor torques and speeds, motor electric powers are computed,

\[ P_{em,1} = \frac{T_{em,1} \omega_{em,1}}{\eta_{em,1}} \quad P_{em,2} = \frac{T_{em,2} \omega_{em,2}}{\eta_{em,2}} \tag{22} \]
\[ \eta_{em,1} = f_1(\omega_{em,1}, T_{em,1}) \quad \eta_{em,2} = f_2(\omega_{em,2}, T_{em,2}) \tag{23} \]
The battery cell provides power to both motors together,

\[ P_{b,\text{out}} = \frac{1}{n_s n_p} P_{em,1,2} = \frac{1}{n_s n_p} (P_{em,1} + P_{em,2}) \] (24)

Therefore, the cell output power is a function of vehicle operating condition and torque split. The optimal torque split is found by minimizing the cell power for a given operating condition,

\[ P_{b,\text{out}} = f(v_{vel}, T_w, \gamma) \] (25)

\[ \gamma^*(v_{vel}, T_w) = \arg\min_{\gamma \in [0,1]} \left( P_{b,\text{out}}(v_{vel}, T_w) \right) \] (26)

\[ \gamma^* = f(v_{vel}, T_w) \] (27)

This is how the optimal torque split is computed, and is simply referred to by \( \gamma \) in the further sections. It should be mentioned that the procedure to find optimal split does not consider driveline behavior and torque dynamics.

To summarize, based on the Mode Selection throttle and brake commands, the front motor torque request (positive for propulsion, negative for regen-braking) is computed along with the brake line pressure command for a single motor FWD architecture. For a two motor AWD architecture, the rear motor torque request is also computed in the controller.
3.4. Simulation Setup

The vehicle model is developed in MATLAB R2017b in a mixed environment using Simulink, Simscape, and Powertrain Blockset tools [27]. Runge-Kutta ode4 solver is used with a fixed step time of 0.0005 secs.

3.5. Sanity Test

The vehicle model developed is tested by comparing the energy consumption values against standard industry values. The model results are compared against the energy consumption data for Nissan Leaf and Chevrolet Bolt EV. The vehicle is modeled to represent Leaf and Bolt by using their dimensional data, weight, drag coefficient, frontal area, rolling radius, etc. The motor peak and rated characteristics are also matched as closely as possible. The vehicle is simulated on the EPA Urban cycle (UDDS) and Highway cycle (HWFET), and the simulated fuel economy data are recorded. Combined data are a 55-45% weighted average of urban and highway data [45].

Energy consumption/fuel economy of an electric vehicle are generally presented in kWh/100mi and MPGe (Miles per gallon equivalent). MPGe roughly means the number of miles driven using energy equivalent to the energy stored in a gallon of gasoline. These values are computed from the energy consumption as follows [47],

\[
\frac{kWh}{100\text{mile}} = \frac{\text{Energy} [MJ]}{3600} \times \frac{100}{\text{Distance} [\text{mile}]} \quad (28)
\]

\[
\text{MPGe} = \frac{33.7}{\frac{kWh}{100\text{mile}}} \times 100 \quad (29)
\]
Figure 37. EPA UDDS and HWFET Drive Cycle [46]

Table 4. Comparing model results of fuel economy with EPA data

<table>
<thead>
<tr>
<th>Model</th>
<th>Data</th>
<th>UDDS</th>
<th>HWFET</th>
<th>Combined kWh/100mi</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MPGe</td>
<td>MPGe</td>
<td>MPGe</td>
</tr>
<tr>
<td>Leaf</td>
<td>EPA</td>
<td>124</td>
<td>101</td>
<td>112</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>130</td>
<td>114</td>
<td>123</td>
</tr>
<tr>
<td></td>
<td>Error [%]</td>
<td>4.84</td>
<td>12.87</td>
<td>9.82</td>
</tr>
<tr>
<td>Bolt EV</td>
<td>EPA</td>
<td>128</td>
<td>110</td>
<td>119</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>124</td>
<td>109</td>
<td>117</td>
</tr>
<tr>
<td></td>
<td>Error [%]</td>
<td>-3.13</td>
<td>-0.91</td>
<td>-1.68</td>
</tr>
</tbody>
</table>

The values are compared with the EPA published data in Table 4.
From Table 4, the model predictions of MPGe for Leaf are higher than the data and are within 13% and for Bolt, are lower than the data and are within -4%. Considering the lack of complete vehicle data such as motor maps, battery efficiencies, transmission efficiencies and lack of control logic, the simulation results are deemed acceptable. Addition of more refined data and models would improve the results.
Chapter 4. Powertrain Optimization

A systems design problem is typically expressed as an optimization problem. In order to formalize the design problem as an optimization problem, an objective function based on the optimization criteria, decision variables, constraints, and a method to find the best design choice need to be defined.

The optimization problem depends on the application for which the powertrain is optimized. Here, two such applications are considered. The first application is Autonomous Driving (AD). This represents pure autonomously driven vehicle with no human driving functionality. The second application is Human & Autonomous Driving (HAD), which is an autonomous vehicle, but with a human driving functionality. The details for both the applications are discussed in the further sections. The optimization requirements and constraints are dependent on the type of application. The driving pattern will also vary due to the fundamentally different driving functionality. These requirements and drive cycles are detailed along with the application below.

**Design space:** In the case of the powertrain design problem, the design space is the discrete powertrain options and model parameters. There are two architectures to choose from with multiple motor options.

**Objective function:** The optimization criteria comes from the requirement of fuel economy, cost, and weight. The powertrain cost is assumed to be directly associated with
the powertrain power since actual powertrain cost is not known. The weight of the powertrain system should also be minimized.

A tradeoff between these conflicting objectives is represented using Pareto fronts. Pareto front exploration method is used to find the Pareto optimal solutions. The best solution needs to be hand-picked by the designer using the trade-off curves obtained as Pareto fronts.

**Static Constraints**: The constraints for the design space come from the performance requirements. Requirements such as acceleration performance, top speed, and gradeability need to be satisfied by the powertrain under consideration.

**Dynamic Constraints/Inputs**: The dynamics of the powertrain adds constraints to the design problem. In order to evaluate the performance metrics and constraints, we need to simulate the dynamic constraints. Inputs for the dynamic constraints are the drive cycles (typical driving pattern).

