Intelligent Vehicle Development through Scalable Data Collection Processes and Simulation

by

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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 be made electronically available to the public.

Abstract

With current automotive trends in both vehicle electrification and intelligent features such as Advanced Driver-Assistance Systems (ADAS), there is a significant need for a modern vehicle development process which makes use of big data. In the following report, a scalable, phone-based, driving data collection system is developed and applied to powertrain design through a motivating example. Initial project efforts are directed towards the development of both a data collection platform and a system which is capable of interpreting and storing the collected drive data. The developed UWAFT Innovation Platform (UIP) and Monocular Vision Pipeline (MVP) are a functional system which attempt to precipitate crowdsourcing of data collection through a low system cost and open software approach. In an application of this platform data is collected by a test driver for a month in the form of a pilot project, with results evaluated in terms of geographical coverage and with the development of a statistical event profile detailing events of simulation value. The data collected contains over 6 million data points, and over 7.45hrs of driving. In evaluating MVP performance, the You Only Look Once (YOLO) multi-object detector and Markov Decision Process (MDP) multi-object tracker are implemented, with results demonstrating robustness to occlusions and the capability to detect far-away pedestrians and vehicles. With this data collection system functional, and the data from the pilot project experiment, a powertrain simulation environment for University of Waterloo Alternative Fuels Team (UWAFT) is developed. Given the Advanced Vehicle Technology Competition (AVTC) process, it is crucial to continue to explore and design novel powertrain configurations in an environment which is conducive to flexible configuration and with acceptable ease-of-use. Of the environments available, Simscape is selected and a novel Metal-Air Extended Range Electric Vehicle (MA-EREV) powertrain model is developed as a validation of the simulation tool. Upon validating simulated VTS

against existing work, results are consistent excluding a 15% reduction in estimated range and a 41% decrease in 50-70 mph acceleration time. To provide an example of the data-driven approach, a winter-driving scenario where the pilot project driver demonstrated slipping is imported as a drive cycle in the MA-EREV model and simulated in an experiment. In analyzing results traction performance of the MA-EREV is evaluated. The MA-EREV weighs 677kg more than the pilot project vehicle, and has increased starting torque due to electrification. In analyzing the results of this scenario replication, the longitudinal slip on the tires reached a maximum of 41% slip (94% of available traction) during stopping and 84% slip (55% of available traction) during acceleration from stop, with more slipping overall during acceleration than stopping. This result indicates that the MA-EREV may need additional traction considerations for safe performance in winter conditions.

Acknowledgments

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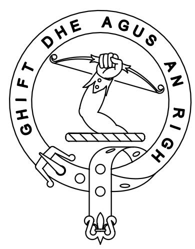
To my Family



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List of Abbreviations

ADAS Advanced Driver-Assistance Systems iii, 1, 12, 14, 17, 18, 21–23, 25, 27, 29, 32, 56, 59, 60, 70, 73–75, 78, 79

ANL Argonne National Laboratories 8, 34

AVTC Advanced Vehicle Technology Competition iii, v, 1, 2, 4, 5, 7, 21, 22, 33, 34, 37, 54, 77

BEV Battery Electric Vehicle 3, 4

CD Charge-Depleting 6

CIL Controller in Loop 7

CS Charge-Sustaining 6, 48

ECM Equivalent Circuit Modelling 10, 11

eLSD electronic Limited Slip Differential 5

EPA Environmental Protection Agency 4, 34, 49, 51, 56

ESS Energy Storage System 5, 6, 37, 48, 79

FOV Field of View 30

GPS Global Positioning System 1, 22, 28–30, 74

HEV Hybrid-Electric Vehicle 4, 6

HIL Hardware in Loop 7

HSC Hybrid Supervisory Controller 7

HWFET Highway Fuel Economy Test 4, 5, 52, 57, 63

ICE Internal Combustion Engine 2–4

KITTI Karlsruhe Institute of Technology and Toyota Technological Institute 30

MA-EREV Metal-Air Extended Range Electric Vehicle iii, iv, 2, 37, 39, 41, 43, 44, 47–50, 57, 58, 63–66, 68, 71, 72

MDP Markov Decision Process iii, 15, 16, 27, 70, 78

MIL Model in Loop 7

MOT Multi-Object Tracking 15

MVP Monocular Vision Pipeline iii, 1, 2, 26, 30–32, 73–75

OBD On-board Diagnostics 1, 22, 23, 27, 31, 73–75, 77

P2 Pre-Transmission 6

P3 Post-Transmission 6

PHEV Plug-in Hybrid Electric Vehicle 4, 5

SIL Software in Loop 7

SOC State of Charge 6, 48, 52, 63

UDDS Urban Dynamometer Driving Schedule 4, 5, 52, 57, 63

UIP UWAFT Innovation Platform iii, 22–27, 29–31, 56, 57, 71, 73–75, 77, 86

UWAFT University of Waterloo Alternative Fuels Team iii, 1, 2, 4–8, 10, 12, 19, 21–27, 29, 30, 34–37, 60, 61, 71, 73–75, 77, 79

VTS Vehicle Technical Specifications 2, 6, 34, 48, 51, 63, 71, 77, 79

WTW Wheel-to-Well 3

YOLO You Only Look Once iii, 14, 15, 26, 78

CHAPTER 1

Introduction

In the following thesis, a data-driven design approach to developing vehicles with intelligent features for AVTCs and industry is explored. Topics within this thesis were initiated for the EcoCAR 3 AVTC, which provides students at 16 universities in North America with hands-on automotive development experience, closely mirroring the processes in the industry. Recently, as vehicles adopt an increasing number of ADAS and other intelligent capabilities, the EcoCAR AVTC has included events involving these technologies - with a focus on computer vision systems.

In a response to this shift in competition focus, the UWAFT has developed cross-disciplinary partnerships, with a focus on autonomous vehicle research involving the 'Autonomoose', Canada's first autonomous vehicle approved for driving on public roads. Through this partnership, and the ADAS development of EcoCAR 3, a significant demand for developmental data was identified. With ADAS and autonomous vehicle development, a significant quantity of training and simulation is required, along with vast quantities of data to support the training and testing of systems for which reliability is vital. In addressing this need for data, UWAFT has developed an innovation platform based upon an android app, server backend and On-board Diagnostics (OBD) interface system. This system has the capability to record high-quality video, with Global Positioning System (GPS), accelerometer and OBD data simultaneously at a cost of below 500 Canadian dollars. This system is proven capable in a pilot project experiment where millions of datapoints are recorded, capturing unusual events and objects which are valuable in the generation of testing scenarios. Additionally, to make use of the data captured by the phone system, a MVP is implemented to identify and track objects in the video feed. With the combination of both the innovation platform and the MVP, it becomes possible to analyze and replicate the recorded data for testing or continuous improvement purposes. Given the affordability of the data capture platform it is possible to crowdsource data collection on much larger scales, fostering diversity and robustness in intelligent vehicle systems. By providing the data as an open resource, additional benefits to the industry are realized through the conduction of open innovation which has been effective in the past.

In a second, parallel, activity a powertrain simulation experiment is conducted in an environment selected for its ease of use and flexibility. Given that metal-air type batteries have a theoretical energy density multiple times better than conventional lithium-ion type batteries, it is feasible that in future AVTCs UWAFT will want to consider this technology. One promising application of metal air technology is in a powertrain configuration called the MA-EREV, which uses a range-extending battery in place of an Internal Combustion Engine (ICE). As this powertrain's Vehicle Technical Specifications (VTS) are fully developed in existing work, an experiment validating a model in the selected Simscape environment for the simulation of VTS is conducted and results are compared as a validation of model accuracy.

In an experiment which demonstrates the data-driven design approach, data captured during the pilot project driving experiment is applied to the powertrain development process in the form of a simulation experiment. In this experiment, the time and velocity of the driver's vehicle during a loss of traction event on a snow-covered road is fed into a simulation using the MA-EREV powertrain model to identify potential issues with traction performance. It is expected that behaviour will differ given the significant difference between the curb weight of the driven ICE vehicle and the MA-EREV, which has significantly increased starting torque.

The experiments and tools are described in two major sections: platform development and applications. First, in the platform development section, the implementation of the scalable data capture platform and the MA-EREV powertrain simulation are described. Second, in the Applications section, a vehicle and environment simulation is conducted and the pilot project and vision pipeline results are presented alongside the powertrain validation.

CHAPTER 2

Literature Review

2.1 Motivation for Electrification in Road Vehicles

In Ontario, in 2016, 71% of the electrical energy produced is sourced from nuclear, hydro, wind and solar sources which minimize carbon emissions, providing a significant environmental benefit to vehicles which consume electrical energy in comparison to conventional ICE vehicles [1]. The concept of quantifying environmental impact through analysis of the entire power generation, supply, and consumption process is called Wheel-to-Well (WTW) emissions; and with this perspective it is clear that electrified powertrains, backed by clean power generation, provide a significant reduction in global carbon emissions. Due to the possible WTW benefits many nations are taking steps to minimize the emissions of transportation vehicles now and in the future through support of powertrain electrification in combination with clean power generation.

2.2 Hybrid-Electric Vehicle Adoption

There are multiple ways in which a powertrain can be electrified. Though all options provide a method of reducing the environmental impact of transportation, some are more attractive to consumers than others.

In the purest sense, an approach to electrified powertrains is to use a single, electrical, power-source in the form of a Battery Electric Vehicle (BEV). These vehicles do not have a secondary power source, requiring charging by the operator. A significant barrier to the adoption of BEVs without a secondary range-extending power source is that potential owners may experience ‘range anxiety’, or a fear of expending the available electrical energy before reaching their destination [2, 3]. This fear is compounded by the low availability of electrical charging infrastructure in public spaces and workplaces.

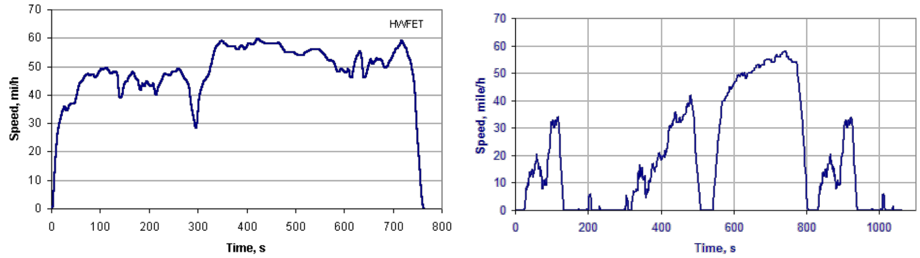
Range anxiety is alleviated in Hybrid-Electric Vehicles (HEVs) such as Plug-in Hybrid Electric Vehicles (PHEVs), which operate similar to a BEV with an additional, range-extending, power source. HEVs with smaller battery packs and an ICE typically burn more fuel with the intention of mixing power consumption more evenly between sources, and with the expectation that drivers will regularly fuel them as with conventional ICE vehicles. An approach which minimizes emissions and which is appealing to consumers is to design PHEVs which operate on the primary, electric power source over the average commuting distance of 40.55km [4]. This approach provides a significant reduction in emissions generation, as a majority of the driving is electrically-powered. By relying more heavily upon electrical power, and investing in clean-energy sources, the world can reduce the environmental impact of transportation significantly.

2.3 Drive Cycles and Emissions Ratings

Drive cycles are a speed-demand traces which are developed for the purpose of characterizing the efficiency and environmental impact of vehicles. Through testing procedures developed by the Environmental Protection Agency (EPA), these dynamometer-based tests develop emissions and efficiency ratings in terms of weighted highway and city performance [5]. The drive cycles used in this rating are the Highway Fuel Economy Test (HWFET) and the Urban Dynamometer Driving Schedule (UDDS) respectively, shown in Figure 2.1 below.

2.4 University of Waterloo Alternative Fuels Team

The UWAFT has competed in 6 AVTC since 1996. Currently the team is competing in the EcoCAR 3 AVTC and has approximately 60 active members on campus. The team is currently operated from the University of Waterloo Student Design Center, where



(a) HWFET drive cycle (b) UDDS drive cycle

Figure 2.1: The highway (a) and city (b) drive cycles

there is a vehicle garage, lift and office space for students to work. Currently the student team has faculty advisors from a variety of backgrounds, including electrical engineering, mechanical engineering and chemical engineering. Due to the University of Waterloo Co-op program, volunteers are typically present in 4 month periods, with a rotation of a large portion of the active members occurring at the end of each period.

2.4.1 EcoCAR 3 Advanced Vehicle Technology Competition

The EcoCAR program is an AVTC which has the aim of engaging students and researchers at 16 universities across North America in the conversion of a provided production vehicle to a hybrid vehicle test platform. The EcoCAR 3 AVTC program is structured across four years, with a yearly competition focus on: powertrain design, vehicle integration, dynamic performance and long-term performance respectively. In EcoCAR 3, a 2016 Chevrolet Camaro is the vehicle for conversion to a hybrid vehicle test platform.

2.4.2 UWAFT Camaro

The Camaro which UWAFT has converted, seen in Figure 2.2, is outfitted with dual 89kW GKN AF130-4 motors, a Weber MPE 850cc turbo-charged engine, and a 16.2kWh Lithium-ion A123 ESS. The UWAFT camaro is a PHEV.

The developed vehicle configuration places the motors at both pre- and post transmission, with a clutch between the pre-transmission motor and Weber engine allowing for control of engine engagement. Channeling the developed torque into the rear wheels is an electronic Limited Slip Differential (eLSD) which increases the dynamic

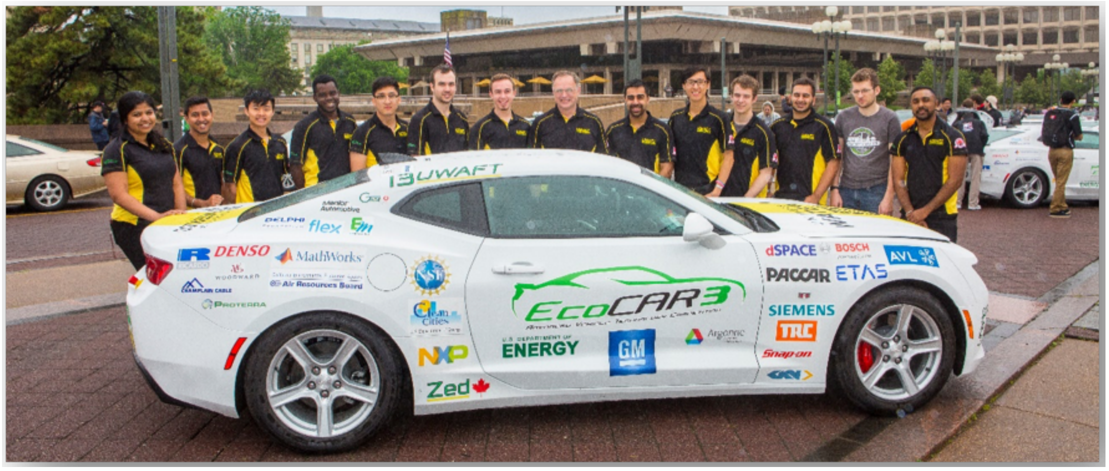


Figure 2.2: UWAFT and the EcoCAR 3 2016 Camaro test platform

handling capabilities of the vehicle. By actuating the clutch, the vehicle can be operated in either Charge-Sustaining (CS) or Charge-Depleting (CD) mode depending on the demands of the driver and the ESS State of Charge (SOC). The primary benefit of the chosen architecture is that it is flexible enough to provide both performance and efficiency without adding significant mechanical integration complexity to the stock vehicle platform. With this architecture, the UWAFT Camaro should be able to maintain or exceed the original VTS in terms of performance and efficiency. A diagram which describes the interconnection and high-level technical specifications of each component is shown in Figure 2.3.

2.4.3 Camaro Powertrain Operating Modes

Demonstrating the flexibility of HEV powertrains, there are three principal operating modes for the UWAFT Camaro, which are detailed in Figure 2.4.

In electric CD mode the motors consume electrical power from the battery to propel the vehicle using one or both electric motors. When the vehicle has depleted the ESS to approximately 20%, CS operation is entered, allowing the vehicle to be driven by the Post-Transmission (P3) motor while the battery is charged by the Pre-Transmission (P2) GKN AF130 motor and Weber engine ‘generation set’. In performance mode, it is possible to use the torque developed by all the components together to drive the vehicle, maximizing acceleration.

Component Description	Performance Specifications	
Engine: Weber MPE 850cc Turbo	Peak Power	92 kW
Transmission: GM 8L45 AT	Number of Gears	8
	Type	Long. Auto
Final Drive: GM 3.73 Final Drive, eLSD	Final Drive Ratio	3.73 : 1
Motors: GKN AF 130-4	Peak Power at 292V	90 kW
	Cont. Power at 292V	64 kW
Battery: A123 6x15s3p	Capacity	16.2 kWh
	Nominal Voltage	292 V
	Peak Current	400 A
Charger: Brusa NLG513	Peak Power	3.3 kW

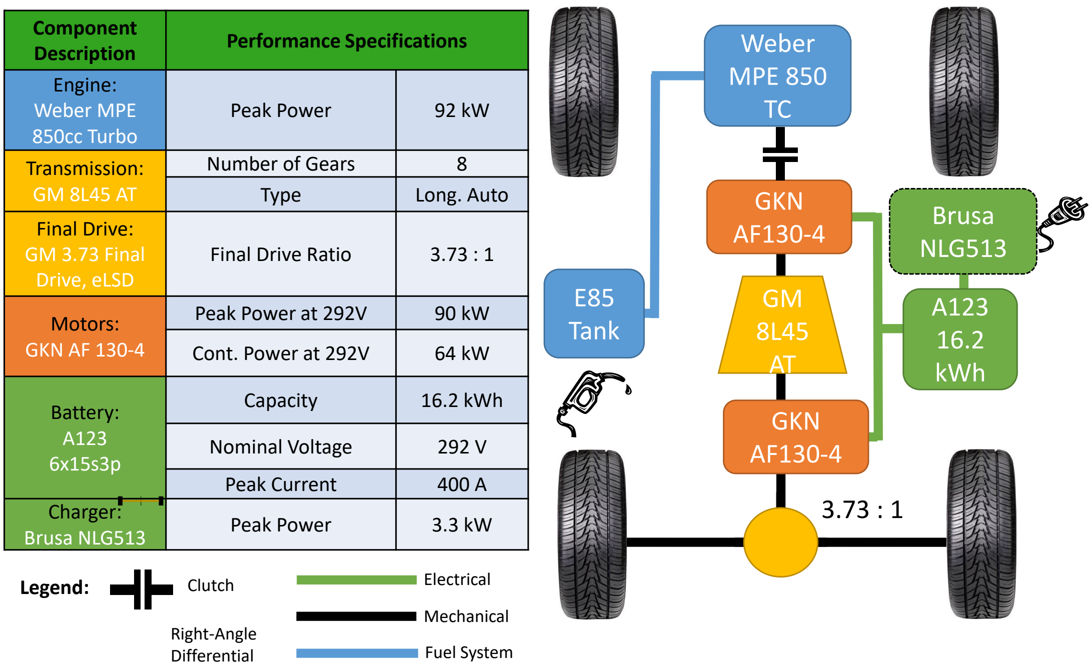


Figure 2.3: The UWAFT Camaro powertrain configuration

2.4.4 Powertrain Development and Simulation Process

One of the most significant aspects of the EcoCAR 3 AVTC timeline is the use of powertrain simulation techniques to tune and develop vehicle performance in stages. The process of developing requirements, implementing software and validating the performance is best represented as a 'V' diagram, seen in Figure 2.5.

Specific testing stages which are used to validate the powertrain functionality are: Model in Loop (MIL), Software in Loop (SIL), Hardware in Loop (HIL), and Controller in Loop (CIL) testing. Each of these stages involve testing of increasing portions of controls software until the vehicle is functional in all powertrain modes. Note that powertrain components are validated in software until the HIL stage, at which point the physical powertrain components are interfaced with their corresponding controls software. An example of using this design process to develop an motor controller in the vehicle and the physical equipment setup used is seen in Figure 2.6 below. Note that the HIL controller is used to simulate the motor-inverter component connected to the the microAutoBox II Hybrid Supervisory Controller (HSC) in this example.

To develop the controllers and software models, there are two options sponsored

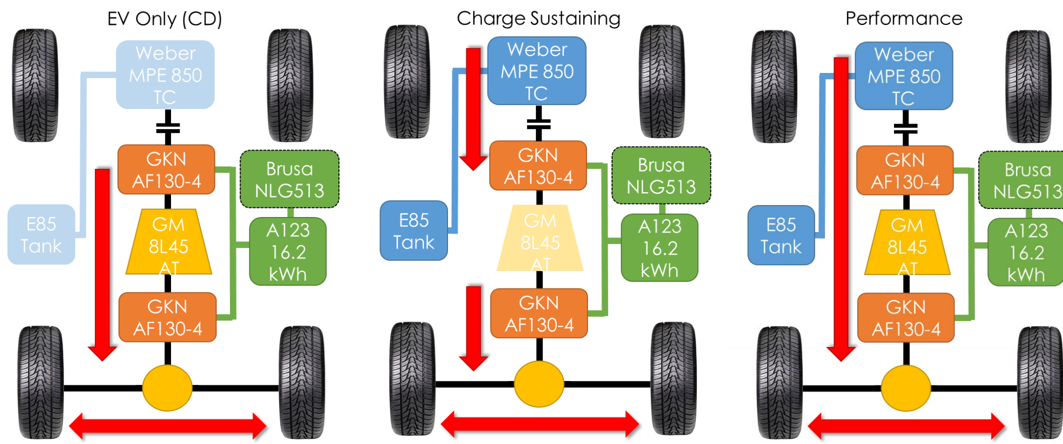


Figure 2.4: UWAFT Camaro powertrain operating modes

by the EcoCAR AVTC series: Autonomie and Simscape. Both of these options are based upon Matlab's Simulink product.

