Predictive Powertrain Management through Driver Behaviour Recognition

by,

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A Thesis

presented to the University of Waterloo

in fulfillment of the

thesis requirement for the degree of

Master of Applied Science

In

Mechanical and Mechatronics Engineering

Waterloo, Ontario, Canada, 2018

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may become electronically available to the public.

Abstract

With automotive trends leading towards electrification and inclusion of intelligent technology for advanced driver assistance systems (ADAS), there is a need to research the use of advanced control strategies. This report touches on the development of a powertrain model built in Simulink used for simulation testing and vehicle development. While addressing the needs of incorporating state-of-the-art technology, this report shows how a LiDAR and camera system can function together as ADAS sensors for vehicle detection and range estimation. Lastly, the main purpose of this report is to show how the UWAFT powertrain model and ADAS sensors, along with behaviour recognition software, can be used to reduce emissions and energy consumption while also increasing driveability.

Machine learning techniques are used to classify a driver's behaviour on a spectrum from aggressive to eco-cautious. 288 hours of driver behaviour data is simulated using the UWAFT's vehicle model built in Simulink. The data is labelled as aggressive, normal, or eco-cautious depending on the scaling factor applied to the drive cycle inputted. Linear discriminant analysis is performed to maximize the separation between classes and reduce the dimensionality. Support vector machines are used to classify the driver's behaviour. Lastly, fuzzy logic is used to assign a driver an aggressiveness value between 0 and 100. The classifier implemented achieved 81.53% accuracy; however, the aggression value assigned to the data via fuzzy logic is a more accurate representation. Vehicle testing is performed with the use of a closed-loop testing track and a chassis dynamometer. An acceleration test is conducted by applying a wide-open throttle in various operating modes. This identified drive traces that are only achievable in certain modes, thus concluding that if the driver's behaviour is predicted prior to an acceleration event, the correct operating mode could be selected ahead of time, increasing the driveability. Additionally, a regenerative braking test is conducted on a chassis dynamometer to determine the optimal regen torque parameters for a given braking rate. It is concluded that using the best parameters for a stopping distance of 2 mph/s would result in a 0.003% state of charge gain per second. Therefore, by knowing a driver's braking behaviour the UWAFT PHEV could select the best parameters for the current drive to decrease energy consumption.

Acknowledgments

I would like to thank a family for their support through my entire education. I would also like to thank Dr. Fraser and Dr. Fowler for their guidance in all past AVTC series pushing the entire team to do their best. Lastly, I would like to thank the all the UWAFT team members who committed time and resources to the EcoCAR 3 Camaro making all of this possible and developing lots of good memories.

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List of Abbreviations

ADAS	Advanced Driver Assistance System
APP	Accelerator Pedal Position
AV	Autonomous Vehicles
AVTC	Advanced Vehcile Technology Competition
BEV	Battery Electric Vehicles
BPP	Brake Pedal Position
CAD	Computer Aided Design
CAN	Controller Area Network
CD	Charge Depleating
CIL	Component-in-the-loop
CS	Charge Sustaining
ECU	Engine Control Unit
EPA	Environmental Protection Agency
ESS	Energy Storage System
GPS	Global Positioning System
HEV	Hybrid Electric Vehicles
HIL	Hardware-in-the-loop
HUD	Heads-up Display
HV	High Voltage
HWFET	Highway Fuel Economy Test
LDA	Linear Discriminant Analysis
LV	Low Voltage
MIL	Model-in-the-loop
NHTSA	National Highway Traffic Safety Administration
OBD	On Board Diagnostic

P2	Pre-Transmission
P3	Post-Transmission
PCA	Principal Component Analysis
PHEV	Plug-in Hybird Electric Vehicles
R-CNN	Regions with Convolutional Neural Nets
SAE	Society of Automotive Engineers
SIL	Softare-in-the-loop
SOC	State of Charge
SVM	Support Vector Machines
UWAFT	University of Waterloo Alternative Fuels Team
VMT	Vehicle Miles Travelled
YOLO	You Only Look Once

CHAPTER 1

Introduction

In the following thesis, a predictive powertrain management strategy based on driver behaviour recognition is explored. The topics discussed in this thesis were initiated by the EcoCAR 3 Advanced Vehicle Technical Competition (AVTC) run by the U.S. Department of Energy and General Motors. The AVTC series provided students from across 16 North American universities (14 American, 2 Canadian) with the opportunity to gain hands on automotive experience. From modelling and architecture selection, to vehicle integration and road testing, students followed automotive industry standards and best practices to design innovative vehicles of the future [1]. The EcoCAR 3 competition challenged students over the course of four years to reduce the emissions of a 2016 Chevrolet Camaro while maintaining its legendary performance. Motivated by the competition to explore leading-edge technologies, the University of Waterloo Alternative Fuels Team (UWAFT) chose to look for areas in which machine intelligence could be incorporated in the supervisory control of the vehicle. The particular area UWAFT chose to explore was the use of machine intelligence to recognize a driver's behaviour and predict their next move. Learning a driver's behaviour can be beneficial for a wide range of applications, which can be directly applied to a vehicle's supervisory controller. These include the following: assisting the powertrain energy management leading to reduced emissions, improved fuel economy, improved drivability, providing feedback to the driver to suggest driving habit improvements, and changing vehicle parameters to suit a specific driver's needs [2].

The need for more complex and integrated control strategies stems from the rise of more complex vehicle architectures. The future of vehicle powertrains no longer consists of only an engine and transmission. As the industry pushes to adopt green, environmentally friendly vehicles, the vehicles are becoming more complex, incorporating components like electric motors, battery packs, and fuel cells [3]. Thus, there is a need for more complex power management control systems to maximize the range and use of each power source (fuel, electricity, hydrogen, etc.). The

UWAFT-designed Camaro, a plug-in hybrid electric vehicle (PHEV), was used for experimental data collection supporting the proof of concept and development of the driver behaviour recognition algorithm.

The UWAFT PHEV has a series-parallel split architecture that is comprised of a 2-cylinder 850cc engine, two electric motors, 8-speed transmission, a friction disk clutch and a 16.2kWh battery pack. With such a multifaceted powertrain, it is difficult to determine which operating mode is the best to be in at any given time. By predicting the driver's behaviour, UWAFT's power management strategy can be greatly improved. A simple example of this is, if the vehicle knows the driver behaves aggressively it may leave the engine on longer with the anticipation that the driver may request torque shortly after braking. Two different experiments were conducted using the UWAFT PHEV to show areas in which the behaviour recognition software could be used as a solution to impact emissions and energy consumption.

This thesis uses the comprehensive powertrain model created for the controls development of the UWAFT PHEV to assist in the training and validation of the recognition algorithm. The model was first developed to validate the vehicle's architecture design and determine the technical specifications of the proposed architecture [4]. Over the course of the competition, the model achieved higher fidelity through the incorporation of experimental data. This thesis discusses some of the ways in which the model's fidelity was improved, as well as how the model was used to collect driver behaviour data.

Along with conventional vehicle data to determine a driver's behaviour, advanced driver assistance system (ADAS) sensors were investigated. With the future of the automotive industry pushing toward autonomous vehicles, there is now an abundance of sensors all over vehicles collecting a plethora of situational and environmental data [5]. This thesis explores the integration of ADAS sensors onto the UWAFT PHEV and the possibilities of using them for driver behaviour recognition. The ADAS sensors on the UWAFT PHEV focus on detecting vehicles in the front, in the same lane, as well as in neighbouring lanes. Object detection, tracking, and range are all taken into consideration. Lastly, this thesis outlines how the following machine learning techniques were used to classify driver behaviour and assign them an aggression value: linear discriminant analysis (LDA) for dimensionality reduction, support vector machines (SVM) for classification, and fuzzy logic to assign an aggression value.

1.1 Objective

The objective of this thesis is to provide the initial resources required to develop and apply a predictive powertrain management strategy based on driver behaviour recognition, while also highlighting the potential incorporation and use of a powertrain model and multiple advance driver assistance system (ADAS) sensors. Additionally, provide a feasibility study for a unique approach to driver behaviour recognition utilizing machine learning techniques that have yet to be applied to this application.

1.2 Outline

The development of the tools and algorithms used for the predictive powertrain management strategy are discussed in Part I of this report. The components that are discussed in this section of the report are:

Chapter 3. **University of Waterloo Alternative Fuels Team** – Highlights how the advanced vehicle technical competition and the target market influenced the innovation project. As well, discuss the unique vehicle architecture chosen and current controls strategy used with non-predictive aspects, which will later develop into a predictive powertrain management controls strategy.

Chapter 4. **Powertrain Modelling –** Provides a brief overview of the powertrain model developed for the UWAFT PHEV showing how comprehensive it is.

Chapter 5. **Advanced Driver Assistance System** – Discusses the integration and algorithms used for the UWAFT PHEV ADAS sensors relating to object detection and range estimations of vehicles in front of the driver.

Chapter 6. **Predictive Controls Strategy Based on Driver Behaviour –** Outlines the technical goals and impact metrics for the innovation project, as well as provides details of the machine learning algorithm used for driver behaviour recognition.

Part II of this thesis focuses on the applications of the discussed tools and algorithms from Part I. Through basic testing the feasibility of a predictive powertrain management strategy based on driver behaviour is evaluated.

Chapter 7. **Vehicle and Environment Simulation –** Shows how the powertrain model is used to create labelled data for the machine-learning algorithm.

Chapter 8. **Experimental Results –** Four different experiments are conducted to show the effectiveness of each tool developed in Part 1. The first experiment applies the labelled data collected in Chapter 7 to the driver behaviour recognition algorithm developed in Chapter 6 to show the effectiveness of driver behaviour recognition. Acceleration and regenerative braking experiments are conducted to show the feasibility of a predictive powertrain management strategy. Lastly, the ADAS sensors are tested to evaluate their accuracy.

Part III of this thesis concludes the results found in Part II and discusses recommendations and future work.

CHAPTER 2

Literature Review

2.1 Hybrid Vehicles

Currently, fossil fuels are a major resource for the world energy supply. Due to the decline in fossil fuel reserves it has ben predicted that there would be a scarcity of fossil fuel by the middle of the 21st century [1]. The automotive industry is continuing to shift its resources into alternative fuel sources. Automotive trends also show customers getting behind this shift with the sale of electric vehicles in Canada growing 68% in the last year [2].

Figure 1: Year Over Year Electric Vehicle Sales by Month in Canada [2]

One of the most popular alternative fuels is electricity with the inclusion of a high voltage battery. Battery electric vehicles (BEV) have only the battery as an energy source. BEVs are currently trying to overcome the issue of range anxiety in customers. Essentially, customers do not want to have to worry about whether or not their vehicle will make a longer trip. Neubauer [3] finds that the effects of range anxiety can be significant, but are being reduced with access to additional charging infrastructure.

Another way to alleviate range anxiety is with hybrid vehicles. Hybrid vehicles have two energy sources, the most common being electric and gasoline. Having a small engine coupled with electric motors reduces emissions as well as eliminates range anxiety as customer can fill up their car at any gas station. A plug-in hybrid electric vehicle (PHEV) allows the vehicle to regain charge by plugging into an external energy source.

UWAFT's approach to designing a hybrid architecture was to minimize emissions and appeal to customers with a PHEV that would primarily run on the electric power source over the average commuting distance of 40.55 kilometers [4]. This approach results in significantly reduced tail pipe emissions as the majority of the driving would be done in a full electric mode. At the same time, having an engine still helps to remove the range anxiety that might be present in customers. By shifting towards electric power and investing in clean energy sources the automotive industry can reduce its environmental impact significantly.

2.2 Drive Cycles

Drive cycles are a velocity time graph used to represent the speed a vehicle is expected to match during a testing procedure. In order to follow a drive trace properly, a large open track or a chassis dynamometer is often required. Drive cycles are designed to test city driving, highway driving, or a combination of both. The Environmental Protection Agency (EPA) has developed numerous drive cycles for emissions and fuel economy testing for numerous scenarios [5]. They also provide detailed information on drive cycles used by California, Europe and Japan. UWAFT has used a variety of these drive cycles for vehicle testing and simulation as it provides a good tool to compare UWAFT's performance against other vehicles in the market.

2.3 Influence of Driver Behaviour

The major motivation behind the behind the predictive powertrain management strategy based on driver behaviour recognition stems from the fuel saving opportunities related to a driver's behaviour. More so in hybrid vehicles, where range anxiety is a common concern, energy consumption is a major focus for car manufacturers. Jimenez [6] incorporates a driver's style to predict their energy consumption over a given route. The results showed an increased reliability in predicting energy consumption as well as enhanced customer confidence in the capabilities of electric vehicles. These findings help to support the fact that a particular driving style has a significant effect on an electric vehicle's energy consumption as well as a conventional vehicle's fuel economy.

Not only do companies want to improve the range of their vehicles, they are also interested in creating more environmentally friendly ones. Through reviewing a number of studies involving fuel economy and driver behaviour there is a general agreement that 10% fuel savings can be achieved by modifying the driver's behavior. "Considering the effects of real-world driving conditions, efficient driving behaviors could reduce fuel use by 20% on aggressively driven cycles and by 5-10% on more moderately driven trips" [7].

Various papers discuss the cause of increased fuel economy; however, what it comes down to is aggressive drivers requesting more power, thus needing more fuel to produce that power, as well as the torque producing components not being able to operate in their most efficient speed. Through large amounts of data collection, conclusions are drawn between the cause and effect of a vehicle's fuel economy. Ericsson [8] uses a large amount of driving cycle tests to determine the impact of 62 driving pattern parameters on fuel economy and emissions. The study showed that power demand, gear changing behavior, and speed level have an important effect on fuel consumption and emissions. Lee and Son [9] found a relationship between fuel consumption, vehicle speed, gear selection, steering angle, as well as acceleration/brake pedal position. They concluded that fuel efficiency was significantly affected by average accelerator pedal position on the highway.

Along with these findings come countless attempts to mitigate a driver's aggressive behaviours through a feedback system in the vehicle. The aim is to improve the customer's driving behaviour without affecting their expectations and requirements. Driver feedback systems can be integrated into a vehicle in a number of ways, the most popular are described briefly below.

1. **Heads-Up Display (HUD) –** An LED screen projected onto the glass windshield. Example: Used by General Motors to display vehicle speed.
2. **Flashing Lights –** LED lights incorporated into the interior or a part of the HUD to convey warning signs. Example: General Motors flashes a red light on the HUD when it predicts a head-on collision is near.
3. **Haptic Seat –** Vibration motors placed inside the driver's seat. Example: General Motors uses haptic seats to warn the driver they are exiting the right side of a lane unintentionally by vibrating the right side of the seat.
4. **Haptic Steering Wheel** – Vibration motors placed inside the driver's steering wheel. Example: General Motors vibrates the steering wheel to warn the driver it is leaving super cruise and the driver must take over vehicle operations.

Conveying to the driver better habits is proving a difficult task, partly due to the delay in a driver's response to a feedback system. If the driver has already accelerated aggressively, alerting him to slow down can be annoying as well as too late. Therefore, for a feedback system to be non-intrusive, it will be unable to recover all the fuel saving associated with a driver's behaviour; however, it can still do a good job. Syed et al. [10] statistically quantified fuel economy improvements using haptic and visual feedback mechanisms. The study results demonstrated that a driver feedback system could achieve up to 6% fuel economy improvements without significantly affecting the drivability of the vehicle.

2.4 Autonomous Levels

Autonomous vehicles (AVs) are complex systems that interact with humans using a range of computational, sensing, and control capabilities [11]. The benefits of autonomous vehicles are being seen from every manufacturer, and the race to develop the first full autonomous production vehicle has started. According to IHS Markit forecasts [12], it is expected that the annual worldwide sales of AVs in 2040 will exceed 33 million units. Several companies have already released products that have limited autonomous capabilities. The Society of Automotive Engineers (SAE) has defined levels of autonomy in order to categorize these features, shown in the table below [13].

Table 1: SAE (J3016) Autonomy Levels [13]

SAE Level	Name	Definition
Human driver monitors the driving environment		
0	No Automation	The full-time performance by the human driver
1	Driver Assistance	The driving mode-specific execution by a driver assistance system of "either steering or acceleration/deceleration"
2	Partial Automation	The driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration
Automated driving system monitors the driving environment		
3	Conditional Automation	Expectation that the human driver will respond appropriately to a request to intervene
4	High Automation	Even if a human driver does not respond appropriately to a request to intervene
5	Full Automation	under all roadway and environmental conditions that can be managed by a human driver

Due to safety concerns from the competition organizers, UWAFT is unable to exceed level 0 automation with their integrated advance driver assistance system, nor can they interfere with level 1 driver assistance features that came stock in the 2016 Camaro. Therefore, efforts were put in place to develop a sophisticated driver feedback system.

2.5 Advanced Driver Assistance Systems

In 2016 there were more than 37,000 automotive related fatalities and over 6 million police-reported crashes [14]. Theses alarming statistics are which cause the automotive manufactures to pursue new safety technologies and embedded systems. A major cause behind road crashes are human errors, such as: distracted driving, slow reaction time, inability to read signs in a particular situation, etc [15]. Advanced driver assistance systems (ADAS) of a vehicle can largely help to reduce car crashes through features, such as: autonomous emergency-braking, adaptive cruise control, forward-collision warning, lane-departure warning, parking assistance, back-side monitoring, night vision, driver monitoring, and traffic-signal recognition [16]. According to the National Highway Traffic Safety Administration (NHTSA) in the United States there has been a downward trend of deaths per billion vehicle miles travelled (VMT) [14], which can be partially attributed to the advancement of those systems.

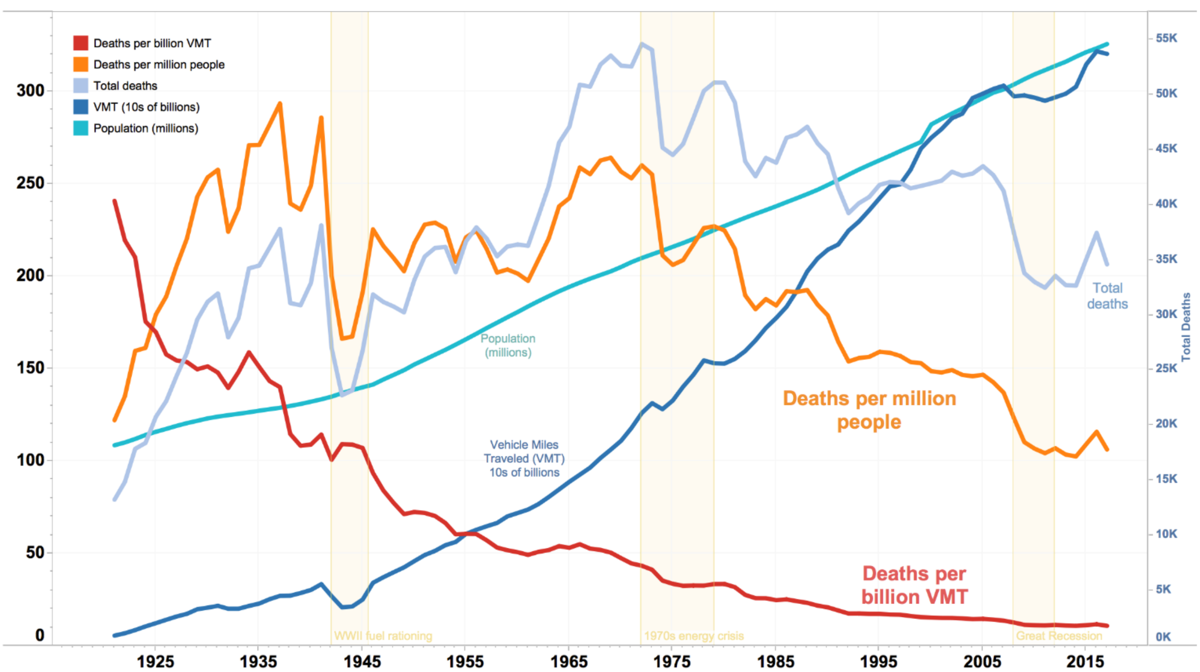


Figure 2: NHTSA United State Motor Vehicle Fatalities [14]

The field of advanced driver assistance systems (ADAS) has developed into a wider range of vehicle features with increased complexity. ADAS assumes control of vehicle functions to increase safety and make driving easier. The most common ADAS feature is cruise control, which takes over the accelerator pedal to maintain a constant speed set by the driver. Over the years, this and many other ADAS features have developed towards more autonomy. ADAS sensors are used to detect environmental factors such as other motor vehicles, pedestrians, or obstacles in the way. Todays vehicles are equipped with LiDAR, RADAR, and numerous camera has to capture as much information as possible.

