TRAFFIC LIGHT PREDICTION USING CONNECTED VEHICLES

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Master of Science in Mechanical Engineering

Georgia Institute of Technology
May 2019

TRAFFIC LIGHT PREDICTION USING CONNECTED VEHICLES

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ACKNOWLEDGEMENTS

I would like to thank Dr. Bert Bras for his advice and guidance through my work and thesis.

I would like to thank Ford Motor Company who funded much of this work, and specifically Ford team members Jacob Mathews, Anne Marie Graham-Hudak, and John Snider without whom this would not be possible.

I would like to thank everyone in the Sustainable, Design, and Manufacturing lab at Georgia Tech for their support and feedback.

Finally, I would like to thank my friends and family for their support throughout my time in school, and especially Darby Mokry for her continuous support for me throughout my time in graduate school.

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SUMMARY

As vehicles contain more and more sensors is there a way these sensors can provide useful information to the driver? Currently drivers receive feedback on the speed of the vehicle, the RPM of the engine, and a few other signals. Because of these new sensors it is now possible to advise the driver on factors that are external to the vehicle. Studies have shown that it is possible to improve a driver's fuel economy through various driver coaching techniques. This paper proposes and tests a new form of driver coaching by proving a new form of driver feedback.

Traditional driver coaching focuses on having the driver use less throttle, use less brake, drive slower, and turning off the engine while idling. These approaches have seen fuel economy improvements by as much as 20% depending how aggressive the driver is. Research has also shown that with ideal approaches and future knowledge of traffic lights fuel economy improvements of up to 30% can be observed. Studies involving Traffic Light coaching and optimizations have been done using simulations. There is evidence that proving useful feedbacks to the driver can improve the fuel economy.

A multi vehicle approach called leader-follower traffic light prediction method is developed to advise drivers on the future behavior of the route. The leader-follower method works for static traffic lights. This approach has 3 steps: learning, leading, and following. The learning phase learns relatively static traffic light properties. The leader portion is performed as frequently as possible and captures traffic light properties that expire. This approach uses multiple vehicles to share information between them. Any vehicle can be a

follower and receive the traffic light prediction information, but only vehicles with advanced vision systems can act as a learner or leader.

The leader-follower method is tested on a public road using four drivers. The drivers perform 120 miles worth of testing. The route has 10 total traffic lights and is 1 mile long. 9 of these are coachable traffic lights. Road conditions and variables are reduced by driving at the same time every day. Recording devices are used to capture the information during testing.

The testing results show an average fuel consumption reduction of 18.7% for the coached drivers. The fuel consumption reduction agrees with what has been shown in literature and is a valuable feedback to provide to drivers on routes with traffic lights. The fuel consumption reductions have been correlated with braking and throttle performance for each driver.

CHAPTER 1. INTRODUCTION

1.1 Opportunities and Potential for Driver Led Fuel Improvements

When drivers analyze their miles per gallon (mpg), they may notice differences between the Environment Protection Agency (EPA) mpg rating and the actual mpg. Because the user has control over the vehicle's mpg, this is a possible opportunity for maximization. Oil is a resource that will run out eventually, but the exact year is up for debate. Oil is very inelastic, so when a user can save oil they are directly saving money and an expendable resource (Dale 2016). Eco driving is the practice of driving in a manner to increase fuel economy of the vehicle, while eco-coaching is the practice of instructing users how to increase the fuel economy by changing their driving habits. By practicing eco driving, literature shows gains of 5-30% fuel savings (Alam and McNabola 2014). Policy makers see these gains and target them as a way to reduce cash flow to the Middle East(Dale 2016). Figure 1 shows the impact of various factors on the vehicle fuel economy. Factors such as the tune of the engine, the road grade, speed, cruise control, and aggressive driving have impacts on fuel economy over 7% (Sivak and Schoettle 2012). The driver has more control over some of these elements than others. Some of these factors are easily solved with proper vehicle maintenance, while other factors are uncontrollable, such as the time of day to avoid high traffic levels. Some of the factors can be targets for optimization and improvements. Speed is a great parameter for optimizations because the driver has direct control over it with the accelerator and brake pedal. Speed is easily measured by the vehicle, so it is simple to report on. Aggressive driving is a parameter that is commonly associated with eco-coaching. It relates to high accelerations which wastes fuel.

Technology like adaptive cruise control is better optimized by the automotive manufactures because the driver has no control of how the technology functions besides what speed the user would like to travel.

Level	Factor	Effect
Strategic	Vehicle class	38%
	Vehicle model	800% all cars; 355% cars excluding fully electric; 227% cars excluding fully electric and hybrids; 100% all pickups
	Vehicle configuration	18% cars, 28% pickups
	Out-of-tune engine	4–40%
	Tires with 25% higher rolling resistance	3–5%
	Tires underinflated by 5 psi	1.5%
	Improper engine oil	1–2%
Tactical	Route selection: road type	Variable
	Route selection: grade profile	15–20%
	Route selection: congestion	20–40%
	Carrying extra 100 lb	≤2%
Operational	Idling	Variable
	Driving at very high speeds	30%
	Not using cruise control	7% (while at highway speeds)
	Using air conditioner	5–25%
	Aggressive driving	20–30%

Figure 1-1: Effects of factors on vehicle fuel Economy(Sivak and Schoettle 2012)

Users expect to get the EPA rated mpg but may be receiving lower mpg values. The variability in actual mpg is a target for improvement. Improvements will vary depending on the target chosen for optimization. Driver aggression accounts for 20% variance in fuel economy (Sivak and Schoettle 2012). Managing driver aggression focuses on maintaining a constant speed and lowering accelerations. When idling a passenger car consumes 18.11 mg/s of fuel. The idling fuel use compares to 39.10 mg/s while cruising, and 62.62 mg/s under acceleration. Therefore idling uses 46% of fuel compared to cruising (Tong, Hung et al. 2011). Reducing idling time can save fuel by preventing a user from racing to a stop. Racing to a stop results in increased accelerations and idol time that consume more fuel. A better approach to the stop is to start idling while the vehicle is cruising. An improved stopping approach reduces the use of the brakes. Maintaining a steady speed saves 7% fuel economy (Sivak and Schoettle 2012). These factors show that there are potential gains depending how the user is using the vehicle.

1.2 Challenges for Driver Coaching

Not all drivers will be willing to change their driving styles to accommodate better fuel economy. Cristea et al. shows that drivers were more willing to follow speed limits, but not time headway associated with eco driving practices. Time headway refers to the spacing or time between vehicles in a transit system. The speed limit is more associated with safety while time headway is associated with emissions and deemed less important by drivers (Cristea, Paran et al. 2012). While drivers are less likely to seek out an eco-coaching device, they would use it if it comes standard with the vehicle (Boriboonsomsin, Vu et al. 2010). Driver's lack of motivation is not the only problem with driver coaching. Many forms of coaching involve forms of driver feedback. If a feedback is too involved it can distract the driver and become dangerous. In a 100 car study nearly 80% of car accidents and 65% of near accidents found that the drivers had looked away from facing forward before the crash (Dingus, Klauer et al. 2006). Driver compliance with the device and device safety are two of the main challenges for any driver coaching systems.

1.3 Proposed Solution – External Vehicle Coaching

As previously discussed, the driver can reduce fuel economy by up to 55% through factors they can control (Sivak and Schoettle 2012). The large effect that a user can have over their vehicle presents an opportunity to maximize the fuel efficiency. In the future with autonomous vehicles, coaching techniques will not exist because there will not be drivers. Autonomous vehicles using optimized driving profiles can achieve 22-31% less fuel in acceleration conditions than a traditional vehicle (Wu, Zhao et al. 2011). Autonomous vehicles are the best-case scenario for fuel efficient driving. Most vehicle coaching revolves around trying to improve control over the internal aspects of the vehicle, such as reducing harsh acceleration, maintaining speed within certain bounds, and turning off the engine when idling for certain periods of time. Implementing these strategies only shows big fuel economy improvements for drivers who are driving very aggressively (Gonder, Earleywine et al. 2012). There is opportunity for a modern approach to coaching.

An approach that changes driver behavior only addresses part of the problem. Coaching a driver on external factors is the next opportunity for fuel improvements. Knowing how to advise drivers, not only on internal factors such as use of the throttle and brakes, but also on external factors such as the immediate vehicle in front, the average traffic flow at that time, and the traffic light timings provides more opportunities for unpursued coaching techniques. Traffic light prediction will be pursued in this paper for its ability to have big impacts on driver's fuel consumption. Predicting traffic light timings remains difficult. There are a variety of different traffic systems that are available and implemented by different levels of government in the U.S. The different level of government implementation makes one single approach to predicting all traffic lights impossible due to the nature of how these different traffic light control systems work. The traffic light systems are explained more in depth in Chapter 2. However, a system is introduced in Chapter 3 that works for all two-cycle fixed time traffic lights. This system is called the leader-follower traffic light prediction method. The leader-follower method is a connected vehicle approach to traffic light prediction. The coaching information can go beyond just a driver feedback and can be provided to an autonomous vehicle as another feedback in the future.