Simulink

Simulink builds upon Mathwork's Matlab software, and it provides a graphical programming environment of foundational 'blocks' and drawn interconnections. Many libraries are included with the provided EcoCAR 3 license which enable the simulation of many diverse signals and functions.

Autonomie

Autonomie is a simulation environment which is developed by Argonne National Laboratories (ANL) for the purpose of vehicle powertrain simulation and development. It builds significantly upon the simulink environment, adding a number of common conventional and hybrid powertrain component models such as DC/DC converters, differentials and motor/inverters which can be connected and configured with use of a graphical interface.

The workflow when using Autonomie is to select from the pre-developed models for components and to batch-run simulations over selected drive-cycles. An additional characteristic of Autonomie powertrain models is that because component-model connections are automatically generated, the resulting graphical representation can be challenging to view or modify.

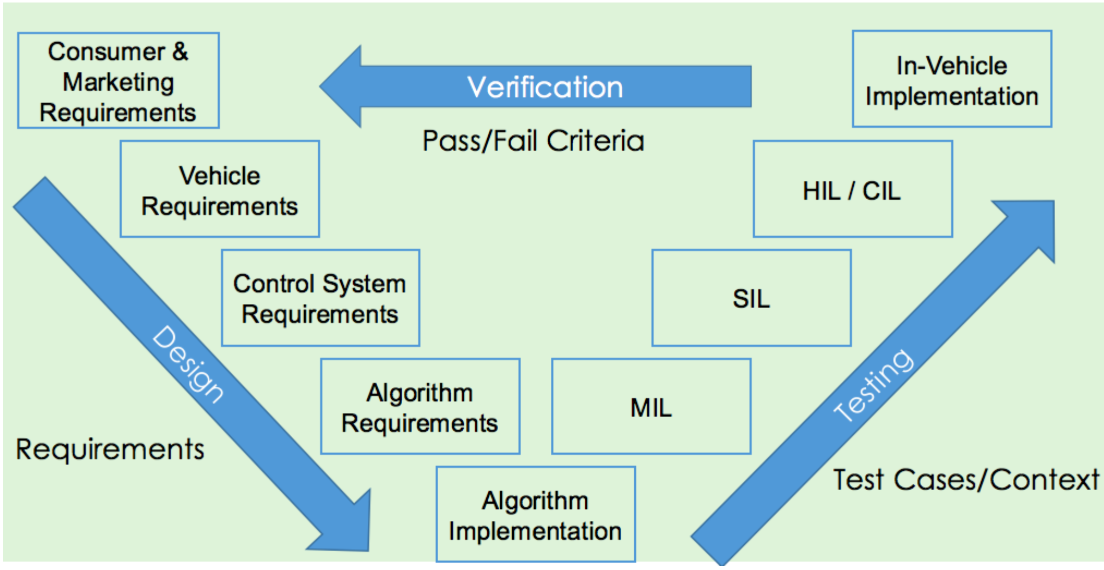


Figure 2.5: The development approach encompassing verification, design and testing

Simscape

Simscape is a toolbox for Simulink that adds capability for the simulation of effort and flow busses akin to those used in conventional bond-graph modelling [6]. In the simulink environment with Simscape, there exist busses which intuitively connect physical displacement, rotational, hydraulic, and electrical domains to component ports directly. Note that many powertrain components are easily integrated from Simscape libraries with minimal parameterization and configuration required; though this can pose issues when fine-tuning the performance or behaviour of an included component model given the inability to change the underlying model. An example of this is in how a tire model transforms from the rotational (green) domain to the translational (dark green) domain, seen in Figure 2.7.

2.5 Battery Modelling

One of the most important components to develop and size appropriately in a hybrid vehicle is the electric battery. Through modelling of a vehicle powertrain with different battery configurations, it is possible to explore the impact of battery parameters and configuration in terms of mileage and performance outcomes. Of relevance to the powertrain models discussed in this paper are the Lithium-Ion battery technology,

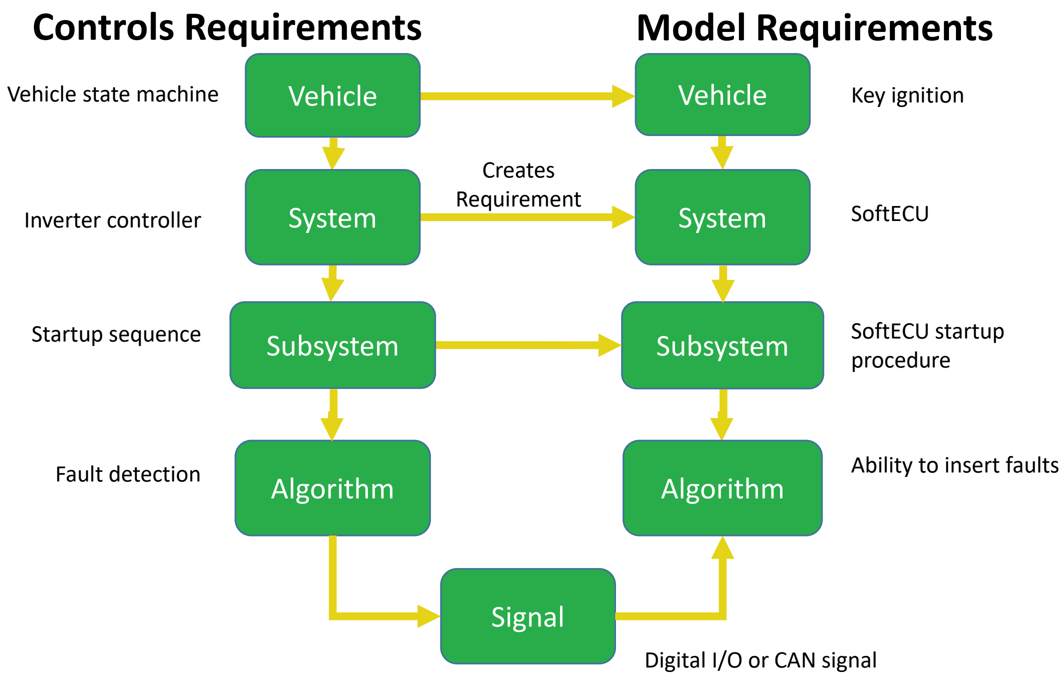


Figure 2.6: In this application example, controls requirements are mapped to model requirements down to a physical signal level

Metal-air battery technology, and Equivalent Circuit Modelling (ECM).

Lithium-ion Battery

Lithium-ion type batteries are desirable for vehicles in comparison to other battery technologies due to having an increased energy density, power density and lifespan, [7, 8]. Through EcoCAR competition sponsor A123 Inc, the UWAFT Camaro is supplied LiFePO4 type batteries seen in Figure 2.8 which have high power density and are more resistant to thermal runaway when compared to traditional Lithium-ion batteries [9, 10].

When a lithium-ion battery discharges, ions traverse from the anode to the cathode through an electrolyte layer and are discharged from the battery [10]. Cells are composed of layers and can be packaged in multiple ways depending on the application. In the A123 batteries, prismatic type cells are utilized with bus-bars connecting multiple cells in series to produce 60 volts per rectangular battery module.

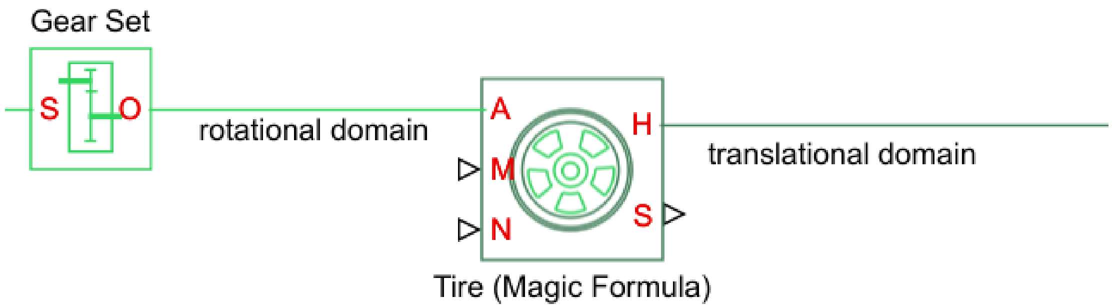


Figure 2.7: The simscape tire model transforms rotational domain energy to translational domain energy

Metal-Air Battery

Metal-air batteries are designed such that the cathode electrode is porous and exposed to air from the environment. Of particular interest to the transportation field is the Zinc-Air battery, which has a theoretical energy capacity of 1084W/kg [11]. A Zinc-air cell is detailed in Figure 2.9 [11].

Currently zinc air type batteries are used in medical applications, and the technology was discovered in 1878 [11]. Due to the unique construction of metal air batteries, it is possible to replace the consumed metal anode and effectively recharge the battery without a lengthy recharging process as in conventional lithium ion batteries [11]. Current metal air batteries suffer from issues with cathode material and crystalline growth, also requiring highly purified metals to function appropriately, but current research is attempting to resolve these issues [11].

Equivalent Circuit Model

A simple ECM for use in modelling battery performance has been developed by the US Department of Energy and is known as the 'rint' model due to its approach of modelling internal cell resistance during both charging and discharging [13]. With the rint model, the open circuit voltage droop of the battery can be determined as a function of current flow from or to the battery. Through a characterization processes [13], the rint model can be scaled and implemented to emulate the behaviour of most battery technologies without requiring low-level chemical process modeling within

Figure 2.8: 6, LiFePO4, A123 battery modules in the configuration used for the UWAFT Camaro test platform

vehicle simulations.

2.6 Object Detection and Tracking for Driver Assistance

ADAS rely upon accurate data representing obstacles, other vehicles, and the road ahead to take actions which protect the driver. One cost effective way of developing ADAS is to utilize forward-facing monocular video to interpret the environment in the direction of travel.

A foundational step of ADAS environment interpretation is the identification of objects within the video frames. When this per-frame information is processed to identify the motion of persistently-visible objects, tracking occurs. Currently, the most effective object identifiers use neural networks which have been trained through exposure to objects [14].

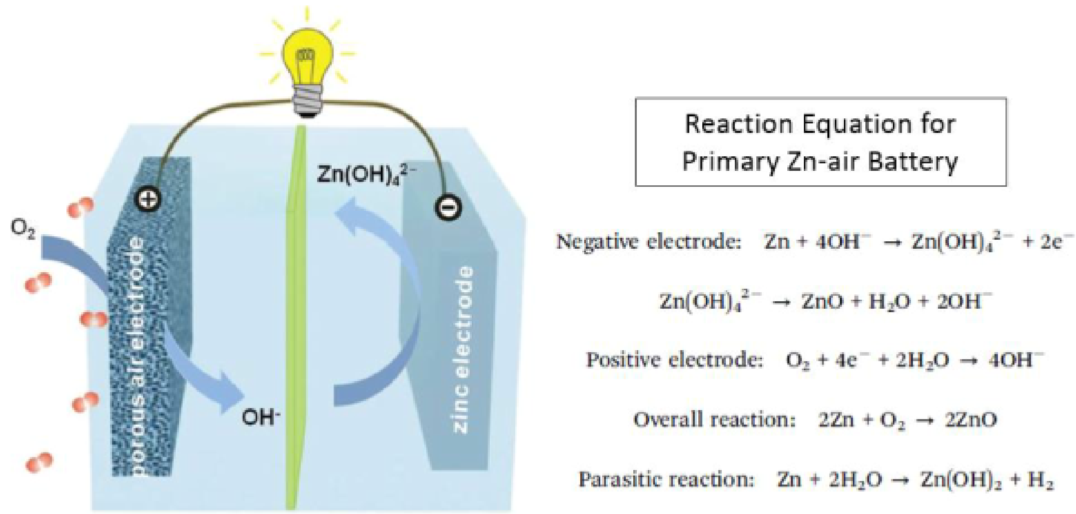


Figure 2.9: Construction of a zinc-air battery cell with associated electrochemical process [12]

Note that three-dimensional position data can be successfully extracted from monocular image frames using ground-plane identification techniques [15].

Neural Networks

Neural networks are a class of algorithm which are inspired from modelling the thinking process of biological nervous systems [16]. A property of neural networks in computer vision is the that, once trained through exposure to a set of labelled image 'ground truth', they are able to identify previously un-seen objects under different poses and lighting conditions [17].

A good case study is in the development of neural networks as an approach to performing facial recognition. In identifying the features of the face, the neural network is first provided many images labeled to be eyes, mouths, noses and complete faces for the creation of a ground truth [18]. By training the neural network with this labelled ground truth, the algorithm is able to learn to identify facial structure and facial features of human faces, identifying faces beyond those used to train the network. In the automotive industry, vision algorithms are expected to identify many complex features such as pedestrians or other vehicles, many times a second, and under many different environmental conditions [17].

You Only Look Once Object Detector

The YOLO algorithm uses multiple novel techniques to execute state-of-the-art object detection accuracy at frame rates which are more than acceptable for automotive applications [19]. YOLO is a general-purpose object detector, able to recognize 9000 different object categories in real-time conditions [19].

There are multiple innovations which YOLO has developed to improve performance compared to larger, slower neural network object identifiers. By treating the object detection problem as a regression problem, the YOLO algorithm is able to predict object identification through analyzing portions of images and developing a probability map for object bounding box locations [20]. This process is illustrated in Figure 2.10.

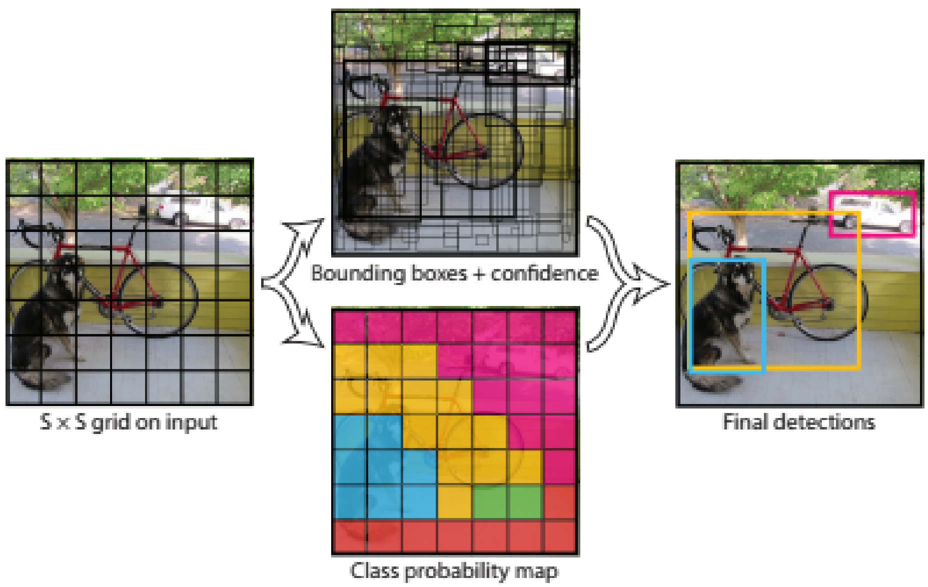


Figure 2.10: YOLO treats the multi-object detection problem as a regression-type problem by subdividing image frames [20]

Improving object classification is the development of a hierarchical tree of visual concepts which makes object classification faster and more robust when identifying new objects within trained object categories. An example of this structure used for object classification, called the WordTree, is seen in Figure 2.11.

Neural network algorithms like YOLO provide the foundational tools in the development of not only ADAS but also autonomous vehicles, given the real-time func-

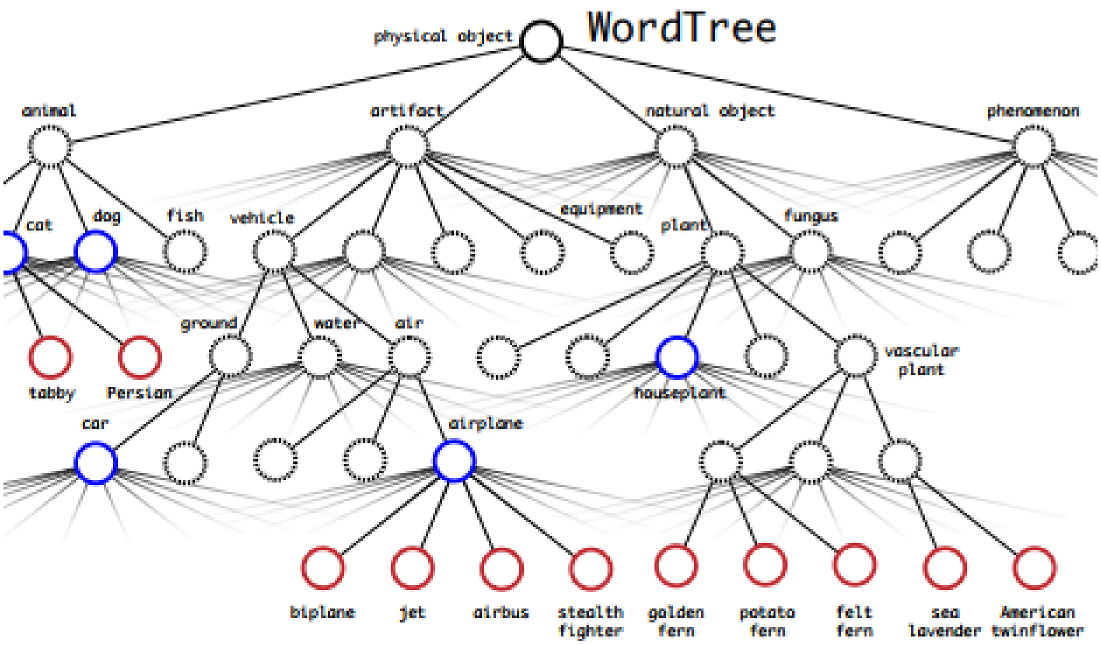


Figure 2.11: The WordTree is foundational to object classification in the YOLO algorithm [19]

tionality, accuracy, and precision of this approach.

Markov Decision Process, Multi-Object Tracker

While object detection is itself foundational to building capabilities to respond to environments and other vehicles, the process of identifying the motion of objects in the surroundings is also crucial, but represents its own challenges. Though there are many tracking algorithms and approaches, this thesis is primarily concerned with the approach of Multi-Object Tracking (MOT) with use of a MDP and optical flow.

Currently many MOT techniques involve tracking by detection; using the per-frame bounding boxes in combination with the object trajectory to label persistent objects via non-causal batch processing [21]. One way of performing tracking causally, or while 'online', is to develop a MDP to identify the state and activity of tracked objects. After an initial ground truth training of the MDP, the algorithm is capable of identifying and handling object appearance or disappearance via state transitions in the MDP. The framework for the MDP, MOT algorithm is shown in Figure 2.12.

While in an active state, the MDP tracking algorithm uses computed optical flow

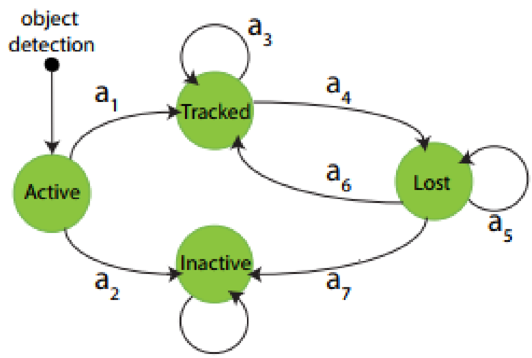


Figure 2.12: The MDP state transition tracks the persence of objects within the scene [21]

traces, the movement of pixel colour between image frames, and the object bounding boxes to identify objects between frames or as they pass behind occluding objects. A visual representation of this type of tracking process is shown in Figure 2.13.

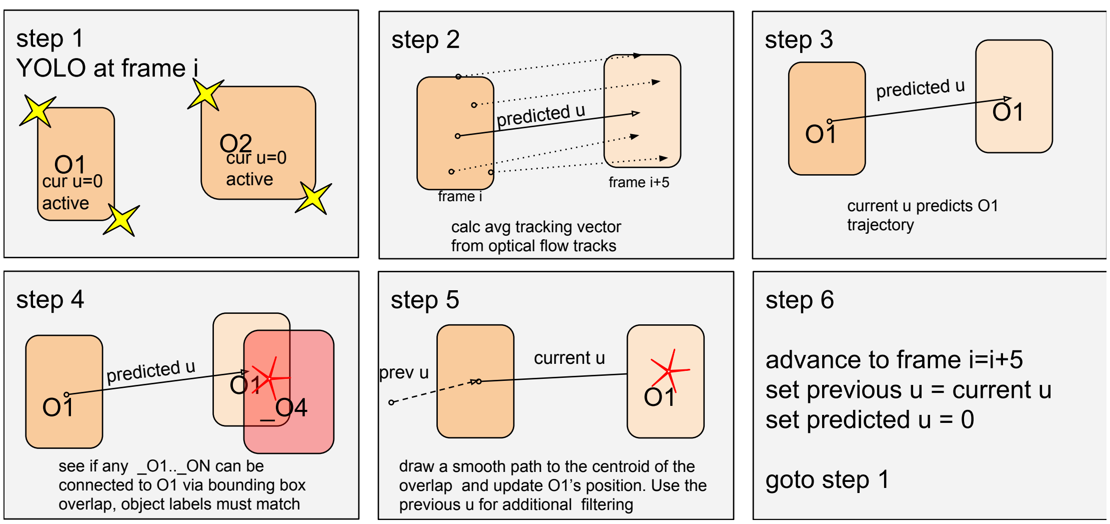


Figure 2.13: An example of a tracking procedure with optical flow techniques

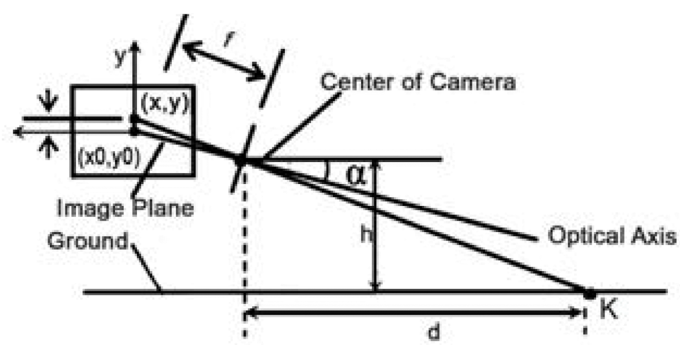
Currently optical flow techniques can be significantly enhanced with application of convolutional neural networks, which attempt to learn the paths of objects within the frame to simplify the matching process, and to overcome the weaknesses of optical flow tracking [22].