2.6 Driver Behaviour Recognition Approaches

One of the main functions of a predictive powertrain management strategy based on driver behaviour is being able to accurately learn and classify a driver's behaviour. Fortunately, many different researchers have already explored driver behaviour recognition due to the increase in autonomous driving needs. Machine intelligence is a relatively large field of study and growing in interest; therefore, there are lots of different techniques and algorithms available. Often times there are multiple approaches to solve a problem and finding the best one can be difficult. Thus, it is important to investigate the approaches already taken and their individual successes. This ultimately helped UWAFT to determine their own approach for learning driver behaviour.

Investigating different machine learning projects can be broken down into three main parts: the characteristic chosen to classify, the data used to train the algorithms, and the algorithms or techniques used for classification. Some of the approaches found are highlighted below.

Lui [17] was able to successfully characterize and detect driving maneuvers related to different types of lane changes.

1. **Characteristic –** Classify driver behaviour during lane changes into three categories, emergency lane change, ordinary lane change, and lane keeping
2. **Data –** Collected vehicle data with the use of a driver simulator
3. **Techniques –** Hidden Markov Models

Clustering is a machine learning technique in which the specific classes or the number of classes is unknown. Clustering will determine the right number of groups and cluster the data in each group. Si [18] demonstrated the possibility of recognizing different patterns in various driving circumstances.

1. **Characteristic –** Driving pattern clusters (i.e. a specific type of driver will belong to cluster of data with similar driving style)
2. **Data –** Vehicle-related parameters (e.g. acceleration and jerk), in combination with additional environmental and road characteristics (e.g. road style, and inclination)
3. **Techniques –** K-Means Clustering

Apart from using vehicle data, there have also been attempts to use external sensors to collect data for classification. Brombacher [19] mounted a Raspberry Pi with inertial and GPS modules on the dashboard creating a low-cost measurement device.

1. **Characteristic –** Classify driving events into different longitudinal and lateral event class, such as defensive acceleration, sporty acceleration, defensive light turn, and sporty light turn.
2. **Data –** Longitudinal acceleration, lateral acceleration, yaw rate, and velocity.
3. **Techniques –** Artificial Neural Networks

Similarly, Trividi [20] and Minh [21] uses lateral and longitudinal acceleration values as indicators to determine aggressive drivers. Trividi concluded that 97% of aggressive events were correctly identified.

Supervised machine learning methods are widely used; however, they require a large amount of labelled training data. Wang [22] avoided this need by implementing a semi-supervised approach to classify drivers into aggressive and normal styles.

1. **Characteristic –** Two classes: aggressive and normal driving behaviour.
2. **Data –** Throttle, braking force, steering wheel angle, longitudinal and lateral speed.
3. **Techniques –** Semi-supervised Support Vector Machines

One of the simpler techniques uses the readings of a two-axis accelerometer and speed to feed into a fuzzy logic system to classify a driver [23]. After reading numerous techniques to recognize a driver's behaviour, the most common data used is vehicle velocity, acceleration, and jerk. An investigation reveals that the acceleration and jerk-based driving style classifications are only applicable to certain driving conditions, prompting the need for a more comprehensive classification of driving style [24]. Along with the need to require large amounts of labelled training data for supervised learning [22], UWAFT aimed to develop a comprehensive classification of driver behaviour via supervised learning techniques. To overcome the hurdle of obtaining large amounts of labelled training data, UWAFT used a vehicle model to simulate the data.

2.7 Controls Strategies Based on Driving Style

Very few have attempted to incorporate driver behaviour recognition into a controls system. However, there have been several successful implementations of adaptive changes to vehicle parameters and supervisory controllers, based on driving behaviour. Malikopoilos [25], demonstrated the feasibility of a self-learning controller for optimal injection timing in a diesel engine based on individual driving styles. “That is, while the driver drives the vehicle, the controller identifies engine realization as designated by the driver’s driving style. At the same time, the controller utilizes a lookahead algorithm to derive the values of the controllable variable for this realization” [25]. Ultimately, Malikopoilos achieved 8.4% fuel consumption improvements. This is very successful given that they were focusing their efforts for only one parameter change and still achieved meaningful results.

Lee et al. [26] investigates the application for hybrid electric vehicles (HEVs). “The consideration of different driving patterns in supervisory control design improves the fuel economy further and makes the HEV performance less sensitive to variations of driving conditions. Thus, Adaptive strategies with respect to driving patterns in HEVs can lead to further fuel economy improvement under real-world driving conditions” [26]. Lee goes on to discuss how the operating mode of HEV and various propulsion and braking parameters can be optimized based on a driving pattern.

The UWAFT PHEV’s unique architecture posses as an excellent test subject to learn how such driver behaviour recognition algorithms can be incorporated into the supervisory controllers. The UWAFT hybrid supervisory controller’s most important job is to handle torque requests and determine how to split the torque between the electric motors and engine. UWAFT has decided to develop experiments to show how the use of driver behaviour recognition can help determine the optimal mode of the vehicle as well as help tune regenerative braking parameters. It was decided not to experiment with engine tuning based on driving style, as there was a lot of mechanical downtime related to getting the engine to run. On the other hand, the post-transmission electric motor that handles all of the regenerative braking torque requests was very reliable for testing.

PART I - Development

CHAPTER 3

University of Waterloo Alternative Fuels Team

3.1 Advanced Vehicle Technology Competition

The University of Waterloo Alternative Fuels Team (UWAFT) is a student design team established in 1995 with a rich history in Advanced Vehicle Technology Competitions (AVTC). EcoCAR 3 is the latest AVTC run by the U.S. Department of Energy, which challenged teams to convert a 2016 Chevrolet Camaro into a Plug-in Hybrid Electric Vehicle (PHEV) by demonstrating emerging automotive technologies, while still maintaining the expected performance associated with the Camaro. One of the main goals of the EcoCAR 3 competition was to reduce emissions and create the ultimate energy-efficient, high performance vehicle [27].

EcoCAR 3 was a four-year competition (2014-2018) with different goals and milestones set out each year. Year 1 focused on vehicle architecture selection and target market research. Year 2 was the integration year where a 'mule' vehicle (60% ready) was developed. Finally, years 3 and 4 were refinement years to get the designed vehicles roadworthy. One of the major goals for teams in year 4 is reaching the 99% milestone, which is a "showroom ready" vehicle [1].

The competition was split into multiple swim-lanes as established by the competition organizers (U.S. Department of Energy). Each swim-lane had its own defined set of goals and tasks within a specific disciplinary focus. The swim-lanes were as follows:

1. **Project Management** – provide management and planning for the overall project so that the team can operate more efficiently and better align with business and automotive industry practices [28].
2. **Mechanical** – develop a comprehensive computer-aided design (CAD) model of the vehicle, reach 100% integration of system for full functionality, optimize mechanical systems (safety, weight, serviceability, consumer appeal), and tune vehicle dynamics [29].

3. **Controls and Modelling** – refine hybrid strategies to improve reliability, energy consumption, emissions, drivability and performance in all modes. Utilise a combination of software-in-the-loop (SIL), hardware-in-the-loop (HIL), and vehicle testing environments to accomplish these activities [30].
4. **Electrical and Advance Driver Assistance Systems (ADAS)** – obtain 100% integration of low voltage (LV) and high voltage (HV) systems, develop and deploy ADAS and driver feedback systems [31].
5. **Innovation** – develop a selected topic and obtain actual data and functionality by the end of the year [32].

UWAFT's team structure also followed the swim-lanes defined by the competition, creating four sub-teams: mechanical, controls, ADAS, and innovation.

3.2 UWAFT Target Market

The target market is the customers that, through research, UWAFT believes would be interested in purchasing the UWAFT PHEV. It is important to reflect back on the target market decided upon in year 1. Given the limited time and resources UWAFT has at its disposal, projects are often scrapped due to lack of one or the other. Therefore, determining a project's impact on the target market can help determine its importance.

In order to identify the target market for UWAFT's Camaro, segments based on income, performance expectations, environmental considerations, population density, and age were created [33]. UWAFT decided to focus on people in their late 20s and 30s who are high-income earners, performance oriented, and live in urban areas. This will be herein referred to as UWAFT's target market, and is graphically shown in the spider diagram below. The spider diagram is created using a scaled qualitative (fuel economy and performance) and quantitative (age, income, and rural/urban) analysis between zero and one.

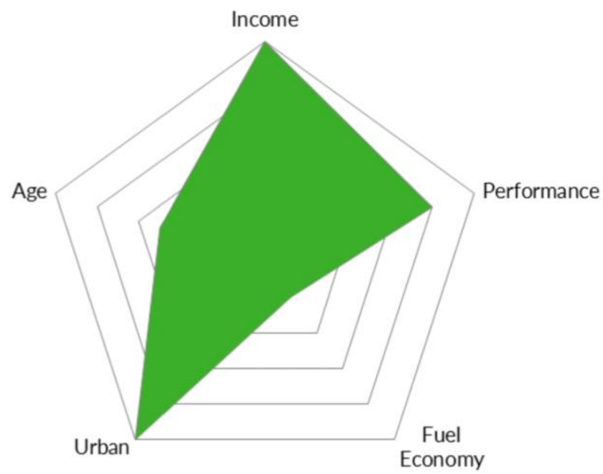


Figure 3: UWAFT Target Market

UWAFT was developing an eco-friendly, high-tech, performance-oriented Camaro. As a result, the team's target market shows these preferences in accordance with the team's direction in EcoCAR 3. Though an emphasis was put on performance, fuel economy and other eco-parameters were still important. Trends show Generation Y being more environmentally conscious and living in urban centres more than rural areas; both are traits of UWAFT's target consumer and product development [34] [35]. These consumers are pushing for more innovation in their vehicles, breaking the tradition of brand loyalty and demanding constant updates to the highest technology components. [36]. Therefore, UWAFT targeted high-tech components and vehicle features to appeal to the connectivity requests of Generation Y. UWAFT's vehicle technical specifications are shown in Appendix A.

3.3 Vehicle Architecture

The chosen vehicle architecture was a split-parallel configuration (has both a series mode with an engine connected to a generator, and a parallel mode with the engine providing torque directly to the wheels), using two GKN AF130-4 electric motors in a P2 (pre-transmission) and P3 (post-transmission) position to supplement power from a Weber MPE 850cc turbo engine [37]. The engine and P2 motor connect to the drive shaft through a General Motors 8L45 automatic transmission. The vehicle uses an A123 6x15s3p battery and two Rinehart PM100 inverters to power the electric motors. These components are capable of supplying a maximum of 232 kW to the road with a battery capacity of 16.2 kWh.

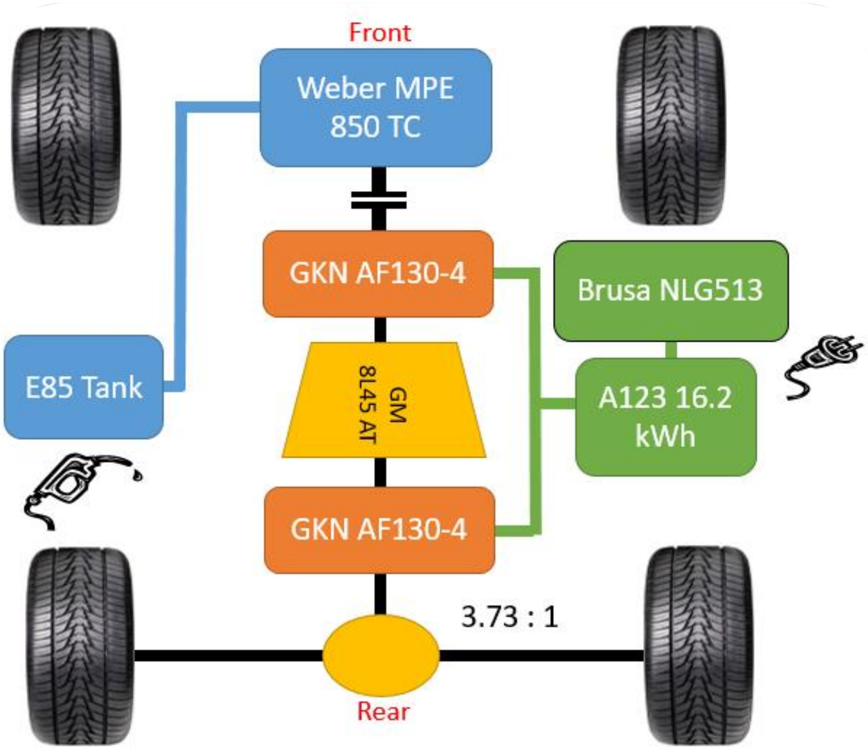


Figure 4: UWAFT PHEV Architecture

This architecture allows for multiple operating configurations with unique benefits in each. The parallel configuration utilizes all torque producing components and delivers all the power to the wheels. This configuration is used for high power demand applications, such as acceleration events and maintaining the Camaro performance expectations. The series configuration is initiated by sending a neutral override command to the automatic transmission. It is used to add energy back into the battery pack and ultimately help increase the range of the vehicle. Lastly, the engine can be decoupled from the powertrain via the clutch between the P2 and engine, thus allowing the vehicle to be in a full electric configuration, producing zero tailpipe emissions. These are the three main operating configurations, which are shown below with accurate representation of the component packaging in the vehicle. Note that the orange and black lines represent high voltage electrical and mechanical power transfer respectively.

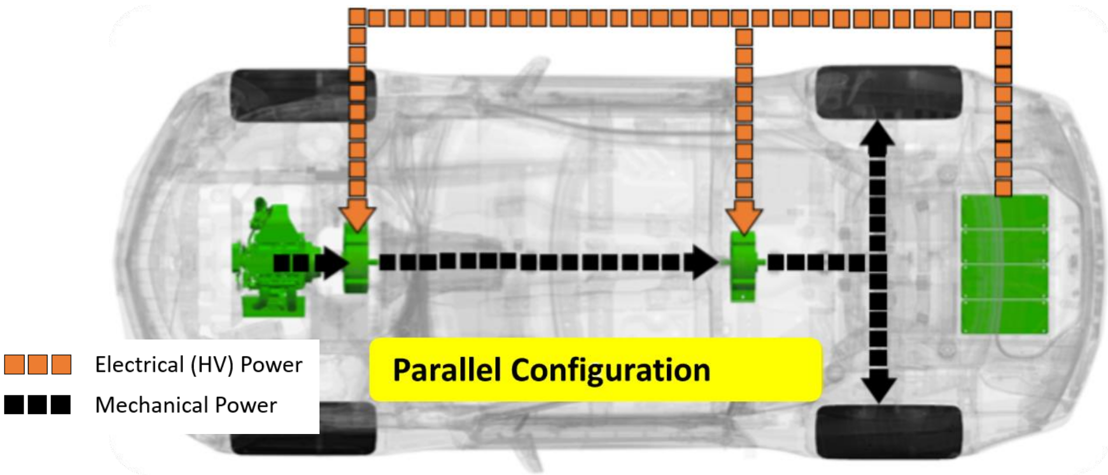


Figure 5: UWAFT PHEV Parallel Configuration

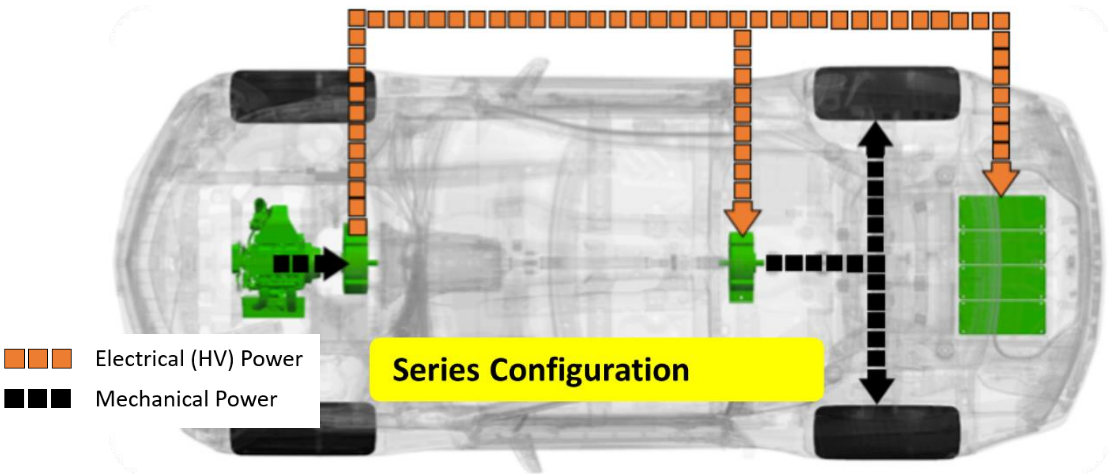


Figure 6: UWAFT PHEV Series Configuration

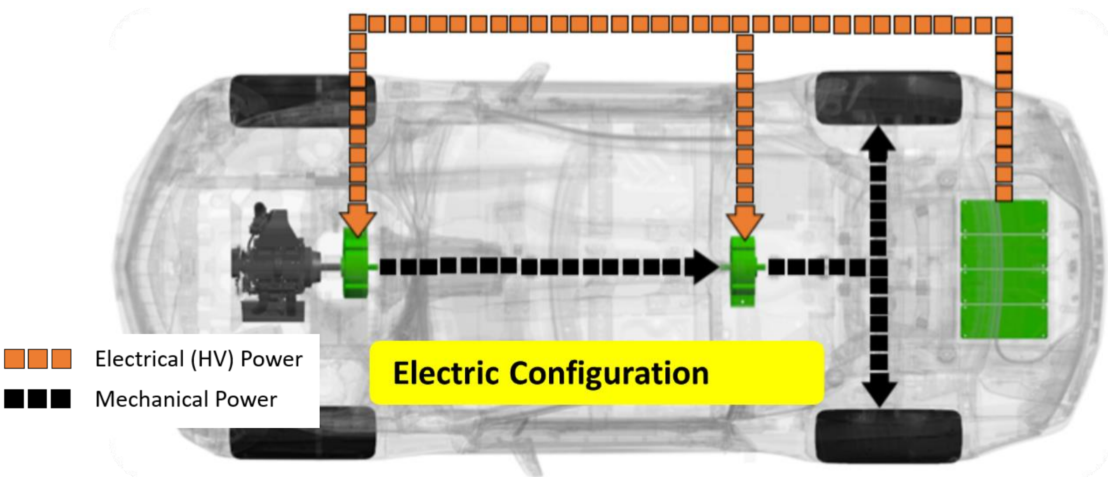


Figure 7: UWAFT PHEV Electric Configuration

Along with these operating configurations come many variations depending on the state of the vehicle. For the ease of controls organization, the different vehicle configurations are split into six different operating modes depending on the state of the powertrain components. There are various charge-depleting (CD) modes and charge-sustaining (CS) modes that the vehicle can operate. The selected drive mode and drive mode transitions are determined by factors such as energy storage system (ESS), state of charge (SOC), and torque demanded. When the net charge of the battery pack is decreasing, the vehicle is in a charge depleting mode.