CHAPTER 2. BACKGROUND

Chapter 2 provides an overview of the literature and previous work done in the areas of driver coaching, adaptive cruise control, traffic light technology, and traffic light research. An estimated 6 billion gallons of fuel are wasted every year by light and heavy-duty vehicle's idling; the 6 billion gallons of wasted fuel during. Some local and state governments have even made unnecessary idling illegal in their jurisdiction (Center). One of the causes of idling occurs sitting at traffic lights. The techniques mentioned in Chapter 1 aim to reduce idling and other forms of wasted energy such as excessive acceleration. To understand why the idling occurs the traffic conditions and traffic light technology needs to be understood. Driver coaching is discussed in Chapter 2 and improves the driver's use of the vehicle. Chapter 2 reviews traffic light technology, eco driving coaching, traffic light coaching, vehicle to vehicle communication, and industry.

2.1 Traffic Light Technology

Traffic intersections are a source of idling for vehicles in the U.S. Several different technologies have been proposed for traffic lights such as fixed time control, coordinated control, adaptive control, and traffic light to vehicle communications. In 1998 there is a total of 330,000 traffic light intersections in the US. These traffic lights are controlled by different local, state, and federal governments. The non-unified source makes getting all these traffic lights all on to one unified system difficult (Baily 1998). Section 2.1.1 discusses fixed time traffic light control, the most basic form of traffic light control. Section 2.1.2 covers coordinated, and adaptive traffic light control. Coordinated, and adaptive traffic light control is a method that relies on a complete picture of the traffic light network.

Section 2.1.3 discusses traffic light to vehicle communications (TLVC); TLVC relies on direct communication between the vehicles and the intersection. The different traffic light control schemes affect the performance of a vehicle in that network.

2.1.1 Fixed Time Traffic Light Control

Fixed time cycle traffic lights are common; they account for 80% of the U.S. traffic lights. A fixed time cycle traffic light holds the green and red light times constant between cycles (Kerper, Wewetzer et al. 2012). Fixed time cycles do not vary based on the type of traffic being encountered at the intersection. Fixed time cycles have been well studied and many properties such as queue length and delay are predicable based on the cycle and level of traffic (van Leeuwaarden 2006). Presenting drivers with future knowledge of a fixed time traffic light can increase the fuel economy by 31% to 91% (Vahidi 2012). Expected real world results won't reach the ideal situations of Vahidi's simulation, but these fuel consumption decreases show potential for optimizing of fixed time traffic lights. An issue, predicting fixed time traffic light cycles, is how the clocks of the traffic lights are not synchronized in most cases and have significant amount of drift per day. The drift, or random walk, can range from 5 to 40 seconds per day. Random walk has been confirmed by tests conducted for the experiment in Chapter 4. Relative to the traffic light cycle the random walk is a large percentage of the cycle (P.-S. Lin 2010) (Vahidi 2012). The traffic light time cycles are not optimized for the amount of traffic being seen by the intersection. Other methods for traffic light control have been studied, designed, and implemented.

2.1.2 Coordinated and Adaptive Traffic Light Control

Coordinated traffic systems often implement adaptive control, and it can be difficult to separate these two concepts. One example of a coordinated traffic system is the Sydney coordinated adaptive traffic system (SCAT) implemented in Sidney Australia. The purpose of a coordinated traffic system is to create a green wave between traffic lights. A green wave allows an increase in traffic flow and reduction of stoppage time. A green wave occurs when the traffic lights aim to improve the flow of traffic in one direction by managing the times where the lights turn green in order to keep traffic moving without stopping. A preliminary study for the SCAT system offers up to 14.5-39.5% reduction in journey time over measurements obtained for a fixed traffic light network(Baily 1998). While coordinated traffic lights offer many benefits, they require infrastructure investments from the government.

2.1.3 Traffic Light to Vehicle Communications

Traffic light to vehicle communications (TLVC) has existed in literature for decades, but implementation of such systems has been slow. As of May 2018, only 10 U.S. cites have implemented any TLVC systems that are compatible with the Audi traffic light information system. The Audi system tells the driver what when the traffic light will change. Figure 2-1 shows an implementation of the Audi Traffic light information system. The Audi system includes 2,250 intersections (Koons 2018). TLVC allows the traffic lights to share information with the vehicle so that the traffic light and vehicle can make decisions based on that information. The amount of fuel saving based on TLVC varies from 7 to 8%. (Tielert, Killat et al. 2010, Katsaros, Kernchen et al. 2011). However, in single vehicle simulations fuel savings can be seen of up to 22% (Tielert, Killat et al. 2010). The distance to advise vehicles trying to improve fuel economy via TLVC is optimal at ranges from

300-600m (Tielert, Killat et al. 2010, Katsaros, Kernchen et al. 2011). In urban environments, 300-600m is a long distance to be advising, and distance between traffic lights can be shorter than this distance. The way the driver is informed of the traffic light information makes it one form of driver coaching.

Figure 2-1: Audi Traffic Light Information System(Koons 2018)

2.2 Eco Driver Coaching

Driver coaching is providing information to a driver on how to drive to decrease the fuel consumption. Eco-coaching is broken up into 5 levels. Level 1 is traditional eco-coaching using offline advice. Level 2 is providing feed back to the driver using the OBD-II port. Level 3 involves an integrated system that uses predictive models. Level 4 uses advice from other external sources. Level 5 uses external source information and will make changes to the power train according to the external information. Most hybrid and electric vehicles have implemented solutions between levels 1 and 3 (Ivens, Spronkmans et al. 2013). The approaches implemented Chapter 3 focus on levels 1 through 4. The proposed solution is a level 4 solution.

Automobiles waste fuel through the factors listed in figure 1. Not all the factors are coachable. One factor that affects fuel economy and is coachable is excessive acceleration (Hooker 1988). Excessive acceleration is targeted by most driver coaching methods; however, it is not the only parameter that is targeted. Studies of how to coach a driver have different methods. Gains from driver coaching depends on how aggressive the current user drives the vehicle. An aggressive driver can see up to 20% fuel savings by implementing driver eco-coaching techniques. A more moderate drivers will see fuel savings around 5-10% by implementing driver eco-coaching techniques. Gonder et al. recommends driving between 25 and 55 mph, slow down by using the engine, when above 10 mph accelerate at a rate of 3 seconds for every 10mph, turn off the engine when parked or idling, and avoid speed fluctuations. Time to collisions (TTC) is closely related to high accelerations, and increased fuel consumption (Gonder, Earleywine et al. 2012).

A completely different approach to coaching focused simply an analyzing the fuel savings and time effects of lowering the maximum travel speed. A reduction in speed by 20 km/h resulted in a fuel savings of 14% and a speed reduction of 10km/h resulted in a fuel savings of 5 percent (McLeod 2017).

Yanzhi Xu focuses on a power train approach to driver coaching (Xu, Li et al. 2017). As opposed to just focusing on general concepts such as low accelerations, Yanzhi Xu takes a different approach focusing on scaled tractive power (STP). STP is:

$$STP = \left(\frac{A}{M}\right)v + \left(\frac{B}{M}\right)v^2 + \left(\frac{C}{M}\right)v^3 + \left(\frac{m}{M}\right)(acc + sin\theta)v$$

where a is rolling resistance in kW s/m, B is rotating resistance kw s^2/m^2, C is aerodynamic drag in kW s3/m3, m is the vehicle mass in metric tons, acc is acceleration second by second in m/s2, v is velocity second by second in m/s, M is fixed mass factor, and θ is road grade. STP can then be limited to a certain factor and will advise the driver when they have exceeded the factor. The STP method sees fuel reduction of 5 percent for local transit and 7 percent for express bus service (Xu, Li et al. 2017). The STP approach focuses only on the power use of the vehicle and not external factors. Keeping a consistent speed is approached through use of cruise control. Modern approaches of driving coaching involve user feedback through either the dashboard or through a smartphone app. One approach is to take data from the OBD-II port of the car, and offer feedback hints such as “switch off engine” or “acceleration is too high” (Araújo, Â et al. 2012).