By using object detection and tracking methods, it is possible to extract valuable information from video frames with not only the locations of objects within the driving environment, but also their trajectories and past behaviours. With this foundational information, ADAS for autonomous driving become more apparent.

Monocular Distance Estimation

In monocular vision, a single viewpoint is used to develop depth estimations, primarily with use of camera parameters and object detection position relative to an estimation of the horizon. Whereas in stereo vision, with two coplanar cameras a known distance apart, the distances can be additionally estimated given the viewpoint differences. Monocular vision presents more significant challenges in accurate distance estimation as target range increases, and small measurement errors create large range fluctuations [23]. Given the current automotive industry push towards integrating inexpensive monocular vision systems, and the ease of obtaining monocular vision data, it is prudent to make use of this type of camera system for distance estimation as well as object detection [23].

With knowledge of camera optical parameters, mounting position relative to the ground plane, and an object bounding box, it is possible to estimate object distances in 3-D space with a satisfactory degree of accuracy [24, 25]. A graphical illustration of a geometry-based distance estimation process is seen in Figure 2.14.



A.

Figure 2.14: The monocular camera pinhole distance estimation uses geometry to produce estimations [26]

With utilization of monocular distance estimation techniques in combination with object detection and tracking, it becomes possible to process video frames observed by real-world drivers into data representations, valuable in end-to-end testing of autonomous or ADAS algorithms.

2.7 Autonomous Vehicle Industry and Crowdsourcing

Currently the development of intelligent vehicle features such as ADAS is hindered by the availability of naturalistic driving data, especially data which contains test cases for continuous improvement. In a world where autonomous vehicles are operating, exposure of the employed neural networks to edge cases can significantly increase the performance of the vehicle in terms of safety and reliability. Automated driving requires significant quantities of data [27].

Need for Data in Training Neural Networks

Currently, many researchers are approaching the issue of automating the driving process, but there are significant barriers to progress in terms of data availability. Compounding the data availability issue, much of the current research is unavailable to the public due to the cost of obtaining driving data and the strong competition amongst industry leaders in autonomous vehicle development. The current approach of many researchers is to use expensive instrumented cars but these are often not available for data collection and are few in number. This is a significant motivation to develop an openly accessible resource, enabling external innovation by a diverse range of researchers using the data from a centralized resource.

A specific example of the need for data in the industry is the use of neural networks in both perception and path planning of autonomous vehicles. These neural networks require large quantities of data with a broad coverage of driving behaviours in order perform effectively. Even more data still is needed for the training of these neural networks to approach the issue of infrequent edge-case scenarios which pose safety risks as in a recent Tesla autopilot accident [28].

Crowdsourcing

A strong real-world example of the crowd-sourcing approach details the collection of geospatial data in England with use of cellphones by untrained volunteers as a part of the OpenStreetMap project [29]. In this research, it was found that despite formal training or quality assurance procedures for participants, the quality of resulting geospatial data provided 80% coverage at a geometric accuracy of about 6 meters for major roads in the London area compared to Ordnance Survey Meridian 2 [29]. In investigating the quality metrics of the crowd-sourced data, researchers found that because of the approach, repetitions of the data collected occur much more frequently, and this statistically minimized errors in the results [29]. Using the crowd-sourcing method, nearly 30% of England was mapped in just four years, with a focus upon metropolitan areas [29]. The OpenStreetMap project produced volumes of statistically acceptable data using its cellphone-based crowdsourcing approach, and has proven the viability of cellphone data collection systems.

There is also much to be gained by applying the crowdsourcing approach to vision algorithm development for automotive applications as Automated driving requires significant amounts of driving data to design, test, and validate intelligent features [18]. In research dealing with the identification of road signs, the authors identified a major barrier to identification being the impossibility to predict an object's appearance given so many degrees of freedom [30]. Crowd-sourced driver footage inherently collects footage of the same objects across a variety of lighting, weather, and driver conditions from many drivers in different vehicles. Through this approach, it is possible to approach possible algorithm robustness issues inherent in collecting data from a small number of sources with inadequate environmental coverage of objects.

External Innovation

As described in the innovation proposal, UWAFT aims to deliver not only a solution for data capture, but also to provide the anonymized drive data to external researchers for the purpose of progressing the art of autonomous vehicles. It has been proven by the success of companies like Procter and Gamble in the past, that this outsourcing of innovation to external stakeholders invites significant creativity and problem solving benefits [31]. In the case of Procter and Gamble, their innovation success rate more than doubled while the cost of innovation decreased through the open innovation approach [32].

Further support of an open innovation approach is found in the closed approach of financial big data preventing the understanding of links among financial markets by firms [33].

Part I

Platform Development

CHAPTER 3

Data Collection with Vision Pipeline

3.1 Overview

As a part of the EcoCAR3 AVTC, competitors are to develop and present research topics for consideration in the innovation stream of the competition. Upon approaching Dr. Czarnecki of the University of Waterloo Generative Software Department, who has been involved in past UWAFT innovation topics, a need is identified for a data collection platform which provides the information needed to perform continuous improvement of autonomous driving algorithms. The innovation is comprised of two major components: a data collection platform which can be scaled to obtain significant quantities of driving data, and a machine vision backend which can process the obtained information to obtain directly useful information in the areas of end-to-end testing of autonomous vehicles. The duration of the project from time of proposal to the competition is one year.

Currently the development of intelligent vehicle features such as ADAS are hindered by the availability of naturalistic driving data, especially data which attempts to enable continuous improvement or to model baseline performance. In a world where autonomous vehicles are operating, exposure of the employed neural networks to edge cases can significantly increase the performance of the vehicle in terms of safety and reliability.

By providing an open, crowdsourceable platform for the development of data which captures meaningful driving information, UWAFT can approach the data-availability issue in a way that is not only immediately useful to researchers at the University of

Waterloo, but which is also useful for enhancing the UWAFT Camaro's testing capabilities through simulations driven by real-world data.

The developed UIP is an phone application which runs on a conventional Android smartphone to record driving video as a dashcam would with additional OBD, GPS and accelerometer data.

In evaluating the capability of the UIP, experimental designs which demonstrate the value of the data collected are used. Given the nature of the platform, it is necessary to expand the current pilot project as discussed in this section (one person one month) to realize the full potential of this innovation. Experiments conducted with the pilot project center upon the following metrics:

- Coverage of data collected with the system (google map)
- Statistical Event Profile
- Quantity of data collected with the system

After the platform is developed, it is been used in two major experiments:

1. Pilot project data collection with one driver for one month using the UIP
2. Video collection of intersections to evaluate the monocular vision pipeline

3.2 Technical Goals for Innovation Project

Over the course of the EcoCAR 3, year 3, innovation project, UWAFT identified multiple technical goals. These goals are described and defined in the list bellow in terms of their value to EcoCAR 3 AVTC and UWAFT directly:

1. **App Development** After deciding to pursue an Android smartphone-based platform, UWAFT began to develop an app which would capture driving data (video and GPS at minimum) from an android phone mounted to the windshield below the rear-view mirror. Each vehicle costs $450 CAD to fully instrument (cost breakdown in Appendix 5), and the collected data is immediately useful for UWAFT ADAS evaluation and in documenting UWAFT Camaro testing.

2. **Website Backend** To fully crowdsource information with the UIP, it is necessary to develop a centralized resource for participants to contribute to. Upon public operation, this will take the form of a website which provides researchers access to the anonymized video and drive data of the participants, as well as a place for participants to review their own drive data. Note that there are two distinct goals for this system:

    - The functionality of a simplified backend internal to University of Waterloo for pilot projects supporting algorithm development and testing
    - Functionality of the backend as a public research effort to precipitate crowdsourcing supporting industry research efforts

3. **Machine Learning Algorithm** To demonstrate the UIP platform as a viable data collection method in the industry, the UWAFT innovation team plans to develop and test autonomous vehicle neural networks using information captured with the UIP. Immediately, this represents the development of a pipeline supporting algorithm development.

4. 60 **Hours of Video Footage** This technical goal is selected early in the project as a means of defining a meaningful amount of collected information with the UIP to demonstrate metrics of success effectively.

5. **OBD Logging Functionality** This goal is developed because the android phone portion of the UIP must be enhanced with OBD logging capabilities to maximize research opportunities. With OBD data captured, it is possible to capture the driver's physical inputs and to take full advantage of the UIP data in developing and testing systems which aim to model driver actions or responses. This data will also provide direct benefit to UWAFT given the possibility to develop test cases which include human behaviour and vehicle environment factors.

6. **Ground Truth System Integration** In order to evaluate the performance of ADAS and other vision based systems, it is crucial to integrate a ground-truth annotation system which is UIP compatible.

7. **Vision Pipeline** This goal has evolved from a need for automated driving scenario testing in the industry. By extracting additional information from the UIP

data in terms of the agents present around the vehicle, it is possible to approach this need and immediately apply the UIP in autonomous research such as path-planning.

3.3 Impact

Impact Metrics

Impact metrics which use the outlined information are challenging to develop due to the diverse nature of benefits to researchers, however UWAFT has identified two major metrics which can be used to gauge the immediate and crowd-sourced impacts of the UIP data:

The Statistical Event Profile

This profile measures the quantity of events captured which generate a non-baseline human behaviour. This can take the form of response to slipping in icy weather, or the response of a human driver to an ambiguous four-way stop and is best presented in the form of a histogram of events. This metric is developed through manual annotation of captured video.

Data Coverage

The coverage metric represents paths where driving is captured with the UIP. By keeping track of what geographic regions have been logged by the UIP, coverage in terms of road surfaces and road infrastructure can be determined. In the context of the pilot project, this metric is crucial to understanding the expected impact of each contributor to the open database web-resource.

Note that by extrapolating the capability of the one person, one month pilot project to those of the crowd-sourced one, these impacts are also more meaningfully conveyed and understood. In particular, with adoption of the UIP in crowd-sourced quantities, it becomes possible to identify edge case scenarios more easily. Specific, quantifiable impacts are summarized in the following sub-section

3.3.1 Immediate Benefits to UWAFT

Safety-System Performance Benchmarking

A key way in which the UIP has proven useful is in benchmarking ADAS performance with annotated UIP video. A motivating example of this is in road-line detection in the University of Waterloo area. Many existing road line identification algorithms expect road lines to be present and not degraded in terms of the quality of the line [34]. This is not the case in the Waterloo region, currently experiencing a large volume of construction and harsh winter snaps —in many places the road lines are either minimally present or not present at all. By using the footage collected by the UIP, UWAFT has evaluated the performance of road line identifiers, and is able to tune and select an algorithm which operates well with footage of road lines in the region as well as road lines in geographic regions. Given the capability of the UIP to crowd-source data from many geographic regions simultaneously, it becomes possible to develop testing conditions for a diverse range of environments and to inspect the capability of current ADAS features to function in these regions across weather conditions.

Scenario Replication

An additional impact is directly upon the UWAFT Camaro, enabling the recording of vehicle testing and augmenting the existing data collection systems on the vehicle with environmental information. By capturing input from the video camera in particular, output from the monocular vision pipeline proves useful in the recreation of failing vehicle tests or in tracing back the conditions of intermittent failures.

3.4 Data Collection Platform

3.4.1 The UWAFT Innovation Platform

Currently the approach of using a modern, affordable ($289 CAD), android smartphone and a corresponding dashcam/data collection app is proving successful. The UIP is what will be used to engage drivers to participate in the project. Note that the UIP costs less than comparable dashcam products with GPS functionality and a full cost breakdown of the UIP parts list and corresponding costs can be found in Appendix B. UWAFT anticipates due to the prevalence of android smartphones it will enable participants to use their own old smartphones in a way that may be novel to them while participating in generating valuable research data (could-enabled dash-cam functionality). The UIP android app and vehicle mounting position are shown in Figure 3.1.

Figure 3.1: The UIP installed and operational in the pilot project test vehicle.

3.4.2 Agent Identification, Tracking and Positioning

The way that the information from the UIP is interpreted to develop testing and design information is with the MVP. Currently the approach with this pipeline is to perform object identification, tracking and 3D position estimation such that all agents in video frames are described by data output. The following describes how these state of the art tools are integrated to accomplish this data generation in the MVP. The object detection algorithm identifies bounding boxes of objects in video frames, filtered to include only pedestrians, vehicles and signs. In investigating the available algorithms YOLO is selected due to its exceptional use of computing resources and state of the art detection performance [20]. YOLO can be run on the UIP directly, adding additional value to the data collection app in the future. YOLO is a neural network based tool. Tracking is a complex task involving the matching of objects between frames, and further attempting to recognize occlusions and presence of objects. Currently a state-based, neural-network and optical flow tool based on the MDP is integrated into the pipeline to do this, though a second tool called ‘Followme’ is also integrated [21] [35]. Finally, to provide the position of objects, a robust monocular distance estimation is developed, as described in a paper which focuses on Forward Collision Warning systems [36].

3.5 Pilot Project Experiment

3.5.1 Procedure

The procedure used to capture and interpret UIP data is as follows:

1. Android phone loaded with latest version of UIP data collection app.
2. Android phone mounted to windshield below rear-view mirror facing forwards, parallel to the road surface. Phone is plugged into a high-current phone charger in vehicle 12V accessory port.
3. UWAFT data collection app is launched, and driving data capture begins. Note that OBD integration was not complete at the time of the pilot project data capture, but does not require additional procedure to initialize.
4. Experimenter drives to desired destination
   - If the experimenter identifies a situation or object which is important to current ADAS development, he/she taps the “+” in the center of the phone screen and the timestamp is recorded.
5. Upon arriving at the destination, capture is stopped by pressing the “stop record” button in the app and at this point the phone’s microSD card has all drive data recorded to it.
6. If arriving at the UWAFT bay, the participant plugs the phone into a specific Linux workstation, which uses Android debug USB access to transfer the recorded drive data onto the UWAFT file server into a limited-access folder sorted by date-stamp.

7. The footage is reviewed for situations of interest, stored in an excel spreadsheet for generation of the event profile metric:
    - Situations where traction is affected
    - Situations where obstacles suddenly appear or disappear in the path of the vehicle

3.5.2 Variables

Using the UIP, the following variables are captured directly while driving the vehicle during the experiment and are recorded on the UWAFT file server, encoded by the timestamp of the drive date:

1. Phone Timestamp —MM:SS:MS, this enables synchronization between the `.csv` file and the frames of `.mp4` video recorded.
2. GPS Position —HH:MM:SS latitude and longitude, saved into `.csv` format
3. Screen Tap —Boolean flag indicating the driver witnessed an event of interest and tapped the screen, saved into `.csv` format
4. Event of Interest —Timestamped information in an excel spreadsheet manually generated to capture any significant events which occurred beyond the screen taps to develop the Desired Statistical Event Profile metric.
5. Forward-Facing Video —720p, 30fps, monocular video captured by phone mounted under rear view mirror, saved in `.mp4` format.
6. Environmental Conditions —human annotated data capturing both the type of road surface (asphalt/concrete/dirt) and the weather condition (wet/snow/clear) of the drive observed in the video by a volunteer. This information is saved into a spreadsheet along with relevant timestamps.
7. Accelerometer Readings —$[a_x, a_y, a_z]$, saved into the `.csv` file. The `.csv` file developed is saved such that each row of data is written at a rate of 15Hz, containing all measurements at the time of formatting the row.

3.5.3 Assumptions and Influences

One major influence affecting the extension of these results to a larger user-base is that the driver in the experiment is a UWAFT member and thus was motivated to use the UIP as a contribution to the team. Given this limitation, coverage results are influenced as the experimenter is internally motivated to capture driving data. Currently it is assumed that the GPS fix provided by the phone defines the location of the vehicle correctly. Given that the region of the data collection is of importance to the context of the data, extra steps should be taken in the app to validate GPS fix information before distribution of the data to researchers. Finally, it is also assumed that all tap events registered were for the intended use of identifying stop signs to train an ADAS tool, and that no tap events were made in error.

3.6 Monocular Vision Pipeline Experiment

3.6.1 Procedure

To develop the vision pipeline for feature extraction from drive data, a simple experiment is performed to collect statically-shot video from roads around the University of Waterloo Ring Road.

1. Initial prospection to select seven viewpoints around the campus Ring Road which maximize the trackable objects within the field of view of the camera (and which have the busiest traffic). This is done by recording GPS coordinates of selected viewpoints and taking pictures of those views for replication.

2. From the initial seven viewpoints, the two busiest ones are selected for filming

    - A camera on a tripod is brought to the same location the viewpoint was identified and video is filmed at 720p, 30fps, for 20 minutes with no movement of the camera during the recording.
    - GPS location is recorded on the UIP to validate the position, and the exact location of the tripod is visually identified in the video at the end of filming.
    - The camera is transported to the next location and filming is repeated

3. Upon completion of static video data collection, the final step is to process both videos to obtain object-tracking and distance estimation data using the MVP.

3.6.2 Variables

The following variables are obtained in this experiment:

1. GPS position —HH:MM:SS latitude and, saved into `.csv` format
2. Video —720p, 30fps monocular video in `.mp4` format.
3. Object Detection Output —per-frame data defined by: bounding box corners, object label string and a confidence % saved as `detections.txt`
4. Tracked Output —per-frame tracker-filtered object detections defined by: unique object id string, bounding box corners, occlusion status int, and presence status Boolean saved as `labels.txt`. Data is Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI) formatted for compatibility with existing analysis tools .
5. Distance Estimation Output —per-frame estimation of each object's 3D x,y,z [m] position using monocular distance estimation methods. Data is in KITTI format [37].

3.6.3 Assumptions and Influences

One limitation which impacts the UIP is the desirability of a wider Field of View (FOV) than that available on the phone hardware so that data of large intersections is not lost. Approaching this issue, UWAFT will investigate performance gains from an attachable wide-angle lens in future experiments. An additional assumption, which is supported in application, is that the moving viewpoint case is an expansion of the static viewpoint case, and that technologies can be expanded to function in motion environments given additional frame of reference processing. An influence upon the selection of viewpoints is that any views which were commonly occluded by vehicles were not selected. This approach maximized the available data capture to demonstrate the pipeline, but actual UIP positioning will not be as ideal.

3.7 Review of Project Timeline

The current project timeline, is seen in Appendix 2.

It aims to, in parallel, develop the UIP and the MVP such that a larger pilot project can be conducted as soon as possible by delivering a functional backend and app. Initially tasks are to do with research and needs identification (tasks 1, 5), but tasks quickly progress to developing the platform and then the pipeline (69). After these tasks are accounted for, by the end of March it was planned to deliver metrics for overage (10) and a ground truth framework (11). Tasks from the time of writing into the future are where major scheduled differences exist, to do with developing a pipeline and backend and launching internally instead of developing ground truth systems and launching publicly. Specific task variations are discussed in the following list in terms of task ID in the current timeline: (seen in Appendix 2).

Task ID 8: Pilot Project Data Capture (one person one month)

- This task was originally more ambitious of an experiment, with multiple participants and a 126 day duration, but it was shortened to month-long program after it was discovered that the quantity of data collected in that time was sufficient to develop the vision pipeline.
- By developing the pipeline, and adding OBD features to the app at the same time in February, development phone resources were taken up and by reducing the pilot project duration one of the development phones was freed up for the innovation team to work with.

Task ID 9: Monocular Vision Pipeline for Pilot Project

- This task is added to reflect the identified need for a vision pipeline which demonstrates the value of the UIP. The decision to pivot from a ground-truth system to a MVP system was made and work commenced on this in the beginning of February. This decision also led to the removal of the 60 Hours of Footage task given the satisfaction of need with one month of footage.

Task ID 10: Development of Coverage Metric

- This task occurred later than planned due to resources allocated to the MVP. It did not take nearly as long as anticipated.

Task ID 11: Ground Truth Framework Integration

- This represents work done by the ADAS team to integrate Matlab's Training Image Labeler toolkit, which facilitates annotation for ground truth development. The task is shifted due to this team's own timeline needs and took longer than anticipated.

Task ID 13: Additional Data Capture

- This represents the plan to scale up the innovation data capture efforts for a second pilot project composed of more drivers and using the MVP to extract useful information for immediate testing needs. It replaces the time allocated for launching a publicly available website, which is deemed beyond the scope of this year and which represents privacy issues.

Task ID 14: Back End Development (website)

- Although not a public resource, it is still important to develop a website which can be used internally to the University of Waterloo to organize and serve research data. This is scheduled to occur in the final month of this competition year.

Task ID 15: Monocular Vision Pipeline (MVP) and App Refinement

- Between May and August, the final-integration improvements are to be made to bring the app and pipeline up to functional standards for scenario reconstruction in autonomous research. During this task the data collected will begin being processed to apply the extracted information.

- Specific improvements to the app are mostly bug fixes, while the MVP requires enhancements to function using non-static data and to track and distance estimate more precisely.

CHAPTER 4

Powertrain Modeling

4.1 Overview

In the early stages of EcoCAR AVTCs, the focus of competition responsibilities lie in defining and developing vehicle performance specifications such that a powertrain can be fully designed in preparation for implementation in following years. Given the aforementioned simulation tools available to UWAFT, there is significant flexibility in the selection of components integrated and modelled within the powertrain, as well as in the powertrain configuration itself. This flexibility allows for the simulation of novel powertrains which may provide a competitive advantage given the performance targets set in the upcoming AVTC phases.

The following chapter develops simulation objectives such that AVTC powertrains can be evaluated effectively and that the model is of adequate breadth. With the model objectives identified, the most appropriate modelling tool for AVTC design at UWAFT is then selected for model implementation. To provide a measure of simulation accuracy through comparison to existing work, the powertrain simulated is of the range-extended, dual-ESS design developed by Caixia Wang [12].