The UWAFT PHEV can operate in three different CD modes.

1. **CD P3 Only mode**
2. **CD Full Electric mode**
3. **CD Performance mode**

The UWAFT PHEV is capable of two all-electric CD modes: one utilizing just the P3 motor and the other utilizing both electric motors. The P3 only mode is beneficial for applications where the SOC is high and the torque demand is below the specification of the P3 motor. When an increase in torque is requested beyond the limits of the P3 motor alone, the P2 electric motor will engage through the transmission providing additional power. Additionally, the P3 only mode is used when the vehicle is in reverse.

If the torque demanded exceeds the limits of the combined P2 and P3 motors, the clutch will engage the engine that will work with the motors to provide additional power. This is called performance mode since it offers the most power to the wheels.

A vehicle is in charge sustaining mode when the charge of the battery remains level or rises. The UWAFT PHEV switches to charge sustaining mode when the SOC of the battery pack falls below a certain threshold. Similarly, the UWAFT PHEV is capable of three different CS modes.

1. **CS Series**
2. **CS Parallel**
3. **CS Engine Only**

In CS series, a neutral override is sent to the transmission allowing the P3 motor to drive the wheels while the engine and P2 motor act as a generation set providing power to the battery pack. Having the generation set disconnected from the wheels allows it to operate at the highest efficiency point. If the torque demands exceed the limits of the P3 motor, the vehicle will enter CS parallel mode where all torque-producing components connect to the wheels. When all of the torque produced by the engine is not required at the wheels, the P2 motor acts as a generator (applies braking torque) to sustain the charge of the battery pack. Lastly, in engine only CS mode the vehicle behaves as a conventional vehicle. This drive mode is beneficial when the electric powertrain is no longer useful (zero charge/failure).

3.4 Non-Predictive Controls Strategy

UWAFT follows a model-based design approach for controls development. By following the stages of Model-in-the-Loop (MIL), Software-in-the-Loop (SIL), Hardware-in-the-Loop (HIL), and Component-in-the-Loop (CIL) before integrating hardware into the vehicle, the team was able to change modeling information and control algorithms quickly. As the fidelity of the results increase so does the complexity of the model. Validation can be performed at each stage of development, and the team can go back in the process should any new developments occur. The hybrid supervisory controller is modelled by the SIL. Although the supervisory control takes care of an abundance of controls in the vehicle, for the purpose of this report it is only important to discuss the torque control strategy in a bit more detail as it pertains directly to the systems discussed in the following chapters.

The torque control strategy of the UWAFT PHEV is complex in nature due to the complexity of the chosen architecture (having multiple torque producing components and multiple drive modes). The torque control strategy determines the appropriate vehicle drive mode and values (set-points, minimums/maximums) to effectively control the different torque-producing components depending on which drive mode the vehicle is in. The subsection called Drive Mode Aim calculates the desired drive mode given the information of the faults, current drive mode, computed torque splitting between components and other input signals. Kartha’s thesis is a source for a more in depth look at UWAFT’s non-predictive controls strategy [38].

The transitions are determined primarily based on requested torque from the driver and state of charge (SOC) of the battery pack. At a high level, the vehicle will transition into charge sustaining modes when the SOC falls below a certain threshold, and will transition into higher performance modes when there is an increase of torque demanded. This is shown below in the simple block diagram. Additional signals and faults are also monitored to determine when and when not to transition between modes, but for the purpose of this report are not displayed. Note: The arrows representing transitions in the diagram below are reversible if the opposite condition is met.

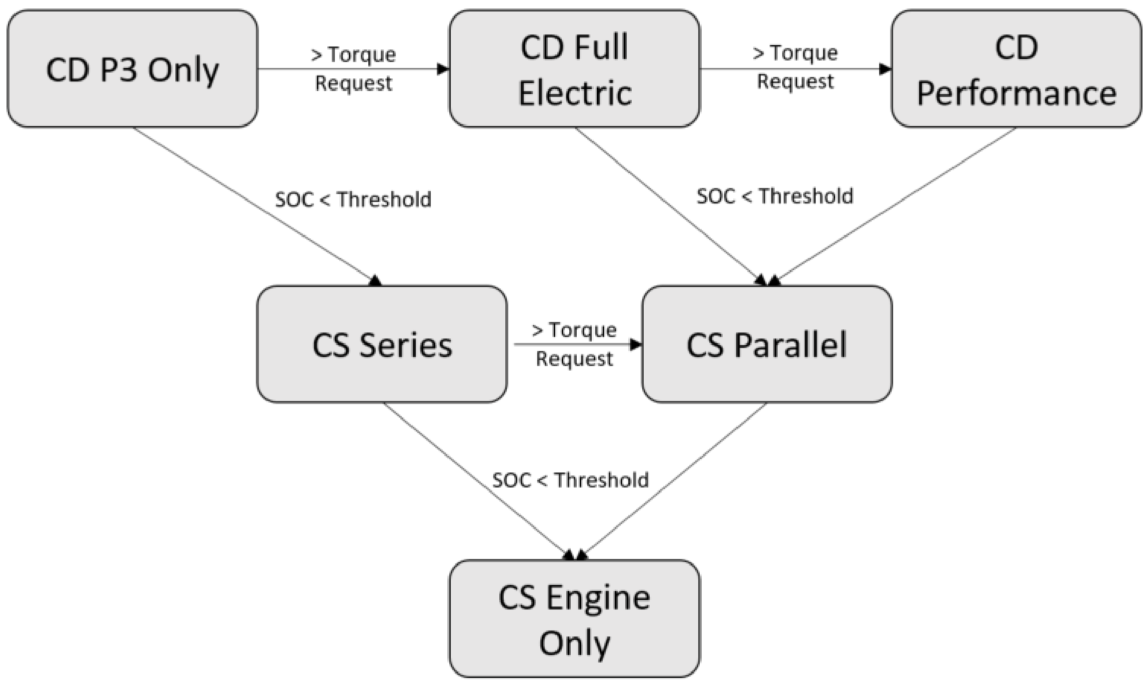


Figure 8: High Level Non-Predictive Controls Operating Mode Strategy

Because the drive mode transitions are based on requested torque, the processing time inherently creates a delay for the driver. Once the hybrid supervisor controller detects the torque request from the driver, depending on the current drive mode there may be delays from the clutch and transmission having to engage components to the driveline. This is one of the reasons UWAFT believes it can improve the vehicle's driveability by integrating a predictive controls strategy based on driver behaviour, which is discussed in detail in coming sections of this report.

CHAPTER 4
Powertrain Modeling

UWAFT's model was developed with the use of Autonomie [39] vehicle modeling software developed by Argonne National Laboratory. Autonomie is a software wrapper that runs on top of MATLAB/Simulink and auto-generates models to run in the Simulink environment. UWAFT began its modelling process by using default vehicles and models within Autonomie, later updating components based on experimental data collected. The UWAFT PHEV architecture in Autonomie is illustrated below.

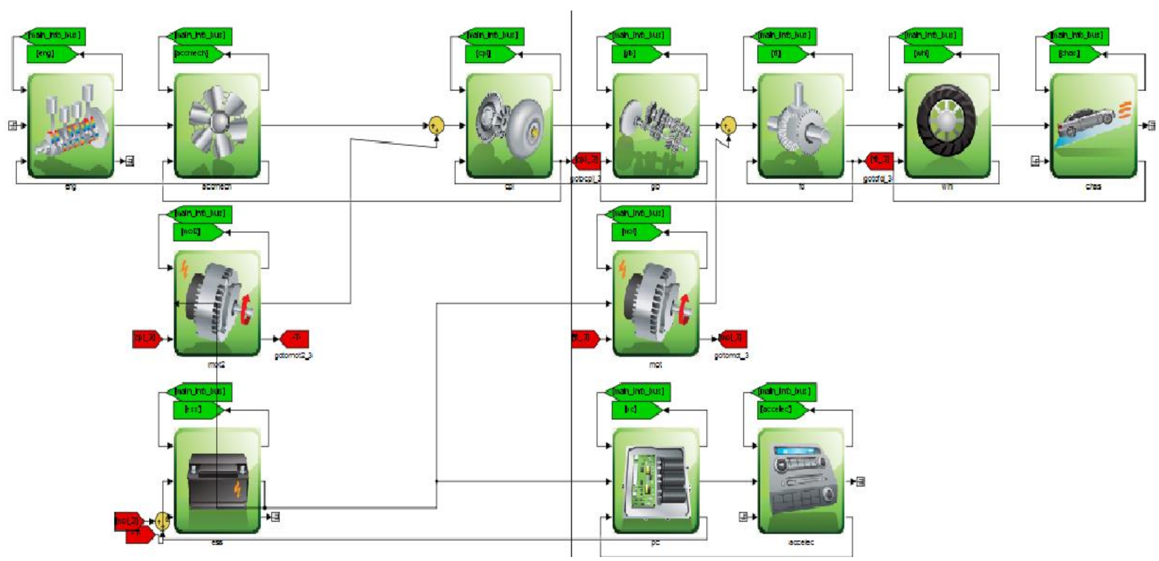


Figure 9: UWAFT PHEV Autonomie Model

For the purpose of the predictive powertrain management strategy, discussed in later sections of this report, it is crucial that the powertrain components be modelled accurately. This is important since UWAFT is trying to develop advanced controls strategies that will be tested and validated by the vehicle model. The predictive powertrain management strategy may have a minor effect on efficiency or other impact metrics, thus requiring a higher fidelity model. How the powertrain components were modelled along with some of the actions taken to achieve high fidelity is discussed in subsequent sections.

4.1 Engine

The engine selected for the architecture is a Weber 850cc. During the early stages of the UWAFT PHEV model development, the engine was modelled with the engine performance curves from the supplier and a stock efficiency map found in Autonomie. However, the engine performance curve from the supplier assumes the engine is running on gasoline. Theoretically, since UWAFT decided to use 85% ethanol (E85) as their fuel, there should be greater peak power output. This is due to ethanol having a higher energy density than gasoline.

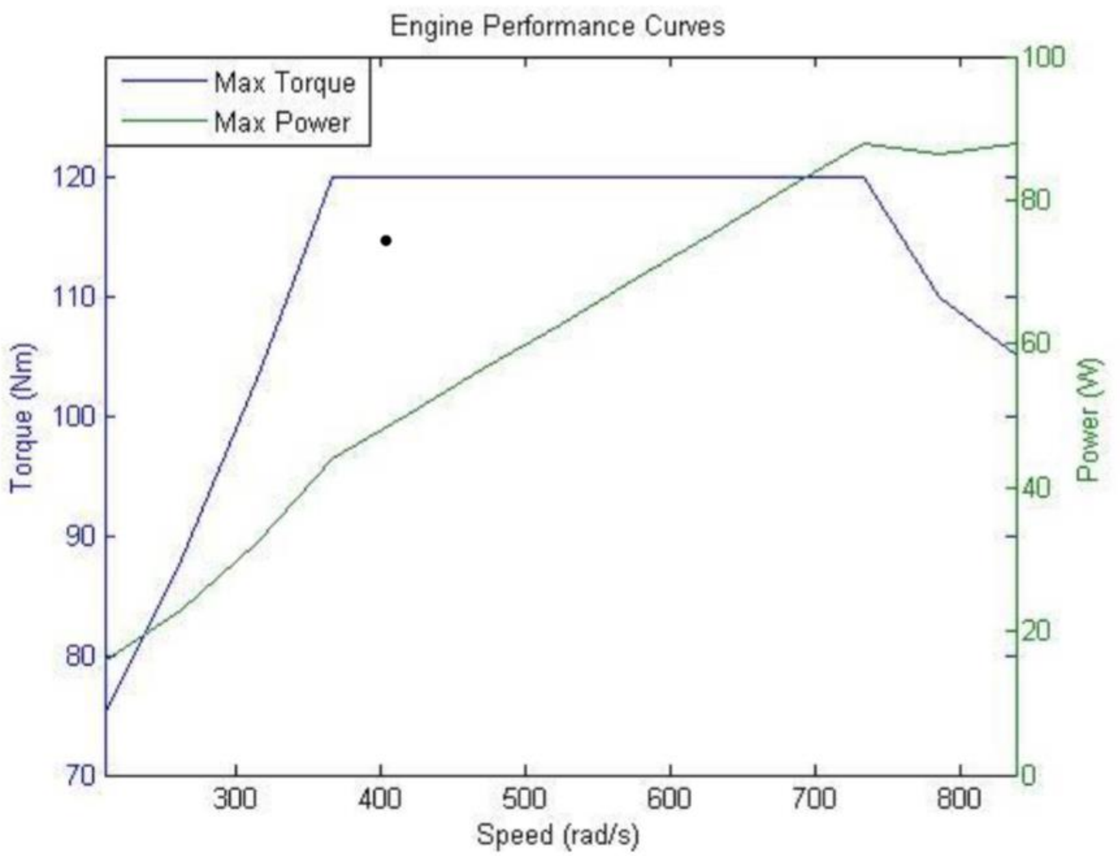


Figure 10: Weber 850cc Manufacturer Performance Curve (Gasoline)

The efficiency map provided by Autonomie is based on a Honda Insight engine model. This engine was chosen from the list of available maps as it closely represents the engine used by the UWAFT PHEV.

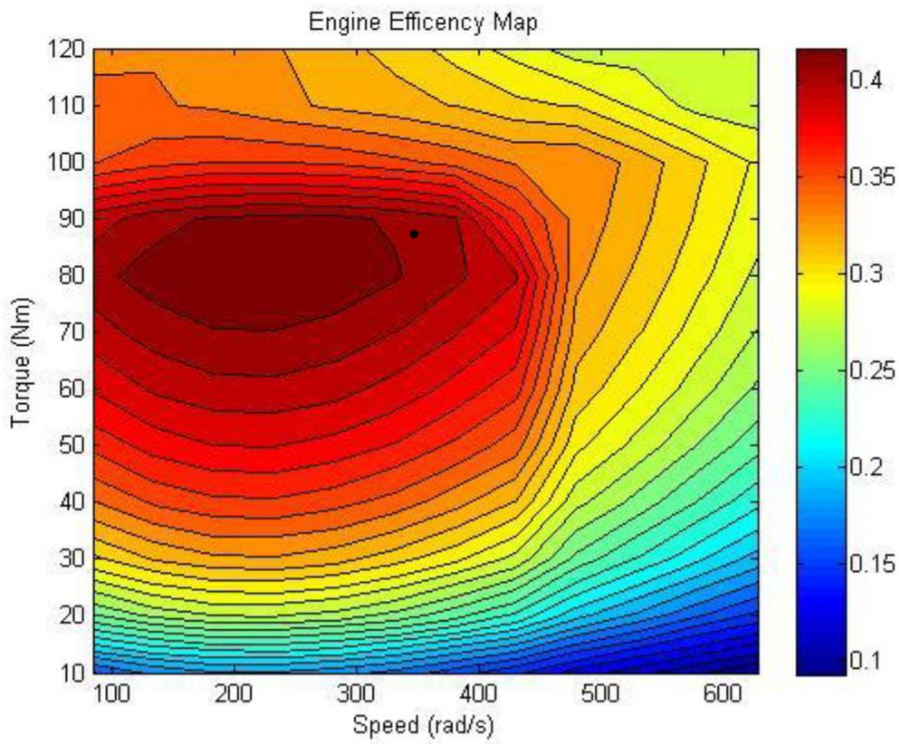


Figure 11: Autonomie Honda Insight Engine Efficiency Map [39]

In years 3 and 4 of the EcoCAR 3 competition, the fidelity of the engine model was greatly improved using experimental data collected from an engine dynamometer. The engine was tuned on an engine dynamometer to make it operate on E85 fuel and to characterize it for more accurate modeling. Motec's engine control unit (ECU) manager is the software used to change all of the parameters relevant to controlling the Motec ECU. Through comprehensive tuning, UWAFT was able to successfully run the engine using E85 fuel. Once open loop tuning was finished, data was collected to determine the most efficient operating point. Using the Super Flow Dynamometer, fuel consumption data was recorded at all possible load points between 2,000 and 5,000 RPM. A brake specific fuel consumption map was then developed as shown below.

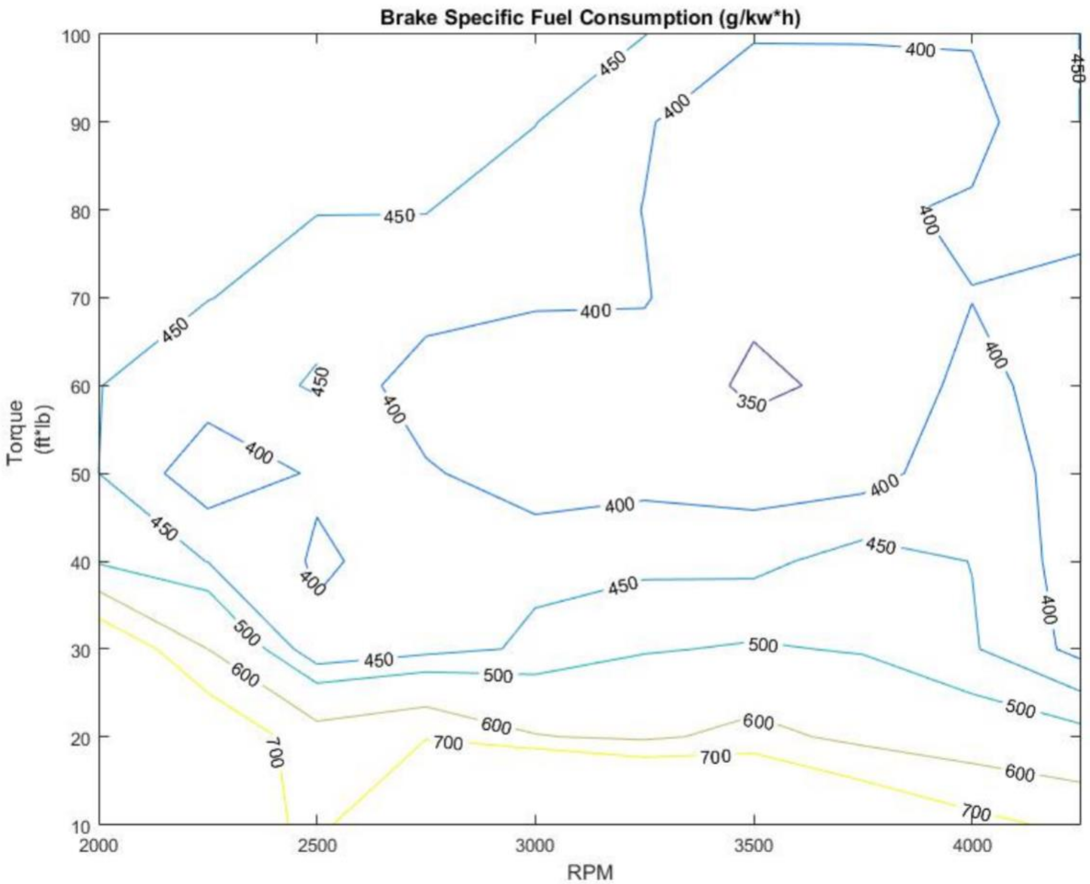


Figure 12: Weber 850cc Brake Specific Fuel Consumption

Additionally, the engine performance curve was captured on the dynamometer with the use of E85 as shown below.