Another study using driver feedback reporting on gear shifting, maintaining steady speed, accelerating and decelerating softly, and turning off your engine, found a 6% fuel savings on the highway and 1% on the interstate. Boriboonsomsin et al. study was conducted using a data logger with access to the OBD-II port and 20 drivers (Boriboonsomsin, Vu et al. 2010). Instantaneous feedback allows the user to change their driving habits in real time. Understanding these topics allows for attempts at improving fuel economy that have not been attempted in a real world setting before, such as fixed time traffic light coaching.

Xu has a comprehensive overview of drive coaching techniques. His literature review shows fuel economy improvements of 5 percent all the way up to 37%. However he specifies the vehicle type and the real world and simulated results. Real world results peak around 13 percent, but simulations so fuel improvements up to 37%. The type of vehicle also changes the fuel savings. However, most of the results lie between 5% and 13% fuel economy improves with driver coaching (Xu, Li et al. 2017).

2.3 Traffic Light Coaching

Approaches to inform the user on traffic light information have been studied but have been slow to be implemented. There are several challenges involved in traffic light prediction. The random walk in timing of traditional fixed time traffic lights makes distant prediction difficult (Sivak and Schoettle 2012). To achieve a high-accuracy prediction the system must have near real-time traffic light information (V. Protschky 2014). The need for recent data makes building prototypes for a traffic light prediction system more challenging given that older data becomes useless in a few hours. However, for more modern or coordinated traffic lights with time synchronization and have fixed cycles, there may be an opportunity for distant prediction with the knowledge of the first state change, and the traffic light cycle's timing. Miguel Sanchez et al. studies a traditional traffic light approach using the IDM which is a "car-following model" and his IDMP model that takes traffic light information into account. The IDM model has two basic behaviors. The first behavior is that the car has a target speed and tries to vary from that as little as possible, and the second behavior is that the driver will keep a safe distance between vehicles by adjusting its speed. The IDMP model has the same two behaviors with the addition of a third behavior. The third behavior is that the traffic light information is known, and the vehicle will change its speed to make it through the intersection. The car will make the necessary speed changes try to make the traffic light. The results of the simulation shows 18% less fuel used by the first car using IDMP and 30% less fuel used by all the trailing cars using IDM (J. Miguel Sanchez 2006). Sanchez et al. study shows that if one lead car can react to the traffic condition, all the following cars can benefit.

A method of feedback control for predicting traffic lights for adaptive traffic lights has been proposed and simulated. The feedback prediction system uses data called signal phase and timing information (SPaT) that is broadcast near the intersection. SPaT data comes from the infrastructure and makes prediction of how the traffic lights will change possible. Their complicated approach relies on historical data of the total range of traffic light lengths. The model creates a prediction that is good for a limited time. The previous prediction is compared to the new prediction. The accuracy between the new and old prediction is sent the manipulated variables database, the prediction is manipulated if the set point accuracy is less than 95%. The system resulted in predictions that 65% of the time had an accuracy of 90 to 98% for 80% of the traffic lights in the system. While the approach is successful it might not provide the user with trust in the system as only 65% of the time the prediction is accurate above 90% (V. Protschky 2014).

Xia et al. work shows fuel improvements in simulation having an ideal intersection approach. The traffic light information is known 300m in advanced of the intersection and comes from SCaT. The simulation investigated performance with different levels of adoption for the optimized intersection approach, and the different levels of traffic. The velocity planning algorithm improves fuel economy by 12% for a standalone vehicle. The overall traffic benefited from the system more than just the car equipped with the system.

The benefit for traffic holds for low adoption rates. The fuel saving for all vehicles was 3.39% and only 1.57% for equipped vehicles with a penetration rate of 20%. Cases with 100% adoption, and low traffic start to approach the 12% gains seen by a standalone base line vehicle (Xia, Boriboonsomsin et al. 2012). Depending on the traffic scenario traffic light prediction can result in a few percent fuel economy reduction to 30% fuel economy reduction. Xia et al. results are shown in Figure 2-2.

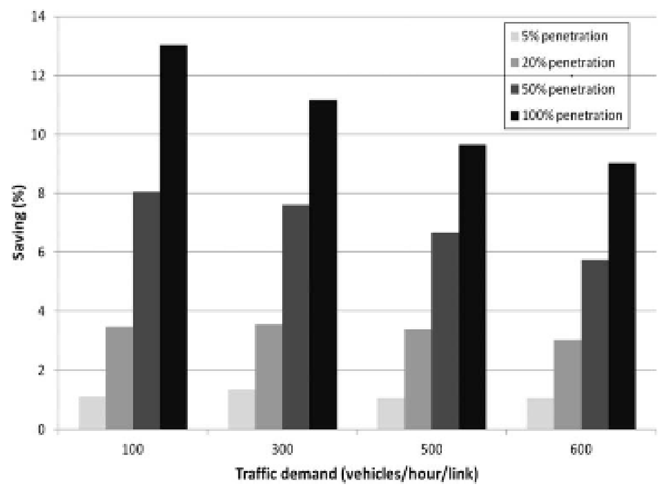


Figure 2-2: Fuel Savings vs Traffic Light Coaching Penetration Rate(Xia, Boriboonsomsin et al. 2012)

Is there bigger gains to be seen if multiple traffic light optimizations are simulated? A 5 traffic light optimization study results agree closely with Xia et al. work with traffic light optimization. Nuzio’s work does not indicate that multiple traffic light optimizations will offer more fuel savings when compared to Xia et al. work. The fuel saving varied from a few percent with a few percent adoption to a 30% with 100% adoption of the system. These results are shown in Figure 2-3 (Giovanni De Nuzio 2016). However, the literature is lacking in real world examples of implemented traffic light prediction systems and results.

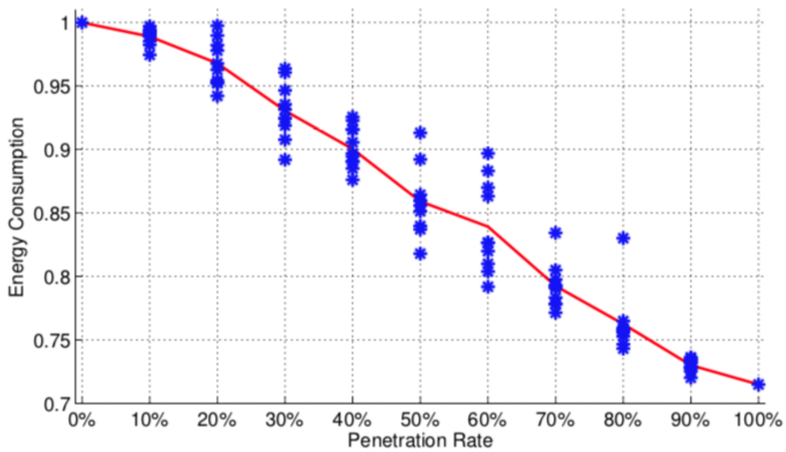
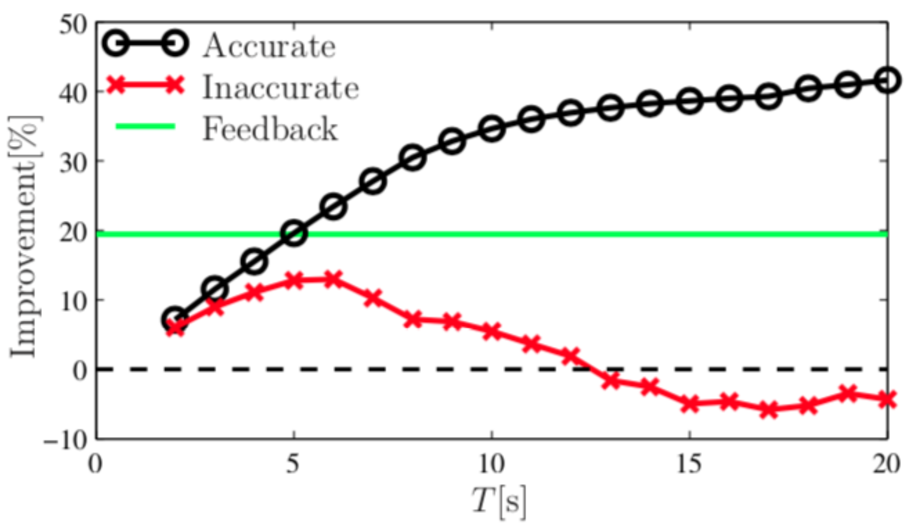


Figure 2-3: Penetration Rates Vs Energy Consumption(Giovanni De Nuzio 2016)

2.4 Vehicle to Vehicle communication

Vehicle to Vehicle communication (V2V) has been researched for purposes of improving road safety and improving fuel economy. V2V is normally implemented through cooperative adaptive cruise control (CACC) or platooning. CACC further improves Adaptive cruise control (ACC) especially in bottle neck scenarios where users normally come to a complete stop. Platooning is a group of many vehicles that are communicating on how they are driving. Platooning offers many benefits. A few of these benefits include reduced air resistance, higher traffic density, and decrease in vehicle accidents (Dianati 2012). A look into two different implantations of CACC shows that there are many ways to implement these systems, and the performance of these different implementations will vary. One method is a feedback method of CACC, and the other is a predictive method called rolling horizon optimal control (RHOC) coordinated cruise control (CCC). Figure 2-3 shows the effect of the preview horizon on the RHOC CCC system. While the feedback method has a fixed 20% efficiency improvement over a standard heavy-duty truck, the performance of the RHOC CCC system varies depending on the accuracy of the information and the amount of time horizon that can be provided. Time horizon is the predicted position and speed of the vehicle directly ahead by taking information from other platooning cars. When a 5 or more second time horizon can be provided the RHOC method, it can outperform a feedback method. However, if the information used to base the time horizon is inaccurate, the performance is always worse than a feedback method (Orosz 2017).