### 4.1. Powertrain Design Space

The powertrain design space consists of the powertrains options a designer evaluates. The design space is varied at two levels i.e. the architecture and the component level. Discrete candidates are considered. The architecture can be either a front-wheel-drive single motor system or an all-wheel-drive dual motor system. In terms of components, 10 motors representing a wide power range are selected. The gear ratio is computed for each combination based on vehicle top speed and motor maximum speed matching.
For AWD, redundant/equivalent powertrain designs are eliminated. For example, motor no. 3 connected to the front axle and motor no. 5 connected to the rear axle is assumed to be the same as motor 3 connected to rear and motor 5 connected to the front axle.

As 10 motors are considered, this results in 10 candidates for FWD and 55 candidates for AWD with a total of 65 candidates.

Table 5. Number of design space candidates

<table>
<thead>
<tr>
<th># of Electric motors</th>
<th>FWD</th>
<th>AWD</th>
<th>Total Candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
<td>55</td>
<td>65</td>
</tr>
</tbody>
</table>
Table 6. Powertrain configuration for design space candidates

<table>
<thead>
<tr>
<th>Candidate #</th>
<th>Front Motor</th>
<th>Rear Motor</th>
<th>Candidate #</th>
<th>Front Motor</th>
<th>Rear Motor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>-</td>
<td>34</td>
<td>7</td>
<td>3</td>
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<td>9</td>
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</tbody>
</table>
4.2. Objective Function

The optimization criteria for the objective function are fuel economy/energy consumption, powertrain cost, and weight. The cost of different motors, electric drive transmissions and axles is not known. Total peak power of the motor/s is assumed to represent cost, with higher power motors being proportionally expensive. Therefore, the peak power of the powertrain candidate is used instead of cost.

Combined energy consumption is computed as a weighted sum from the simulation run on drive cycles, with 55% weightage to urban cycle and 45% to highway cycle consumptions [45].

The weight of the motors is specified in the data. An inverter is assumed to weigh around 10 kg [38], transmission around 28 kg [33] and driveshafts around 15 kg [48]. This total weight of around 53 kg is added for all-wheel drive architecture; the mass of mountings and extra connectors are neglected.

Pareto optimality filter is used to select the dominant candidates. A dominant candidate is superior or equal to another candidate in every criterion and strictly superior in at least one [49]. If one of the criteria is strictly greater and the other is smaller, the inequality between two candidates is undefined – meaning none of the candidates are discarded. The output of this process is Pareto optimal candidates in which improvement in a criterion results in a decrease in another. This generates a Pareto front comprising of candidates, which are optimal subject to tradeoffs. It is the designer’s task to select a powertrain after a thorough consideration of the tradeoffs.
4.3. Autonomous Driving

Autonomous Driving (AD) covers the applications in which the vehicle is used as a means of transporting people, and is designed to run autonomously without a human driver. It is a passenger-centric design, focusing more on the passenger comfort rather than the drivability and driver feel. These types of vehicles can be used in transit services like cabs, shuttles, buses and for consumers who want a personal space but do not want the hassle of driving the car themselves.

This study focuses on the personal segment vehicles; hence, the requirements would mainly relate to such applications.

4.3.1. Performance Requirements

The major performance requirements considered are top speed, maximum cruising speed, 0-60 mph acceleration time and gradeability. Whether a powertrain can meet these requirements or not depends on the vehicle characteristics like mass, frontal area, drag coefficient, rolling radius, rolling resistance coefficient, etc. and the powertrain characteristics like peak power and torque, rated power and torque, base/rated speed and the maximum speed.

a) Top speed requirement

The electric powertrain is designed to meet the top speed requirement, by selecting a gear ratio that does not violate the electric machine maximum speed anytime during the vehicle operation. The electric machine should also provide the necessary power to move the vehicle at that high speed. The power does not have to be provided continuously, as the top speed might be just for passing and not for sustained operation.
This requirement is considered when determining the electric powertrain peak power [11].

Since these requirements are for an AD vehicle, the top speed of the vehicle is limited to 85 mph. That is the highest speed limit in the USA [50]. The Autonomous Vehicle will not exceed the speed limit; therefore, the vehicle is not designed to achieve higher speeds.

b) Maximum cruising speed

The maximum cruising speed is a sustained operation. The vehicle needs to travel at that speed on a level ground continuously. The powertrain should provide the required power at that speed i.e. the rated power. Therefore, the power required for the maximum cruising speed puts a lower limit on the motor rated power.

Due to the speed limit of 85 mph, a customer might expect the vehicle to travel continuously at that speed. Therefore, in this case, both the top speed and the top cruising speed are selected to be 85 mph.

c) Acceleration performance

One of the factors that determine the acceleration performance of a vehicle is the 0-60 mph time. For an electric vehicle, this depends on the maximum power i.e. the peak power of the motor and its base speed. The base speed determines the rate at which the motor can deliver all that peak power. For the same peak power, the lower the base speed, the higher the rate of power delivery, and hence, higher acceleration.

However, an autonomous vehicle is designed for passenger comfort. According to the literature [2], [17], [51], most passengers do not prefer aggressive driving i.e. higher accelerations, decelerations aggressive turns. Also, around 15 to 32% of the world’s
population suffers from motion sickness when engaged in some activity other than
driving, like reading, watching a movie, etc. [52]. Since one of the factors that can
aggravate motion sickness is longitudinal accelerations, these values need to be
constrained. As per Le Vine [22], the acceleration limits of a Light Rail Transit (LRT) of
$\pm 1.34 \, \text{m/s}^2$ are considered for passenger comfort in an AV. Assuming constant
acceleration of $1.34 \, \text{m/s}^2$, results in a 0-60 mph time of around 20 secs. These values
are not hard constraints, as AVs might not be designed for such acceleration events.
Therefore, a low acceleration performance of 0-60 in 20 secs is considered.

d) Gradeability

Gradeability determines the hill climbing capability of a vehicle. The vehicle
should be able to climb a slope at an acceptable speed. The maximum and rated torque of
the motor determines the vehicle’s ability to go up a slope.

An electric vehicle is required to travel at speeds greater than 45 mph on a 6%
grade and be designed for a maximum grade of 25% [53].