4.2 Model Objectives

The developed model should provide students the information they need to make effective decisions for powertrain design and control strategy optimization in the EcoCAR AVTC. The most effective way to develop an understanding of vehicle performance is to identify the VTS through simulation. The following components of the VTS are desired:

Vehicle range over a 55% city, 45% highway weighted drive cycle, as mandated in EPA testing and labeling of vehicles [38].

- 0-60 mph acceleration time [s]
- 50-70 mph acceleration time [s]
- 60-0 mph deceleration time [s]

Note that by applying additional calculations to the data collected for VTS, it is possible to estimate the GreenHouse Gas Emissions via processes outlined by ANL [39].

4.3 Modelling Tool Selection

To ensure that the powertrain development process undertaken is effective for UWAFT in the EcoCAR AVTC, the most effective modelling tool must first be selected.

4.3.1 Criteria

In selecting an appropriate tool for the powertrain model, multiple objectives for the simulation environment are identified to aid in simulation tool selection, summarized in Table 4.1. Note that in terms of the quantity of components available for integration, both tools offer a significant number of models which satisfy design needs.

4.3.2 Weighting

According to the powertrain development environment that UWAFT members expect, weights are assigned to each criterion and justified in terms of relative value to the team in Table 4.2.

Table 4.1: UWAFT modelling environment criterion with scoring

Criterion:	Criterion Description:	Score:
Model Flexibility	With flexibility in the powertrain configuration, components may be swapped or changed without significant amounts of re-integration work	Qualitative score in terms of configuration flexibility given through consultation with users of both tools:[1=slight flexibility, 2=some flexibility, 3=great flexibility]
Learning Resources	The environment should be well documented in terms of supporting resources such that students can help themselves and perform self-learning. Resources should be in the form of included documentation and online resources that describe how to use the tool and the models included.	Qualitative score given through consultation with users of both tools: [1=low resource availability, 2=medium resource availability, 3=high resource availability]
Operating System Support	The simulation environment should be compatible with Mac, Windows, and Linux Operating Systems to minimize compatibility issues with UWAFT students who are assisting in the powertrain development process	Quantitative score given according to the number of OSs supported by the tool [OSs supported, 1$\rightarrow$3]
Time for Experiment	The time required to execute the simulation and collect results should be minimized to maximize time for interpretation of results. Both tools are based upon Simulink solvers so execution time differences are negligible.	Qualitative score given through consultation with users of both tools in comparison to running a simulation in Simulink only: [1=slower than simulink, 2=simulink baseline, 3=faster than simulink]

Table 4.2: UWAFT modelling selection weighting with justification

Criterion:	Weight:	Justification:
Model Flexibility	3	Flexibility in the simulation tool is crucial to the powertrain design process, and is foundational to optimization in early stages.
Learning Resources	3	Without sufficient offline and online resources for students, it is a significant challenge to teach use of the simulation tool and to overcome obstacles such as technical issues.
Ease of Use	2	The ease of use of the tool is important, but with sufficient support, tool complexity can be mitigated.
Operating System Support	1	Ideally the simulation environment is maximally compatible, but computing resources can be allocated to mitigate compatibility issues.
Time for Experiment	1	A low simulation and result collection time will improve efficiency of research overall.

Table 4.3: Raw scores for both modelling environment options

	Model Flexibility [1-3]	Learning Resources [1-3]	Ease of Use [1-3]	OS Support [1-3]	Time for Experiment [1-3]
Autonomie	1	1	1	1	1
Simscape	3	3	2	3	2

4.3.3 Score

In Table 4.3 below the raw scores for each model environment are listed, with per-score discussion in Table 4.4. Upon applying the decision weights, the resulting weighted decision matrix which appropriately reflects the modelling needs of UWAFT for Eco-CAR AVTCs can be made seen in Table 4.5.

From the final decision matrix, Simscape is the clear choice, scoring almost 3 times as many points as Autonomie in the selection process.

4.3.4 Decision

In keeping with the needs of UWAFT for EcoCAR AVTC development, Simscape is selected for the development of this powertrain model. Primary reasons are the model flexibility in terms of configuration and the vast availability of learning resources in Simscape vs. Autonomies much harder to use environment which does not have the same level of support available.

4.4 Powertrain Description

The MA-EREV is driven by a single AC induction motor. As in existing work, the modelling of transmission gear changing is not essential due to the wide power band of the YASA motor, which is not significantly limited at maximum wheel speed. The powertrain configuration is described in Figure 4.1 below. A dual ESS configuration is a viable alternative to internal combustion engines for range-extended, hybrid vehicles due to the high energy density of Zinc-Air batteries, sustaining charge in the smaller lithium ion battery while driving distances beyond the standard 40.55km commute distance [4].

The powertrain per-component technical specifications are described in Table 4.6 below.

Table 4.4: Model environment scoring justification

Criterion:	Score Justification:
Model Flexibility	In developing a custom powertrain with Autonomie, significant effort is required to identify and resolve issues within the automatically generated code, requiring significant deep knowledge of Autonomie. In Simscape, components can be connected using common physical I/O ports and reconfigured without requiring intricate knowledge of component models.
Learning Resources	Autonomie, being an industry tool, provides some resources in the form of large documents that often lack specific information regarding component behaviour. It is very challenging to get technical assistance for a specific version of Autonomie online, requiring consultation of researchers familiar with the tool. Simscape is well documented online and given that the environment is a Simulink library, it is trivial to get technical assistance through search engines.
Ease of Use	Despite being built upon Simulink, Autonomie's workflow and user interface are significantly different and pose many usability issues in the workflow. Given that Simscape is a library within Simulink, it is almost as easy to use as placing conventional Simulink blocks. Simscape is significantly easier to use and will provide the best tool for students to conduct self-learning.
Operating System Support	Autonomie only supports Windows Xp and Vista operating systems, causing compatibility issues on UWAFT computers. Simscape is supported in the Simulink environment, which means it can be used in all modern Windows OSs, Macintosh OSs and Ubuntu.
Time for Experiment	Autonomie's complex workflow and lack of clarity when sorting through results add time to the experiment, making result gathering cumbersome. In Simscape, results are easily captured using familiar Simulink blocks such as scopes.

Table 4.5: Adjusted model environment scores and net scoring for both options

	Model Flexibility	Learning Resources	Ease of Use	OS Support	Time for Experiment	Net Score
Autonomie	3	3	2	2	1	10
Simscape	9	9	4	3	2	27

Table 4.6: MA-EREV per-component technical specifications

Component:	Specification:	Rating:
Electric Motor	Type	AC induction motor
	Peak Power	260 kW
	Continuous Power	60 kW
Lithium-ion Battery	Type	A123 7x15s4p
	Capacity	23 kWh
	Nominal Voltage	340 V
	Maximum Discharge	400 A
Zinc-air Battery	Type	Research 4x72s13p
	Capacity	67 kWh
	Nominal Voltage	340 V
	Maximum Discharge	400 A
Tires	Tire Diameter	25 inches
	Tire Width	7.68 inches
	Aspect Ratio	65
transmission	Gear Ratios	1.86, 1.00
Final Drive	Gear Ratio	3.73

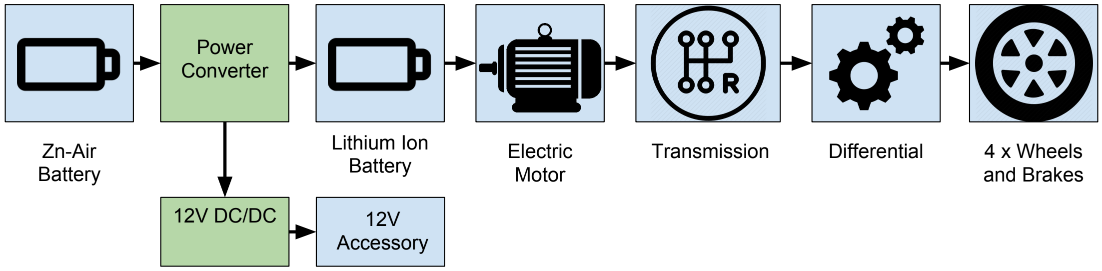


Figure 4.1: MA-EREV powertrain configuration

4.5 Model Description

By using Simscape components, the development and simulation process is familiar to student already familiar with using Simulink, with some additional details regarding the handling of physical signals.

4.5.1 Model Overview

The model Simscape developed is seen in the Simulink interface of Figure 4.2 below. Note that the green busses represent rotational-domain physical connections, in this case propeller shafts and drive shafts - this is a feature which Simscape has added to Simulink.

This model has multiple components including user-configurable features which are described in the following sections according to the overview of Figure 4.3 below.

At a high-level, the model functions by mapping driving commands to per-component demands, and then propagating outputs to the SimScape powertrain model where the vehicle dynamics are modelled such as tires, gearing, and braking. Performance is measured by inspecting the Simscape powertrain model in Simulink scope blocks.

4.5.2 Drive Cycle and Driver

When modelling a vehicle powertrain, the aspect of modelling a human driver controlling the vehicle must also be considered. With the addition of driver inputs, the vehicle should be able to drive a commanded ‘trace’, satisfying speed demands such as those specified in an EPA drive cycle. In the developed model, the issue of driver controls is easily approached with use of the included longitudinal driver block and

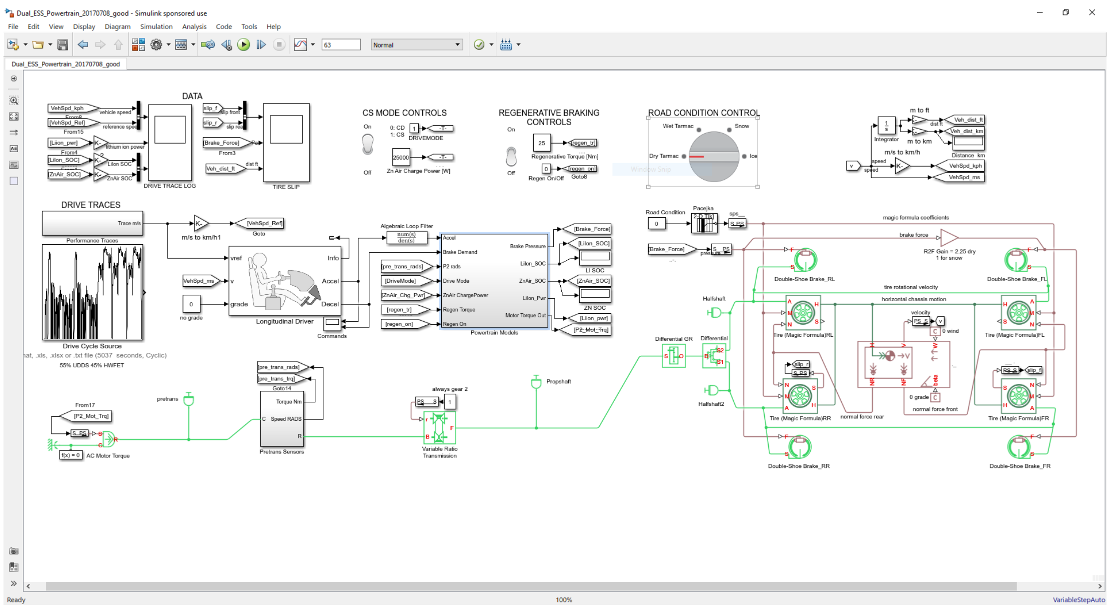


Figure 4.2: The MA-EREV powertrain model as seen in the simulink user interface

an additional Simulink Driving Cycle block, available through the simulink website. The blocks and their interconnections are detailed in Figure 4.4 below.

The drive cycle source block can be easily configured to provide reference velocities of many EPA tests for fuel economy measurement in vehicles. Visible in the block's mask of Figure 4.5 is the currently-selected HWFET drive cycle, through customized drive cycles can also be also be selected. The interface to select other drive cycles is seen in Figure 4.5 below, note that in range determination simulations, the

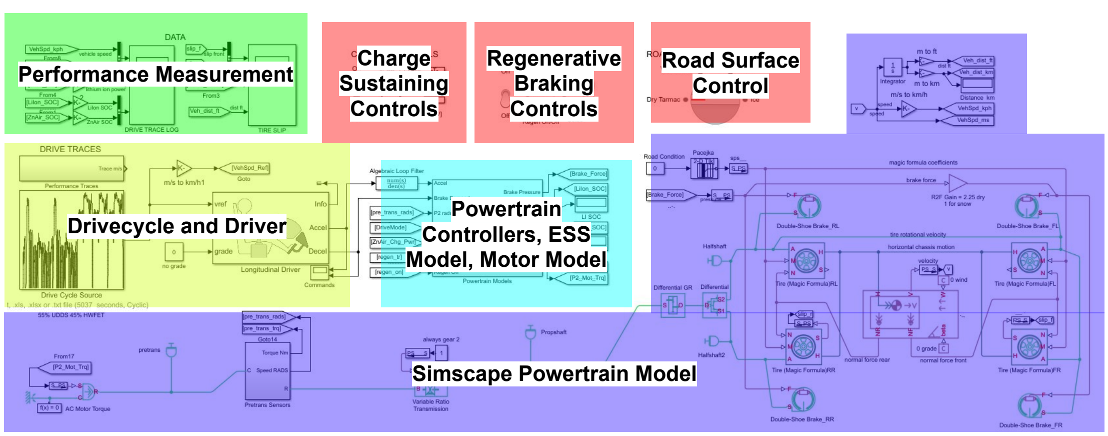


Figure 4.3: The MA-EREV model components with annotated function

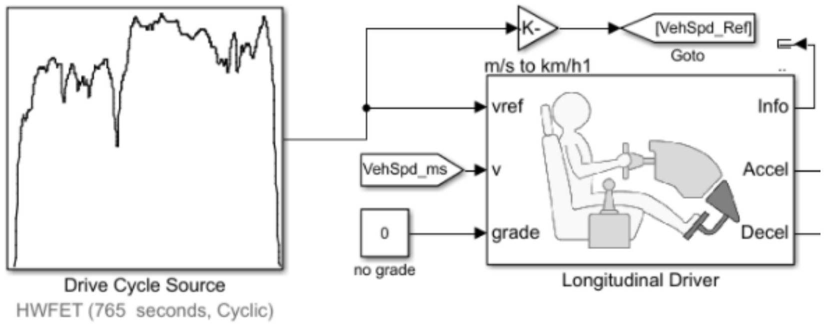


Figure 4.4: Longitudinal driver block with drive cycle source

drive cycles can be repeated cyclically.

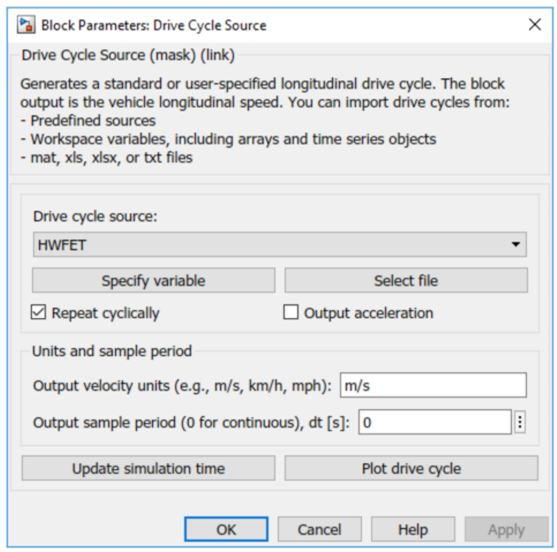


Figure 4.5: Drive cycle source block parameters

The longitudinal driver model is supplied the desired vehicle velocity as well as the current vehicle velocity feedback, and is able to interpret the error as acceleration and deceleration (braking) demands. The model for the driver is designed using many tunable constants such that the response can be characterized to suit driver modelling needs. The currently selected constants are tuned to provide desirable braking and acceleration performance for the developed powertrain, matching traces without issue. Note that given the model objectives do not include the modelling of sophisticated vehicle suspension dynamics, and that the developed model is longitudinal, with a driver driving in a straight, flat path.

In these blocks the approachability of the Simulink-Simscape interface is apparent given the ease of fine-tuning driver characteristics to suit the attached powertrain.

4.5.3 Powertrain Controllers and Models

To transform the acceleration and deceleration demands into power demands for components, models and controllers are required. Figure 4.6 below shows the models within the powertrain block.

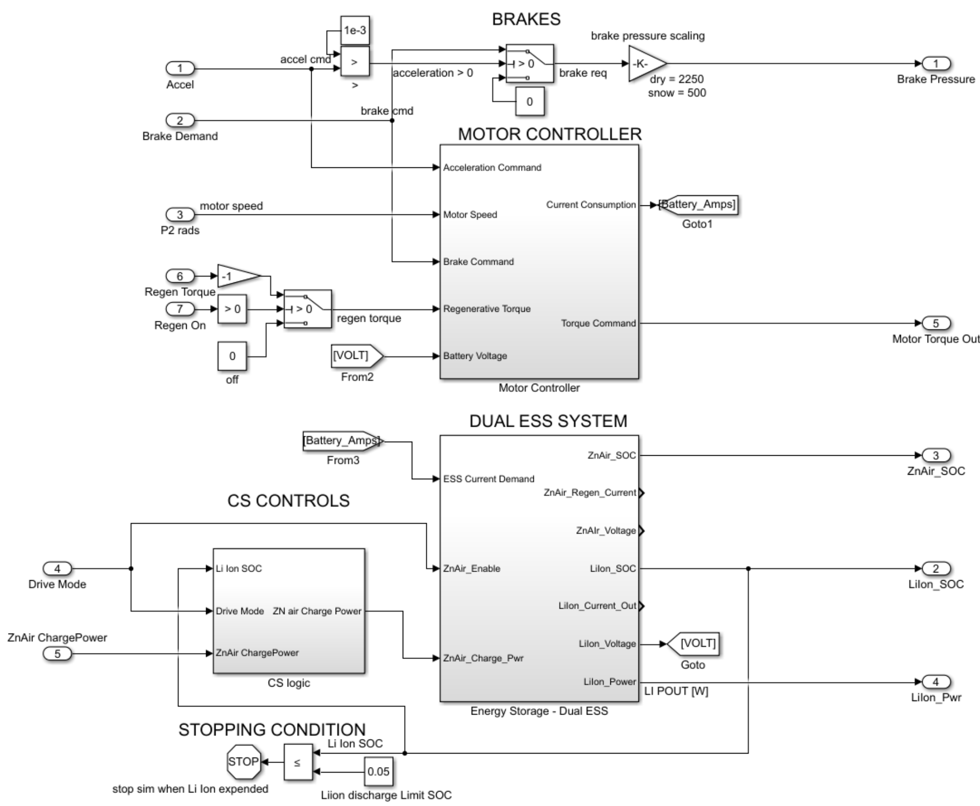


Figure 4.6: MA-EREV powertrain models and controllers

Of the controllers and plants within this block, the Dual-ESS System block contains simulink logic from the existing Autonomie model, with an interface created for this model.

4.5.4 Brake Model

The braking model uses check logic to check that deceleration demands from the driver do not occur at the same time as acceleration demands, and then applies a constant scaling to map valid deceleration demands into a force value at the physical port of the four drum brakes in the Simscape model. The map between driver commands and the simscape drum brake model is seen in Figure 4.7

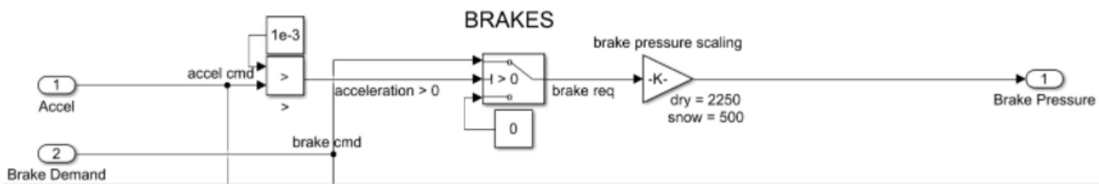


Figure 4.7: The MA-EREV brake model adapts driver commands into brake forces

The brake model is a double-shoe type brake, with configurable drum radius and shoe properties. There are four brakes in the model, seen in Figure 4.8 below.

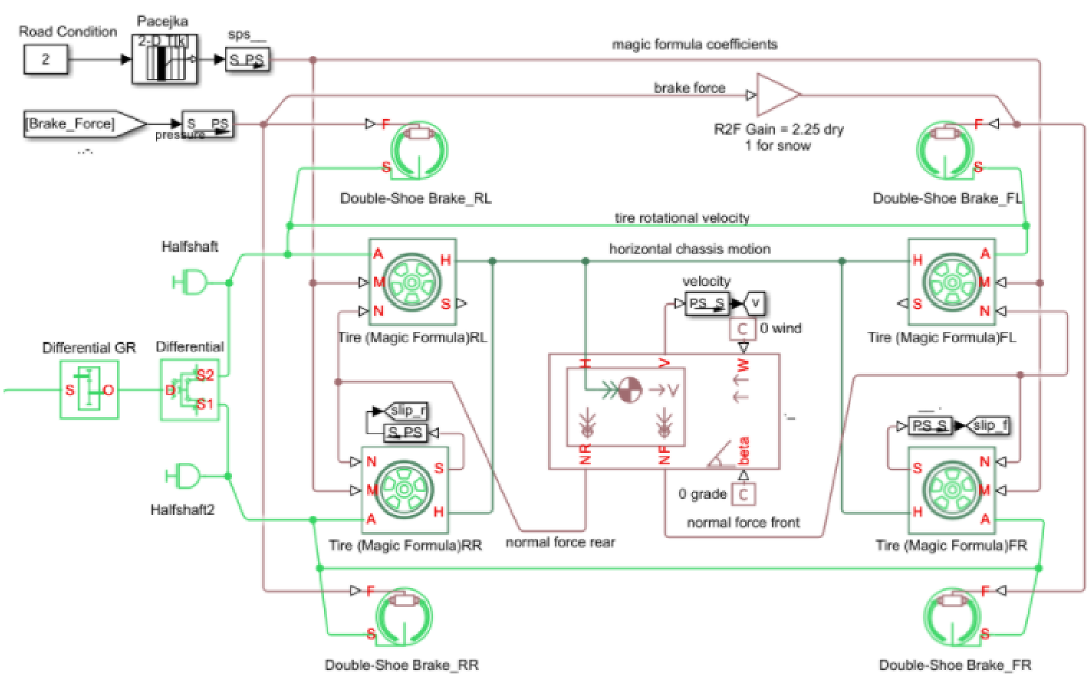


Figure 4.8: The Simscape vehicle chassis, tires and associated drum brakes

Note that when enabled, regenerative torque is sent to the motor controller during

Table 4.7: Matlab-provided Pacejka tire model coefficients [40] to simulate the traction of different road surfaces

Surface	B	C	D	E
Dry Tarmac	10	1.9	1	0.97
Wet Tarmac	12	2.3	0.82	1
Snow	5	2	0.3	1
Ice	4	2	0.1	1

braking operations as a constant, negative, torque which takes the place of motoring commands during forwards motion.