V2V communications can be shown to reduce crashes. Out of three crash scenarios a combination of V2V and ADAS-ACC is able to stop all crashes with a 40% penetration rate (Aso Validi 2017). Having V2V and I2V provides not only the ability to react to the other cars around, but also predict the environment around you. Knowing that these possibilities exist Barik et al. simulated what happens if the driver optimizes its speed as it travels across two real world routes. The information comes from V2V communications. The result shows a 3.5% fuel economy improvement over the base line.

The vehicle was a Chevy volt gen II (Barik, Krishna Bhat et al. 2018). The Chevy volt gen II has the benefit of regenerative braking over an IC vehicle, and still managed 3.5% fuel improvement. 3.5% is a modest gain, but over a long distance with significant road grade changes, traffic, and intersections. V2V communications can improve fuel economy and is one of many opportunities that the automotive industry is looking into.

2.5 Review of Industry

The automotive industry has been faced with regulations to push the fuel economy of the vehicle up, and big fuel economy gains have been seen for light duty vehicles over the last 50 years. Industry has not widely adopted eco-coaching tools in every vehicle, but some tools have become wide spread. Tools such as mpg reporting inside the vehicle have become standard in vehicles. Automakers such as Ford have introduced a braking coach into hybrid or electric vehicles that attempt to maximize the energy recovered through regenerative braking. Ford's braking coach provides feedback as a percentage after each braking attempt. Mercedes has implemented the ECO display. The tool uses is a display that claimed by Mercedes to raise fuel economy by up to 30%. The tool focuses on threes aspects of driving: coasting, acceleration, and steady state . Audi has implemented the traffic light information system. The traffic light information system informs the user when traffic lights will change as discussed in section 2.3. The cars receive these updates through integrated 4G LTE hot spot. The traffic light information comes from a centralized Audi system (Koons 2018). With automakers adding more sensors to the vehicles, especially external facing sensors pose an opportunity to use these sensors typically implemented for safety purposes for other purposes that have never been available before.

2.6 Conclusion

When looking at the literature review, there is a great volume of research focusing on improving driver fuel economy through steady driving, with less accelerations. The traditional approach shows fuel economy gain of up to 20% depending how aggressive the driver was to begin with(Alam and McNabola 2014). There are many studies in this field with real world tests and results, but when it comes to coaching traffic light information there is no research that goes beyond simulations. Results from traffic light coaching shows fuel economy improvements of around 3% to 30%. These improvements required hundreds of meters of space to optimize the approach to the intersections. Larger improvements can be seen from the intersection optimizations when they are able to provide distant predictions at least 300m in advance or perform multiple traffic light pathing optimizations, but these vehicle traffic light optimization paths have not been tested in real world scenarios with live traffic. Many other variables that are difficult to plan for and model such as differences in time of day, or construction dynamically affecting traffic flow. Since fixed time traffic lights are a large portion of the traffic lights in the U.S. They serve an excellent starting point for a real-world traffic light coaching implementation.

CHAPTER 3. METHODS

3.1 Introduction of Methods

Literature shows that coaching a driver can measurably improve a driver's fuel economy. In the past, eco-coaching techniques focus on internal factors, such as having the driver use less throttle, use less braking, and drive between certain efficient speeds (Gonder, Earleywine et al. 2012). The approach in Chapter 3 coaches on external factors that cause the driver to use the brake or to use the throttle. Traffic light prediction coaching is another external factor that has been shown to improve fuel economy. After a traffic light prediction method has been developed, the coaching application will be provided to the driver in real time while the driver is operating the vehicle. The results from the desired traffic light feedback, led to the development of the leader-follower traffic light prediction coaching.

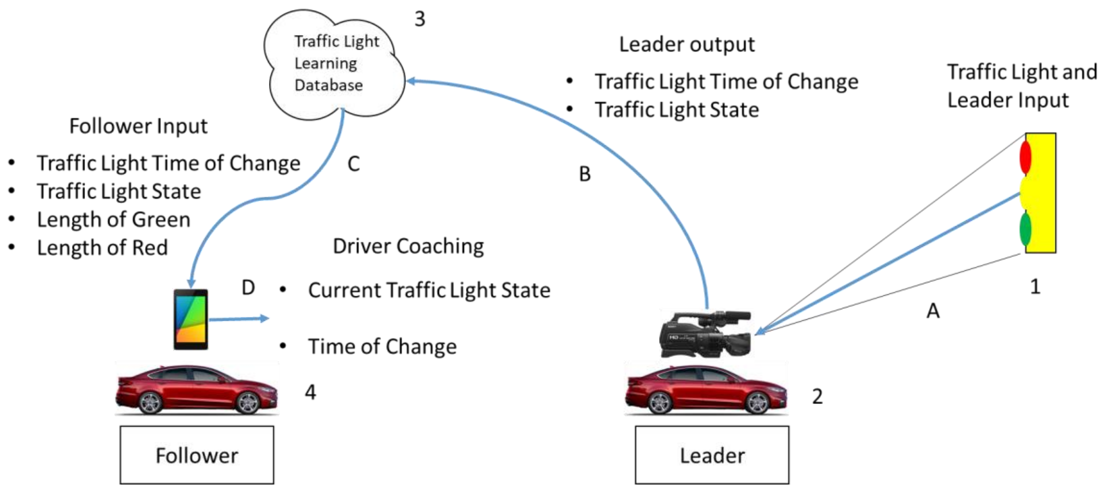
3.2 Traffic Light Prediction Opportunities, Challenges, and Design

Coaching a driver on traffic light timing has shown fuel economy improvements by up to 30% based on the research previously mentioned in chapter 2. There are challenges to implanting traffic light coaching. The biggest challenge is showing a correct prediction of when the traffic light will change in the future. Showing the future timings for a traffic light are difficult for two reasons. The first reason is because of the variety of traffic lights: fixed time traffic lights and adaptive traffic lights. Adaptive traffic lights have complex computer algorithms that have many inputs that effect their output. Coaching the user on these kinds of traffic lights requires the infrastructure to send a signal to the vehicle regarding the traffic light timings. The requirement for the infrastructure to send a signal to the vehicle increases the cost of the system. Fixed time traffic lights make up 80% of the traffic lights in the U.S. (Kerper, Wewetzer et al. 2012). Fixed time traffic lights are the focus of the traffic light prediction system, because fixed time traffic lights have been widely implemented. The second problem with traffic light timing prediction is the random walk associated with fixed time traffic lights. Random walk has been discussed by Cristea et al., and has been directly observed during method development (Cristea, Paran et al. 2012). Traffic light cycles can vary by a few seconds to forty seconds per day depending on the traffic light because of the random walk. A traffic light prediction algorithm needs to compensate for the random walk the lights can have.

To predict two-cycle fixed time traffic lights four parameters are required. Two-cycle fixed time traffic lights have a constant length of green and red times for a given time of day. The length of time that a light is green or red can change depending on the time of day according to a set schedule. The four required parameters for accurate prediction for a two-cycle fixed time traffic light are the length of the green time, the length of the red time, the absolute time of change for the traffic light, and the state that is associated with the time of change. From these 4 inputs, 2 outputs are produced: the current state of the traffic light and the time until the traffic light changes state. The leader-follower traffic light prediction coaching is a method that obtains these 4 inputs and outputs the 2 outputs.