All the performance requirements for Autonomous Driving (AD) are summarized
in Table 7.

Table 7. Performance requirements for Autonomous Driving application

<table>
<thead>
<tr>
<th>Top Speed [mph]</th>
<th>85</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Cruising Speed [mph]</td>
<td>85</td>
</tr>
<tr>
<td>0-60mph Time [s]</td>
<td>20</td>
</tr>
<tr>
<td>Gradeability</td>
<td>Max Grade: 25%; Max Speed: 45mph @ 6%</td>
</tr>
</tbody>
</table>
4.3.2. Drive Cycles

Drive cycles are speed profiles that represent a typical driving pattern for a vehicle. These cycles are used to assess the vehicle’s fuel consumption and emissions quantitatively by the industry to develop a better product and by the government regulatory agencies to uniformly assess and certify all vehicles. There are multiple cycles depending on drive scenario, application, type of vehicle, OEM and country [54].

There are multiple drive cycles for conventional vehicles like the EPA UDDS cycle to represent city driving and the EPA HWFET to represent highway driving [46]. However, there are not many drive cycles in the traditional sense to assess the potential benefits of autonomous vehicle technology. This is difficult to evaluate since how an autonomous vehicle would be typically driven will depend on the manufacturer and the infrastructure; the decisions that an AV would take to navigate through environment would depend on the algorithm being used, which can be different [25], along with the information that the vehicle might receive.

Therefore, a best-case scenario of complete connectivity is considered, which results in optimal trajectories detailed in the following section. Such generated cycles are used to optimize the powertrains for Autonomous Driving (AD) application.

**Autonomous Drive Cycle**

There are two factors to consider for deriving an Autonomous Drive Cycle (ADC). One deals with the constraints on autonomous driving like acceleration/deceleration rates, trip time, trip distance and maximum speed. The other deals with the method of deriving the cycle.
In this study, ADCs are generated by converting the existing drive cycles of UDDS and HWFET into the ones that are representative for an AV. Therefore, the constraint of trip distance is the same as the conventional cycle. The trip time can change; can decrease due to an efficient traffic flow; can increase due to lower average speeds to reduce energy consumption. For a fair comparison, the trip time is also not changed from the conventional trip time, but it is not a hard constraint. The maximum speeds depend on the speed limits along the trip. As discussed earlier (4.3.1. Performance Requirements), major emphasis is placed on the acceleration/deceleration constraints to ensure comfort. The acceleration/deceleration are limited to $\pm 1.34 \text{ m/s}^2$ for autonomous vehicle drive cycles.

Once the constraints for autonomous drive cycles are evaluated, the method to generate the cycles is discussed. The approach simulates full autonomy, wherein the vehicle has complete information of the future trajectory and constraints. This serves as the bounding case. Vehicles are not limited due to traffic constraints in between stops. The drive cycle representing this scenario is simulated by generating an optimal speed profile by using Dynamic Programming [26].

*Optimal Speed Trajectory using DP*

To simulate the autonomous vehicle driving profile, the optimal trajectory is computed using Dynamic Programming. It is assumed that the vehicle has complete information on the route and the speed limits.

Similar to the conventional case, an urban profile and a highway profile are considered. The urban profile constraints are derived from the UDDS cycle and similarly from HWFET for highway drive profile. Constraints derived from drive cycles include
the speed limits, stop locations, trip distance and trip time. Stops are simulated by assigning a speed limit of 0 mph. Trip distance for autonomous driving is the same as the drive cycle distance. Trip time, even though flexible, is considered to be the same as the drive cycle time for fair comparison between powertrains.

Speed limits are derived as a function of distance from the conventional drive cycle. A speed limit vector is generated based on the common speed limits in the US ($v_{lim} = [0, 15, 25, 35, 45, 50, 55, 65, 70]$ mph). The speed limit for distance $d_i$ is computed as follows,

- Find index $j$ such that $v_{lim}(j - 1) + mgn < v(d_i)$ & $v_{lim}(j) + mgn \geq v(d_i)$
- $v_{max}(d_i) = v_{lim}(j)$
- For $v(d_i) = 0$, $v_{max}(d_i) = 0$

A speed margin ($mgn$), which acts as a soft speed limit, is considered. This is to simulate some drivers tendency to exceed the speed limit [26]. A lower speed limit of 40mph is considered for segments where the speed limits are above 55mph.

The basic method to compute the optimal trajectory is derived from Mensing [26], which deals with two dimensional DP, having distance and speed as the two dimensions. Total travel time is not explicitly constrained in this method, but it is included in the cost function with a penalty. The two variables that set up the problem of vehicle motion are given by,

$$X = \begin{bmatrix} d \\ v \end{bmatrix} \quad X_{k,i} = \begin{bmatrix} d_k \\ v_i \end{bmatrix} \quad (30)$$
The vehicle position/distance is given by ‘\(d\)’ and the velocity is given by ‘\(v\)’. Velocity is the state variable and distance is the stage variable. The index for velocity is ‘\(i\)’ and for distance is ‘\(k\)’. The initial and final conditions are given by,

\[
X_0 = \begin{bmatrix} d_0 \\ v_0 \end{bmatrix} \quad X_f = \begin{bmatrix} d_f \\ v_f \end{bmatrix}
\]  

(31)

The grid space is discretized by ‘\(\Delta d\)’ for distance and ‘\(\Delta v\)’ for velocity. The problem is divided into ‘\(N\)’ steps, where,

\[
d_f - d_0 = N\Delta d
\]

(32)

Figure 38: Dynamic Programming optimization method
The cost function to minimize is given by,

\[ J(k, i_1 \rightarrow (k+1, i_2)) = P_{veh} \left( v_{i_1}, a_{v_{i_1} \rightarrow v_{i_2}} \right) \Delta t + \beta \Delta t \]  
(33)

\[ J^*_i(k, i_1) = \min_{a \in A} \left( J(k, i_1 \rightarrow (k+1, i_2)) + J^*_i(k+1, i_2) \right) \]  
(34)

\[ a^*_i(k, i_1) = \arg\min_{a \in A} \left( J(k, i_1 \rightarrow (k+1, i_2)) + J^*_i(k+1, i_2) \right) \]  
(35)

The control input is vehicle acceleration \( a \), which is constrained as mentioned earlier [22].