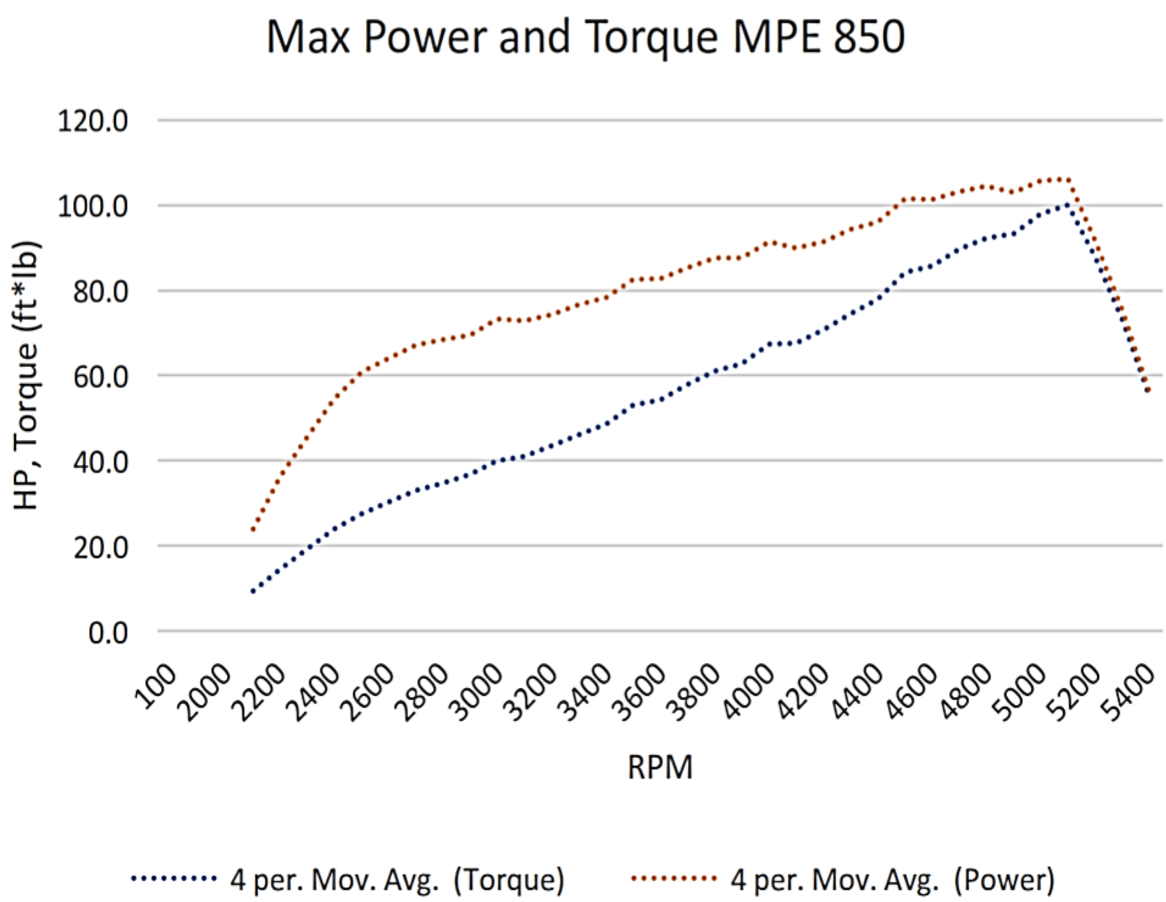


Figure 13: Weber 850cc Dynamometer Performance Curve (E85)

Both the efficiency map and power curve of the engine differ from the originals used at the beginning of the model development. Collecting experimental data from the dynamometer and updating the information in the model helps to create a higher fidelity model.

4.2 Transmission

The UWAFT PHEV uses a GM manufactured transmission (8L45) that came stock in the Camaro. The transmission allows the engine and P2 motor to be used in their most efficient operating point during series operations. UWAFT's modelled transmission is based on a stock transmission model found in Autonomie. The gear ratios and their corresponding efficiencies are shown below.

Table 2: Transmissions Gear Ratio Efficiencies [39]

Efficiency	0.96	0.95	0.95	0.95	0.95	0.98	0.93	0.93
Ratio	4.62	3.04	2.07	1.66	1.26	1.00	0.85	0.66
Gear	1	2	3	4	5	6	7	8

4.3 Electric Motor

UWAFT's PHEV utilizes two electric motors in the pre-transmission (P2) and post-transmission (P3) locations. They are both the same GKN manufactured AF130-4 motors. These motors are axial flux permanent magnet motors, packaged in an extremely compact enclosure.

Having the high voltage bus at a nominal voltage of 292 volts, results in the GKN AF130-4 power versus torque curve used in the model shown below.

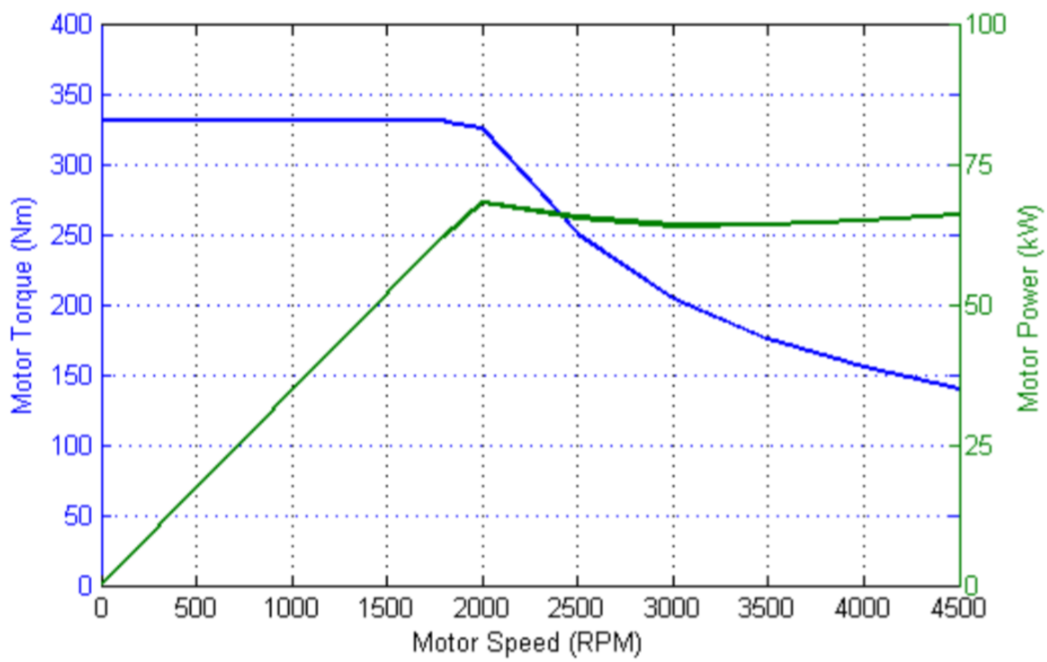


Figure 14: GKN AF130-4 Power/Torque Curve

Additionally, the efficiency map of the electric motors is not included in this report due to a non-disclosure agreement signed by UWAFT. The efficiency map implemented into the model for the electric motors is a 4D map. The inputs are torque, speed, and temperature.

4.4 Model Limitations

Modelling is a very important engineering tool as it provides insight and validation to new ideas. Although accurate, it is often difficult to achieve a model that takes into consideration every input possible. To reduce the processing power required to run simulations, models are often simplified to only include the most significant information. It is crucial to understand a model's limitations and what assumptions were made when the model was developed. The UWAFT PHEV powertrain model has two major aspects that limit the fidelity of the results obtained.

1. **Look-Up Tables** – The UWAFT PHEV uses look-up tables (maps) to determine values such as component efficiency. This is a useful tool in modelling as it avoids the use of complex computations. Instead of using an equation to calculate the engine's efficiency continuously, the UWAFT PHEV model looks up a value based on engine speed and torque. The limitation exists due to the coarseness of a look-up table. A look-up table will only have exact values for a given set of inputs; therefore, if the inputs fall between two cells of the look-up table, the output needs to be interpolated. A well constructed look-up table will have enough cells such that linear interpolation between two cells will meet the accuracy requirements of the model. One of the UWAFT PHEV's powertrain model's biggest limitations is the engine efficiency map. The Super Flow Dynamometer that was used to tune the engine and create the efficiency map is designed for larger engines. The biggest drawback this created was the resolution of the fuel flow meter. Naturally, larger engines consume larger amounts a fuel and thus higher resolution flow measurements are not required. This resulted in a coarser engine efficiency map as shown previously.

2. **Inputs –** As previously mentioned it is difficult to develop a model that includes all inputs. Thus, inputs that have minimal effects on the results are left out as long as their effect is below the accuracy requirements of the model. For example, the vibrations from the road could effect the power output of the engine; however, since the effect so miniscule it does not make sense to waste computational power to include it. Thus, the number of inputs omitted can limit the model's fidelity. The UWAFT PHEV is limited by excluding various

inputs. The engine's efficiency map is not a function of temperature like the electric motor's map. This is acceptable, as the operating temperature of the engine does not vary as much as the electric motor's. However, it does limit the model in accurately calculating start-up efficiency as the engine warms up.

CHAPTER 5
Advanced Driver Assistance Systems

UWAFT designed and integrated an Advanced Driver Assistance System (ADAS) for the 2016 Chevrolet Camaro. The primary focus of ADAS is to increase system performance around detecting and measuring vehicle targets, and using those measurements to provide feedback to the driver. The scope has been limited to focus on detection and ranging of vehicles in uncluttered environments. This direction was chosen to enable time for simulation and testing of vehicle efficiency impacts through driver feedback. The systems will therefore be tested in environments resembling highway and country roadways, without complications such as urban environments, pedestrians, or traffic lights. Due to safety concerns of the AVTC organizers, systems are not allowed to modify torque distribution, powertrain behaviour, or steering controls [40]. However, the concepts and knowledge developed are directly applicable to develop autonomous features such as adaptive cruise control and automatic braking. Rather than actively controlling the vehicle, the information from the ADAS sensors was utilized to provide feedback to the driver in an attempt to improve vehicle efficiency.

The UWAFT PHEV designed system consists of a forward facing camera for detecting regions of interest and a LiDAR for range and range rate measurements. A NXP S32V board is used for preprocessing and streaming video to a NVIDIA Jetson TX2 where a majority of the computations are done. Lastly, a Raspberry Pi and HD-Link communicate to the centre console HMI screen to provide driver feedback features. The entire ADAS architecture is graphically laid out below and the ADAS sensors used for the UWAFT PHEV are described in the following sections.

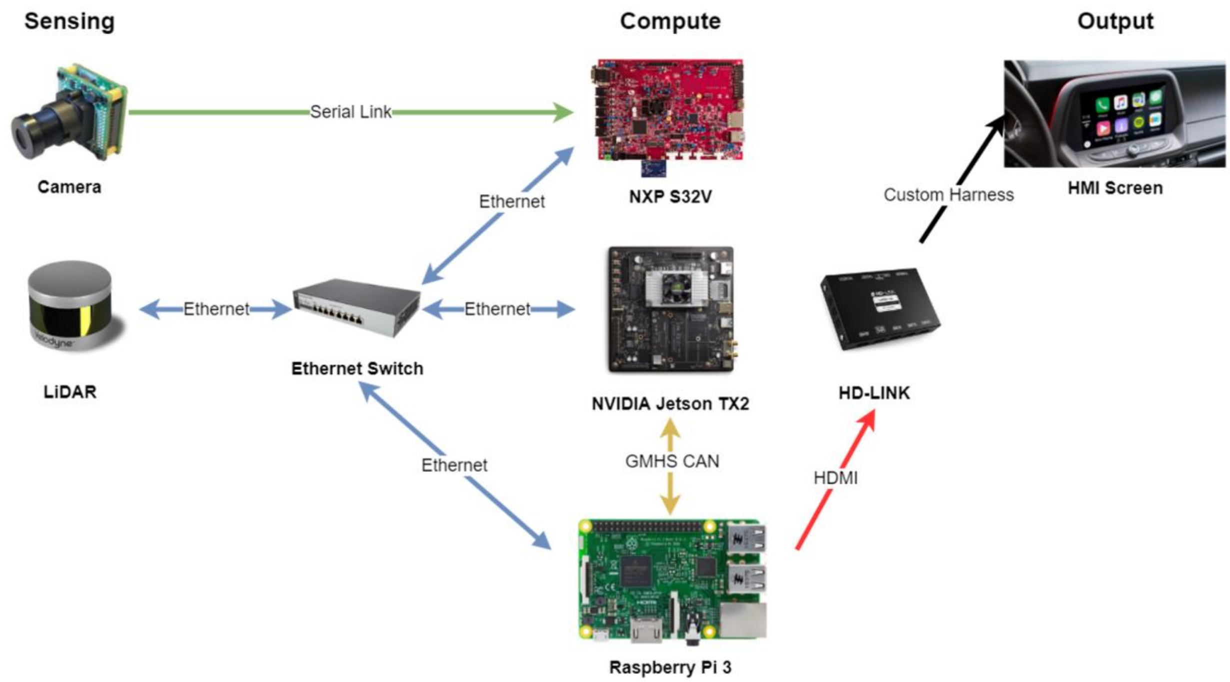


Figure 15: UWAFT ADAS Architecture

5.1 Sensors

Forward Facing Camera

The forward facing camera is an OmniVision 10635 with a standard focal length lens recording at 1280x800 pixels at 30 frames per second. It has a measured range of 30 metres with a 50° field of view with the current setup. The 50° field of view provided by the standard lens captures the vehicles lane and two adjacent lanes to detect vehicles that may be merging.

Figure 16: UWAFT PHEV OmniVision Camera Integration

Light Detection and Ranging

The chosen LiDAR is a Velodyne VLP-16, which has a 360° field of view and scans the environment using 16 independent lasers. The LiDAR is able to retrieve reflectivity and distance data for each point in its point cloud. It has a range of 100 metres for distance measurement on retro-reflective surfaces such as road signs, licence plates, and vehicle lights and is able to measure as close as 50 centimeters accurately.

Figure 17: UWAFT PHEV Velodyne LiDAR Integration

The range rate accuracy of the LiDAR system is a function of the ranging accuracy of the LiDAR and the time accuracy of the computing system. The computing system (NVIDIA Jetson TX2) is accurate down to the microsecond level, therefore the range rate will be limited by the ranging accuracy (+/- 3cm) of the Velodyne. The error under good conditions with a sample rate of 15 samples per second is calculated below resulting in a range rate accuracy of +/- 0.45 m/s. This error would increase in adverse conditions such as precipitation or non-retroreflective surfaces.

$$\frac{Ranging\ Accuracy}{Sample\ Rate} = Range\ Rate\ Accuracy \tag{1}$$

$$\pm\frac{0.03m}{\frac{1}{15}s} = \pm 0.45\ m/s$$

Sensor Fusion

There are two data sources in this system, a 3D point cloud from the LiDAR, and 2D image frames from the camera. The camera feed is processed using a neural network to identify bounding boxes around vehicles in the camera frame. These bounding boxes are then passed to the LiDAR processing code, which identifies corresponding 3D points in the point cloud to estimate the distance of the vehicles. 3D points are first mapped to the camera's 3D reference frame, then the distances of points in the bounding boxes are estimated by using a pinhole camera model, and determining the 3D rays for given pixel coordinates.

5.2 Object Detection

Multiple object detection algorithms were developed and tested on UWAFT's ADAS equipment. However, due to the complexity and time needed to train algorithms, all the methods that were developed by the team for object detection lagged behind industry standards. Ultimately, it was decided to go with an existing method for object detection developed by You Only Look Once (YOLO) [40]. YOLO takes each frame from the camera and a single convolution network on the image, and then creates a bounding box around the detected object if the confidence score is above a certain threshold.

YOLO operates similarly to a Fast Regions with Convolutional Neural Nets (R-CNN) method. However, R-CNNs require some very powerful computers to run and a very long time to train. This would not work well on the embedded system inside UWAFT's vehicle. YOLO addresses this issue by approximating the weights in the R-CNN to binary values that are much smaller. The nature of these values allows for the convolution operations to require much less computing power. The binary input is passed to the XNOR-network with the binary weights. The binary XNOR operations are very fast since both the inputs and weights are binary valued approximations. This brings R-CNN levels of accuracy into the realms of possibility in the embedded space. UWAFT was able to run YOLO at real-time speeds at around 20 frames per second on the NVIDIA Jetson TX2.

5.3 Range Estimation

The distance a vehicle is ahead of UWAFT's vehicle is determined with the use of the LiDAR. First the LiDAR outputs a 3D point cloud which is cropped to only use the field of view overlapping with the camera. Next the data is down-sampled, using a voxel grid. After down-sampling, the 3D points are mapped to the camera's reference frame. Using a pinhole model of the camera, a 3D vector is obtained for given pixel coordinates. Points in the point cloud that lie along the direction of this vector are selected as distance candidates and averaged. This averaged distance is then returned and stored so that range rate and the time step can be calculated.

5.4 Object Tracking

To track vehicles, a bounding box overlap method was used. The overlapping area between a previous bounding box and all new bounding boxes in the frame was calculated. If any box overlaps with at least 50% of a previous box (if the overlap area is greater than half of the area of the old box) it is determined to be the same vehicle. If multiple boxes meet this criterion, the box with the highest percentage of overlap will be chosen. It is identified that this is not the most robust method of doing object tracking but was implemented for simplicity.

CHAPTER 6

Predictive Controls Strategy Based on Driver Behaviour

6.1 Overview

A major part of the AVTC series is to challenge students to develop industry-leading ideas and take them from proof of concept to vehicle insertion. This is the primary focus for the innovation stream each year. The major milestone for the innovation stream is to develop a selected topic and obtain actual data and functionality by the end of the year. It was chosen to address a continuous need in the automotive industry, which is to reduce energy consumption and emissions of vehicles. With the increase in alternative fuels energy sources, vehicle architectures are becoming more complex. Rather than having just an internal combustion engine connected to the wheels, there are now multiple torque producing components in numerous different configurations. This ultimately leads to a more complex controls strategy to control vehicle operations.

It is decided to investigate how advance controls techniques (particularly machine learning) can be incorporated into the hybrid supervisory controller to improve energy consumption and emissions of a PHEV. While reflecting on the target market defined by UWAFT in year one, it was important that the innovation project bring state-of-the-art technology to consumers and create a unique experience while reducing the environmental impact of the vehicle. A predictive controls strategy based on driver behaviour recognition was selected as the year 4 innovation project.

It is believed by recognizing the driver's behaviour and ultimately learning who they are as a driver it would help give UWAFT's PHEV a personalized feel while reducing the energy consumption of the vehicle. Utilizing facial recognition to identify who is driving, and a database of the driver's behaviour history (recognized via machine learning); the UWAFT PHEV could change its control strategy and specific control parameters to adapt to each driver. This can influence various driving scenarios, with situational and environmental factors all coming into effect. It was decided to narrow the scope to investigate the effect during simple braking and accelerating events, with no external factors taken into effect. For example, given an aggressive accelerator the UWAFT PHEV will pre-emptively be in a configuration to provide maximum torque, eliminating the engagement time of certain powertrain components. Alternatively, given an eco-cautious accelerator (easy on the pedal) UWAFT PHEV will pre-emptively be in a configuration to optimize for energy consumption and emissions. Experiments conducted with the predictive controls strategy include:

1. Energy consumption during acceleration events in different configurations
2. Regenerative energy captured during braking events

6.2 Technical Goals for Innovation Project

At the start of the EcoCAR 3, year 4 innovation project, multiple technical goals to achieve over the course of one year were identified. The innovation project aimed to add value for the target market, as well as value to EcoCAR 3 AVTC and UWAFT directly. The goals developed by UWAFT are described in the list below.