3.3 Leader-Follower Traffic Light Prediction Coaching

Advanced driver assists systems, such as autonomous vehicles, require the development of traffic light vision systems. These vision systems are intended to guide an autonomous vehicle on how to approach the intersection. These sensors and systems provide the required data, allowing the ability to make predictions of how the traffic lights will behave in the future. The leader-follower method has 3 phases: learning, leading, and following. The three-phase approach is required because the random walk of fixed time traffic lights is large enough that accurate predictions are impossible for extended periods of time. The traffic light random walk is discussed by Cristea et al., and has been directly observed during method development (Cristea, Paran et al. 2012). The leader-follower method focuses on maximizing performance of two-cycle fixed time traffic lights, where a two-cycle fixed time traffic light has one length of time for the red part of the cycle and one length of time for green part of the cycle. A similar approached could be used for four-cycle fixed time traffic lights or any type of fixed time traffic light; The leader-follower method implementation focuses on two-cycle fixed time traffic lights. A four-cycle fixed time traffic light has two red and two green timings contained in one complete cycle. Vehicles that have advanced driver assist systems can acquire the information required for the learning and leading phases, while any vehicle can participate in the following phase. Figure 3-1 shows a visual depiction of the leader-follower method. As a leader vehicle approaches the traffic light it gathers the required data. Then a follower can predict the traffic light. A leader vehicle can also be a follower at the same time, but would have to be using previously acquired data from another leader for its predicitons. The following sections explain all the phases of the traffic light prediction algorithm.



1 is the traffic light and the input to the leader. "A" shows the traffic light signal. 2 is the leader with a vision system. "B" contains the time of change and the traffic light state. 3 is the learner that stores the traffic light data. "C" contains the 4 inputs to the follower phase. 4 is the follower who receives the traffic light coaching. "D" is the output of the coaching.

Figure 3-1: Leader-Follower Method Diagram

3.3.1 Learning Phase

The learning phase estimates the length of the red and green portions of the fixed-time traffic light cycle, with the yellow cycle included in the length of the green. The inclusion is a small, but important detail; treating yellow as green simplifies the amount of information that must be captured and requires less input from the data acquisition system. The learning phase is ideally performed with machine learning on the data overtime that is provided by the leading portion of the algorithm. The length of the cycle for a given traffic light is learned from the recorded data of the traffic lights' time of change and corresponding state. A minimum of 3 traffic light changes need to be recorded continuously to learn the traffic light in that direction. Three traffic lights are required to have confidence that the traffic light is indeed a fixed time traffic light, and that the correct cycle lengths have been determined. More than 3 traffic light changes are desirable to compare how the cycle is performing over time. The leader-follower method requires a static traffic light for a given time of day, meaning that the red and green lengths of the cycle are constant for a set amount of time. Once the red and green cycle times are known for the light, the learning phase is complete for that intersection, and the leading phase can begin. Advanced traffic light systems, such as adaptive traffic lights, will not be predicted by the leader-follower system because of the varying length of red and green parts of the cycle. Some of these advanced systems can currently broadcast the signal information to vehicles; however, for this coaching method, advanced traffic light systems will not be utilized (Koons 2018).

3.3.2 Leading Phase

The leading phase obtains the last time of change and the traffic light state associated with that time of change. This data expires because of the random walk of the traffic light. The data needs to be updated as frequency as possible because of the random walk of fixed time traffic lights that do not contain advanced time keeping equipment. The system works best if updated more than once an hour. The time of change and state are recorded when the leader observes the traffic light change states. The two pieces of information will be used in the following phase. The leading phase is implemented with forward looking cameras and a traffic light state vision system. Now, the following phase can begin.

3.3.3 Following Phase

The following phase requires data from the two previous phases and can be performed by any vehicle with access to the 4 pieces of data. The 4 pieces of data needed are the length of the green, the length of the red, the last traffic light state, and the last traffic light time of change. From these 4 parameters the current state of the traffic light and time of change can be extrapolated from the last recorded state and last recorded time of change. The determination of the time until the traffic light changes is done in equation 1.

$$(Tc - Tr)\%(Tred + Tgreen) = TLrem \tag{1}$$

Where Tc is current time. Tr is the absolute time that the traffic light changed. Tred is the length of time of the red part of the cycle. Tgreen is the length of time of the green part of the cycle. TLrem is the length of time remaining in the current cycle. Figure 3-2 shows the traffic light prediction algorithm for two-cycle fixed time traffic lights. TLstate is the last recorded state of the traffic light; it must be red or green. Delta T is the time until the traffic light will change, and CTLstate is the current state of the traffic light. The leader-follower method is effective when implemented in real time and requires the minimal amount of information about the traffic light. Now the CTLstate and Delta T can be displayed to the driver.

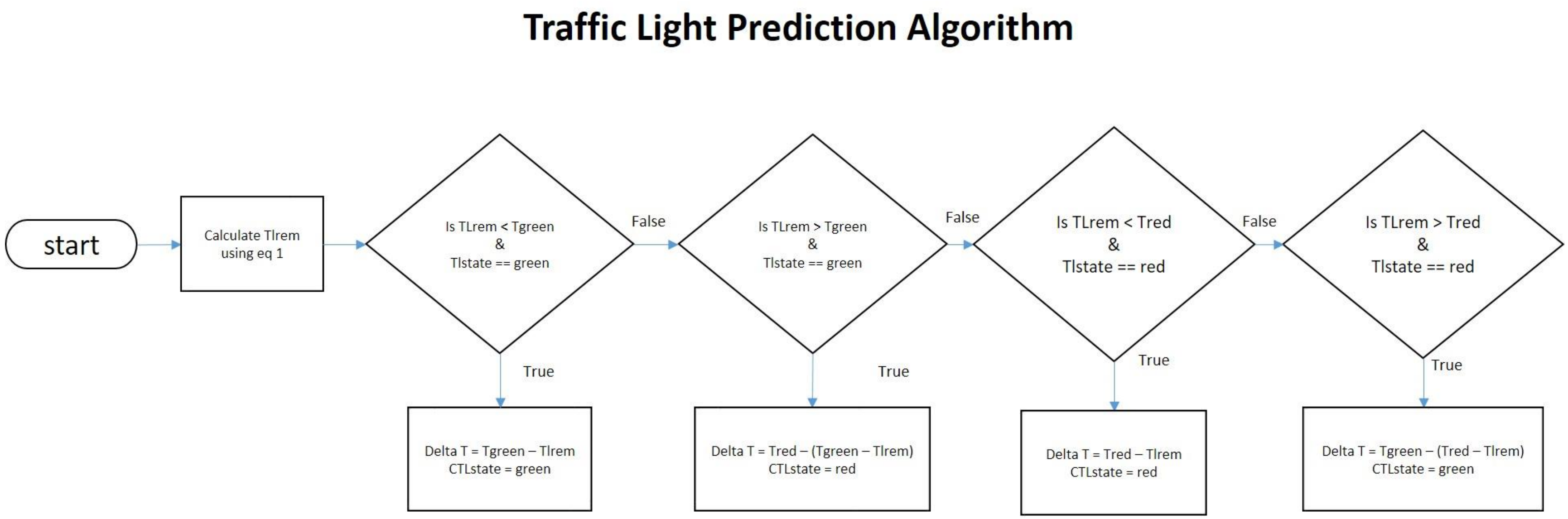


Figure 3-2: Traffic Light Prediction Algorithm

3.4 Leader-Follower Traffic Light Prediction Coaching Prototype

Traffic light prediction coaching is implemented in real time with an Android tablet. The tablet runs on Android O.S. 6.0.1. The traffic light prediction application GUI is shown in Figure 3-3. The application has 4 user inputs: next, previous, TLG, and TLR. The “next” and “previous” buttons select the traffic light along the route, and the “TLG” and “TLR” buttons serve the leader functionality. This prototype implements the following portion of the algorithm. The learning portion needs to be performed manually before the experiment. This is not a problem because the time of the cycle remain constant for years in some cases.Instead of the leader portion being performed by a vision system, this portion will be performed by a human operator. When the “previous” or “next” button is pressed, the system obtains the traffic light’s 4 properties from the local traffic light file or from the traffic light server. “TLG” and “TLR” record the time of the button push and assign the state of the traffic light. Then the time of the traffic light change is written to the local traffic light file and uploads that file to the server. The system can be improved by automation of the systems that require user input. The performance and effectiveness of the system needs to be determined before future work goes into automation of these 4 inputs.