\[ a \in \{a_{min}, a_{max}\} = \{-1.34, +1.34\} \frac{m}{s^2} \]  
(36)

The optimal input is dependent on the stage and state variable and is denoted by \( a^*_i(k, i_1) \). \( P_{veh} \left( v_{i_1}, a_{v_{i_1} \rightarrow v_{i_2}} \right) \) is the power used by the vehicle at step \( k \) to go from \( v_{i_1} \rightarrow v_{i_2} \) by applying acceleration \( a \). It is a function of vehicle velocity (state) and acceleration (input). The state update equation is given by,

\[ v_{i_2} = \sqrt{v_{i_1}^2 + 2a\Delta d} \]  
(37)

\[ \Delta t = \frac{2\Delta d}{v_{i_1} + v_{i_2}} \]  
(38)

The inputs that result in negative velocity are infeasible.
The value of $\beta$ is found iteratively using the Bisection method. Low value of $\beta$ does not penalize time taken to cover distance $\Delta d$, hence the velocity selected will be very low to minimize power consumption. This will result in longer trip duration. High value of $\beta$ will result in smaller trip duration and higher velocities. Since the problem of $\beta$ vs time follows an inverse trend, bisection method can be used. The desired time is kept between ± 10 secs of trip time for UDDS and ± 5 secs of trip time for HWFET. These limits only result in a change of around 0.1% for UDDS and around 1% for HWFET in energy consumption values.

To calculate vehicle power/energy consumption, wheel power is required, which is computed based on the vehicle velocity and acceleration. This is equal to the inertial load along with the road load consisting of aerodynamic load, rolling resistance force and grade force [8].

\[
F_w = F_{acc} + F_{aero} + F_{roll} + F_{grade} \quad (39)
\]

\[
P_w = F_w v_{veh} \quad (40)
\]

The acceleration load is given by,

\[
F_{acc} = M_{eff} \frac{dv_{veh}}{dt} = M_{eff} a \quad (41)
\]

where $M_{eff}$ is the effective vehicle mass, incorporating the rotational inertia of the driveline along with the vehicle mass.
The aerodynamic load is given by,

\[ F_{aero} = \frac{1}{2} \rho C_d A_f (v_{veh} + v_{hw})^2 \]  \hspace{1cm} (42)

The drag coefficient \( C_d \) depends on the flow of air over the vehicle, but is considered to have a constant value. Frontal area \( A_f \) is the projection of the vehicle’s area perpendicular to the net wind flow direction. \( v_{hw} \) is the headwind velocity. It is apparent that the aerodynamic force increases with the square of the net velocity.

The rolling resistance load is given by,

\[ F_{roll} = C_r M g \cos(\theta) \]  \hspace{1cm} (43)

It is caused mainly due to the tire deformation. The rolling resistance \( C_r \) depends on the tire characteristics, pressure, temperature, road surface, etc. For the system level study, \( C_r \) is approximated as a constant. Rolling resistance depends on the normal force acting on the tires, hence depends on the angle (grade) of the road \( \theta \) in radians.

The grade force is the vehicle weight acting either against or with the propulsion force.

\[ F_{grade} = M g \sin(\theta) \]  \hspace{1cm} (44)

Unless specified, the slope of the road is assumed to be 0, hence grade force would not be considered.
The wheel torque required is,

\[ T_w = F_w R_w \]  \hspace{1cm} (45)

\( R_w \) is the rolling radius of the wheel/tire.

The powertrain i.e. electric motors in this case, through a transmission, supply this wheel torque.

The electric motor can operate in both directions of energy flow. Based on the flow direction, electric power through motor changes.

The motor torque and speed is given by,

\[ T_{em} = \frac{T_w}{\eta_e \lambda} \hspace{1cm} \omega_{em} = \lambda \omega_w = \lambda \frac{v_{veh}}{R_w} \]  \hspace{1cm} (46)

Based on the motor torque and speed, motor efficiency and motor electric power are computed from Eq. (1), (2) and (3).

The battery supplies this electric power to the motor. The battery current and power is computed as follows [26],

\[ P_{b,\text{out}} = \frac{P_{em,\text{elec}}}{n_s n_p} \]  \hspace{1cm} (47)

\[ P_{b,\text{out}} = V_{out} I_b = V_{oc} I_b - I_b^2 R_0 \]  \hspace{1cm} (48)

\[ P_{b,\text{in}} = V_{oc} I_b \]  \hspace{1cm} (49)
where, $P_{b,out}$ is the power output of each cell, $P_{b,in}$ is the power drawn through each cell. This power, multiplied by the number of cells in series and parallel gives the battery pack power, which is the vehicle power that needs to be minimized. The change in SOC is modeled as [55],

$$
\Delta SOC = - \frac{I_b \Delta t}{C_{nom}}
$$

To reduce a state in the dynamic programming problem, SOC dynamics are not considered. The above assumption does not have much impact on the results, as the battery variables do not vary considerably during the DP problem [56]. The values for $V_{oc}$ and $R_0$ are computed at SOC 60% for the dynamic programming problem.

The above equations are valid for a single motor architecture. For two motors, the wheel torque is a summation of the torques provided by the motors and the battery provides power to both the motors. The split between the motors is selected to minimize energy consumption. The optimal value ($\gamma$) is defined as a function of the vehicle velocity and total requested wheel torque. This is described in Eqs. (18)-(27).

Various grid sizes are evaluated for a front wheel drive architecture with Motor #8 for the urban drive profile (Table 8). It is found that reducing the size does not affect the result significantly. However, computational time increases exponentially. Therefore,
a grid size of $\Delta d = 5m$ and $\Delta v = 0.2m/s$ is selected based on this tradeoff. These values are also used by Mensing [26].