1. **Driver Identification** – It needs to be able to identify who is driving the vehicle to activate a predictive powertrain management strategy that is specific to the driver. This is to be accomplished via a driver-facing camera utilizing facial recognition algorithms. Additionally, once the driver is recognized, the vehicle settings such as seat, mirror position, and HMI settings will automatically be adjusted resulting in a refined driver experience. The facial detection system may also double as a security feature, disabling the vehicle for unknown drivers.

2. **300+ Hours of Driver Data** – In order to train and validate driver behaviour algorithms driver data will need to be collected. Driver data can be collected via the onboard diagnostic (OBD) port on all types of vehicle via OBD loggers. Depending on the machine learning technique chosen, labelled or unlabelled data may be necessary. Labelled data refers to data that has already been identified or given a ground truth. In the described scenario, it refers to driver data logged from the OBD port of a driver who has already been labelled as aggressive, normal, or eco-cautious. Conversely, unlabelled data is essentially unknown.

3. **Driver Behaviour Recognition** – 80% reliability in identifying driver behaviour as characterized in Section 8.1. Algorithms that are available for use include but are not limited to; fast Fourier transform, finite/hybrid state machines, graphical methods, hidden Markov models, Bayesian networks, k-nearest neighbour classifiers, decision tress, fuzzy logic, clustering, Kalman filtering, and support vector machines. Based on literature review, drivers can be profiled based on their acceleration/braking and vehicle speed; however, as the innovation project develops it may prove beneficial to include data from GPS, ADAS, situational factors, and environmental factors as well.

4. **Powertrain Management Strategy** – Once the driver has been classified, the optimal powertrain management strategy needs to be determined for that specific driver. This includes determining which mode the vehicle should be in, parameter optimizations, and regen braking calibrations. This thesis aims to do as much in vehicle testing as possible to optimize the controls strategy, but ultimately will be limited by any mechanical failures experienced by the team.

5. **Effect on Competition –** The innovation project must facilitate the accomplishment of the team's competition goals. Two of UWAFT's major goals for the competition are to reduce emissions and have a vehicle range of 300 kilometres. By completing this innovation project, it will have investigated numerous ways to reduce vehicle emissions and power consumption thus developing a thorough understanding of the vehicle's powertrain management. This will ultimately allow UWAFT to select the best powertrain management strategy to achieve the highest scores at competition events. (Such as the emissions and energy consumption event)

6.3 Impact Metrics

Four metrics were determined to use in order to gauge the success of the predictive controls strategy and driver behaviour recognition.

1. **Energy Consumption** – The more energy saved by the predictive controls strategy the more successful it will be. By analyzing the energy saved during one driving event, the data can be extrapolated over the course of an entire trip to determine the cost savings associated with the implementation of a driver behaviour recognition algorithm.

2. **Emissions** – Similar to energy consumption, by comparing the emissions of the predictive controls strategy to that of the stock, "one size fits all", controls strategy, there should be a noticeable reduction difference.

3. **Driveability** – A successful implementation of a predictive powertrain management strategy should go unnoticed by the user, as changes would be incremental at first as the driver's behaviour is being learnt. Vehicle test laps on a closed course and survey can be used to receive feedback from various types of drivers.

4. **Recognition Accuracy** – By validating the algorithm for driver behaviour recognition, an reliability value can be obtained to represent how well the algorithm preforms. Using cross validation a group of labeled data (aggressive, eco-cautious, and normal drive cycles) can be inputted into the algorithm, and then the predicted label can be compared to the actual label.

6.4 Machine Learning Methodology

An algorithm designed to recognize and classify driver behaviour based on features extracted from CAN data was developed. The algorithm was developed in a Python environment due to its dominant use in machine learning and various open source machine intelligence libraries available. The algorithm architecture follows a standard set sequence described below:

1. **Feature Extraction** – Extracts unique characteristics from the raw data.
2. **Feature Normalization** – Normalizes the features so each feature has equal effect on the outcome.
3. **Dimensionality Reduction** – Determines the most important features and reduces the complexity of the problem.
4. **Classification** – Classifies the features into distinct categories.

This methodology was applied to a supervised and unsupervised learning approach to determine which would perform better. The feature extraction and normalization were the same for both the supervised and unsupervised approach. However, different dimensionality reductions and classifications were used for each. The supervised approached used linear discriminant analysis (LDA) [41] and support vector machines (SVM) [42] for dimensionality reduction and classification, respectively. Whereas the unsupervised approach used principal component analysis (PCA) [41] and k-means [43] for dimensionality reduction and classification, respectively. The unsupervised learning approach initially seemed to be an appropriate solution; however, the team ultimately chose to pursue a supervised learning method due to the various drawbacks encountered, namely, the larger amount of data required. The supervised approach and techniques chosen are discussed in more detail in the following sections.

Feature Extraction

A feature is a quantitatively measurable property that serves as a unique characteristic of the data being studied. The driver specific signals used for classification in this paper are accelerator pedal position (APP), brake pedal position (BPP), and vehicle speed. A total of five features were extracted for each input signal recorded from a specific driver (APP, BPP, and vehicle speed). The features explored were the raw signal value, discrete first derivative, moving mean, moving median, and moving standard deviation. An individual data point was created by averaging all of the features over the time driven. Thus, for an individual driver the data set would be a 1x15 array.

$$[APP \quad APP_{rate} \quad \dots \quad BPP]_{1x15}$$

Once all of the labelled data points were created, representing individual drivers, the features were normalized to produce a standardized set of data which the classifier can operate on. This is a necessary step as normalization ensures that all features have a proportional contribution to the classification. Additionally, during dimensionality reduction the linear discriminant analysis results improve when using normalized data.

Dimensionality Reduction

Linear discriminant analysis (LDA) was used as the dimensionality reduction technique during the pre-processing step. LDA projects the dataset onto a lower-dimensional space that has high class-separability as well as low interclass-separability, both of which are desired, reducing computational costs.

LDA begins by calculating the mean of each feature separately for each class (eco-cautious, normal, aggressive). Two scatter matrices are then calculated, one to represent inter-class scatter and one that represents class separation. The goal of LDA is to find dimensions that minimize inter-class scatter while maximizing class separation. The inter-class scatter is computed by the following equation using the variance of the data.

$$S_W = \sum_{i=1}^{c} S_i \quad (2)$$

$$where, \;\; S_i = \sum_{x \in D_i}^{n} (x - m_i)(x - m_i)^T \quad (3)$$

The class separation can be calculated using the following equation.

$$S_B = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T \quad (4)$$

$$where, \;\; m = \; overall\ mean,$$

$$N_i = sample\ size$$

Lastly, to minimize S_W and maximize S_B, the generalized eigenvalue problem for the matrix $S_W^{-1} S_B$ needs to be solved. Sorting the eigenvectors by decreasing eigenvalues allow the most important dimensions to be determined. The eigenvectors with the highest eigenvalues bear the most information about the distribution of data. Thus, the data will be projected onto the eigenpairs with the greatest variance, setting up the problem nicely for classification.

Classification

The classification approach, chosen for supervised learning, was support vector machines (SVM). SVM finds the vector or hyperplane that creates the widest gap between the classes. Classification can then be done on unlabelled data by determining which side of the support vectors the data point lies on. The processed training data was used to fit the SVM classifier using a linear kernel, thus returning three vectors that divide the three driver behaviour classes.

As opposed to purely classifying drivers into three distinct classes, eco-cautious, normal, or aggressive, it was decided to assign an aggression value between 0 and 100 to each driver using fuzzy logic [44]. Due to several areas of overlap between classes, this approach is desirable to minimize misclassification. Thus, instead of misclassifying in those areas, the driver's behaviour can be assigned a value somewhere between eco-cautious, normal, or aggressive, resulting in a more descriptive classification. The consequent membership function for aggression level is defined in the figure below.

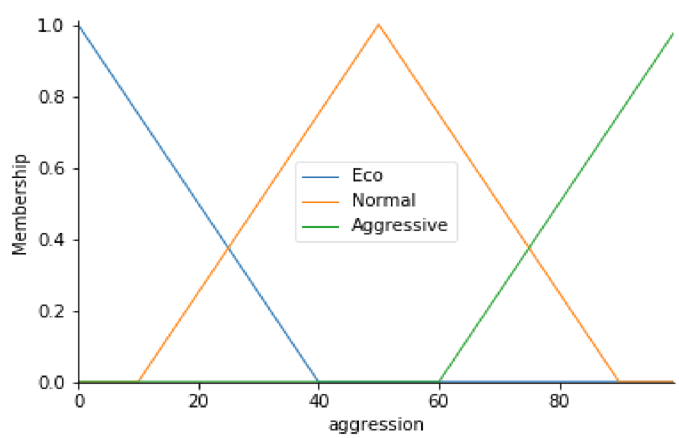


Figure 18: Aggression Membership Function

Additionally, three antecedent membership functions were also defined for each of the support vectors. These antecedent membership functions use the distance from the support vector as the input, meaning the closer the data point is to the support vector the more "fuzzy" the classification. These membership functions are all defined similarly as shown in the figure below. The two classes intersect when the data point falls on the support vector and the distance is equal to zero.

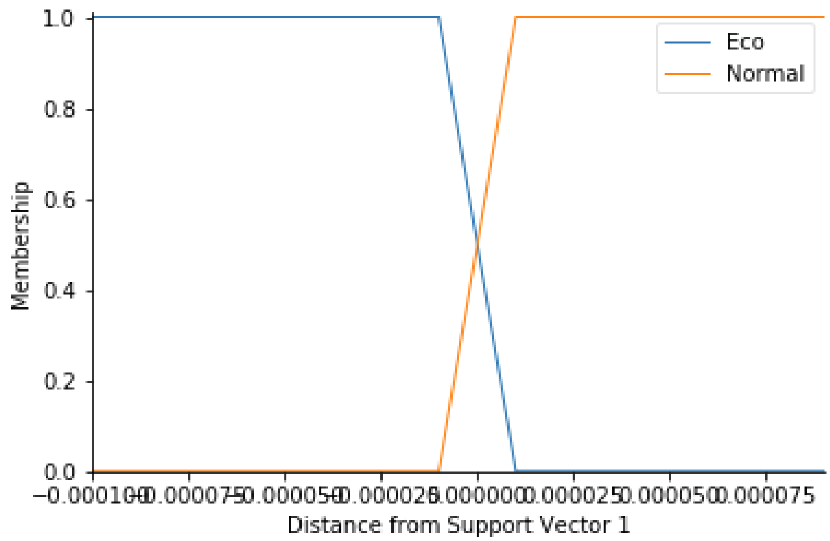


Figure 19: Distance from Support Vector Membership Function

The distance to the support vectors was calculated via the following formula:

$$distance = \frac{|ax_0 + by_0 + c|}{\sqrt{a^2 + b^2}} \qquad (5)$$

Part II - Applications

CHAPTER 7

Vehicle and Environment Simulation

In order to use the machine learning methodology, discussed in previous sections, labelled data is needed first to train the algorithm. The data used was collected from various streams through the duration of this project. The training and validation data was simulated using the UWAFT PHEV powertrain model discussed in a previous section. Furthermore, unlabelled data was collected via the onboard diagnostic (OBD) port on various vehicles logging their day-to-day driving.

The UWAFT PHEV model was used to rapidly generate unique driver behaviour data by recursively running the model through a collection of standard drive cycles and logging various controller area network (CAN) signals. The drive cycles used as inputs to the model were vehicle speed as a function of time. A sample drive cycle is shown in the figure below. This drive cycle is the highway fuel economy test (HWFET) developed by the United States Environmental Protection Agency for the determination of fuel economy of light duty vehicles [45]. Similarly, the other 11 drive cycles used were sourced from various institutions for standard vehicle testing applications. This ensured that the values inputted into the model were realistic.

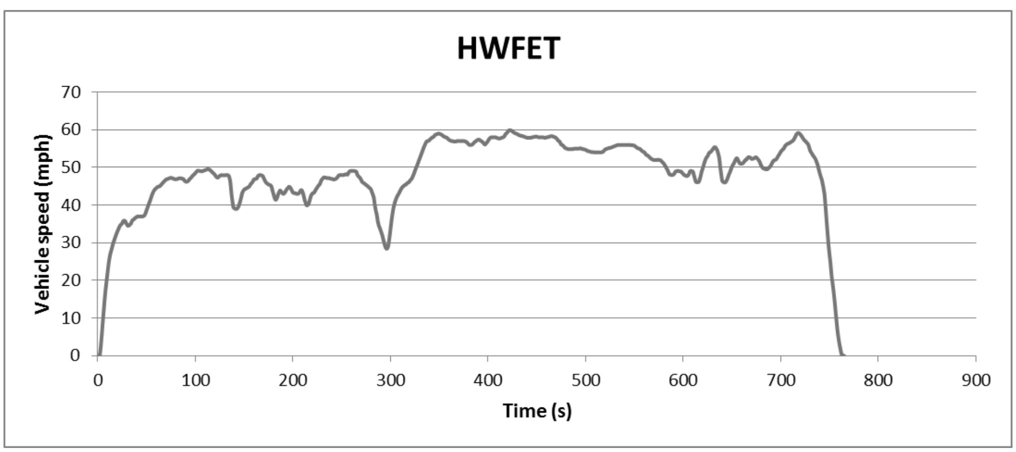


Figure 20: HWFET Drive Cycle [45]

The data collected via the simulation was labelled by scaling the drive cycles' vehicle speed and time by a random factor from 0.60-1.55 using the following equations.

$$vehspeed = vehspeed * scale\_factor \qquad (6)$$

$$time = \frac{time}{scale\_factor} \qquad (7)$$

A scaling factor of 0.60-0.75 results in lower speeds and slower accelerations, thus the driver was labelled as eco-cautious. Similarly a scaling factor of 0.9-1.1 was labelled as normal, and 1.25-1.55 labelled as aggressive. The raw signals that were logged during the simulation were the accelerator pedal position (APP), brake pedal position (BBP), and vehicle speed, which were then able to be fed into the feature extraction algorithm.

In total, 144 log files were simulated using 12 randomly scaled drive cycles. There are 48 unique log files for each labelled class, eco-cautious, normal, and aggressive. This results in more than 288 hours of driving data.

In addition to simulating vehicle CAN data, several FleetCarma [47] C2 data logging devices were obtained and used to collect the day-to-day driving logs of various drivers. This data was used to ensure that the final algorithm would be compatible with real world data collected from various types of vehicles.

CHAPTER 8

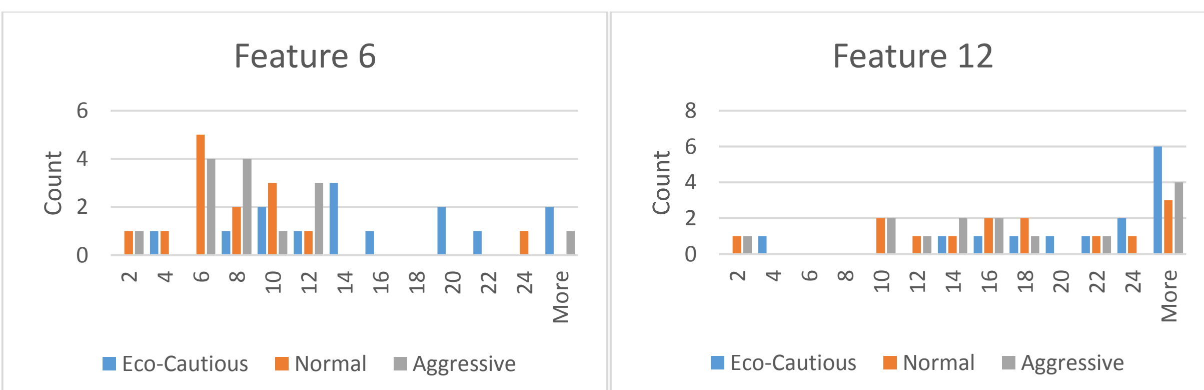
Experimental Results

8.1 Driver Behaviour Recognition

The following sections display the results obtained when applying the machine learning methodology described to the 288 hours of labelled driving data simulated by the UWAFT PHEV powertrain model. Additionally, once the algorithm was trained and validated with simulated data, it was tested using real world vehicle data from various types of cars.

Driver Behaviour Classification

Prior to preforming LDA on the dataset there are 15 features (dimensions) that individually have poor class-separability. Shown below is a visual representation of the training sample distribution over two randomly selected features in one-dimensional histograms. The classes displayed on the features below clearly cannot be classified and there is no separability between the classes.



(A) (B)

Figure 21: Data Projected onto Feature 6 (A) and Feature 12 (B)

After performing LDA on all 15 features, the eigenvectors that contain the most information about the distribution of the data can be found as they correspond to the largest eigenvalues, shown in the table below.

Table 3: LDA Variance for Each Eigenvalue

Eigenvalue	**Variance as Percentage**
2.44	63.5%
1.38	36.1%
0.0157	0.41%
⋮	⋮
$2.84x10^{-13}$	0.00%

The first two eigenpairs are by far the most informative ones, and not much will be gained expanding beyond the 2D-feature space based on the first two eigenpairs. Below is a figure of the training data set projected onto the first two linear discriminants.

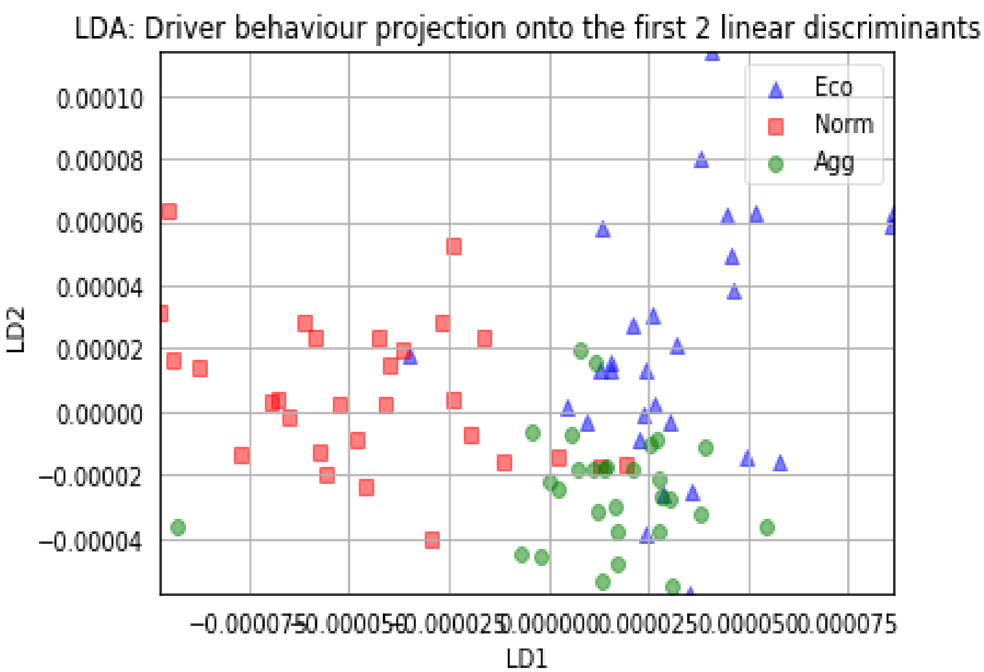


Figure 22: Data Projected onto the First Two Linear Discriminants

SVM was then used to determine the vectors that separate the data best. The figure below shows the processed data with each support vector.