Figure 3-3: Traffic Light Coaching

Figure 3-4 shows the code flowchart for the traffic light coaching app. If the “next” or “previous” button is pushed, the next intersection is selected. The JavaScript Object notation (JSON) file is searched for that intersection and the appropriate traffic light properties are retrieved. The leader-follower traffic light prediction algorithm is then implemented and the answer is displayed in the “Time to Change” block and the “Current Traffic Light State” block. If the “TLG” or “TLR” button is pushed, it rewrites the time of change and traffic light state properties for that traffic light inside of the JSON file. With the prototypes built, the testing methodology can be discussed in the next section. This prototype does not implement the learning portion since the traffic light length of green and length of red times must be manually implemented into the JSON file.

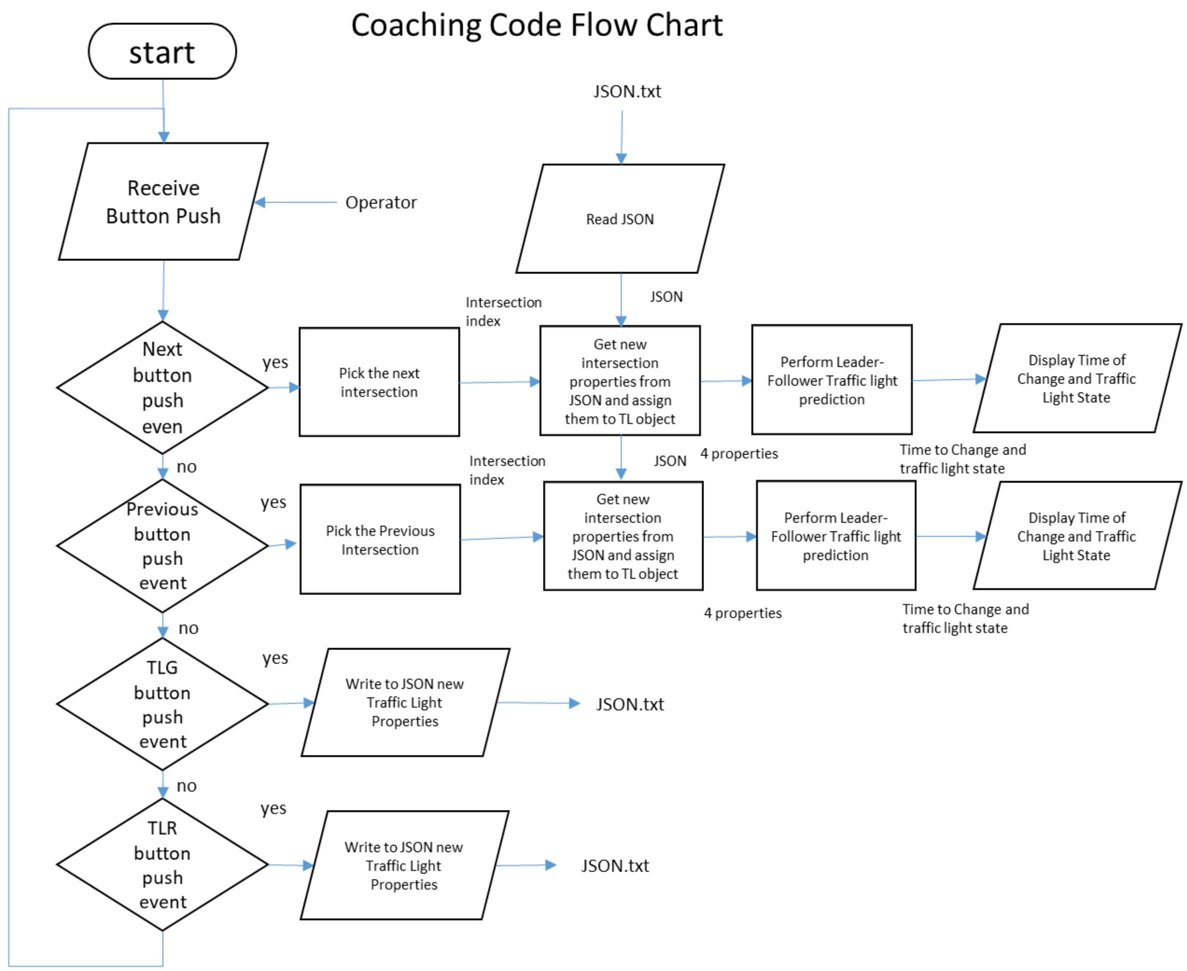


Figure 3-4: Leader-Flower Traffic Light Predicition Coaching Flow Chart

3.5 Conclusion of Methods

The leader-follower traffic light prediction coaching is successful. The leader-follower traffic light prediction method is a multi-vehicle approach to coaching on traffic lights changes in front of the vehicle. While the system is not fully automated, it does work with a human operator and is at the point where the functionality of the follower portion can be tested. The fuel consumption performance will be tested in Midtown Atlanta, Georgia. The test route is 1 mile long with 10 traffic lights. The results of the experiment are shown in Chapter 4.

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Testing Methods for the Leader-Follower Traffic Light Coaching

The leader-follower traffic light coaching system will be tested by having drivers utilize the application on a public road. The velocity and fuel consumption will be monitored while the vehicle is on the predetermined route. The route will contain 10 total traffic lights of which 9 are fixed time traffic lights where the cycle of the light is known. The control variables are the time of day, the vehicle, and the driver. The vehicle, route, and test steps are core components of the experiment and will be discussed in section 3.5.

4.1.1 Test Vehicle

The vehicle used in this experiment is a 2016 Ford Fusion Energi. The Ford Fusion is a plug-in hybrid vehicle. The curb weight is 3913 lb. The vehicle has a 2.0L inline 4-cylinder internal combustion engine mounted to a continuously variable transmission. The EPA rating for the Ford Fusion is 40 mpg in the city and 36 mpg on the highway. The vehicle has a 20 mile all-electric range but running in pure electric will be disabled for this experiment; the electric battery will be drained and unable to drive in all-electric mode. The combined powertrain is rated for 195 horsepower at 6000 RMP (2016). The vehicle will be functioning as a hybrid vehicle during this experiment.

4.1.2 Test Route

The route contains a total of 10 traffic lights. The driver will be coached on 9 of the 10 fixed time traffic lights during driving. The 6^{th} traffic light is not a two-cycle fixed time traffic light therefore the user will not be informed about it. The next traffic light on the route will be displayed to the driver. The route is shown in Figure 4-1. The total length of the test is 1.0 mile and takes about 7 minutes to complete each run. The 10 traffic light timings are in Table 4-1. The traffic levels are an uncontrolled variable but will be mitigated by driving at the same time of day. The driver will drive 3 un-coached runs and 3 coached runs each day. The first 3 runs will be un-coached runs, and the next 3 runs will be coached. The first 3 un-coached runs provide the observer the opportunity to perform the leading portion of the traffic light prediction algorithm. In a full-scale implementation, the leading portion could be completed by a vision system and a network of connected vehicles through a traffic light database. The route is designed to test the fuel consumption performance of the follower phase. The learning data will already be taken before the test begins and leading data will be taken during the un-coached laps. The accelerator pedal, brake force, regenerative energy, velocity, and fuel will be recorded during the test through the OBD-II port, from the controller area network (CAN) bus. The regenerative energy will be expressed as microliters of fuel with a conversation factor of 32.05MJ/L from the EPA's labelling guidelines. SAE specifies how drive cycles should be tested for hybrid and electric vehicles. Over the course of a test, the stored electrical energy needs to be credited back to the fuel consumption numbers. For the specified drive cycle testing the net energy stored over the test should be less than 1 percent or up to 5 percent if corrected. (International 2010) because this test is conducted on a public roach, and with a variety of driving styles this is not achieved, but the corrected fuel consumption and IC fuel consumption numbers will be provided. Corrected fuel consumption will be specified clearly when referring to fuel economy numbers that take into account the sored energy of the battery. The test steps are shown in the next section.