4.5.5 Tire Model

As previously shown in the overview figure 4.2, there are controls which enable the configuration of road conditions in the model. This is possible due to the Pacejka model-based tire blocks provided by simscape which have the capability to be supplied coefficients in the model [40]. This is seen in the controller's use of a direct inspection type lookup table which provides the below coefficients of Table 4.7 depending on the state of the dial in the model.

A limitation of the tire model is that rotational power develops a translational force, but this does not occur in the reverse direction. Due to this limitation, the rotational conserving ports of the front tires and rear tires must be connected when simulating braking operations such that all tires are able to contribute to the generation of braking forces.

Rolling resistance is configured to a simple constant coefficient of 0.015, though a more sophisticated pressure and velocity-dependant model is easily enabled. The tires in the simulation are 26.8 inches (0.682m) in rolling diameter, and there is capability to model compliance and inertia, though these features are not enabled in this experiment.

An additional desirable feature of the tire models which is useful when tuning acceleration/deceleration control and evaluating tire performance is the ability to record tire slip coefficients from the S port of the block. Slip coefficients are the ratio of tire motion to surface motion, where -1 indicates tire locking during stopping and 1 indicates tire slipping without acceleration of the vehicle chassis.

4.5.6 Motor Model

In Simscape, multiple options are available for implementation of rotational power-generating components. Most applicable to this use-case are models which use lookup tables such that accurate torque-curve performance can be parameterized. Additional logic is required to turn the driver acceleration command into a torque command for the motor however. The developed approach is shown in Figure 4.9 below.

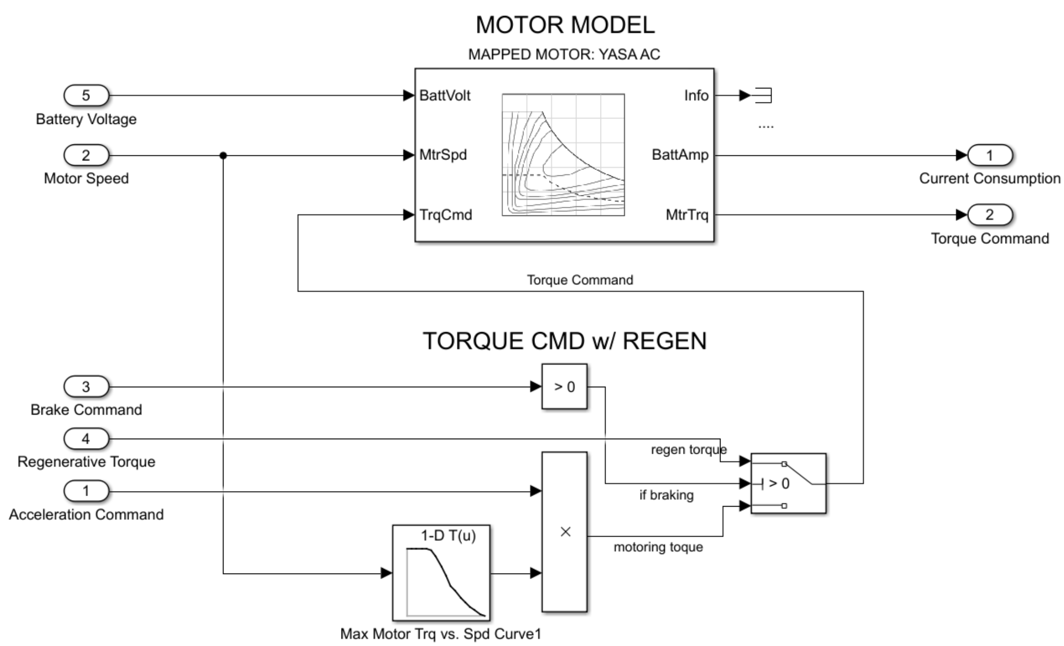


Figure 4.9: Lookup-table based motor control and plant within the powertrain model block

By using a 1-D lookup table to identify the maximum-available torque for the motor at a given speed, and multiplying the result with the driver's acceleration demand, which is between 0 and 1, a torque command is commanded to the mapped motor model block. The mapped motor block includes the calculation of motor power consumption and losses using manufacturer data obtained from the existing model. The motor has a stall torque of 826 Nm and a rotational speed limit of 8000 rpm as based on the existing model [12].

Additional logic ensures that during braking commands, the regenerative torque is propagated to the mapped motor block, which is able to calculate the resulting power generated from this operation.

To transform the simulink torque command signal into a rotational-domain torque signal, in the Simscape bus, an ideal torque source block is used - seen in Figure 4.10 below.

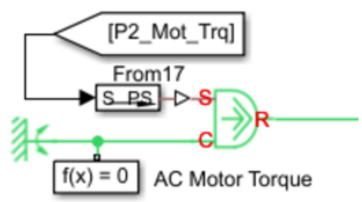


Figure 4.10: Simscape's ideal torque source is used to transform the torque signal from the motor model to the physical rotation-domain bus

4.5.7 Dual Energy Storage System

There exist multiple models for use in lithium-ion type batteries, but currently there are no metal-air battery specific models included with Simscape. Due to this, and to minimize differences in battery model performance between the existing model and the current Simscape one, the existing energy storage model is not re-implemented using Simscape components and is instead connected to supply motor demands within the powertrain block. Both the Zinc-air and Lithium Ion battery models are developed by Meagan Wang, and are well documented in published work as the MA-EREV [12].

At a high-level, the battery system is comprised of a primary, Lithium Ion battery pack and a secondary, range-extending, Zinc-Air battery of a larger capacity. The Zinc air battery exhibits more capacity fade with charge/discharge cycles than the lithium ion battery and as-such is not intended to be used in a majority of commuter driving occuring within the range of the lithium ion battery capacity. Both batteries are modelled using a rint equivalent circuit model [12]. The interconnection of battery systems within the Dual ESS block is shown in Figure 4.11 below. Note that both power convertors are 95%.

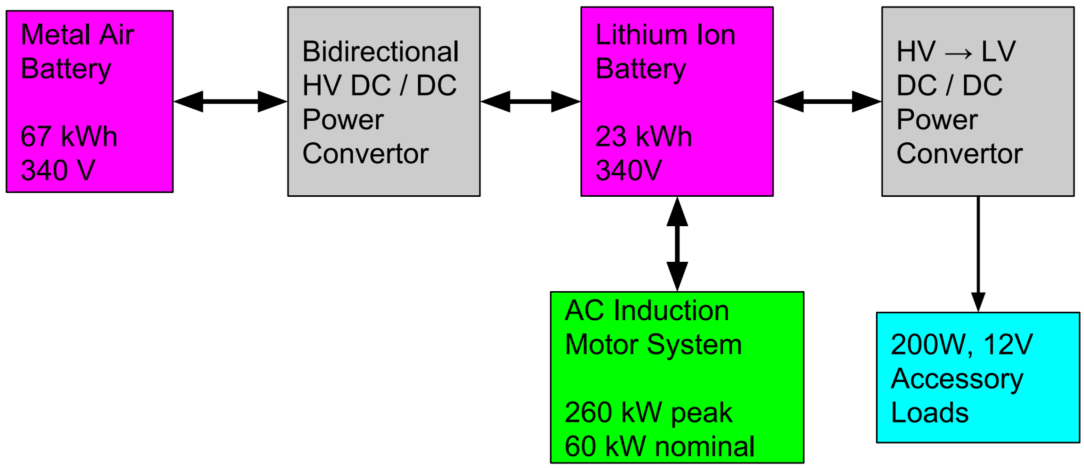


Figure 4.11: The MA-EREV dual-ESSconfiguration

Table 4.8: MA-EREV charge sustaining logic

Lithium Ion Battery SOC:	Zinc Air Battery SOC:	Action:
SOC > 50%	n/a	Discharge from Lithium Ion Battery only
50% < SOC < 70%	SOC > 15%	Charge sustain at specified power from Zinc Air → Lithium Ion battery such that range is extended
n/a	SOC <= 15%	Disable Zinc Air battery, minimum SOC reached
SOC <= 10%	n/a	Disable Lithium Ion battery, minimum SOC reached

This model is functional within the dual ESS block, but additional logic is required to control the range-extending function where power from the metal-air battery sustains charge in the lithium ion battery. This logic is shown in Figure 4.12below.

A truth-table which describes this control logic in terms of CS operation and battery limits is seen in Table 4.8 below. This control strategy uses minimal discharge limits once the zinc air battery is discharged, which degrades lithium ion battery life but provides a maximal range for VTS.

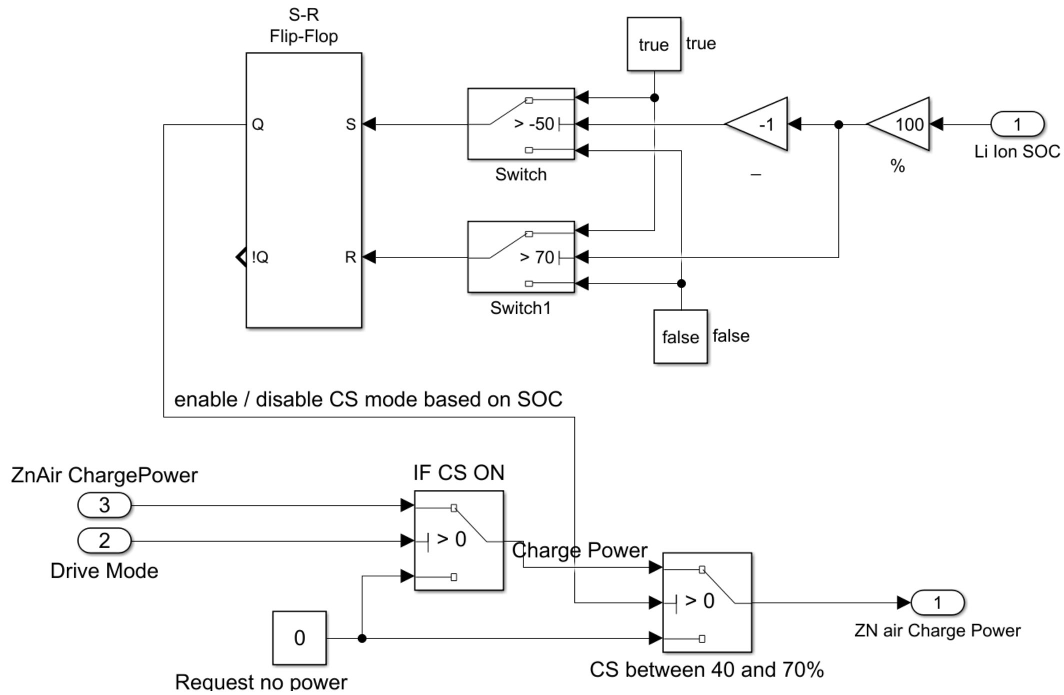


Figure 4.12: The charge-sustaining control logic to provide the desired behaviour

4.5.8 Vehicle Chassis Model

It is simple to implement and configure longitudinal vehicle dynamics models in Simscape given the included Vehicle Body block with ports for tires and environmental characteristics. Currently, with the longitudinal model approach, there is no road incline or head wind added to the drive cycle, this ensures that EPA drive cycle results are representative and comparable to existing work in Autonomie. The vehicle body block and the provided Simscape description/parameterization are seen in Figure 4.13 below. Note that the developed mass specification is set to match the value of the existing model's MA-EREV.

4.5.9 Transmission Model

Within Simulink, multiple options for sophisticated automatic transmission are available which well-represent the available options in modern powertrains. However, to ensure comparisons to existing model results are accurate, a variable gear ratio is implemented,as only a single gear ratio is required due to the wide powerband of the AC motor. The selected component has configurable compliance and losses, with a gear

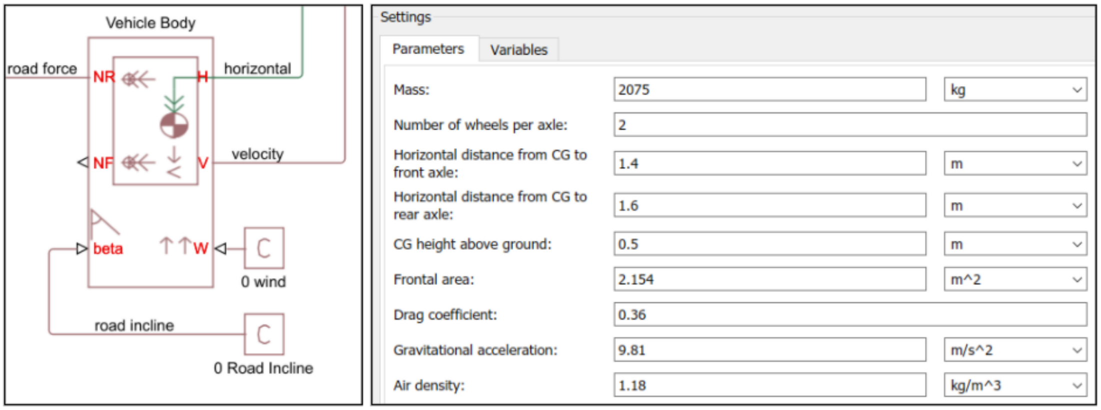


Figure 4.13: vehicle chassis model with parameters for the MA-EREV

ratio set via physical port = 1 as specified in the existing model. An example of one such available pre-configured 8-speed transmission available for direct connection to the rotational bus is seen in Figure 4.14 below alongside the available transmission model blocks.

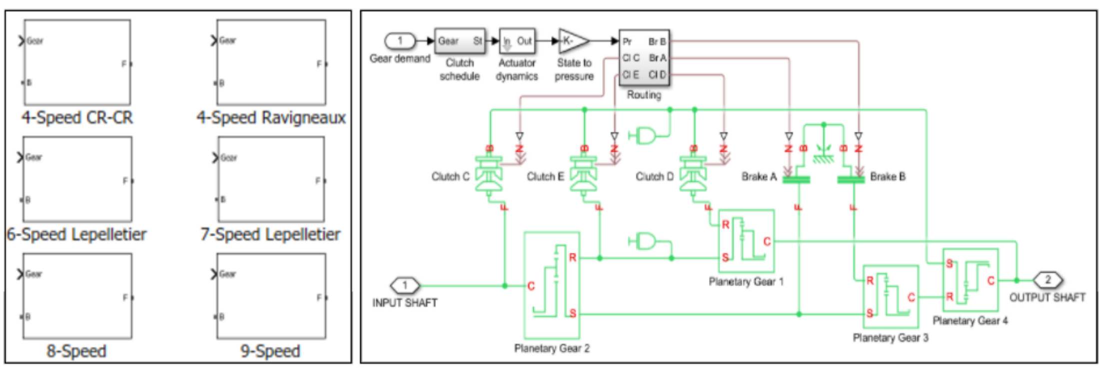


Figure 4.14: provided Simscape transmission models and the internal simscape model of the 8-speed transmission

4.5.10 Powertrain Model

Connecting the component models together, there are inertias placed to more accurately represent shaft dynamics on the pre-transmission shaft, propeller shaft and half-shafts. There is a sensor array places pre-transmission which provides measurement of shaft speeds used in the motor controller as well as torques for use in debugging. Post-transmission there is a gear ratio of 3.73 and a differential to split the torque between the two rear driven tires. The front tires share a rotational bus but are not driven. The powertrain components and interconnections are shown in Figure 4.15 below.

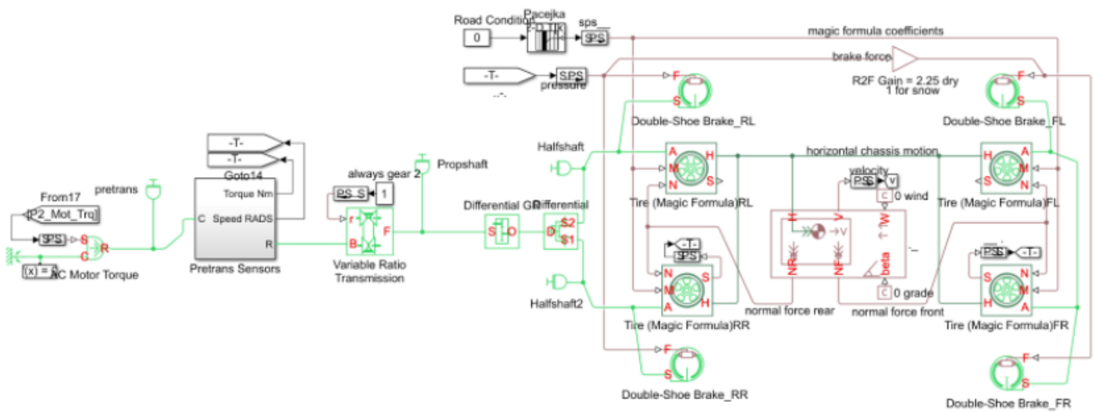


Figure 4.15: The physical powertrain modelled in simscape with multiple domains of physical bus

An additional element which has been added to improve the model's mathematical stability in the pre-transmission sensor feedback is an algebraic loop filter show in Figure 4.16 below. Note that the rotational and torque sensing blocks are provided in the Simscape library.

4.6 Vehicle Technical Specification Experiment

To validate the developed model by way of estimating VTS, an experiment is conducted which gauges vehicle performance and efficiency under a number of customized drive cycle tests. The procedure for the experiment in terms of evaluating each technical specification is described in the following subsections.

4.6.1 Vehicle Range Estimation

One of the aspects of purchasing a new vehicle is the investigation of energy consumption, usually this is available to the consumer by way of an EPA sticker on the vehicle. The rating for the vehicle is developed from a weighted average of dynamometer drive cycles which aim to simulate a variety of driving conditions. This EPA labelling uses a

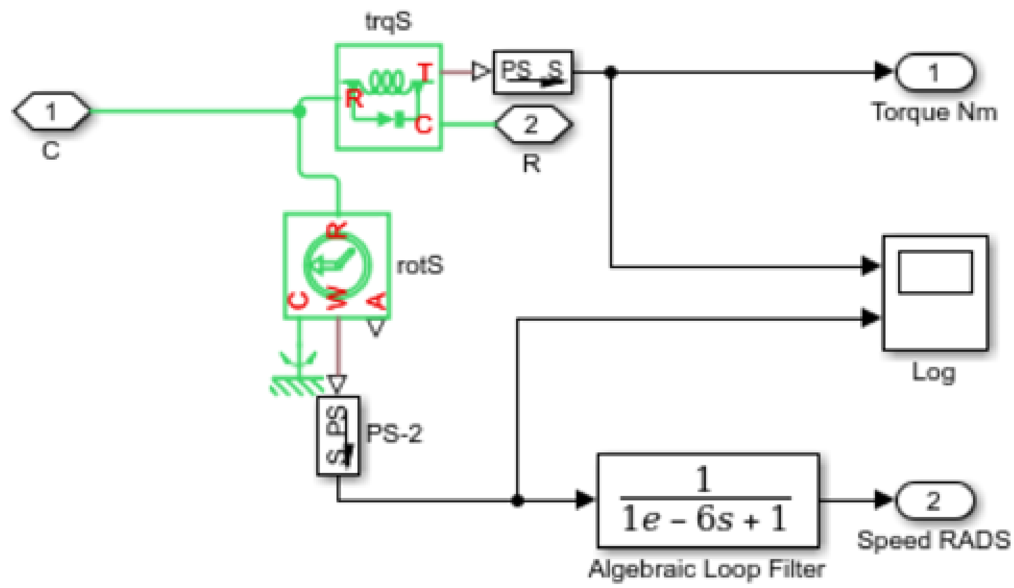


Figure 4.16: the pre-transmission torque and rotational velocity sensors with filter for improved model stability

weighted average of 55% city and 45% highway driving, using the UDDS and HWFET drive cycles respectively. By running the vehicle powertrain model on a drive cycle which contains 2 UDDS drive cycles (2738 seconds) and 3 HWFET drive cycles (2295), this weighted average is respected in terms of the driver's proportion of driving time, and the vehicle's range can be determined through simulation.

The customized drive cycle composed of 2 UDDS cycles and 3 HWFET cycles is run in a continuous loop, until the lithium ion battery is run down to 10% SOC which stops model execution automatically. By tracking the distance of the vehicle, the complete range can be observed upon the time of stopping. The experiment is run with the vehicle operating upon dry tarmac, and without the front-to-rear connection for performance braking. The customized drive cycle is shown in Figure 4.17 below.

In the interest of capturing the range-extending capabilities of regenerative braking, a further range simulation is executed using 50 Nm of constant regenerative torque during braking operations configured with the model's user controls.