<table>
<thead>
<tr>
<th>$\Delta d$ [m]</th>
<th>$\Delta v$ [m/s]</th>
<th>Energy Consumption [MJ]</th>
<th>Computation Time [sec]</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1</td>
<td>6.536</td>
<td>3.8</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>6.506</td>
<td>7.4</td>
</tr>
<tr>
<td>5</td>
<td>0.2</td>
<td>6.531</td>
<td>14.8</td>
</tr>
<tr>
<td>2</td>
<td>0.2</td>
<td>6.506</td>
<td>33.2</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>6.533</td>
<td>61.9</td>
</tr>
<tr>
<td>1</td>
<td>0.1</td>
<td>6.501</td>
<td>119.4</td>
</tr>
</tbody>
</table>

After computing the optimal cost value and optimal control input matrix, a forward run from the vehicle initial condition generates the optimal velocity trajectory. This entire process of dynamic programming results in optimal profiles for urban driving and highway driving as shown below.
Figure 39. Optimal Speed vs Distance for urban driving – derived from UDDS

Figure 40. Comparing UDDS and optimal trajectory
Figure 41. Optimal Speed vs Distance for highway driving – derived from HWFET

Figure 42. Comparing HWFET and optimal trajectory
As seen in the above figures, the optimal profile generally tends to be at lower speeds, to minimize aerodynamic losses. The vehicle tends to accelerate quickly (limited by the acceleration constraints) to an optimum cruising speed and stays there as long as possible. The optimum cruising speed is a function of speed limits, desired trip time, vehicle aerodynamic losses and powertrain efficiency profile.

These cycles are only optimal for a single powertrain. Each powertrain option will have a different optimal profile. Therefore, how a vehicle is driven is inherently linked to the powertrain of the vehicle.

The cycles generated after this process of dynamic programming are termed as the Autonomous Drive Cycle (ADC). This trajectory is then used as an input for the autonomous driving powertrain optimization.

4.4. Human & Autonomous Driving (HAD)

While most of the vehicles on road in the future would be completely autonomous, there is still a large population who want the ability to drive their vehicle, even with all the autonomous features in their personal cars [57]–[59]. As per Schoettle and Sivak [57], an overwhelming 94.5% of people want the ability to control the vehicle using conventional controls when desired. The vehicles that are completely capable of autonomous driving, but still have traditional controls for the driver fall under Human & Autonomous Driving (HAD) case.

The difference with this type of vehicle is that even though the operation might be completely autonomous, the requirements stem from conventional vehicles for customer acceptability.
Another challenging part is defining the most representative drive scenario for powertrain optimization, as it is not clear what the mix is between autonomous and convention driving. It might depend on the autonomous technology advancement, trip type, driver preference, Government regulation, etc.

This study tries to address this issue by using a weighted average based on usage. This weight is a proportion between autonomous and conventional driving, where 0% denotes no autonomous driving; only conventional driving, and 100% denotes the opposite with autonomous driving for all the trips. It is explained in Section 4.4.2 Drive Cycles.

The performance requirements and drive profiles for HAD are discussed below.

### 4.4.1. Performance Requirements

As mentioned in Section 4.3.1. Performance Requirements, the major powertrains requirements considered are vehicle top speed, maximum cruising speed, acceleration performance and gradeability. Since humans when desired, can drive the vehicle, the requirements would relate to what a driver expects from the vehicle rather than a passenger. These expectations are what conventional vehicles provide, and hence are selected to be industry average values. The requirements are as follows,

<table>
<thead>
<tr>
<th>Table 9. Performance requirements for Human &amp; Autonomous Driving application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Speed [mph]</td>
</tr>
<tr>
<td>Max Cruising Speed [mph]</td>
</tr>
<tr>
<td>0-60mph Time [s]</td>
</tr>
<tr>
<td>Gradeability</td>
</tr>
</tbody>
</table>
The maximum cruising speed is assumed to be 90% of the top speed, where the top speed is only used for passing and not for sustained operations [11].

4.4.2 Drive Cycles

It is difficult to come up with a representative drive cycle for a scenario where the vehicle might be driven autonomously along with conventional human driving. One of the modes might be preferred in a particular scenario; for example, some might prefer to use autonomous mode in an urban setting to free themselves of the stress of daily driving and to increase productivity, whereas some would prefer to drive autonomously on interstate highways, to make the drive less monotonous. These preferences are subjective, and as per the author’s knowledge, there does not seem to be a study regarding such preferences as of now.

To simulate the worst-case scenario, only conventional driving is considered for HAD. EPA UDDS and HWFET drive cycles are considered. This will result in a powertrain that is not optimized for any autonomous operation.

If the split between autonomous and human driving is known, a weighted average of the energy consumption values of the autonomous and conventional drive cycle can be used. This weight \(\alpha\) denotes the fraction of instances the vehicle is driven autonomously. It gives weightage to autonomous cycles against conventional cycles (UDDS, HWFET). This method only considers the gross energy consumption. The results for HAD cycles are obtained by using the following formulation,

\[
HAD = \alpha AD + (1 - \alpha) HD
\]  
(52)
where $AD$ represents the cycles used for autonomous driving and $HD$ represents conventional (human) cycles.

But since the split is not known, $\alpha = 0$ is considered in the further sections.
Chapter 5. Optimization Results

For both cases i.e. Autonomous Driving (AD) and Human & Autonomous Driving (HAD), feasible design space are generated based on powertrains that satisfy the performance requirements. For AD, these shortlisted powertrains are simulated on the optimization inputs i.e. the autonomous drive cycles. For HAD, the shortlisted powertrains are simulated on conventional cycles. The autonomous drive cycles are dependent on the powertrain option; therefore, each candidate will have a different autonomous cycle. The conventional cycle is independent of the candidate. In both situations, the Simulink model was used to simulate the vehicle operation.

Values for the optimization criteria are extracted from the simulation results i.e. the energy consumption to compute fuel economy. For AD, fuel economy just depends on the energy consumption results of autonomous drive cycles. For HAD, it depends on the weighted average of results from conventional cycles and autonomous cycles, but only conventional results are considered.

Based on the above criteria, powertrain power, and weight, Pareto optimality filter is applied to eliminate the dominated designs. This results in a Pareto front, which will assist in choosing the optimal powertrain subject to tradeoffs.

This marks the completion of powertrain optimization/selection for both the cases. To understand the tradeoff if any, in terms of energy consumption, between
designing an autonomous vehicle powertrain with the human driving capability (HAD) instead of purely autonomous driving (AD), the optimal powertrains for both cases are compared against each other. This is done by simulating both the optimal powertrains on the autonomous drive cycles.