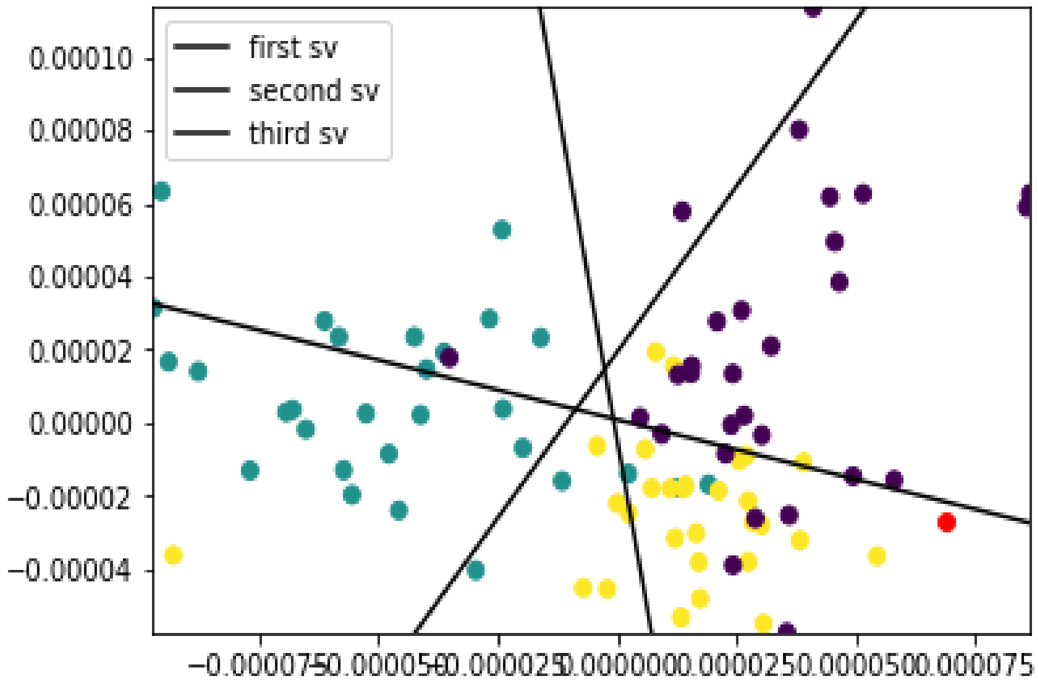


Figure 23: Support Vectors Graphed Over Data

The three separating vectors found are:

$$y = -7.32x + -4.80 * 10^{-6} \qquad (8)$$

$$y = -0.33x + 8.63 * 10^{-6} \qquad (9)$$

$$y = 1.82x + 1.94 * 10^{-6} \qquad (10)$$

Driver Behaviour Validation

K-fold cross validation was used to determine the accuracy of the classification implemented above. The 48 labelled log files for each class were split into 8 groups of 6 log files. The algorithm was run 8 times using a different group for testing each time and the other 7 groups used for training. The results are summarized in the table below.

Table 4: K-Fold Validation Accuracy

Fold #	**Accuracy**		
	Class 1	**Class 2**	**Class 3**
1	76.66%	86.66%	90%
2	76.66%	76.66%	76.66%
3	73.33%	80%	80%
4	73.33%	86.66%	86.66%
5	80%	80%	90%
6	90%	86.66%	80%
7	83.33%	80%	80%
8	83.33%	80%	80%
AVG	**79.6%**	**82.1%**	**82.9%**

Therefore, from K-fold cross validation the implemented algorithm has a total classification accuracy of 81.53%. The algorithm has some degree of misclassification; however, this was anticipated when observing the classes overlapping when the data is projected onto the first two linear discriminants. To account for this and better describe driver behaviour, fuzzy logic was implemented to assign a driver with an aggression value from 0-100. Therefore, the overlapping regions could be represented partially by each overlapped class. Refer to Appendix C for a classification and misclassification example addressed via fuzzy logic.

Real World Results

To maximize its benefit, a driver behaviour recognition algorithm should work in real time as the driver drives. This way it can modify the vehicle's control parameter to adapt to the driver, as well as suggest to the driver to make changes to bad habits.

The best way to test if the algorithm works in real time is by using real world logged data from vehicles driving on the road. As mentioned in a previous section of this paper, data was logged from various drivers driving different vehicles using FleetCarma C2 data loggers [47]. When combining GPS data and the driver behaviour algorithm the following results can be obtained, shown in the image below.

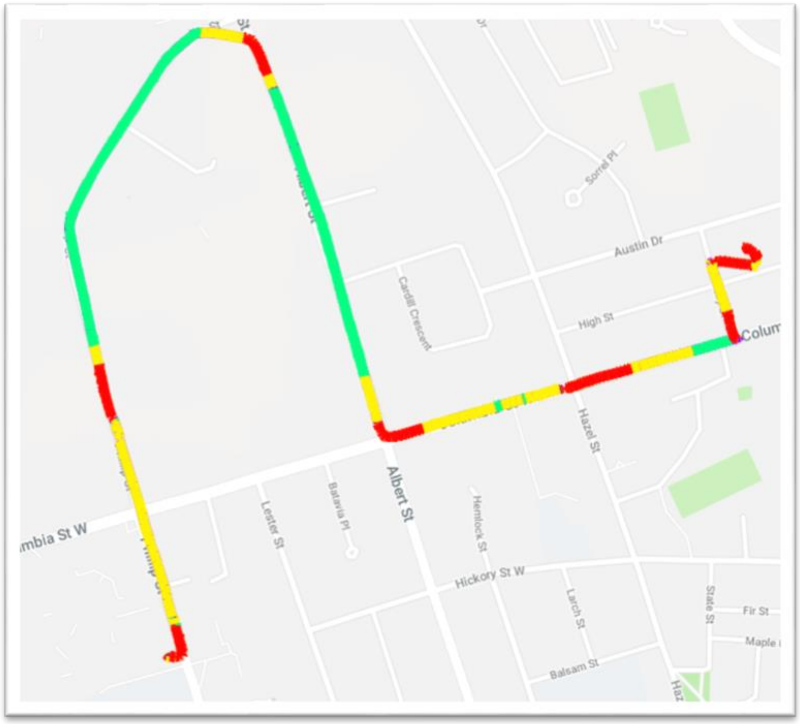


Figure 24: Aggression Level Projected onto City Map

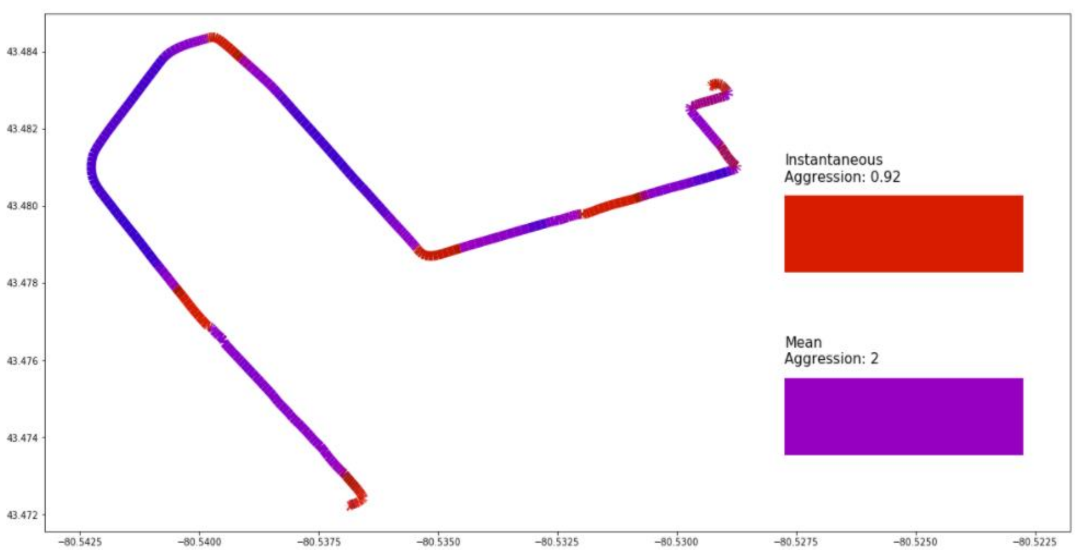


Figure 25: Aggression Level Projected onto GPS Data

As the driver drives from his/her home to work their aggression level changes based on the scenario they are in. An average aggression score is also posted for the entire trip. Having this information can aid the vehicle's controls to determine the best vehicle parameters and operating mode for the driver. As shown in the following sections, a regenerative braking test is used to determine the best applied torque for a specific braking behaviour, and an acceleration test shows the effect of operating in different vehicle modes.

8.2 Chassis Dynamometer Regenerative Braking

The following test aims to study, characterize, and optimize the regenerative braking capabilities of the vehicle's post-transmission (P3) electric motor. Under UWAFT's current control architecture, the P3 motor is typically used as the sole propulsive powertrain component (P3 only electric vehicle mode) in low torque demand applications, and the primary source of regenerative braking in all applications in electric vehicle modes. UWAFT was motivated to optimize and fine-tune its regenerative braking scheme in an attempt to improve overall vehicle range, efficiency, and performance. Additionally, by investigating different regenerative braking parameters, it desired to learn the best parameters based on different braking rates. This directly benefitted the predictive powertrain management strategy, because once the driver's behaviour was determined it could be matched with the regenerative braking parameters that best suited their braking rate. This provided the driver with the most efficient parameters.

Regenerative Braking Test Setup

The aforementioned regenerative braking calibration tests were conducted on the AVL All-Wheel Drive dynamometer (Test Cell 3) located at the Transportation Research Center in East Liberty, Ohio. With the chassis of the test vehicle securely strapped down to the dynamometer, at standstill, and no changes made to the vehicle's control architecture, the test driver was instructed to gradually accelerate from 0-70mph (~113km/h). Once the vehicle had reached a speed of 70mph, the driver was instructed to fully release the accelerator pedal and let the vehicle coast-down until a vehicle speed of 0mph was achieved. Lastly, the test vehicle was allowed to rest at standstill until the P3 motor temperature had cooled to approximately 42°C, ensuring that temperature variation would not have any significant impact on test results. The drive cycle graph is shown below.

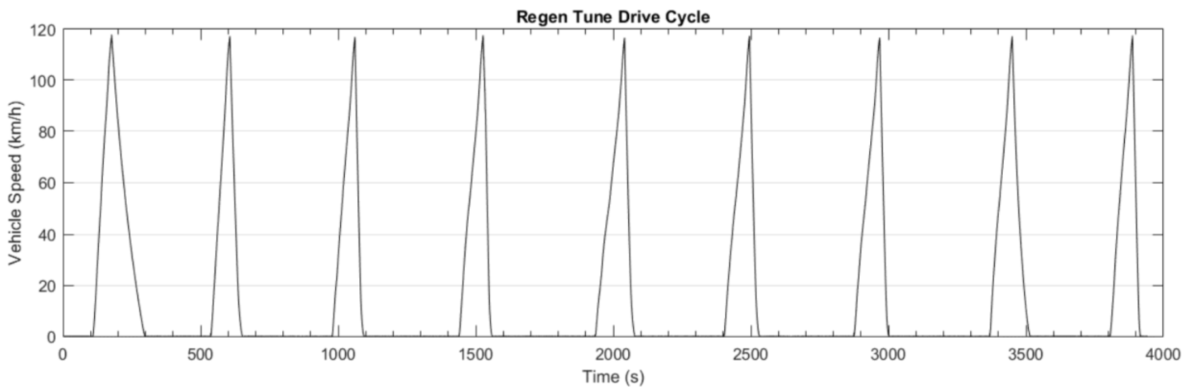


Figure 26: Drive Cycle Used for Regenerative Braking Test

This initial test run was used as a baseline to which all other subsequent test runs would be measured against. The test procedure detailed above was conducted nine times in immediate succession, under the same testing environment conditions. Prior to the start of each test run, various regenerative control parameters, such as maximum regenerative torque applied, were altered. This ultimately simulated various braking rates representing different types of drivers. The following metrics were actively monitored throughout the course of testing and used to determine in which direction parameters would be tuned during the subsequent test-run:

1. **Net energy consumed**
2. **Net SOC gain**
3. **Peak regenerative current**
4. **Battery charge current buffer consumption**
5. **Coast down duration**
6. **Motor temperature**
7. **Motor speed**

Regenerative Braking Results

The results for all nine regenerative braking cycles are described in the table below. The charge gained was calculated by integrating the net battery current for the duration of each braking event. The temperature change in the P3 motor was calculated by taking the difference in temperatures from when the driver let go of the pedal to when the vehicle came to a stop.

Table 5: Calculated Results from Nine Regenerative Braking Events

Event #	**Max Regen Torque (Nm)**	**Stopping Rate (mph/s)**	**Charge Gained (A-hrs)**	**SOC Gain (%)**	**ΔT P3 Motor (°C)**
1	0	0.593	0	0	-13.3
2	160	1.621	0.576	1.00	9.8
3	280	2.304	0.638	1.11	17.6
4	340	2.306	0.586	1.01	18.7
5	190	1.977	0.630	1.09	14.6
6	190	2.071	0.637	1.10	15.7
7	190	2.229	0.638	1.11	15.7
8	120	1.129	0.514	0.89	0
9	210	2.702	0.643	1.11	14.8

The maximum regenerative torque applicable was varied between runs, as well as how this torque would taper with vehicle speed. The figure below shows how the torque command was tapered with speed for each run. The shape of this curve was also varied as a control parameter.

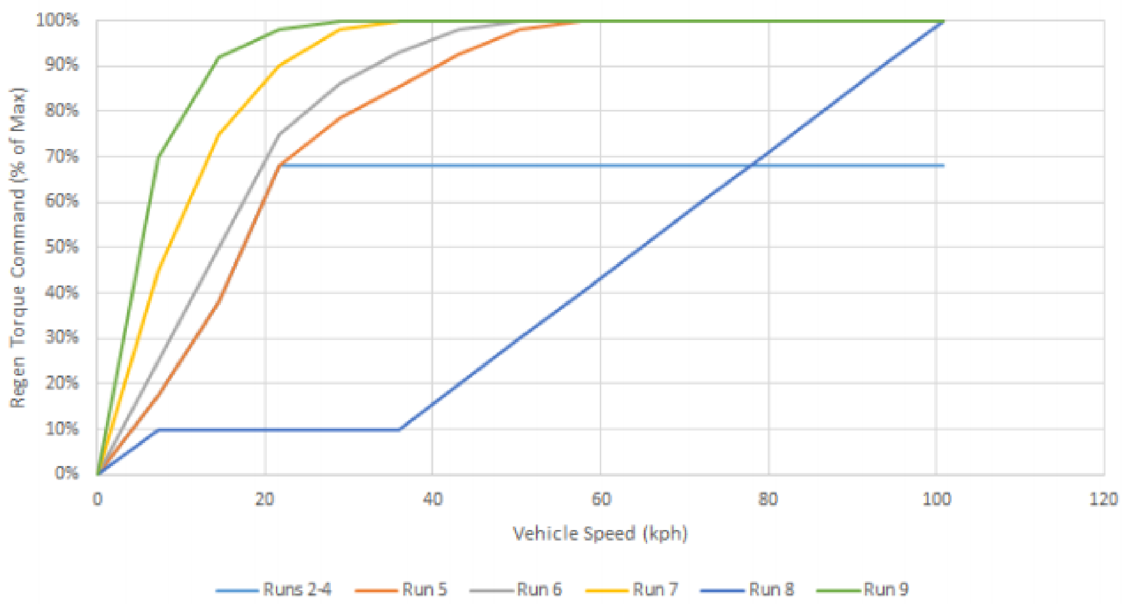


Figure 27: Regenerative Braking Profile Curves

Events 1-4 were conducted using the base regenerative braking curve while varying the maximum regenerative torque. In general, increasing the maximum regenerative torque command decreased the stopping time, increased the battery charge recovery, and increased the change in motor temperature. Significant wheel slip occurred in the run using 340 Nm of torque, so it did not follow this trend. Events 5-7 were conducted using the same maximum regenerative torque while varying the shape of the regenerative braking curve. It is shown that changing the shape of the regenerative braking curve did not have as much of an effect on the stopping time, SOC gain, or P3 motor temperature as did changing the maximum regenerative torque. Lastly, events 8 and 9 were conducted using different maximum torques and curve shapes.

The P3 motor current and temperature during the test can be found in Appendix B. It is important to note that events 3-7 all had a stopping time of around 30 seconds. This represents all drivers who have a similar stopping rate (~2.0mph/s deceleration). In other words, they have the same braking behaviour. Therefore, the results discovered via the regenerative braking test above are used to find the best parameters for the tested driving behaviour class (Eco-cautious drivers). Additionally, this test can be repeated to find parameters for each class of driver behaviour.

8.3 Acceleration Testing

Similar to the regenerative braking test described above, acceleration is a characteristic directly related to a driver's behaviour. Aggressive drivers who push on the pedal harder will accelerate faster, whereas eco-cautious drivers will take longer to reach their desired traveling speed. Due to the complex architecture of the vehicle, the rate at which it accelerates may differ greatly depending on which mode the vehicle is operating in. If they know the rate of acceleration and how the driver behaves during an acceleration event, the controls can predict the best mode for the vehicle.

The following test aims to compare acceleration performance between two different situations: one where the vehicle begins in P3 only electric mode and transitions into performance mode (full drive) due to requested torque and another where the vehicle is already in full drive.

Acceleration Test Setup

The following test was taken on a closed course test track operated by the city of Waterloo. This was to ensure a controlled environment with similar conditions for both accelerations events. Each event consisted of the driver reaching 20 km/h and then applying wide-open throttle (accelerator pedal 100% pressed) for 5 seconds.

Acceleration Test Results

The following graph shows the vehicle speed versus time. The dotted line is the acceleration event when the vehicle is already in full drive and the solid black line is the vehicle starting in P3 only electric mode and eventually transitioning into full drive. The transition occurs around the four-second mark when the graph changes from green to red.

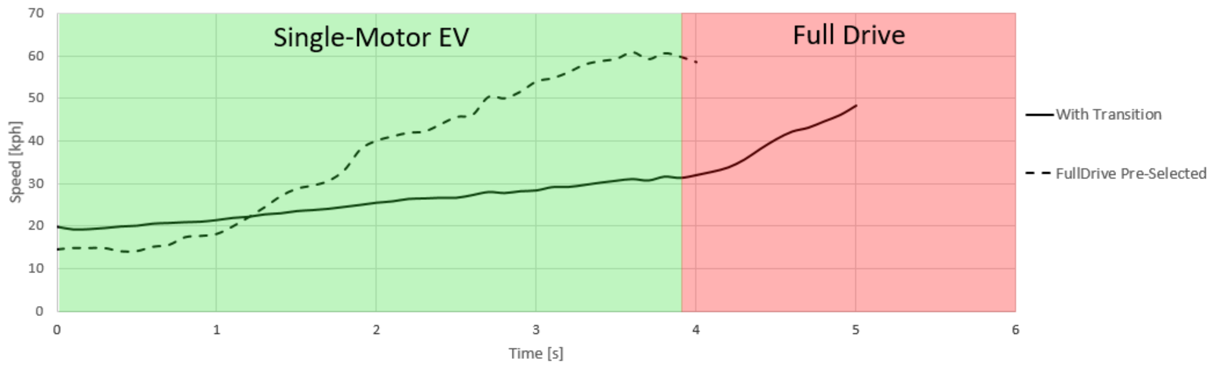


Figure 28: Vehicle Speed Trace during Wide Open Throttle Acceleration Test

By observing the results from the acceleration testing experiment, there are two areas of interest as described and shown in the figures below.