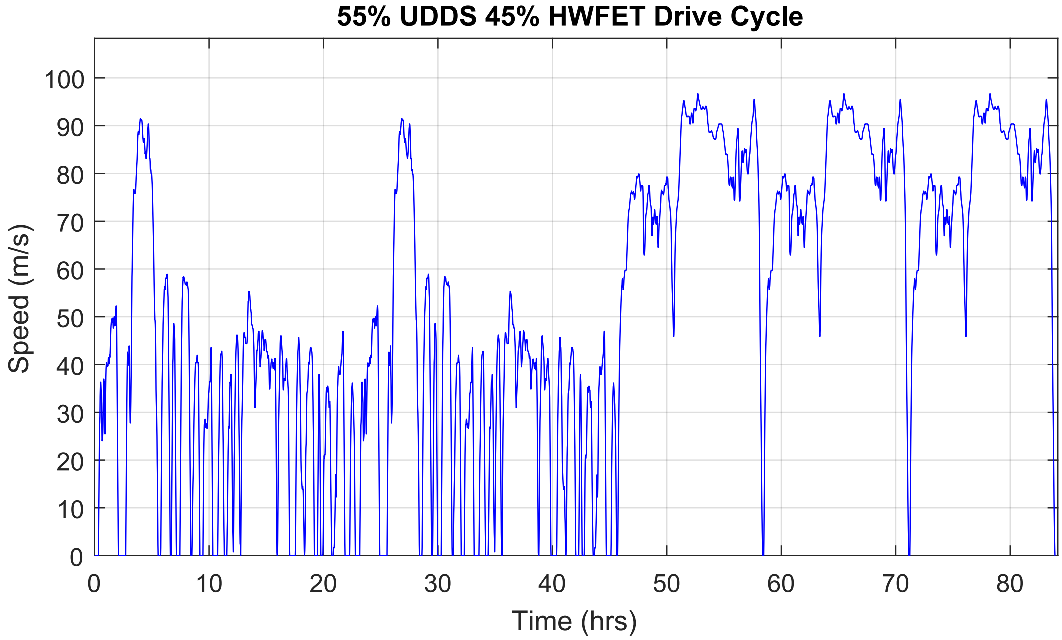


Figure 4.17: The developed 2-stage drivecycle with 55% city and 45% highway driving for range testing

4.6.2 Acceleration - 0 to 60 Miles per Hour

Acceleration is easily calculated with use of a customized drive cycle which commands 60 mph, or 26.8ms, as a square wave type signal. The result of such a significant error between the stopped chassis and commanded speed is that the driver block commands a wide-open-throttle event and the acceleration of the vehicle is maximized. Instead of developing a drive cycle within the drive cycle block, this is most easily accomplished using a constant commanded reference speed, shown in Figure 4.18 below. Acceleration testing is performed on dry tarmac.

4.6.3 Acceleration - 50 to 70 Miles per Hour

This test is intended to gauge the capability of the vehicle to pass other vehicles on a highway, as the higher rotational velocities impose greater strain on the powertrain during acceleration than in the 0-60 test. This test is also most easily achieved using simple source blocks instead of the the drive cycle block, though a customized drive cycle could be implemented. This test is performed using a Simulink step block, which

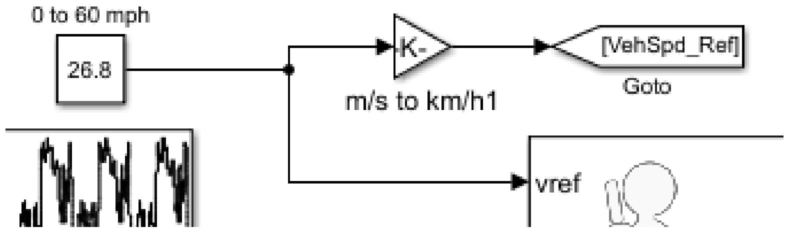


Figure 4.18: With a constant input speed demand, a 0-60 acceleration test can be easily performed

is initially 50 miles per hour (22.35ms), and which steps up to 70 mph (31.29ms) after 8 seconds. The block commands the driver directly as in the 0-60 connection of Figure 4.18.

4.6.4 Deceleration - 60 to 0 Miles per Hour

It is unsafe to design a powertrain which is capable of significant acceleration without also ensuring that the vehicle is able to stop adequately, in the EcoCAR AVTC, adequate stopping distance is a requirement of vehicle participation. By analyzing the distance the vehicle requires to come to a complete stop from 60 mph, this value can be compared to the existing model which satisfied performance requirements by stopping in 121 feet.

Given the capability of the tire models to describe slip, it is also possible to provide additional insight in the tire dynamics of the stopping operation. For example, if the tires are locked during braking, creating a slip coefficient of -1 during the 60-0 simulation, the longitudinal simulation will fail to capture the need for traction control to prevent spinning of the vehicle and other unsafe effects created by locked tires during stopping [41]. By monitoring the slip coefficients during this test, the simulation will also evaluate if the vehicle's 60-0 test is representative of it's maximal safe braking capability. The 60-0 test is performed on dry tarmac.

Part II

Applications

CHAPTER 5

Vehicle and Environment Simulation

5.1 Overview

A significant benefit of collecting data with the UIP is the capability of scenario recreation for testing purposes. In this chapter, an experiment is conducted which demonstrates this application of the data collection platform for powertrain development. By using real-world data to provide validation of the powertrain through simulations which include environmental information, the concept of Rich Environment Simulation is realized.

5.2 Experiment Objectives

Typically powertrain development uses a limited number of drive cycles which are EPA mandated approaches to fuel economy calculation, as well as a number of simple drive cycles which command constant speeds for acceleration and deceleration performance.

By using real-world data, the pool of testable drive cycles is increased significantly, and augmented through real-world scenarios occurring under a variety of road conditions given that data is collected year-round. The objective of this experiment is to demonstrate that the data collected through the UIP is applicable to powertrain development in addition to the ADAS and autonomous vehicle development value identified in prior chapters.

5.3 Scenario Replication Experiment

One of the the major differences between electric vehicles and internal combustion engine vehicles is the addition of weight due to electrical energy storage systems such as lithium-ion batteries. In the case of the MA-EREV, the weight increase upon the stock 2015 Chevrolet Camaro is 396kg [12].Through simulation of the vehicle on exclusively dry tarmac with existing EPA drive cycles such as HWFET or UDDS, the performance impact of non-ideal weather conditions in combination with this increased weight is not investigated.

The following experiment uses real-world data collected by a driver equipped with the UIP who experienced slipping while stopping on a road surface which had a buildup of hard-packed snow, visible in a screenshot from the capture footage in Figure 5.1. The vehicle driven is a 2015 Chevrolet Cruze with a curb weight of 1414kg, equipped with rubber tires of a blocked and sniped design.

Figure 5.1: Footage captured by pilot project test driver during a slipping event on a snowy road surface, showing elongated tire tracks at the stop sign location

To investigate the impact of the winter conditions with the increased weight of the MA-EREV powertrain, the following procedure is applied:

1. By use of the encoded driving conditions database developed in the UIP pilot

project data collection experiment, the scenario containing winter conditions and slipping is identified.

2. A drive cycle capturing intersection of Figure 5.1 is isolated from the .csv data file which includes time and vehicle velocity in m/s The drive-cycle is augmented with a 30-second ramp-up such that the vehicle reaches the appropriate steady-state speed matching the beginning of the recorded data.

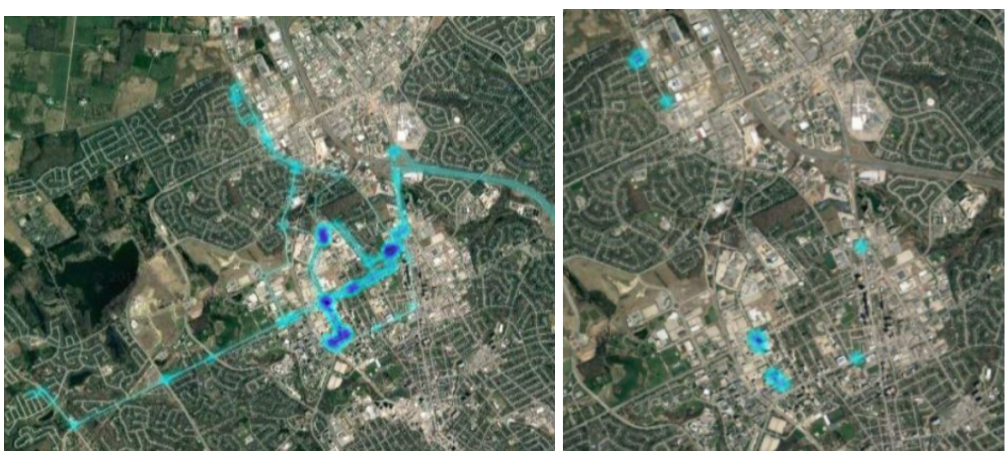
3. The drive cycle is loaded into the powertrain drive cycle block of the Simscape MA-EREV model as detailed in 4.5.2 The road-conditions in the model are set to 'Snow' using the dial control in the Simscape MA-EREV model

4. The scenario is re-created through simulation with the MA-EREV and results containing vehicle path and tire slip are collected

CHAPTER 6

Experimental Results

6.1 Pilot Project Data Capture Experiment



(a) Pilot project coverage (b) Tap locations

Figure 6.1: Heat maps indicating Data coverage via GPS (a) and locations used to train ADAS (b)

The following information is collected over the course of the month-long experiment:

1. $6,152,873$ data points are collected between November 22nd and December 19th, with 7.45 hours of driving recorded.

2. A heat map of the driven paths in the Region of Waterloo is shown in 6.1a. Note that trips to outside of the region are omitted for scale. A majority of driving

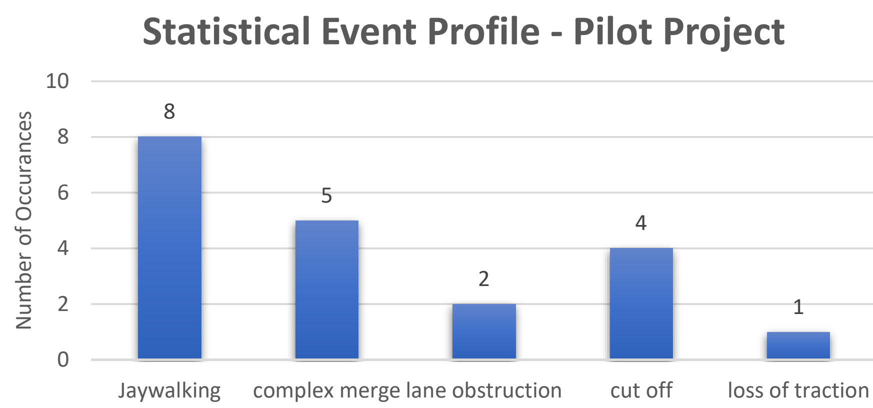


Figure 6.2: Statistical Event Profile for the pilot project data

occurs between the university and UWAFT team member's homes. For more views of the Ontario-wide coverage, see Appendix IV.

3. The screen was tapped 197 times, and this data was used to train a stop-sign detector by the ADAS team, and to identify situations of interest, some of which are included in the statistical event profile. Figure 6.2 shows the tap locations, which correspond to major intersections near the university where there are the most jaywalkers.

4. The video is reviewed by a team member for situations involving the driver responding to: jaywalkers, traction loss, extreme weather events (obscuring visibility with heavy rain or snow), ambiguous merging with other vehicles (ex: zipper merge). In the collected data, seen in 6.2, it is seen that a vast majority of the events involve jaywalking. One interesting situation of a lane obstruction is shown in 6.3.

5. 40.45 gigabytes of video has been captured across 28 trips and all the captured data is stored on the secure UWAFT fileserver.

6. Due to the time of the experiment (November December), a major portion of the footage captures winter conditions, with 8 instances of rain, 1 instance of blizzard conditions and 1 instance of freezing rain. 40% of the driving occurred at after sundown.

Figure 6.3: Some interesting events captured of a specific jaywalker, of being cut off (top right), and of a hwy. lane obstruction (bottom left)

7. Accelerometer data is not plotted, but has been collected alongside all trips in the corresponding .csv file. It is noted that acceleration, deceleration and turning all create distinct readings.

6.2 Monocular Vision Pipeline Experiment

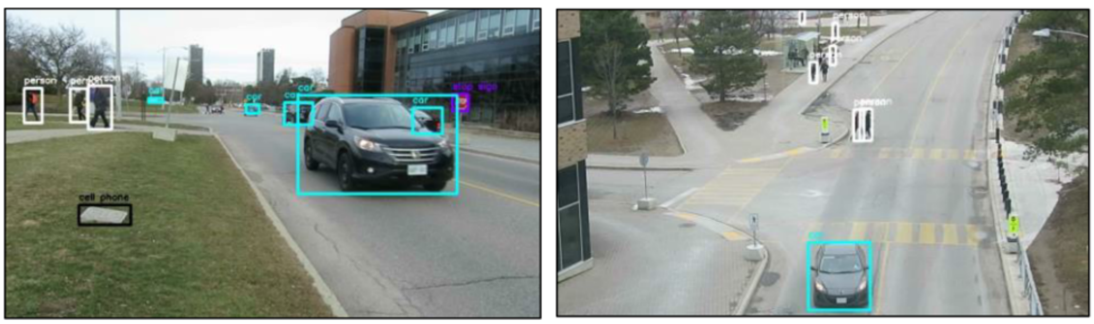
In the experiment, 40 minutes of video is shot at two locations, and this initial version of the monocular vision pipeline is demonstrated. Results are discussed in terms of variables monitored:

1. Video locations are detailed in Figure 6.4.

2. 40 minutes, 720p 30fps .mp4 video files are recorded on the UWAFT file server. Two 2 minute videos are cut from the initial 40 minutes which contained the most feature-rich occurrences to reduce time consumed while developing the pipeline with the long videos.

3. Several keyframes demonstrating the object detector's current capabilities are shown in Figure 6.5a and Figure 6.5b.

Figure 6.4: Monocular video capture locations, circled in red



(a) Multi-object detection

(b) Pedestrian recognition

Figure 6.5: (a) Multi-object detection in front of B.C. Matthews Hall and (b) Recognizing distant pedestrians, in-front of Engineering 5

4. As with object detection, tracking output is challenging to convey, but the capability to maintain identified objects while withstanding occlusions is demonstrated in Figure 6.6. Note that the four views of the scene in this figure are cropped and zoomed from the original camera view, visible in Figure 6.5a.

5. Distance estimates are currently not visualized, but are generated and stored. The current system is not a part of the pipeline but the accuracy of the estimation can be determined using measured distances to objects within captured video.

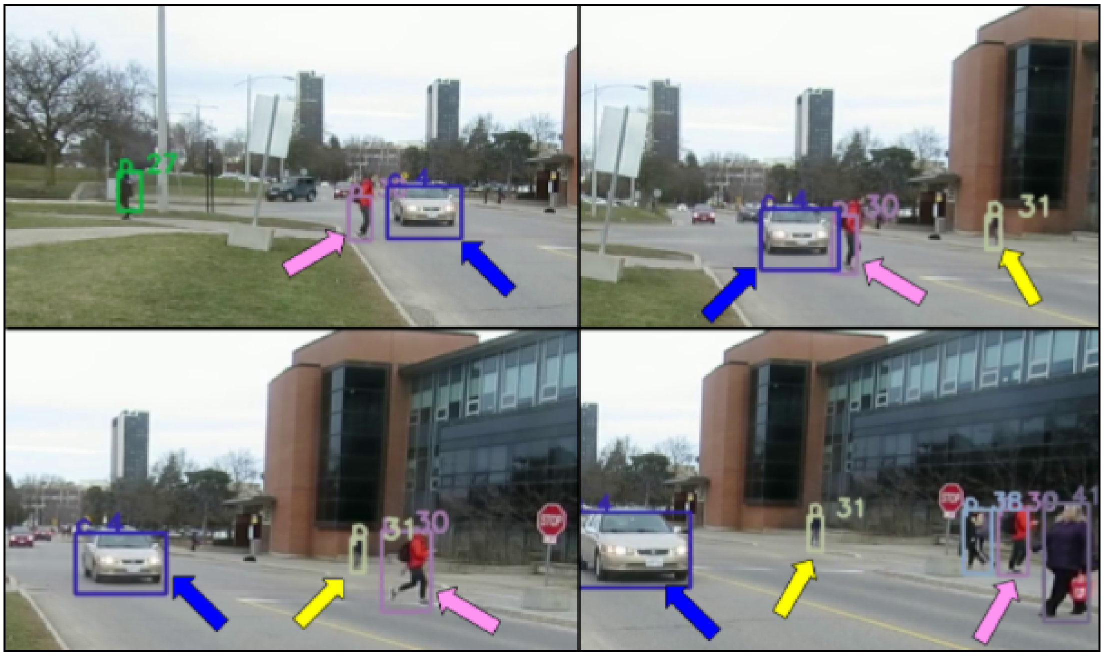


Figure 6.6: Tracker follows vehicle 4 (blue), pedestrian 30 (pink) and 31's (yellow) detected paths despite occlusions in this complex scene captured during the static video capture

6.3 Powertrain Simulation Experiment

As previously identified, the goal of this set of simulations is to develop VTS for a MA-EREV. Data is collected via two scope blocks which together log vehicle speed, battery power output, battery SOCs, tire slip, braking force and braking distance. Results are summarized with inclusion of relevant data and then compared to the existing model VTS and discussed.

6.3.1 Range Estimation

By simulation of the 55% UDDS and 45% HWFET drive cycle repeated until the Lithium-ion and Zinc-air batteries are depleted, a range of 370km is obtained with trace data visible in Figure 6.10. Power discharge peaks at 50kW, and power generation is 35kW - both of which are within acceptable component limits.

Visible in the result of Figure 6.10 is the charge sustaining function of the zinc-air battery, supplying $35,000$W of power to the Lithium-ion battery, maintaining its

SOC between 50% and 70% until both batteries are depleted. In the follow-up experiment to gauge the effect of regenerative braking, the range is extended to 398km, an increase of 7%.

6.3.2 0-60 Acceleration

In the simulation which commands an instantaneous speed of 60 mph (95.6 kph), a time of 6.1 seconds is obtained. Note that the output power does not exceed 225kW during this operation, which is within allowable limits. Acceleration performance for this experiment is seen in Figure 6.7

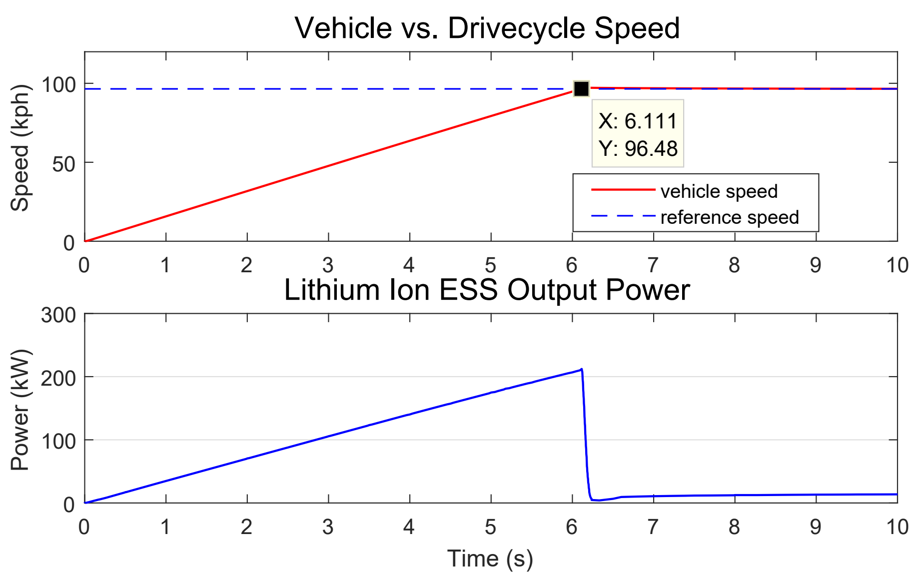


Figure 6.7: MA-EREV 0-60 acceleration performance with supplied power

6.3.3 50-70 Acceleration

Relevant to vehicle highway performance is the 50 $\rightarrow$ 70 mph acceleration, which puts more strain on powertrain components. The drive trace commands 50 mph instantaneously, and steps the command to 70 mph at 8 seconds of simulation time. Visible in Figure 6.8 the resulting simulation trace of Figure 6.8, the elapsed 50-70 acceleration time is 2.14 seconds. Power consumption peaks at 245kW, which is within acceptable limits.

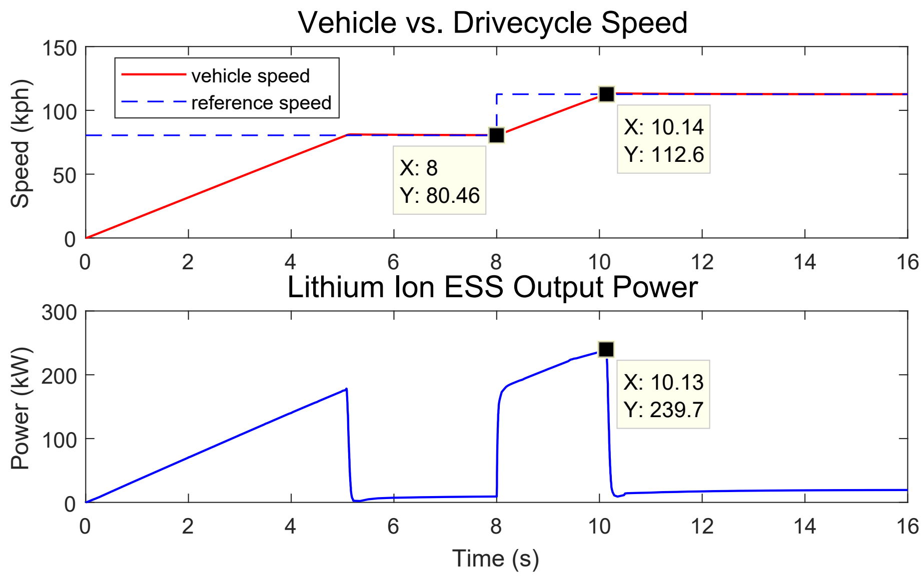


Figure 6.8: MA-EREV 50 to 70 mph acceleration performance with supplied power

6.3.4 60-0 Braking

In this braking experiment, the distance over which the vehicle is capable of coming to a complete stop is investigated. The drive trace brings the vehicle to a speed of 60 mph (95 kph) and then commands an instantaneous velocity of 0 at 50 seconds of simulation time. Visible in Figure 6.9, the tire slip coefficients indicate that tires do not lock during the operation, and that the stopping distance is 121 feet. As in the EcoCAR 3 competition event, regenerative braking is disabled for this test of vehicle safety.