Figure 43. Optimization flowchart

The entire process of powertrain selection and optimization is summarized in the above flowchart.
5.1. Vehicle Design Specifications

The vehicle considered is a midsize SUV with vehicle specifications tabulated below. The vehicle curb mass is modified to reflect an electric vehicle by replacing the conventional powertrain weight (engine and transmission) with electric powertrain (electric motor, inverter, electric drive transmission) and ESS weight. In addition, this weight is not constant for all candidates. The weight changes with each candidate, depending on the weight of the powertrain. Since the same battery is used for all candidates, the battery weight is kept constant.

<table>
<thead>
<tr>
<th></th>
<th>Vehicle A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curb Mass [kg]</td>
<td>1971</td>
</tr>
<tr>
<td>Length [mm]</td>
<td>4684</td>
</tr>
<tr>
<td>Width [mm]</td>
<td>1872</td>
</tr>
<tr>
<td>Height [mm]</td>
<td>1651</td>
</tr>
<tr>
<td>Wheelbase [mm]</td>
<td>2685</td>
</tr>
<tr>
<td>Track width [mm]</td>
<td>1610</td>
</tr>
<tr>
<td>$A_f$ [$m^2$]</td>
<td>2.6</td>
</tr>
<tr>
<td>$C_d$</td>
<td>0.37</td>
</tr>
<tr>
<td>Tires</td>
<td>235/60 R18</td>
</tr>
</tbody>
</table>
5.2. Optimization for AD

Based on the performance requirements (optimization constraints) for Autonomous Driving application detailed in Section 4.3.1. Performance Requirements, the feasible design space is selected. Out of the 65 candidates, 60 candidates satisfy the requirements.

Table 11. Number of feasible candidates for AD

<table>
<thead>
<tr>
<th>Total Design Space</th>
<th>Feasible Design Space</th>
</tr>
</thead>
<tbody>
<tr>
<td>65</td>
<td>60</td>
</tr>
</tbody>
</table>

![Figure 44. Feasible design space for AD](image)

Candidate #1 and 2 do not meet the acceleration requirement, whereas Candidate #7, 8 and 11 do not meet the gradeability requirement.
Figure 45. Acceleration performance of candidates, and the requirement for AD

As seen above, Candidate #1 and 2 have 0-60 mph time of around 36 and 21 secs respectively, which are greater than the AD requirement of 20 secs.

To visualize the other requirements of wheel power required for top speed, gradeability, etc., wheel power required for those cases are plotted below. Power at wheels for two powertrain candidates are plotted with respect to vehicle speed, along with power required for multiple cases:-

Case 1 – Level ground, no wind
Case 2 – 1% Grade, no wind
Case 3 – 25% Grade, no wind
Case 4 – 6% Grade, no wind
According to Figure 46, candidate #8 cannot meet the maximum grade requirement of 25%. This is due to a high base speed for the motor #8 used in the powertrain, which results in lower starting torque. On the other hand, candidate #10 meets all requirements (Figure 47).
Now, these selected candidates are simulated on autonomous drive cycles, wherein the optimal profiles are generated for each candidate using DP. Few of the optimal profiles and motor operating points are illustrated.

Optimal profile for candidate #10 is shown below, along with the motor operating points. Both urban and highway driving are shown.

Figure 47. Wheel power for Powertrain candidate #10
Figure 48. Optimal profile for urban driving – Candidate #10

Figure 49. Motor operating points for autonomous urban driving – Candidate #10
Figure 50. Optimal profile for highway driving – Candidate #10

Figure 51. Motor operating points for autonomous highway driving – Candidate #10
Figure 48 and Figure 50 show the urban and highway optimal trajectory for Candidate #10, and Figure 49 and Figure 51 show the operating points for the electric motor on the respective drive scenarios. The optimal trajectories are compared against the EPA cycles used to derive them. In the optimal profiles, the vehicle accelerates to a constant speed and stays at that speed, unless constrained due to speed limits. It is evident from the operating points that the motor operates at lower speeds for urban driving with increased variability rather than at higher speed and fixed operating points for highway driving.

The above candidate has a FWD (single motor) architecture. Similar profiles and points are illustrated for Candidate #32, which is an AWD powertrain (dual motor). The optimal urban and highway profiles for Candidate #32 are shown in Figure 52 and Figure 54. As mentioned earlier, the optimal profile considers the optimal torque split between the two motors. The two motors always operate with the optimal torque split, which is clear from the operating points shown in Figure 53 and Figure 55. Both the motors try to operate at their high-efficiency points, as seen by the distribution.
Figure 52. Optimal profile for urban driving – Candidate #32

Figure 53. Motor operating points for autonomous urban driving – Candidate #32
Figure 54. Optimal profile for highway driving – Candidate #32

Figure 55. Motor operating points for autonomous highway driving – Candidate #32
The optimization criteria i.e. the results of these simulations in terms of energy consumption values (represented as kWh/100mi) and total powertrain peak power are plotted against each other for all the candidates. The objective is to minimize these criteria (lower energy consumption and lower peak power).

To find the optimal candidates that minimize the objective function, Pareto fronts are computed. Two Pareto fronts are generated, one for each architecture (FWD and AWD), as it is not fair to compare the two on the same level, due to increased component count and cost, control difficulties, packaging and installation considerations for AWD architecture.

Figure 56 plots the energy consumption for all feasible candidates against their powertrain peak power, for urban, highway and combined scenarios. These are for the autonomous drive cycles (optimal trajectories). As evident, less energy is consumed for urban driving compared to highway driving.

The two Pareto fronts (‘o’ for FWD and ‘x’ for AWD) are graphically represented. As expected, a tradeoff is found between energy consumption and power. Generally, low powered powertrains are more efficient (but not by a large margin, as noted later), and the optimal power is around 100 kW. Further decrease in power results in the motors being operated at higher torque and hence, inefficient regions. Therefore, downsizing a single motor architecture might push the operating points to inefficient higher load regions. In addition, downsized AWDis comparable to, and in some cases even better than the FWD architecture, in spite of extra component weight and inefficiencies. This is due to the extra degree of freedom provided by an additional motor, which allows both motors to operate in their efficient regions. However, the gains of
using AWD are reduced for transient applications, like the urban setting, due to increase in inertial loads.