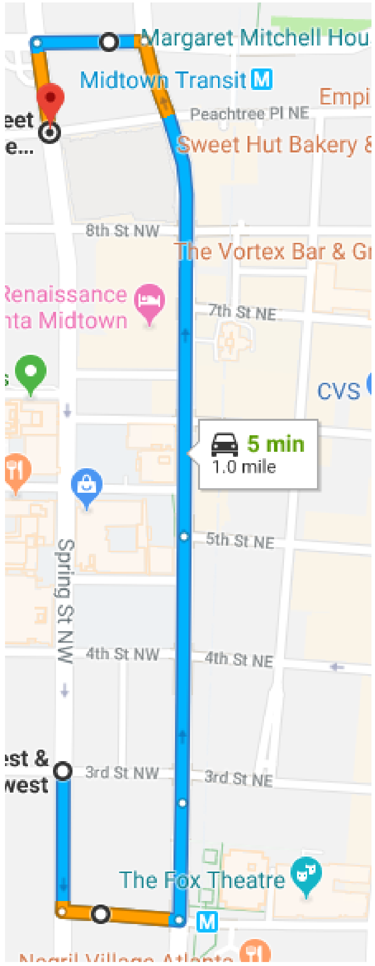


Figure 4-1: Test Route Google Maps Image of Midtown Atlanta, GA

Table 4-1: Traffic Light Timings for Route in Figure 3-5

Traffic Light Timings (seconds)		
Intersection	Green Length	Red Length
1	28	32
2	25	35
3	28	32
4	45	75
5	60	60
6	N/A	N/A
7	28	32
8	25	35
9	45	75
10	70	50

4.1.3 Test Run Steps

The test is performed identically for all 4 drivers. The vehicle starts in a parking lot 0.5 miles away from the start of the run. The driver is instructed to drive the route as he/she normally would drive for the first three control runs each day starting at 10:00 am. While the three control runs are being performed, the other 9 traffic lights are being scouted for the leader portion of the leader-follower method. Specifically, the traffic lights are being scouted for the time of change and the state that corresponds to that change. After the three control runs are completed, the three coached runs start. The coaching is performed by displaying the traffic light prediction coaching to the driver. At the start of the coached run the driver is given two guidelines. The first guideline is to let off the throttle if the driver does not believe that the intersection will be cleared in the amount of time remaining. The second guideline is to accelerate or maintain speed if the driver believes that the intersection will be cleared in the amount of time remaining. Once the driver clears an intersection, the coaching displays the next traffic light information via the operator in the passenger seat. The operator has two tasks. The first task is to operate the leader-follower application. The second task is recording the data off the CAN bus. The results for the tests are shown in Chapter 4. The test is performed with 4 drivers with a combined 120 runs.

4.2 Results

The results in this chapter are from 4 drivers. Each driver is given the same information on the same test route. The first three runs each day are un-coached runs followed by three coached runs using the leader-follower traffic light prediction coaching. Given that the experiment is performed on a public road, there are runs that are going to be outliers because of the events happening that day. These variables were mitigated by driving at the same time each day and doing as many runs as possible. A threshold for statistical significance of 5% and a threshold for highly statistically significant of 0.1% is used in Chapter 4. The following sections start with an overview of each driver, then is proceeded by their results.

4.3 Driver 1 Test Observations

Driver 1 is a 22-year-old male. Driver 1 has a smooth driving style. He has comfortable accelerations and decelerated leaving plenty of space between vehicles for both coached and control runs. Driver 1 exceled at taking his foot off the accelerator as soon as he determined he is unable to make the intersection. On day 4, traffic light 2 was being worked on by the city and was not coachable. Driver 1 had a consistent and moderate driving style for both coached and un-coached runs. Driver 1 results are in the next section.

4.4 Driver 1 Results and Discussion

Table 4-1 shows Driver 1's statistics. Driver 1 fuel consumption for all 30 test runs are shown in Figure 4-1. Figure 4-1 shows the test day on the x-axis and the microliters of fuel consumed during each run on the y-axis. The blue points are the control runs and the red runs are the coached runs. Figure 4-2 shows the average fuel use per day for the coached and un-coached runs. The x-axis is the test day and the y-axis has the fuel consumed in microliters of gasoline. Driver 1's average fuel consumption reduction across all the runs is 19.6%. The corrected fuel consumption reduction is 16.1%. The fuel consumption reduction average is statistically significant with two-tail p value of 0.70%. The driver's standard of deviation for control runs is 17167 microliters and 7822 microliters for the coached runs. The margin of error for a 5% confidence interval is 9507 and 4332 microliters for un-coached and coached runs respectively. When Driver 1 is coached he is more consistent as shown by the 54% decrease for the coached runs standard of deviation over the control run.

Table 4-2: Driver 1 Performance

	Un-Coached	Coached	Percent Improvement	Two Tail P Value
Avg. Fuel Consumption (microliters)	74,795	60,161	19.6	7.01E-03
Corrected Fuel Consumption (microliters)	74,905	62,877	16.1	1.10E-02
Avg. Run Time(seconds)	336	371	-10.2	3.23E-02
Normalized Avg. Fuel Recovery (microliters)	17.2	18.7	1.08	

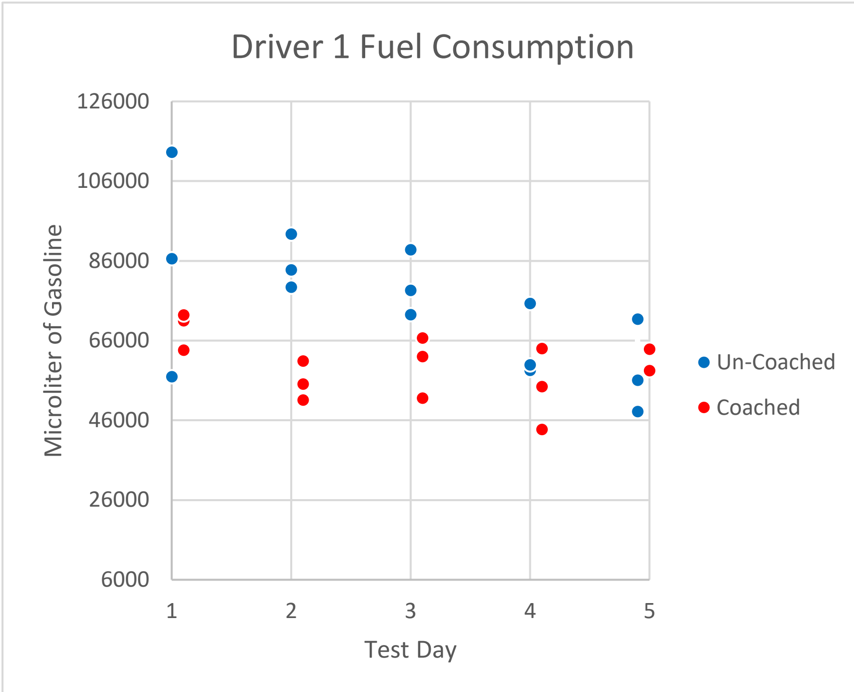


Figure 4-2 Driver 1 Fuel Consumption

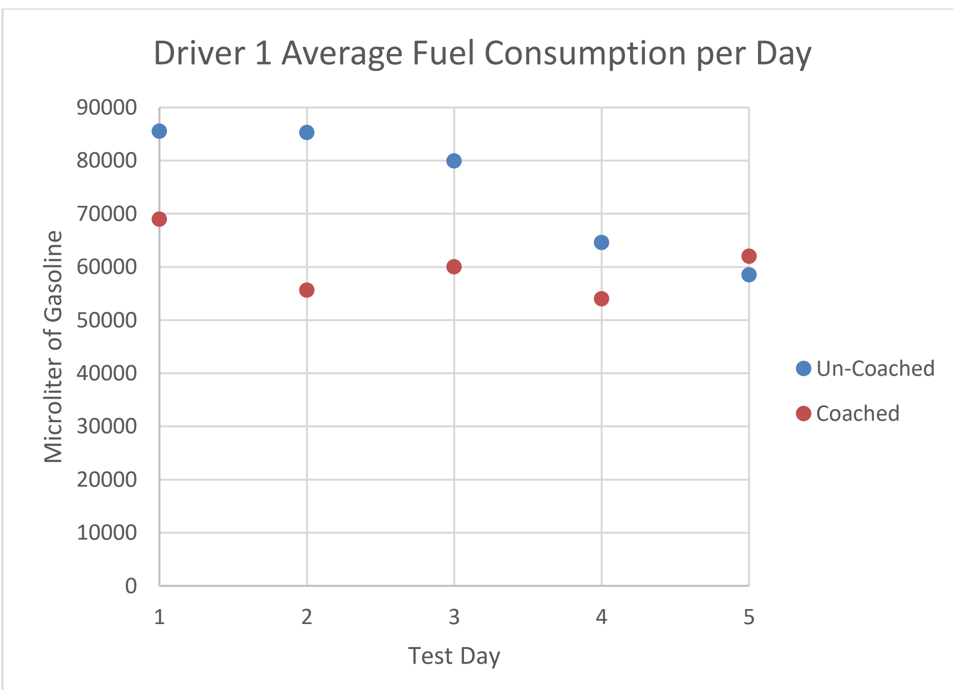


Figure 4-3: Driver 1 Fuel Consumption Average per Day

Figure 4-4 shows the length of time that each of the runs took to complete. The x-axis is the test day and the y-axis is the time in seconds that the run took to complete. The coached run on average took 10% longer to complete than the control runs. The standard of deviation for the coached runs with respect to time is 27 seconds and the standard of deviation with respect to time for the control runs is 51 seconds. Again, the coached runs show more consistency. This result is also statistically significant with a p-value of 0.03. For all of Driver 1's plots, the variance between runs is due to difficulty in perfectly controlling variables. Variables that cannot be controlled range from a vehicle slamming on their brakes to construction closing lanes, and emergency vehicles blocking intersections.