6.3.5 Summary and Comparison of Results to Existing Model

To provide a validation of the model techniques used, the existing model results for the MA-EREV developed by [12], are compared to the results for the Simscape model collected in the simulation experiments.

6.3.6 Scenario Replication Experiment

Resulting data of Figure 6.11 shows that the simulated MA-EREV was able to match the recorded trace with some traction difficulty. Longitudinal tire slip reached a max-

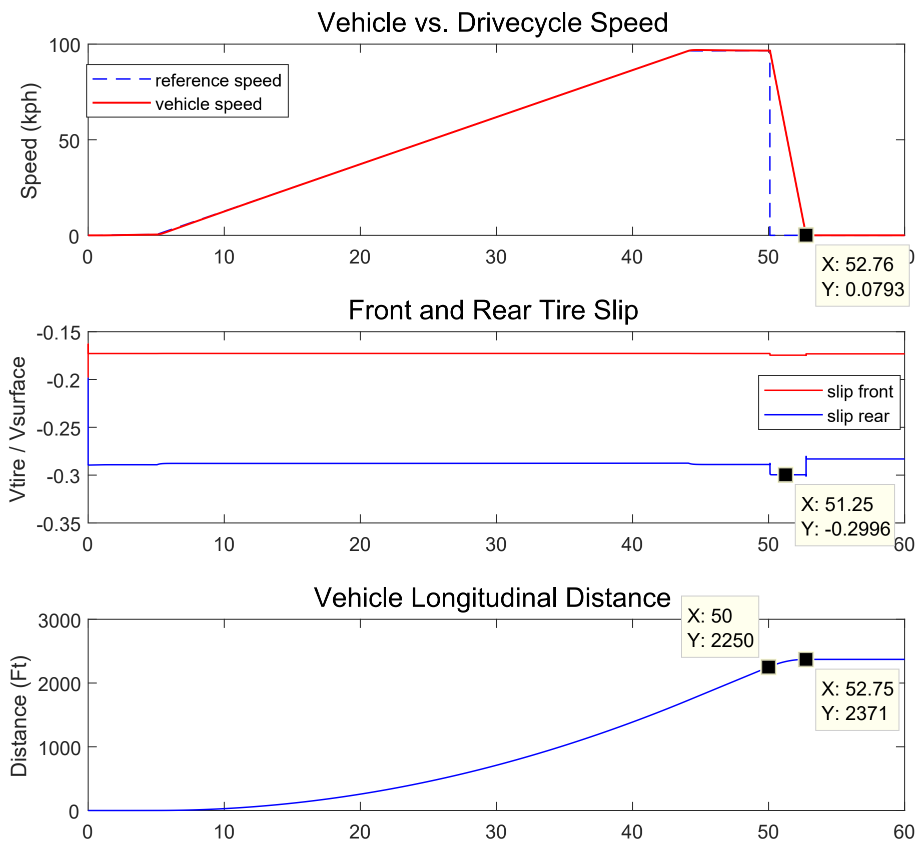


Figure 6.9: MA-EREV braking performance on dry tarmac

imum of 84%, indicating that the MA-EREV has significant difficulty matching the acceleration performance of the Chevrolet Cruze, though the braking performance is better with a maximum slip of 48% and less slipping overall. Note that the recorded data begins at 30 seconds, with the prior trace providing a ramp-up in speed.

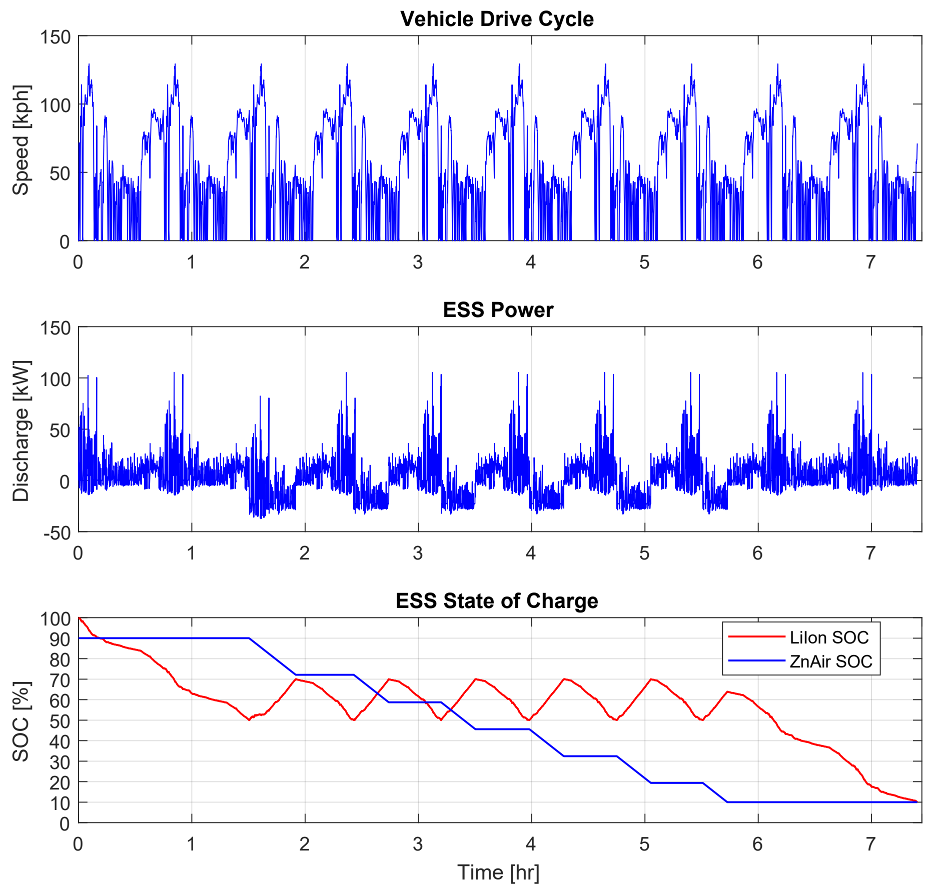


Figure 6.10: Recorded range estimation data demonstrating the charge-sustaining and regenerative braking functions

Table 6.1: Results comparison for purposes of validation of the Simscape model

Vehicle Technical Specification::	Simscape Model:	Existing Model:
Total Vehicle Range [km]	398	462
0-60 mph acceleration [s]	6.1	5.9
50-70 mph acceleration [s]	2.1	3.6
60-0 mph braking [feet]	121	121
Curb Mass [kg]	2075	

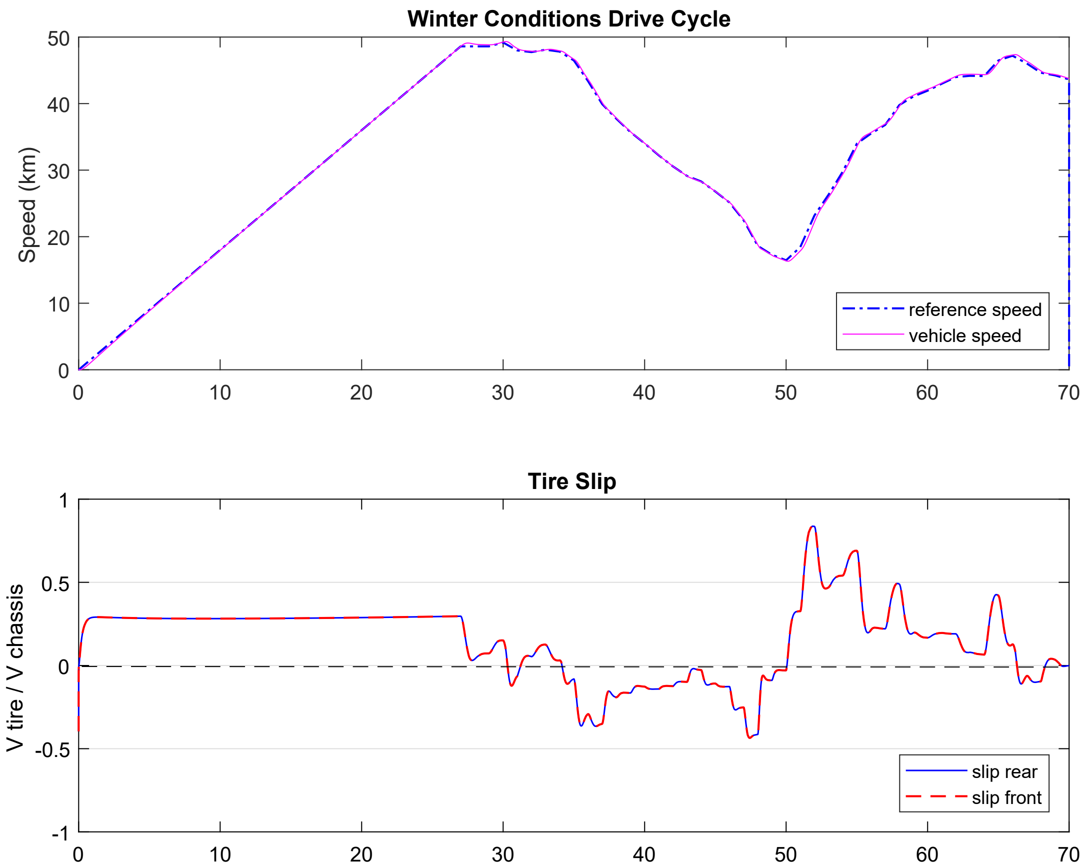


Figure 6.11: In simulation of the recorded slipping trace, the MA-EREV shows more slipping during acceleration than deceleration

Part III

Conclusions

CHAPTER 7

Conclusions

7.1 Pilot Project Data Capture Experiment

In terms of the coverage metrics, it is found that the coverage generated from even a single participant contains significant, statistically desirable, repetition in driving routes - especially in city centers along commute routes. By capturing situations of interest through screen-taps, the process of identifying and reviewing footage is significantly improved and interesting data is more easily extracted for research purposes.

In analyzing the statistical event profile, it can be seen that it is also possible to extract meaningful quantities of edge case scenarios from the data for the training and development of ADAS and autonomous vehicles, or in the development of powertrain technology.

7.2 Monocular Vision Pipeline Experiment

In reviewing the functionality of the multi-object detector, acceptable performance is demonstrated through detection of far-away (˜100m) vehicles, signs and pedestrians.

In reviewing tracking with the MDP, the tracker is demonstrated to have acceptable performance given the ability to maintain the identify of identified vehicles and pedestrians across frames of video and occlusions.

7.3 Powertrain Simulation Experiment

In this experiment the results are ideally the same, providing a validation of the developed Simscape model against the existing model. Any significant differences indicate an unintended change in model behaviour or simulated vehicle performance.

The range of the Simscape model is 13.8% lower (64km shorter) than in the existing model results, indicating a range-significant difference exists in the Simscape model. Given that the battery model used is imported from the existing model, and that the motor model used is parametrized as in the existing model, this difference is due to a different component of the simulation.

In terms of 0-60mi/h acceleration performance, the developed model is consistent with the existing model with a difference of two tenths of a second. This difference is insignificant in terms of powertrain design in the scope of EcoCAR 3 and indicates that the developed model is consistent in terms of this VTS.

In terms of 50-70mi/h performance, the Simscape model performed better, scoring 1.5s faster than the existing model, which is significant in the scope of EcoCAR 3 powertrain design and may impact design choices made by UWAFT. In the EcoCAR 3 year three competition, 6 teams completed the 50-70 acceleration event with times below 7.3s (target VTS), in these scores there is a standard deviation of 1.65 points out of the 20 available points for the event. This indicates extremely close times across participants and the significance of a seconds in the scope of the competition.

In terms of braking performance in the 60-0mi/h deceleration simulation, both simulation environments scored consistently, bringing the 2075kg vehicle to a complete stop over 121 feet of braking distance.

7.4 Vehicle and Environment Simulation

In a replication of a scenario where slipping was observed in a driver equipped with the UIP, the MA-EREV exhibited less longitudinal slipping during stopping than during acceleration on a snow-covered road surface.

During stopping, the MA-EREV exhibited a peak longitudinal slip of 41%, which is non-ideal for traction generation given that traction decreases with increasing slip in the Pacejka tire traction model parametrized for snow [42]. In an analytical longitudinal slip tire model for snow, seen in Figure 7.1, peak traction occurs at 30% longitudinal slip, while a slip of 41% provides 94% of available traction [43].

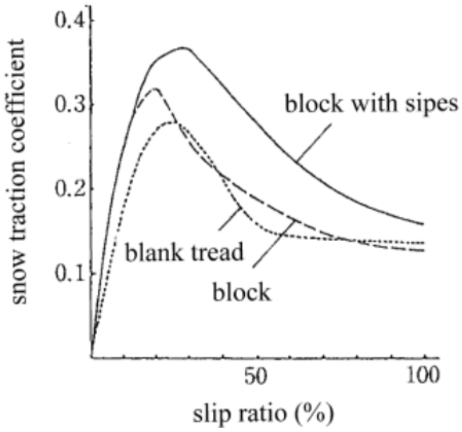


Figure 7.1: Snow traction vs slip as detailed in an analytical study [43]

During acceleration, the vehicle exhibited a more extreme peak longitudinal slip of 84%, producing 55% of the available traction according to the same study [43].

Given that the vehicle accelerated from 17km/h to 42km/h over 21s in the recorded drive trace, this significant amount of slip indicates that the MA-EREV may have difficulty safely performing in winter conditions without additional traction control. The MA-EREV weighs 677kg more than the pilot project test vehicle.

CHAPTER 8

Discussions and Future Work

8.1 Discussions

8.1.1 Data Collection with Vision Pipeline

Although the current dataset is relatively small, it is clear to the UWAFT and the Autonomoose team that this approach is valid in developing valuable automated continuous improvement processes to the research industry. The presently achieved goals provide a stepping stone towards implementing a more complex, publicly accessible research resource which has the potential to enable diverse, external innovation in the ADAS and autonomous research field.

The developed approach of utilizing an affordable and scalable platform with a sophisticated vision pipeline with the promising capability to develop baseline metrics will be of particular impact to the industry, providing an alternative to the prohibitively expensive instrumented car approach. Given the coverage of a single driver, it can be expected that city centers and highways will be particularly well exposed to UIP. As in the OpenStreetMap scenario, the highest repetitions of data can be expected to yield the most accurate information [3], in this project's case that information comes from the MVP and OBD-logged driver inputs.

The current UWAFT innovation project represents successful collaboration between EcoCAR team members and autonomous research stakeholders at the University of Waterloo, providing an internal path to direct application of the platform before public crowdsourcing occurs in the near-future. The initial pilot project with one person collecting data for one month is successful at demonstrating the effectiveness of the UIP and MVP while also pushing the innovation team to develop improved tools.

However, what must be done to precipitate crowdsourcing? One approach, integrated into the earliest concepts of the UIP, is to add value to the platform for everyday drivers in the form of a cloud-connected dashcam service. As most cars currently on the road are not instrumented with video recording devices, many consumers currently turn to dash cams for insurance, safety, or entertainment benefits. UWAFT's own innovation platform and pipeline backend can fulfill this consumer demand while offering additional features to consumers in the phone app such as simple ADAS or statistics. Additionally, dashcams with GPS logging features often cost the same or more than the capable android currently in use for the UIP (Appendix 5). By providing drivers with additional benefits to make the UIP more attractive, it is hoped that crowdsourcing can be precipitated more easily and that the driving data resource can be fully developed in terms of value to the industry.

With a publically-backed project engaged in external innovation, it is possible that the intelligent vehicles of the future will arrive more quickly and with features beyond the scope of current research efforts. This is the vision that the UWAFT innovation team hopes to realize.

Team and Technical Goals Achieved

The UWAFT innovation team was able to meet a vast majority of the established technical goals, pivoting away from some goals in favour of developing a more meaningful monocular vision pipeline experiment. Additional effort was also spent developing the app logging features and tuning app performance.

1. **App Development** The android app is currently enhanced with OBD logging features and all required logging capabilities are implemented.

2. **Website Backend** By reducing the scope of the backend to one which facilitates use internal to the University of Waterloo, the system is effectively functional on an appreciable scale with the present UWAFT file server implementation. The current system offers participants access to their contributions, and a USB transfer script to offload footage, but this system cannot be public-facing without additional security and anonymization efforts. Thus, currently:

- The functionality of the backend internal to University of Waterloo, is within scope for this year of competition
- Functionality of the backend as a public research effort to precipitate crowd-sourcing, is no longer within scope for this year of competition. The current backend is integrated into the MVP such that scripts are run on the collected data in its original format.

3. **Machine Learning Algorithm** This capability was extended beyond the original validation concept. In realizing the value of scenario reconstruction for testing of ADAS and autonomous algorithms, the UWAFT innovation team opted to develop a monocular vision pipeline, extracting enough information to recreate driver scenarios using the UIP data to define baseline driving behaviour. By developing the pipeline to support these goals, there is immediate benefit alongside the UIP output validation.

4. 60 **Hours of Video** Footage This technical goal not met for reasons of app development. In particular the OBD logging functionality pushed back data collection efforts as multiple attempts were made to utilize wireless loggers unsuccessfully, while delaying data collection. Currently, 7.45h of footage have been recorded.

5. **OBD Logging Functionality** OBD data is currently logged using a reliable USB on-the-go protocol and an Arduino with a specialized shield. It is possible to improve this as a wireless system, but it is not possible to integrate many existing cheap Bluetooth or Wi-Fi type adapters due to hardware limitations of those adaptors. The system is currently capable of capturing the driver's physical inputs for: steering wheel angle, brake pedal position and accelerator pedal position.

6. **Ground Truth System Integration** Currently, the video annotation tool integrated is Matlab's Training Image Labeler.

Achieved versus Projected Success

Although the quantity of data collected is smaller than planned, the project already has research interest and is becoming a capable research platform as further technical goals are completed. More work on the Monocular Vision Pipeline will be required before it can be used to develop functional test scenarios to precipitate the expected impacts.

8.1.2 Powertrain Simulation Experiment

Although many of the results in the experiment align with those previously collected, there is identified a significant difference in both the range and 50-70 acceleration time.

With respect to the range difference, one aspect of the Simscape model which provided improved usability, but which may have increased power loss, is the tire model. In the 'Magic Formula' tire model block there is a configuration option for modelling rolling resistance, but the constant coefficient used is not easily compared to the existing model configuration due to differences in the existing tire model architecture which used four independent coefficients to calculate rolling resistance. To further examine the possible impact of a different rolling resistance model, the provided pressure and velocity-dependant rolling resistance model is enabled and settings are left at defaults for the Simscape block. The result of simulating range with this model is a significant decrease in expected range (˜50km shorter), with a significantly increased power drain due to tire losses. Thus, it is surmised that the 15% range difference may be due to differences in the tire models. Note that the rolling resistance value selected for the range experiment is the default value for the Simscape block.

In terms of significantly improved 50-70 acceleration time, the 'Magic Formula' tire block is again a possible source of the difference. In this case, due to the directionality of the block requiring rotational input to determine traction outputs, the vehicle essentially behaves as an all-wheel-drive vehicle when simulating acceleration, and this may result in improved acceleration timings. This is increased tractability means that it is easier to overcome the increased resistance forces from wind and tires during the 50-70$mi/$h acceleration period; forces which are reduced overall within the range of the 0-60$mi/$h test.

Given that the tire model issues can be resolved, Simscape provides a promising powertrain development environment for EcoCAR students who will have an easier time understanding model components than with automatically-generated Autonomie logic. In this environment design decisions can be made with the confidence that, in the scope of the EcoCAR AVTC VTS, the resulting simulations are as accurate as existing Autonomie models.

8.2 Future Work

8.2.1 Innovation Platform and Vision Pipeline

Currently, the experiment requires the participants to upload drive data on a weekly basis using a physical connection to the phone, thus requiring the phone to be removed from the vehicle and re-mounted. This poses a usability issue and a wireless method of file transfer is desired for the final UIP app.

A significant current usability limitation is that the driver is required to manually start and stop data capture in the android app. This is something that UWAFT aims to change in the final integration of the UIP using the OBD interface and accelerometer data to determine effective record start/stop information.

Privacy limitations mean that the data must be anonymized before the UIP back-end can be developed to supply researchers external to University of Waterloo with research information.

Current approaches in development involve blurring faces or down-sampling video to obscure identifying features, an example of this approach, which does not significantly impact the research value of the data is seen in Figure 8.1. Additional privacy filtering is also required to ensure homes and work locations are not easily identified and matched between captured trips.

A final difference between this experiment and the final integrated UIP is that the developed OBD interface is not present at the time of this pilot project experiment, meaning that baseline human actions cannot be determined automatically from raw OBD data at this time. Once captured, the baseline data would be valuable for not only autonomous research topics, but also could be used to tune driver behaviour in the simscape driver block to investigate the impact of drivers on the vehicle performance and to generate driver-impacted VTS.