Figure 57 plots the ratio of best energy consumption (irrespective of architecture) for a driving scenario and the energy consumption for each candidate, as a fraction. This illustrates the variation in energy consumption throughout the candidates, compared to the best possible, for similar operating conditions. It also shows the percentage of energy savings gained by switching to the most efficient powertrain. The energy consumption does not show a strong trend with powertrain power. Increase in powertrain power does not drastically increase energy consumption. There is, however, a slight increase in consumption with power for autonomous urban driving, which is due to the powertrain being oversized. Nevertheless, the best energy consumption is still within 4% of the energy consumption, in spite of 3.5 fold increase in power (from around 100 kW to 350 kW). In addition, irrespective of the driving condition and candidate power, the energy consumption savings are within 10% (for most cases within 5%).

To conclude, based on the tradeoff between architecture, powertrain cost/power, and energy consumption, the designer can select a powertrain from the set of optimal powertrains highlighted by the Pareto fronts. This concludes the powertrain optimization task for pure autonomous driving applications (AD).
Figure 56. Pareto fronts for AD – Autonomous drive cycles
5.3. Optimization for HAD

Similar to the above section, this section deals with the powertrain optimization for Human & Autonomous Driving (HAD) application. Out of 65 candidates, 49 candidates meet all the performance requirements detailed in Section 4.4.1. Performance Requirements, and hence form the feasible design space.
Table 12. Number of feasible candidates for HAD

<table>
<thead>
<tr>
<th>Total Design Space</th>
<th>Feasible Design Space</th>
</tr>
</thead>
<tbody>
<tr>
<td>65</td>
<td>49</td>
</tr>
</tbody>
</table>

Figure 58. Feasible design space for HAD

Figure 59. Acceleration performance of candidates, and the requirement for HAD
The feasible design space for HAD application is graphically illustrated in Figure 58. Candidates that do not meet the acceleration requirements are displayed in red in Figure 59. A threshold of 90% is considered so that the candidates that almost meet the requirements are not eliminated.

An example of a powertrain that meets the HAD requirements are plotted below. As seen, the candidate meets the top speed, cruising speed and gradeability requirements. The wheel power curve is the addition of the two motors’ wheel power curves for AWD architectures as shown below.

![Power at wheel for different cases](image)

Figure 60. Wheel power for Powertrain candidate #34
As discussed earlier, the feasible candidates are simulated on drive cycles that simulate Human & Autonomous Driving. In this case, we consider the worst case i.e. no autonomous driving, and hence simulate the powertrains on EPA drive cycles. For urban driving scenario, UDDS is considered and for highway, HWFET is considered. The drive cycles are illustrated in Figure 37.

An example of operating points is shown below. The plots illustrate the operating points for motor #7 and #3 used in candidate #34 for both urban and highway EPA cycles.

![Motor operating points for UDDS – Candidate #34](image)

Figure 61. Motor operating points for UDDS – Candidate #34
Similar to the results shown in Section 5.2. Optimization for AD, the simulation results of energy consumption are plotted against powertrain peak power for all candidates, for UDDS, HWFET and combined driving scenarios. The difference here is the absence of candidates around the lower power spectrum, as these fail to meet the requirements.

The Pareto fronts for both architectures are illustrated, for the different driving conditions, in Figure 63. Due to performance requirements for HAD, the low powered FWD architectures are not feasible, hence the most optimal candidates are AWD. The
FWD candidates that do pass the requirements are inefficient due to operating points at lower efficiency regions of the map.

In addition, there seems to be an increasing trend in energy consumption with powertrain power, especially for UDDS urban driving. However, the energy savings are still within 5% with a 200% increase in power. For HWFET highway driving, there does not seem to be much of a trend. This is illustrated in Figure 64, which plots the ratio of best energy consumption (irrespective of architecture) for a driving scenario and the energy consumption for each candidate, as a fraction.

Figure 63. Pareto fronts for HAD – Conventional Cycles
To conclude, the overall trend is similar to the ones observed in the Autonomous Driving (AD) conditions. Based on the tradeoff between architecture, powertrain cost/power, and energy consumption, the designer can select a powertrain from the set of optimal powertrains highlighted by the Pareto fronts. This concludes the powertrain optimization task for Human & Autonomous Driving applications (HAD).
5.4. Comparing AD and HAD

Once the powertrains are optimized for both applications, the difference in both applications in terms of operating conditions need to be understood.

Figure 65 compares the two applications by plotting the energy consumption values for the two different type of drive cycles (Autonomous and Conventional drive cycles) together. The values are compared to similar driving conditions (urban, highway and combined). For all cases, the energy consumption in autonomous cycles is lower than the ones for conventional cycles. There is a greater difference in energy consumption between the two for urban cycles compared to highway cycles. The energy savings are due to implementing the optimal trajectory for that driving scenario (urban or highway).

The difference in energy consumption between the autonomous and conventional drive cycles is quantified in Figure 66. Only feasible powertrains for HAD are considered, as they satisfy both the requirements (AD and HAD). Since some of the AD feasible candidates do not satisfy the HAD requirements, they would not operate on those drive cycles.

The percentage energy savings due to implementing optimal trajectory for urban setting ranges from 7 to 10%, and increases with power, due to increase in energy consumption for conventional urban drive scenario. The percentage of energy saved varies considerably with power. On the other hand, the savings due to implementing optimal trajectory on highway driving scenario is fairly constant at around 1.3-1.4%, irrespective of powertrain power.

This illustrates the fact that the energy savings for the highway scenario is mainly due to efficient driving, and is independent of the selected powertrain.
Figure 65. Comparing energy consumption for AD and HAD
Figure 66. Percentage energy savings by running HAD feasible powertrains on ADC
Now, the tradeoffs in terms of energy consumption for operating the vehicle, which is optimized for human driving, in autonomous mode needs to be demonstrated. This answers the question of how much better an optimized powertrain for autonomous operation is compared to the one optimized for human driving but running on the autonomous cycle.

To answer this question, the optimal powertrains for HAD are simulated on the autonomous drive cycles and compared with the optimal powertrains for autonomous driving. This is illustrated in Figure 67. The points marked in red are the optimal powertrains for HAD and the ones marked in blue are for AD.