1. **The Aggressive Driver** – If the driver's acceleration behaviour exceeds the profile of the acceleration test with a mode transition, then starting the UWAFT PHEV in full drive mode will benefit the driver when such acceleration event is imminent. Correctly identifying this increases the driveability of the UWAFT PHEV as the driver will not experience the lag required to set the vehicle into the correct operating mode able to meet the torque demands.

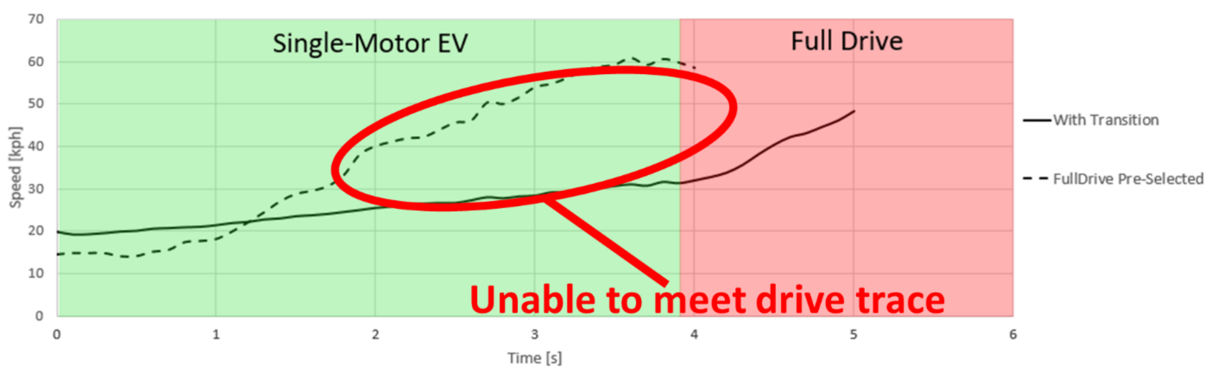


Figure 29: Vehicle Speed Trace during Wide Open Throttle Acceleration Test
(Aggressive Drive Trace Marked)

2. **The Eco-Cautious Driver** – If the driver's acceleration behaviour falls below the profile of the acceleration test with a mode transition, then the UWAFT PHEV should stay in P3-only electric mode. Correctly identifying this increases the efficiency and decreases the emissions of the UWAFT PHEV. Having the vehicle in the correct mode eliminates having

the engine on unnecessarily and allows the UWAFT PHEV to operate in the most efficient mode.

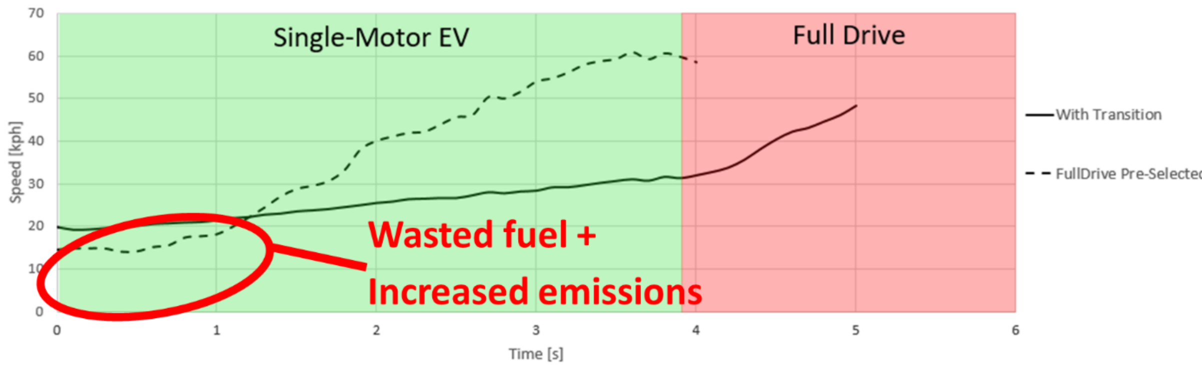


Figure 30: Vehicle Speed Trace during Wide Open Throttle Acceleration Test (Eco-Cautious Drive Trace Marker)

8.4 ADAS Algorithm Performance

The predictive powertrain management strategy based on driver behaviour recognition discussed throughout this report has many areas in which it may be enhanced. One of those areas, for example, is the integration of situational information. Depending on the situation the driver is in, it may cause them to behave differently then normal. An example of this is when a driver gets cut off by another vehicle, causing them to brake aggressively, although this doesn't necessarily mean they always brake aggressively. Therefore, including additional pieces of information from ADAS or GPS can help to improve the driver behaviour recognition. The following section discusses the performance of the UWAFT integrated ADAS sensors.

The test connected was a vehicle approach test from 100 meters away. A stationary vehicle was placed in front of the UWAFT PHEV, which had all of the ADAS sensors integrated, and the driver slowly approached the rear of the stopped vehicle. Pylons were set up every 5 metres to act as the ground truth, allowing the range measurement error to be calculated. It should be noted that the vehicle approach test was conducted during the presence of rain, which affected the performance of the sensors.

Figure 31: ADAS Vehicle Approach Test

Object Detection Performance

The UWAFT PHEV's object detection algorithm managed to detect the vehicle in the correct location for the majority of the test. The first detection occurred around 50 meters and it was able to track the vehicle in the frame until the end of the test. The system has a 96% true positive and 4% false positive rate. However, when the vehicle is too small in the video frame, the algorithm has a high false negative rate while maintaining a high true negative rate. For the intended range of less than 50 meters the algorithm performs well. It is expected that the rates drop when more cars are involved.

Table 6: ADAS Object Detection Accuracy Statistics

Statistic	**Percent Detected**
Avg. True Positive Rate	96%
Avg. True Negative Rate	81%
Avg. False Positive Rate	4%
Avg. False Negative Rate	19%

Range Measurement Performance

While approaching the stopped vehicle, the LiDAR sensor was recording distance measurements of the point of interest determined by the object detection algorithm. The figure below shows that the error of the range measurement decreased as the UWAFT PHEV approached the stopped vehicle. One explanation for this may be the presence of rain and the decrease in droplets between the target vehicle and the LiDAR sensor. Additionally, due to the angled nature of the 16 lasers in the LiDAR sensor itself, more lasers were collecting information the closer the UWAFT PHEV got to the target vehicle, allowing the averaged distance to be more accurate.

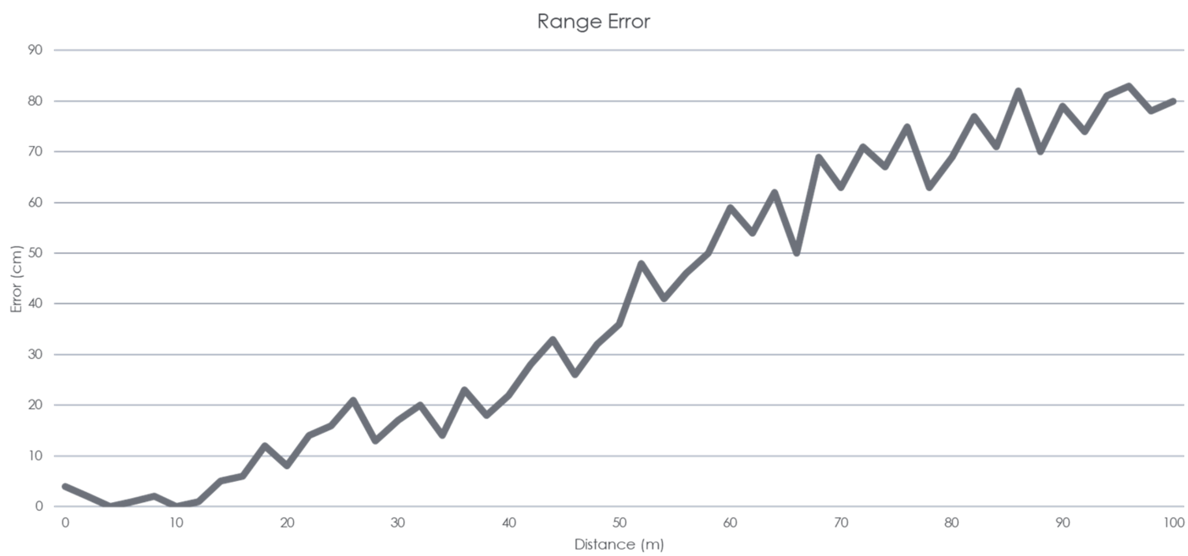


Figure 32: ADAS Range Detection Performance Error

In addition to range measurements, the range rate was also calculated. There is a lot of random error present in the range rate error showed below. This can also be explained due to the presence of rain interfering with the LiDAR's emitted lasers. However, the time measurement technique used was also flawed in this test because processing latencies were not taken into account which would lead to an increase in error.

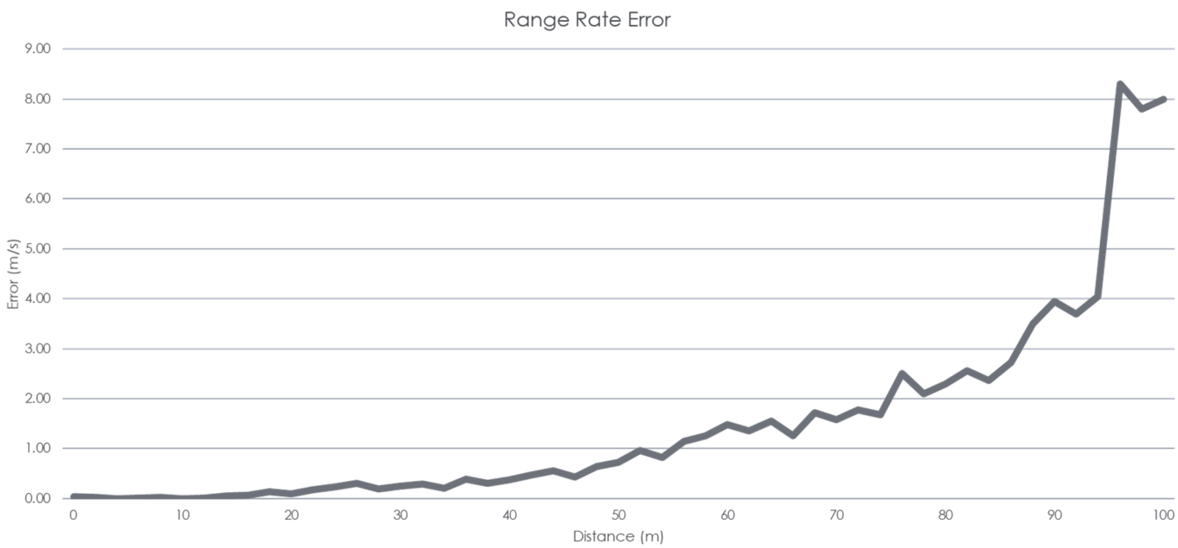


Figure 33: ADAS Range Rate Performance Error

Part III - Conclusions

CHAPTER 9
Conclusions

9.1 Driver Behaviour Recognition Experiment

With the use of the UWAFT PHEV vehicle model developed in Simulink, 288 hours of labelled driving data was simulated. This data represented three different classes of drivers, eco-cautious, normal, and aggressive. The CAN signals that were recorded from the model and used for driver behaviour recognition were accelerator pedal position, brake pedal position, and vehicle speed. Through the process of feature extraction on the logged CAN data, 15 unique features were processed to represent a single driver. Each feature alone was unable to classify an unknown driver behaviour. However, after preforming linear discriminant analysis class separation was more noticeable when projecting the data onto the first two linear discriminants.

Support vector machines were able to take the processed data and classify them into three classes, eco-cautious, normal, or aggressive, with an average accuracy of 81.53%. Some degree of misclassification was expected, as there was crossover between classes; for example, lower-end aggressive drivers and high-end normal drivers. Better representing the classification, fuzzy logic was successfully integrated to assign drivers an aggression value between 0 and 100. Instead of a point near the support vector being classified as either one class or the other, it was given an aggression value through fuzzy logic. The membership functions used for the fuzzy logic were based on the distance the point was to each support vector. This proved beneficial as it helped distinguish between data near the support vector and data further away, also reducing the error of misclassified data near a support vector.

Ultimately, the driver behaviour recognition implemented was successful. As shown, when applied to real world driving data it correctly provided feedback to identify the driver's aggression level.

9.2 Predictive Controls Strategy Experiments

Two scenarios were explored to investigate how a predictive controls strategy could be implemented if the vehicle knew the driver's behaviour. One was an acceleration event where the UWAFT PHEV was in different operating modes, and the other was a braking event using different regenerative braking parameters.

By observing the results from the acceleration testing experiment, two conclusions can be drawn as described below:

1. If the driver's acceleration behaviour exceeds the profile of the acceleration test with a mode transition, then starting the UWAFT PHEV in full drive mode will benefit the driver when such acceleration event is imminent. Correctly identifying this increases the driveability of the UWAFT PHEV as the driver won't experience the lag required to set the vehicle into the correct operating mode able to meet the torque demands.
2. If the driver's acceleration behaviour falls below the profile of the acceleration test with a mode transition, then the UWAFT PHEV should stay in P3-only electric mode. Correctly identifying this increases the efficiency and decreases the emissions of the UWAFT PHEV. Having the vehicle in the correct mode eliminates having the engine on unnecessarily and allows the UWAFT PHEV to operate in the most efficient mode.

By observing the results from the regenerative braking test it can be seen that properly tuning the regenerative braking parameters to match a driver's braking style results in a gain of as much as 0.1% SOC. Although relatively small, the gain in SOC is per braking event, which can add up over the course of an entire trip. This can also be represented as 0.003% SOC gain per second of braking.

9.3 ADAS Performance Experiment

The integrated LiDAR and camera sensors performed successfully in meeting the competition requirements for the ADAS swim-lane. The camera was able to correctly and accurately detect vehicles in the driver's lane and neighbouring lanes, while the LiDAR determined the distance.

The effectiveness of the system will depend on the effective range of the sensors. The system can only react to what it is able to detect and within the stopping distance of the Camaro. The range of the ADAS sensors is susceptible to environmental and operating conditions of the vehicle. Due to the use of lasers in the LiDAR system, environmental conditions such as rain and snow will reduce the range of the system as it adds noise. In turn, this limits the maximum effective speed that the UWAFT PHEV's ADAS sensors can operate at because, the faster the vehicle is moving, the longer the required stopping distance is.

Similarly, the forward-facing camera is susceptible to low light conditions. Nighttime driving will experience reduced range because of the darkening of the image that is used to detect vehicles. This is partially mitigated by the vehicle's headlights, but the system will still have increased difficulty and reduced confidence in detecting vehicles in the adjacent lanes.

Ultimately, UWAFT PHEV made good progress towards a viable ADAS solution. The algorithms proved successful for their intended purpose and with additional refinement, they can be depended upon for detecting dangerous situations.

9.4 Innovation Project

The innovation project proposed and investigated throughout this thesis has a lot of potential to change the way the hybrid supervisory controller makes decisions. By utilizing machine intelligence techniques over time, the UWAFT PHEV has proven it can learn how the driver behaves. With these additional pieces of information the controls system becomes more advanced. By knowing the driver will accelerate aggressively, the UWAFT PHEV can primitively enter a vehicle mode that will be able to provide the torque requested. This reduces the lag the driver would normally experience, increasing the driveability of the vehicle. A few of these scenarios are explored in the predictive controls strategy experiments section above.

Ultimately, this brought a unique feature to the UWAFT PHEV that is desired by the target market. The aim to reach tech savvy individuals pushed UWAFT to implement state-of-the-art technology allowing these features to be first to the market for their customers. Additionally, the benefits of the hybrid supervisory controller knowing the driver's behaviour creates a more environmentally friendly vehicle. This supports the subconscious environmentalist who is drawn to a hybrid vehicle in the first place. Lastly, the increase in driveability helps the Camaro to maintain its iconic role as a high performance car.

CHAPTER 10
Discussions and Future Work

The predictive powertrain management controls strategy based on driver behaviour explored throughout this paper is still very much in the early stages of development. There are several features that still need refinement to advance this project to a point where it can be deployed into a vehicle. Along with need for refinement, there are some areas in which expanding this project could improve its overall impact. Those areas include, incorporating the ADAS data, GPS data, and developing a Bayesian network.

10.1 Recommendations for Future Work

Due to the strict timeline of the competition, only 6 months of development was progressed; however, a strong foundation was built on which this project could continue for the next AVTC series UWAFT participates in. The recommendations for future work are discussed in the following section.

Continued Vehicle Testing

Although only one acceleration event and one regenerative braking calibration were tested in this report it is believed that it can be easily expanded to a wide range of scenarios. Continuing to do vehicle testing of the aforementioned experiments with different goals should be a priority. The following experiments should be repeated with the described goals in mind:

1. **Acceleration Testing** – Repeat the experiment conducted in this report for multiple runs at various starting speeds and acceleration rates in different vehicle modes. This will ultimately create a 3D map of acceleration profiles in different modes, just as the experiment in this report showed the best mode for a wide open throttle event given the predicted drive profile (driver's behaviour). The 3D map would be an extension of this

capturing not only wide open throttle events but as many different acceleration types as possible. This would increase the effectiveness of the predictive powertrain management controls strategy as each scenario tested would result in a scenario where the driver's behaviour could factor into the operating mode decision.

2. **Regenerative Braking** – Similarly, repeating the regenerative braking test conducted in the report to encompass additional driving styles would result in improved effectiveness of the predictive powertrain management. Due to time restrictions on the chassis dynamometer, optimized regenerative braking parameters were determined for only one driving style. To see the benefits of utilizing a driver's behaviour to change parameters, optimal parameters need to be found for multiple driving styles. This way, once the driver's behaviour is detected correctly, the vehicle can change to the parameters that best suit them.

Behaviour Recognition Refinement

The methodology described in the report to classify drivers based on their driving behaviour is sound and should be continued to be used in further development. However, the training process needs to be refined. While creating labelled data with the help of the UWAFT PHEV powertrain model proved viable, it is not the most representative of a true driver. Incorporating more data collected via the OBD port data loggers from vehicles driving around roads in real traffic is a more realistic approach. As opposed to following a drive cycle, drivers are more susceptible to sudden stops, aggressive passing, and lateral acceleration in the presence of traffic. These are all actions that help define a driver's behaviour. Thus, refining the training algorithm to use data that is more realistic may improve the results found.

Additional Input Signals

As discussed previously, using data that is more realistic can improve the results and classification accuracy for a driver's behaviour. In addition to this, using more input signals for the algorithm will increase the effectiveness of the overall project. As discussed, sudden stops, aggressive passing and later accelerations all help to define a driver's behaviour, but this depends on the scenario of the driver. Depending on situational or environmental impacts, a driver may need to come to a sudden stop without displaying habits of aggressive driving. An example of this may be an unforeseen object entering the path of the vehicle. Many scenarios like this can introduce errors into the recognition algorithm. Taking the average over the course of a certain timeframe will help to dilute any of the bias data. However, the inclusion of ADAS and GPS data would help to determine environmental and situational impacts to a driver's behaviour. This adds the benefit of predicting a driver's behaviour given a certain repeated scenario.

Bayesian Network Development

One missing factor required for the implementation of the predictive powertrain management strategy that would greatly increase its effectiveness is the development of a Bayesian network. A Bayesian network is a probabilistic graphical model that can be used as the final piece to determine the actions taken by the controls. In other words, given the following inputs – situational data (ex. ADAS), environmental data (ex. GPS), vehicle data (ex. CAN), and driver behaviour data – what is the probability that the driver will accelerate? Once this probability is determined, if it exceeds a defined threshold then the controls can select an operating mode in which the UWAFT PHEV is ready to accommodate the coming requested torque needs.