In the final integration of the monocular vision pipeline, functionality should be improved in multiple aspects to maximize the value of the pipeline in identifying and

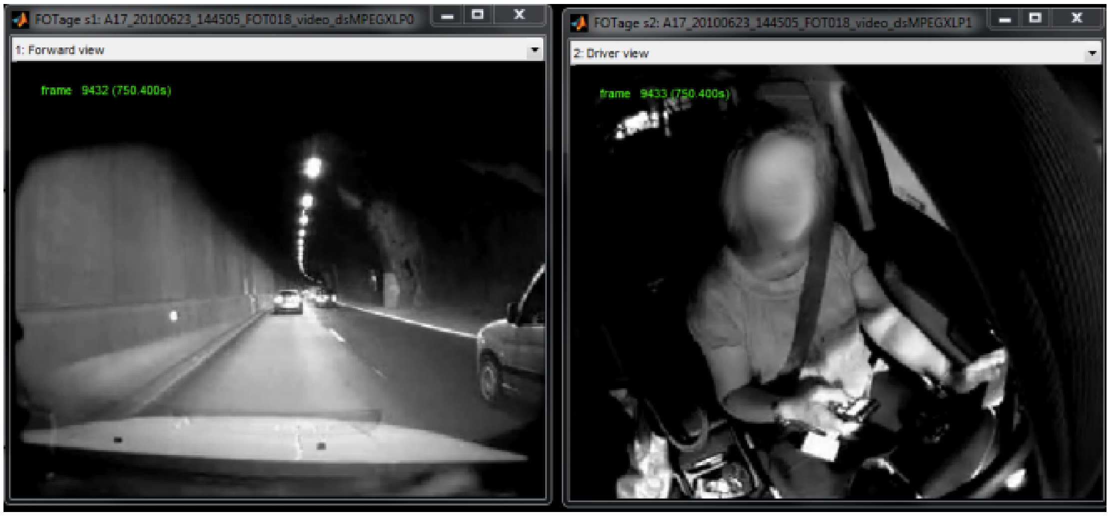


Figure 8.1: With content-aware blurring, identity can be protected [44]

developing test scenarios for autonomous vehicle algorithms or ADAS. Firstly, the system's current distance estimation system should be developed more fully. It is very desirable to have accurate distance estimation as it will significantly improve the ease at which driver-experienced situations are replicated in simulation. A current approach in development is to implement a more sophisticated estimation which estimates the ground plane from image frames [15].

Additionally, the vision pipeline tracking system, though functional, exhibits sporadic re-detection and missed-detection issues for which the object detector is largely responsible. To make the resulting tracks smoother, it is recommended that a lookahead filter be implemented into the pipeline between YOLO and the MDP to reduce the issue of re-detecting and changing the identification number of objects.

Finally, the capability to execute object detection on the phone directly is something which would significantly minimize data transfer requirements from participants at the expense of vision research data. It is additionally possible to extract and send only the identified objects within bounding boxes and to downsample further for a reduced data transfer requirement that still has vision research value.

In conclusion, through developing an open database of naturalistic driving data using crowd-sourcing, the database can be used generate testable cases for continuous improvement and for general algorithm tuning and development, with the added benefits of conducting open innovation. In addition to these broader goals, more immediate outcomes in the areas of scenario re-creation for ADAS, autonomous algorithm testing and powertrain design through simulation are realized at pilot project scales.

8.2.2 Powertrain Simulation

There are multiple aspects of the model which should be improved in future use for VTS simulation.

Most importantly, the front tires should be modelled such that they are capable of inducing tire rotation from translational forces. Though this may be out of the scope of a simscape model component, it is possible to develop a model in simulink components which achieves this with consideration of Pajecka coefficients. Simscape additionally include tire-modelling sub-components which provide Pajecka-type modelling and rotational resistance for the purpose of constructing tire models.

An additional aspect of the model which should be improved is the brake model selection, as the implemented type of brake is not desirable in terms of dynamic analysis of an actual vehicle which typically use disc-type brakes. Currently this is also a limitation of Simscape which does not offer a disc brake model with physical port I/O. As with the ESS model it is recommended that the existing disc brake model from Autonomie be implemented with a simscape interface.

A final recommendation for future use of the model is that the existing dual-ESS model should be augmented to regulate power supply in keeping with peak and nominal discharge time limits. In the current results, these limits are never reached, but with the investigation of powertrains such as the UWAFT Camaro, where there are more motors and a smaller battery, these limits can impact results.

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Part IV

Appendices

APPENDIX A

Innovation Project Timeline

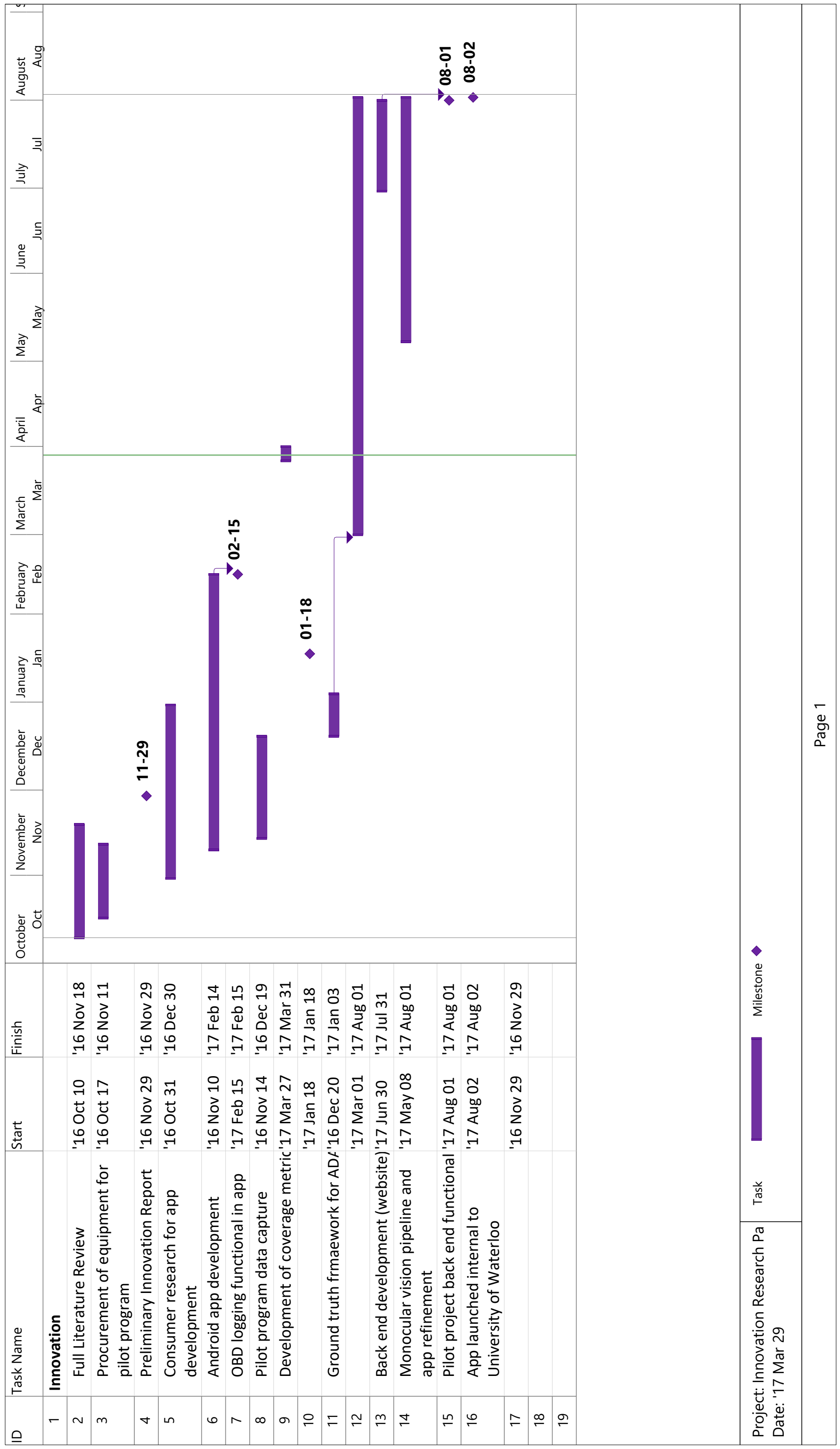

Figure 2: Gantt chart timeline of the innovation project

APPENDIX B
Heatmap Detail

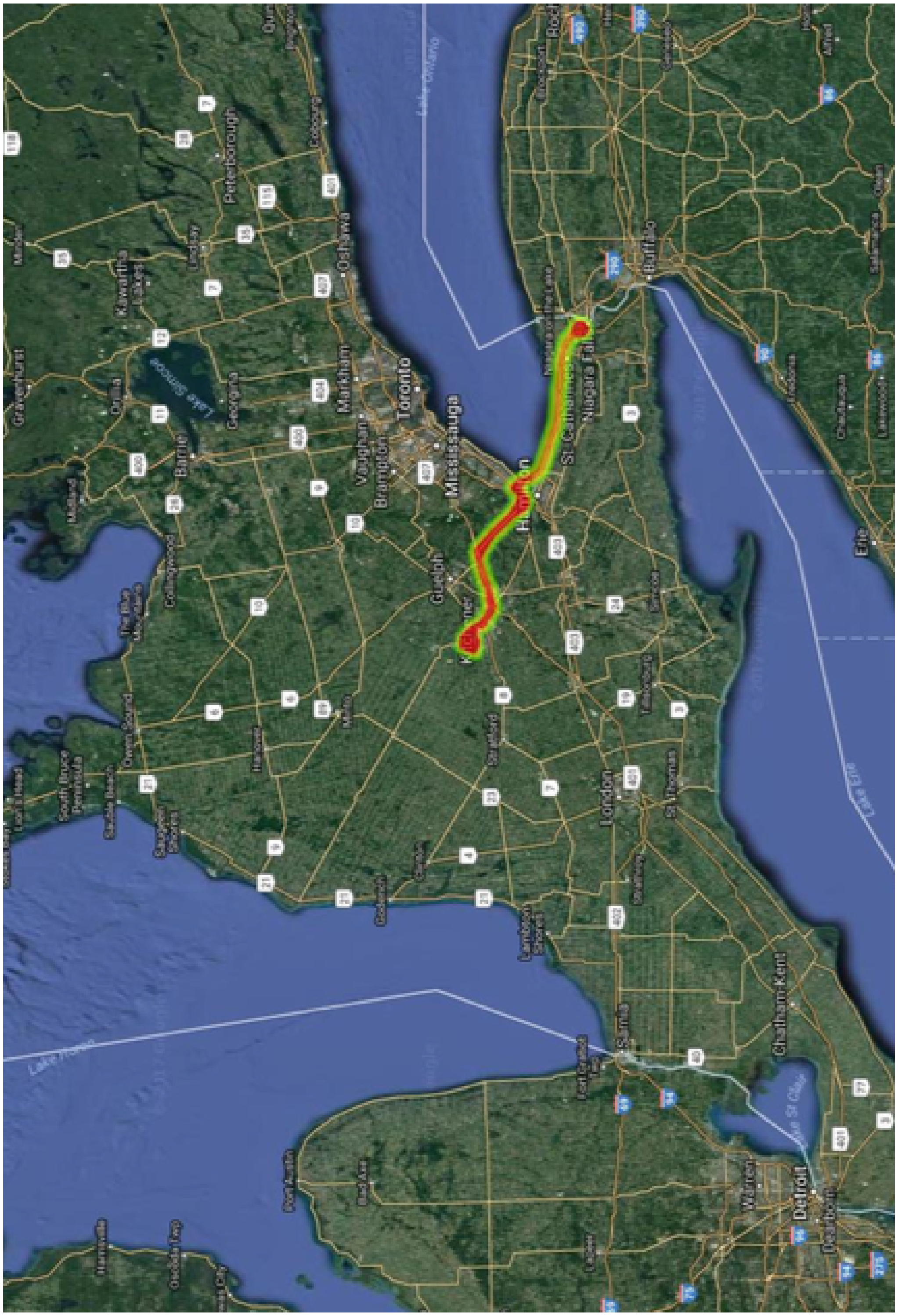

Figure 3: Closeup data coverage of Southern Ontario

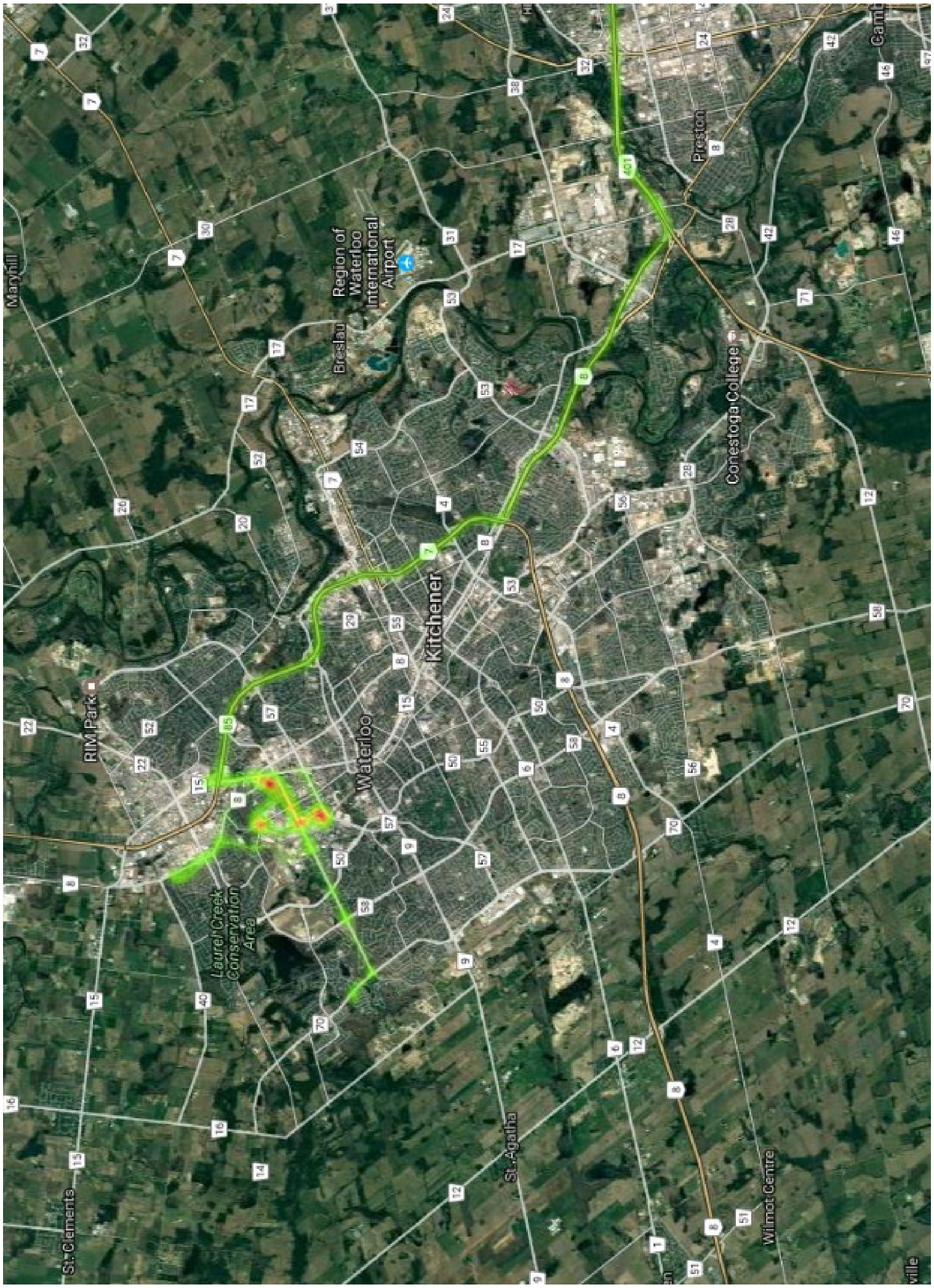

Figure 4: Overview of data coverage showing trips to US

APPENDIX C

Innovation Platform Cost

Item	Item Name	Item Description	Item Model or Part Number	Name of Vendor	Qty	Cost CAD (subtotals, inc.tax)
1	Samsung Galaxy J5 J500M	8GB Unlocked GSM 4G LTE Quad-Core Android Smartphone w/ 13MP Camera - Gray	J500M	JP Mobiles CA	1	287.44
2	SAMSUNG 64GB EVO Class 10 Micro SDXC	64Gb MicroSD card. Up to 48mb/s transfer speed	MB-MP64DA/AM	Ultimait NA	1	63.45
3	TaoTronics Car Windshield / Dashboard Universal Smart Phone Mount	Fully 360 degree rotation for portrait and landscape views, easy tilt adjustment for optimal viewing angles	TT-SH08	Sunvalleytek Canada	1	17.24
4	Anker PowerLine Micro USB (6ft)	Micro USB charging cable (6ft)	A8133011	AnkerDirect-CA	1	10.84
5	USB Car Charger Adapter for Samsung	BC Master 18W 1-Port USB car charger	BCM-C01	BC Master Store	1	10.34
6	Arduino Uno R3	Microcontroller for OBD logging	RB-Ard-34	Robotshop.ca	1	25.99
7	CAN-BUS Shield	Adds CAN bus logging to arduino	RB-Spa-1251	Robotshop.ca	1	33.27
				TOTAL COST PER UWAFT INNOVATION PLATFORM $CAD		**448.58**

Figure 5: The cost of the UIP is below 500$

APPENDIX D
Tracking Algorithm

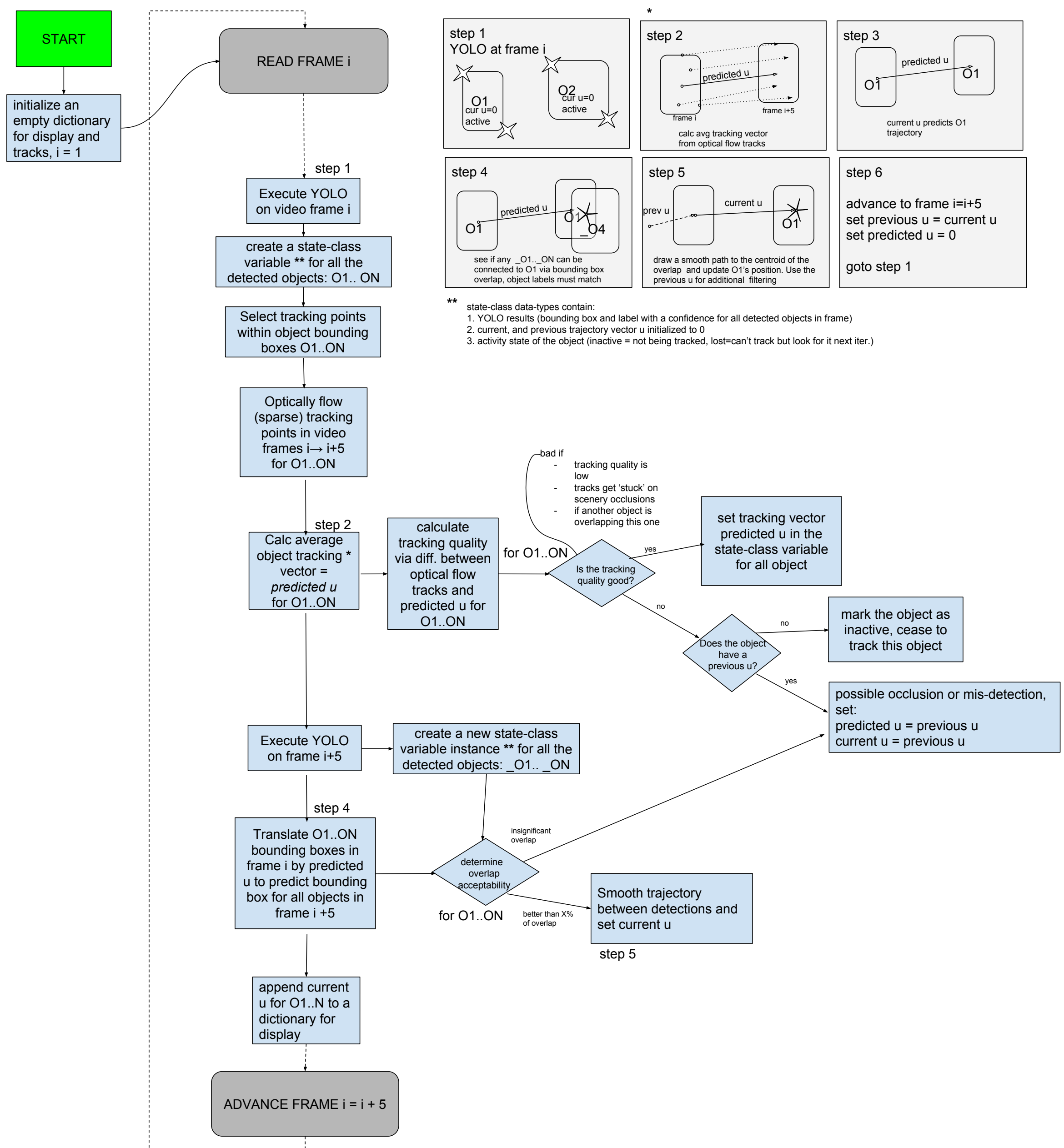

Figure 6: Developed tracking approach using optical flow

Glossary

Advanced Driver-Assistance Systems are systems to help the driver in the driving process. When designed with a safe human-machine interface, they should increase car safety and more generally road safety. iii

Battery Electric Vehicle is a type of electric vehicle (EV) that uses chemical energy stored in rechargeable battery packs. 3

electronic Limited Slip Differential is a type of differential that allows its two output shafts to rotate at different speeds but limits the maximum difference between the two shafts. 5

Global Positioning System is a global navigation satellite system that provides geolocation and time information to a GPS receiver anywhere on or near the Earth where there is an unobstructed line of sight to four or more GPS satellites. 1

Hybrid-Electric Vehicle is a type of hybrid vehicle and electric vehicle that combines a conventional internal combustion engine (ICE) system with an electric propulsion system (hybrid vehicle drivetrain). 4

Internal Combustion Engine is a heat engine where the combustion of a fuel occurs with an oxidizer (usually air) in a combustion chamber that is an integral part of the working fluid flow circuit. 2

Markov Decision Process provides a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker. iii

On-board Diagnostics is an automotive term referring to a vehicle's self-diagnostic and reporting capability. 1

Plug-in Hybrid Electric Vehicle is a hybrid electric vehicle that uses rechargeable batteries, or another energy storage device, that can be recharged by plugging it in to an external source of electric power. 4

Vehicle Technical Specifications these technical specifications provide a measurement of vehicle performance. Typical specifications are acceleration tests such as the 0-60 mph time and curb weight. 2