As observed, the optimal powertrains for both applications have similar energy consumption numbers, and there does not seem to be any particular trend. Even some optimal powertrains for AD perform worse compared to the powertrains optimized for HAD. The benefits, in terms of energy consumption, of designing a powertrain exclusively for autonomous operation, compared to using a powertrain optimized for a human operation depends on the optimal powertrain selected.

This seems counterintuitive, as it is generally expected that a high performing propulsion unit would be less efficient than a low performing one. However, in the case of electric vehicles, there is not much increase in consumption with an increase in power, mainly due to overall high efficiency and efficient torque split between the dual motors.
Figure 67. Comparing Pareto optimal powertrains for AD and HAD on ADC
To quantify the benefits, percent change in energy consumption between the most efficient AD and HAD powertrains (best powertrain) is tabulated. The values are computed for each driving scenario (urban, highway and combined), and for the different architectures (FWD and AWD). The values are computed as follows,

\[
\% EC \ Change = \frac{EC(\text{Best HAD}) - EC(\text{Best AD})}{EC(\text{Best AD})}
\]

(53)

where EC represents energy consumption and Best AD/HAD represents the powertrain with the least energy consumption for AD/HAD, subject to the driving scenario and architecture. This is summarized in Table 13.

<table>
<thead>
<tr>
<th>% EC Change</th>
<th>Urban</th>
<th>Highway</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best FWDs</td>
<td>0.95</td>
<td>1.03</td>
<td>0.95</td>
</tr>
<tr>
<td>Best AWDs</td>
<td>1.21</td>
<td>0</td>
<td>0.34</td>
</tr>
<tr>
<td>Best overall</td>
<td>0.95</td>
<td>0</td>
<td>0.48</td>
</tr>
</tbody>
</table>

From the above table, the highest gain that can be achieved by using an optimized powertrain for autonomous operation, rather than using the optimized powertrain for human driving in autonomous mode is around 1.2%. This is for urban driving, comparing the best powertrains with AWD architecture. For highway driving, there is no
improvement in energy consumption between the optimized AWD powertrains. If combined driving is considered, the gain in energy savings is 0.48% for best powertrains irrespective of the architecture.

To conclude, the two applications are compared by comparing their driving pattern. Energy is saved when a vehicle operates autonomously compared to conventional human driving for a driving condition. These savings are greater for urban driving conditions. In addition, they are generally independent of powertrain candidate.

Also, the energy savings due to designing a powertrain particularly for autonomous driving rather than using a high powered powertrain is less than 1.5%.

5.5. Discussions

This section highlights the key take away points discussed earlier.

Generally, there isn’t a strong trend between energy consumption and powertrain peak power, irrespective of the architecture. However, there is a slight increasing trend for urban driving for conventional HAD application.

For the candidates considered, for any powertrain operating in any condition, the energy savings are not greater than 10% of the best possible value achievable by implementing the most efficient powertrain for that condition.

AWD powertrains are better than or comparable to FWD in terms of energy consumption, due to the extra degree of freedom in modulating the torque split between the two motors, in spite of the overall increase in weight.

Energy consumption is lower for a powertrain when driven on the optimal autonomous drive cycles (ADC) compared to the conventional human drive cycles
(HDC). The potential for saving energy by implementing optimal trajectory is higher in urban driving.

Similar energy consumption for powertrains optimal for conventional cycles when driven on autonomous cycles compared to the optimal powertrains for the autonomous cycle. The energy consumption values for powertrains operating autonomously does not have a strong correlation with power and is generally independent. It depends on the individual motor design i.e. the base speed, maximum power and efficiency maps and the motor pairs rather than just the total power.
Chapter 6. Conclusions

6.1. Conclusion

The thesis highlights the need for powertrain optimization of a Level 5 autonomous vehicle. It describes the different applications possible for AVs i.e. Autonomous Driving (AD) and Human & Autonomous Driving (HAD), demonstrates the powertrain optimization process using the example of electric vehicles and analyzes the tradeoffs in designing the powertrain for pure autonomous driving compared to a mix of human and autonomous driving.

For this purpose, a system level electric vehicle model is developed, to simulate slow dynamics response for vehicle speed, state of charge and energy consumption. This is subject to varying inputs and design parameters to generate energy consumption values.

A process for powertrain design and optimization for two different Level 5 autonomous vehicle application is demonstrated. This includes defining the static constraints i.e. the performance requirements for the application and also, defining the inputs to the optimization problem in terms of driving cycle inputs.

Effect of comfort and motion sickness on performance requirements and driving patterns is considered. The acceleration performance and drive patterns are constrained due to acceleration limits imposed to achieve a comfortable ride for the user.
Drive cycles for the autonomous vehicle (Level 5) are required for representative autonomous driving in urban and highway conditions. Therefore, a method is proposed to derive the drive cycles for autonomous vehicles. This method assumes complete information of the path constraints and finds the optimal trajectory that minimizes the energy consumed by using Dynamic Programming, subject to state and dynamic constraints.

Finally, the results, in terms of optimal powertrains, for AD and HAD, and the tradeoffs between the two are analyzed.

6.2. Future Work

The vehicle model can be refined by including dynamic constraints due to thermal limitations. The data used for the electric motors (efficiency maps) are not specific to the motor considered. Improving the efficiency maps and making them specific for the motors will result in realistic simulations.

Only two architectures are considered in the study. However, as mentioned earlier, multiple architectures are possible for electric vehicles. These can also be considered in future studies. Also, more motor options can be considered, especially with lower power. It would be interesting to also include conventional IC engine and hybrid architectures, and to see whether the trend would be different or not.

In the optimization process, battery sizing is not considered. A single design is considered for all candidates. Incorporating battery sizing in the optimization process will make it more realistic.
Motion sickness model can be implemented, instead of using the acceleration constraints, in optimal trajectory calculations. This will result in better drive profiles that satisfy the constraints.

These constraints and motion sickness models can be incorporated in the vehicle trajectory generation algorithm for comfortable ride experience in real time.

In terms of drive cycles for autonomous driving, the constraints are derived from the EPA cycles. However, the driving constraints might be totally different for the actual autonomous vehicle due to updated infrastructure and V2X communication. For a more realistic simulation, optimal drive cycles can be generated from traffic simulators, simulating autonomous vehicle real-life driving. This might be able to capture reduced stopping, efficient traffic flow, etc.
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