Gamification

Ultimately, the best way to reduce emissions and energy consumption is to change a driver's behaviour. One potential way to do this is through the gamification of the recognition software. Having a leaderboard and reward system showing the top eco-drivers in your area can unleash people's competitive sides and push them to drive more eco-cautiously. Knowing the way you're driving affects your fuel economy and seeing the comparison to others also brings light to the situation allowing you to make improvements. This may also result in a less complex need to have a predictive powertrain management strategy if the recognition software is focused on changing the way people drive rather than adapting to it.

ADAS Potential Issues

Although the implemented ADAS was successful, it is important to keep in mind potential issues identified by the team. Minimal in-vehicle testing was completed due to lack of dedicated ADAS work time, thus there is a possibility of these issues arising.

1. **Transmitting data over CAN** – Ensure that data being sent from the Jetson TX2 is without errors and has the correct identifications number. Sending the data to the wrong receiver could be catastrophic. There is also a need to make sure the Jetson TX2 receives the correct data to perform relative speed calculations. At the same time, UWAFT must be cautious not to overload the CAN bus. Otherwise, the car will not be able to function.

2. **Latency** – Ensure latency of the system is kept to a minimum to maintain real-time reliability. Evaluate performance by benchmarking the ADAS system’s time from detection to alerting. Additionally, for the system to be reliable, the system needs to notify the driver when it is not functional. When the system is not confident in performing in adverse conditions such as low light or heavy precipitation, the driver feedback system needs to alert the driver for attention. Detecting these conditions can be challenging but can be accomplished by analyzing noise in LiDAR signals and the overall light levels in the forward-facing camera.

References

[1] "Advanced Vehicle Techonolgy Competition Series," Argonne National Laboratory, [Online]. Available: avtcseries.org. [Accessed 06 06 2018].

[2] Lulu Si, Mario Hirz, and Helmut Brunner, "Big Data-Based Driving Pattern Clustering and Evaluation in Combination with Driving Circumstances," SAE International, 2018.

[3] E. Schmidt, "Electric Vehicle Sales In Canada, 2017," Fleet Carma, 8 February 2018. [Online]. Available: https://www.fleetcarma.com/electric-vehicle-sales-canada-2017/. [Accessed 8 6 2018].

[4] UWAFT, "Architecture Selection Proposal," University of Waterloo, Waterloo, 2015.

[5] Raed Kadri, Sam Saad, "Connected and Autonomous Vehicles in Ontario: Technology Highlights," 28 March 2018. [Online]. Available: http://www.oce-ontario.org/docs/default-source/default-document-library/avin-report-(28-03-2018).pdf. [Accessed 8 June 2018].

[6] E. T. Shahriar Shafiee, "When Will Fossil Fuel Reserves be Diminshed," *Energy Policy* , vol. 37, no. 1, pp. 181-189, 2009.

[7] E. W. Jeremy Neubauer, "The Impact of Range Anxiety and Home, Workplace, and Public Charging Infrastructure on Simulated Battery Electric Vehicle Lifetime Utility," *Journal of Power Sources*, vol. 257, no. 1, pp. 12-20, 2015.

[8] S. Davis, "Transportation Energy Data Book," U.S. Department of Energy, Tech. , 2000.

[9] "Vehicle and Fuel Emissions Testing," United States Environmental Protection Agency, 31 January 2017. [Online]. Available: https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules#main-content. [Accessed 8 6 2018].

[10] Felipe Jiménez, Juan Carlos Amarillo, José Eugenio Naranjo, Francisco Serradilla, Alberto Díaz, "Energy consumption estimation in electric vehicles," University Institute for Automobile Research (INSIA), Madrid, Spain, 2015.

[11] Jeffrey Gonder, Matthew Earleywine and Witt Sparks, "Analyzing Vehicle Fuel Saving Opportunities through," SAE International, 2012.

[12] E. Ericsson, "Independent driving pattern factors and their influence on fuel-use and exhaust emission factors," *Transportation Research Part D: Transport and Environment,* vol. 6, no. 5, pp. 325-345, 2001.

[13] Taeyoung Lee and Joonwoo Son, "Relationships between Driving Style and," SAE International, South Korea, 2011.

[14] Fazal Syed, Swathi Nallapa, Allen Dobryden, Carrie Grand. et al. , "Design and Analysis of an Adaptive Real-Time Advisory System for Improving Real World Fuel Economy in a Hybrid Electric Vehicle," SAE International, 2010.

[15] "IHS Markit," 2 January 2018. [Online]. Available: http://news.ihsmarkit.com/press-release/automotive/autonomous-vehicle-sales-surpass-33-million-annually-2040-enabling-new-auto. [Accessed 8 June 2018].

[16] "SAE International," 3 September 2017. [Online]. Available: /https://www.sae.org/misc/pdfs/automated_driving.pdf. [Accessed 8 June 2018].

[17] N. H. T. S. Administration, "Crash Stats," February 2018. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812451. [Accessed 8 June 2018].

[18] "Top 25 Causes of Car Accidents," Pines Salomon Injury Lawyers, [Online]. Available: https://seriousaccidents.com/legal-advice/top-causes-of-car-accidents/. [Accessed 8 June 2018].

[19] F. T. D. W. a. F. W. Seunghyuk Choi, "Advanced driver-assistance systems: Challenges and opportunities ahead," McKinsey & Company, February 2016. [Online]. Available:

https://www.mckinsey.com/industries/semiconductors/our-insights/advanced-driver-assistance-systems-challenges-and-opportunities-ahead. [Accessed 8 June 2018].

[20] Andrew Liu, Nobuyuki Kuge, Tomohiro Yamamura and Osamu Shimoyama, "A Driver Behavior Recognition Method Based on a Driver Model Framework," SAE International, Detriot, Michigan, 2000.

[21] Patrick Brombacher, Johannes Masino, Michael Frey, Frank Gauterin, "Driving Event Detection and Driving Style Classification using Artificial Neural Networks," IEEE, Karlsruhe, Germany , 2017.

[22] D. A. Johnson and M. M. Trivedi, "Driving style recognition using a smartphone as a sensor platform," IEEE, Washington, DC, 2011.

[23] Minh Van Ly ; Sujitha Martin ; Mohan M. Trivedi , "Driver classification and driving style recognition using inertial sensors," IEEE, Gold Coast, QLD, Australia, 2013.

[24] Wenshuo Wang, Student Member, IEEE, Junqiang Xi, Alexandre Chong, and Lin Li, "Driving Style Classification Using a Semisupervised Support Vector Machine," IEEE, 2017.

[25] Ahmad Aljaafreh, Nabeel Alshabatat, Munaf S. Najim Al-Din , "Driving style recognition using fuzzy logic," IEEE, Istanbul, Turkey, 2012.

[26] Oussama Derbel, ReneJr Landry , "Driving Style Assessment Based On the GPS Data and Fuzzy Inference Systems," Département de génie électrique, Montreal, Canada , 2015.

[27] Andreas A. Malikopoulos, Dennis N. Assanis, Panos Y. Papalambros , "Optimal Engine Calibration for Individual Driving Styles," SAE International, Detroit, Michigan, 2008.

[28] Tae-Kyung Lee and Zoran Filipi , "Real-World Driving Pattern Recognition for Adaptive HEV Supervisory Control: Based on Representative Driving Cycles in Midwestern US," SAE International, Michigan , 2012.

[29] *Project Management Swimlane: Year 3 Roadmap,* Argonne National Laboratory, 2017.

[30] *Mechanical Swimlane Year 4 Roadmap,* Argonne National Laboratory, 2017.

[31] *Controls Systems Modeling & Simulation Swimlane: Year 4 Roadmap*, Argonne National Laboratory , 2017.

[32] *Electrical and Computer Engineering Swimlane: Year 3 Roadmap*, Argonne National Laboratory , 2017.

[33] *Innovation Swimlane Year 4 Roadmap,* Argonne National Laboratory, 2017.

[34] UWAFT, "Consumer Market Research Report," University of Waterloo, Waterloo, 2014.

[35] K. Foster, "What's Good about Generation Y?," Greater Good, 24 January 2013. [Online]. Available: https://greatergood.berkeley.edu/article/item/whats_good_about_generation_y. [Accessed 10 December 2014].

[36] C. D. a. R. Whelan, "Cities Outpace Suburbs in Growth," The Wall Street Journal, 28 June 2012. [Online]. Available: https://www.wsj.com/articles/SB10001424052702304830704577493032619987956. [Accessed 10 December 2014].

[37] Deloitte, "Gen Y Takes the Road Less Traveled," The Wall Street Journal, 2 December 2014. [Online]. Available: https://deloitte.wsj.com/cio/2014/12/02/gen-y-takes-the-road-less-traveled/. [Accessed 11 December 2014].

[38] R. Kartha, "The Evolution of a Supervisory Controller for a Split Parallel Plug-in Hybrid Electric Vehicle," University of Waterloo, Waterloo, 2017.

[39] "Autonomie," Argonne National Laboratory, Argonne.

[40] A. V. T. Competition, "Non-Year-Specific Rules," EcoCAR3, Argonne, 2018.

[41] Redmon, J., Divvala, S., Girshick, R., Farhadi, A., "You Only Look Once: Unified, Real-Time Object Detection," CVPR, 2016.

[42] A. M. Martinez, "PCA versus LDA," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 2, pp. 228-233, 2001.

[43] Corinna Cortes, Vladimir Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273-297, 1995.

[44] J. B. MacQueen, "Some Methods for classification and Analysis of Multivariate Observations.," *Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability.*, vol. 1, pp. 281-297, 2009.

[45] V. P. I. a. M. J. Novák, "Mathematical principles of fuzzy logic," Dodrecht: Kluwer Academic., 1999.

[46] "Dynamometer Drive Schedules," United States Environmental Protection Agency, [Online]. Available: https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules. [Accessed 06 06 2018].

[47] *FleetCarma*, Waterloo, Ontario: FleetCarma, A GEOTAB Company.

Part IV - Appendices

APPENDIX A

Vehicle Technical Specifications

Table 7: UWAFT Vehicle Technical Specifications

Specification	UWAFT's Target	Simulation Results
Acceleration, IVM-60mph [s]	5.82	5.6
Acceleration, 50-70mph (Passing) [s]	6.6	3.2
Braking, 60-0mph [ft]	121.4	121
Acceleration Events Torque Split (Fr/Rr)	0/100	0/100
Lateral Acceleration, 300ft. Skid Pad [G]	0.84	N/A
Double Lane Change [mph]	54.4	N/A
Highway Grade ability, @60 mph for 20 mins	6%	7%
Cargo Capacity [ft^3]	2.4	2.4
Passenger Capacity	4	4
Vehicle Mass [kg]	N/A	N/A
Curb Mass [kg greater than stock]	275	160
Starting Time [s]	5	N/A
Total Vehicle Range [km]	301	303.79
CD Mode Range [km]	36	53.79
CD Mode Total Energy Consumption [Wh/km]	267.8	223.44
CS Mode Fuel Consumption [mpgge]	30	42.89
UF-Weighted Fuel Energy Consumption [Wh/km]	736.6	232.71
UF-Weighted AC Electric Energy Consumption [Wh/km]	23.8	116.87
UF-Weighted Total Energy Consumption [Wh/km]	758	349.59

UF-Weighted WTW Petroleum Energy Use [Wh PE/km]	621	67.92
UF-Weighted WTW Greenhouse Gas Emissions [g GHG/km]	222.6	113.93
UF-Weighted Criteria Emissions [g/km]	2.64	0.402

APPENDIX B

Regenerative Braking Test Results

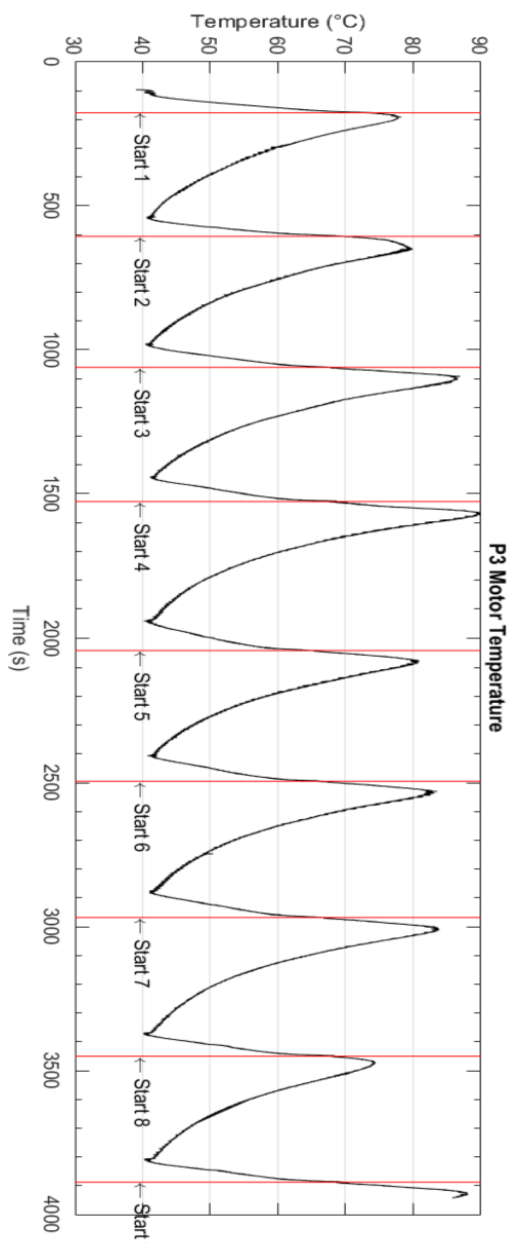


Figure 34: P3 Motor Temperature during Nine Regenerative Braking Tests

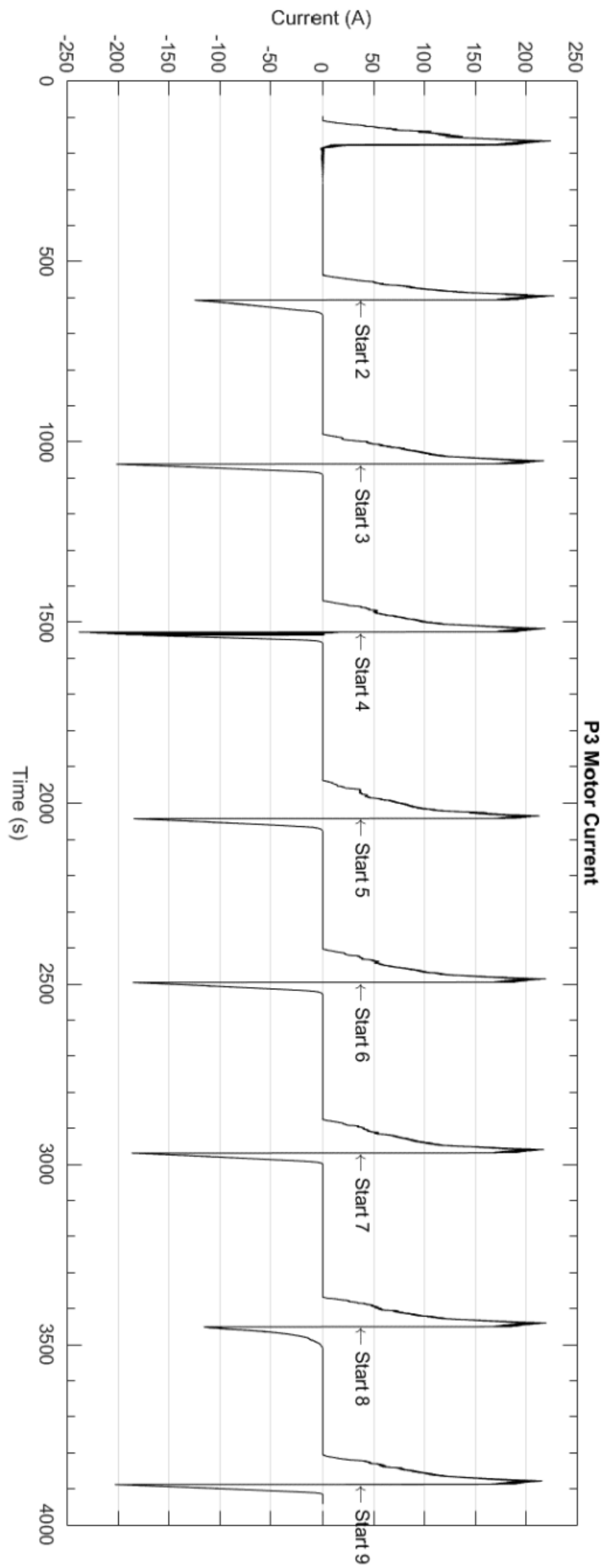


Figure 35: P3 Motor Current during Nine Regenerative Braking Tests

APPENDIX C

Driver Behaviour Classification Example

Below is the fuzzy logic representation of the classification of an aggressive driver after preforming LDA and SVM. The aggression value given to this driver was 85.9% and the driver was classified via SVM as aggressive.

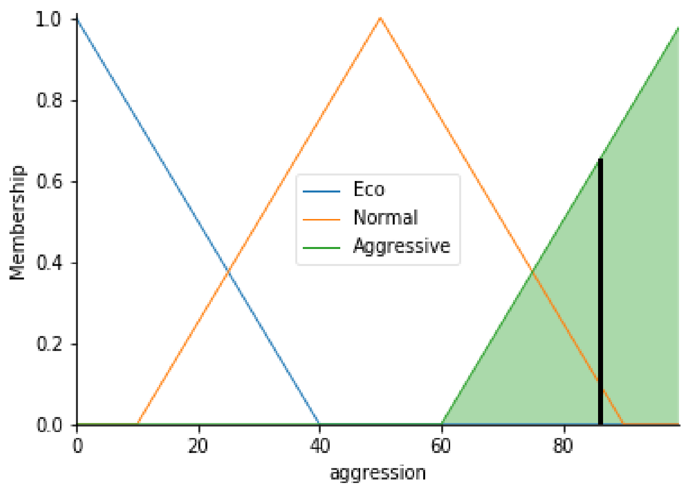


Figure 36: Classification of One Driver Using Aggression Membership Function

Below is another classification of an aggressive driver; however, in the case above the SVM classifier initially misclassified the driver's behaviour. The aggression value assigned to the driver is 74.57%, meaning although it was incorrectly classified, with the use of fuzzy logic the aggression value still accurately represents the driver's behaviour and provides more information as opposed to only identifying which class it belongs to.

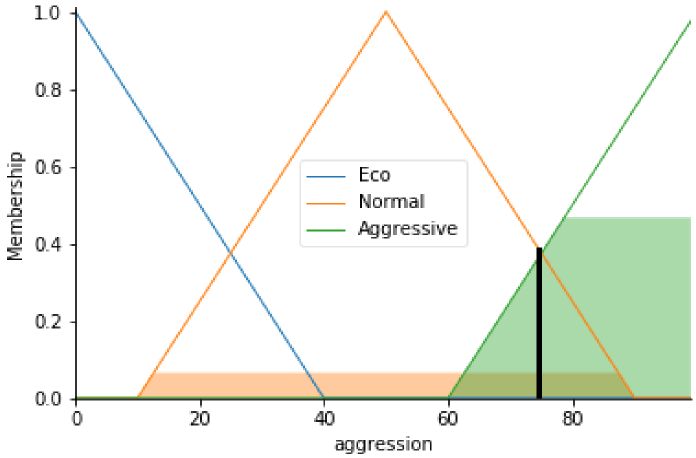


Figure 37: Misclassification of One Driver Using Aggression Membership Function