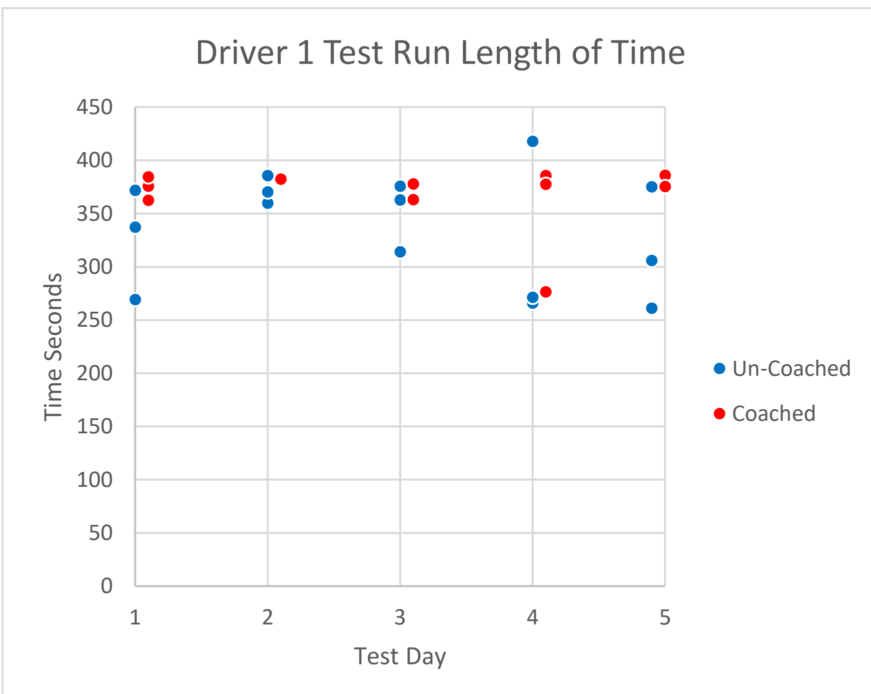


Figure 4-4: Driver 1 Length of Time per Test Run

As Driver 1 uses coaching on the route, learning effects are observed in his un-coached performance. Driver 1 starts predicting which lights would turn red before he got to the intersection because he had seen the coaching on previous days. This behavior is shown in Figure 4-2 by the un-coached runs fuel used start to approach the coached runs fuel used. The first three days show a distinct difference between the coached and un-coached fuel usage. The last two days show less of a fuel difference between the coached and control runs, as the driver has familiarized himself with traffic lights' predicted behavior. This behavior is shown on day 5 in Figure 4-3, where the un-coached runs are more fuel efficient than the coached runs. The average fuel consumed on both the un-coached and coached was approximately 60,000 microliters. 60,000 microliters is a low amount of fuel used for either coached or un-coached run. The inversion of the coached and un-coached average fuel consumption on day 5 does not mean that coaching is hurting the driver's average fuel economy because day 5's average is within margin of error. Figure 4-5 shows the average energy recovered using the hybrid powertrain during the run. The amount of energy recovered at first can be a misleading, because whenever the Internal Combustion (IC) engine is running excess energy is being stored, but energy is also being stored during regenerative braking.

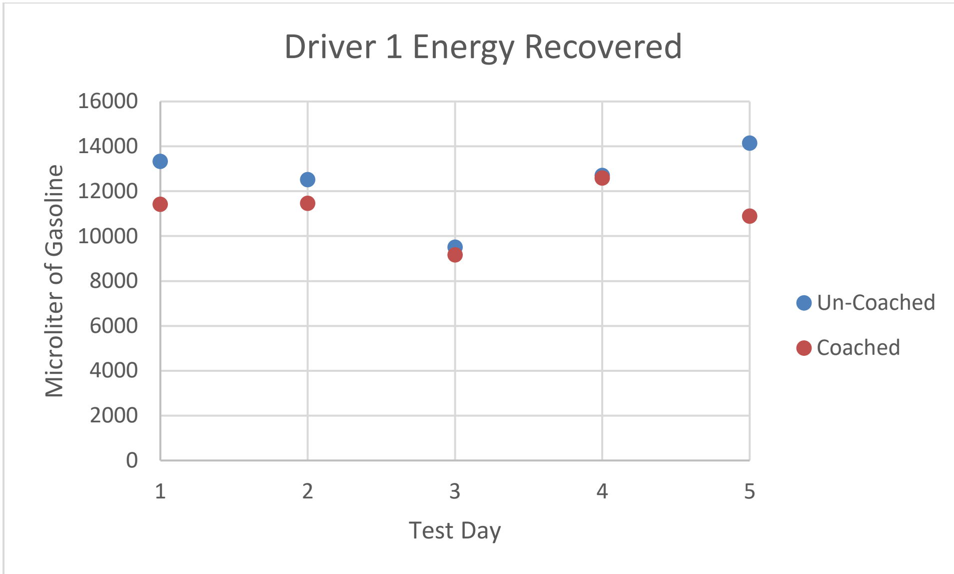


Figure 4-5: Driver 1 Average Energy Recovered

When looking at Figure 4-5, the control runs look like they are better because they are recovering more energy over the course of the run. This behavior changes in Figure 4-6. Figure 4-6 shows the average energy stored during the run but is normalized for the fuel consumed during the run. In every case except day 5 the coached runs can make better use of the hybrid powertrain. On day 5 the fuel consumption for both coached and un-coached runs is almost the same, and the energy recovered is more on the control runs that day. Driver 1 stored 8% more normalized energy when coached.

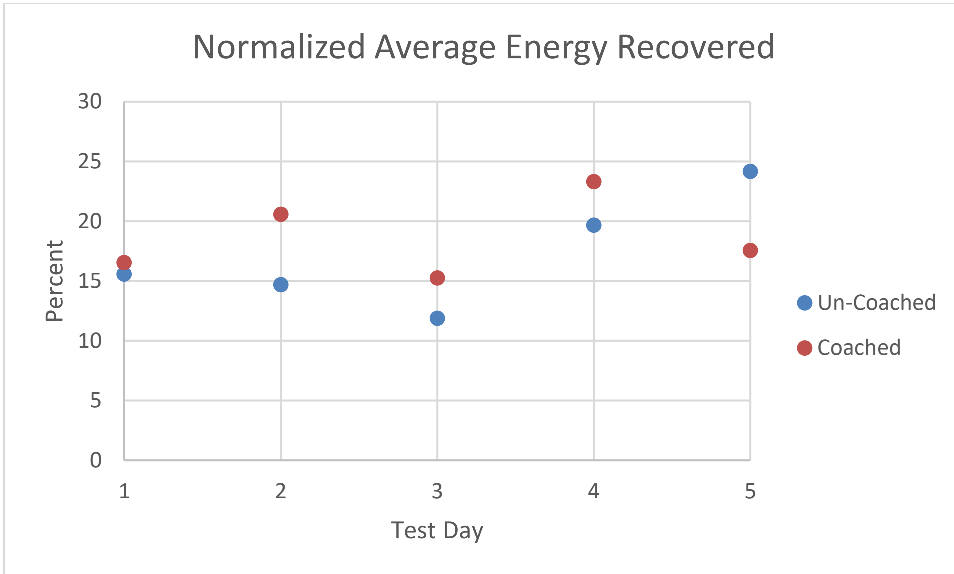


Figure 4-6: Driver 1 Normalized Average Energy Recovered

Figure 4-7 shows data from 2 runs for Driver 1. All the plots have time in seconds on the on the x-axis . The top plot shows the wheel speed in radians per second during the run. The second plot shows the accelerator position as a percentage of maximum travel. The third plot shows the brake torque that is delivered and the fourth plot shows the brake force that is requested. These two look similar except when ABS is engaged, or the requested force is more than the brakes can deliver. The last plot shows the IC powertrain fuel consumed. Figure 4-7 shows how Driver 1 manages his speed and uses the throttle in relation to the brakes. Figure 4-7 shows two runs that match the average fuel consumption for the coached and un-coached runs. One aim of coaching is to reduce the frequency of braking events because they can be followed by acceleration events. The wheel speed plot shows the coached run being smoother than the control run. The smoothness in the coached run shows confidence of the driver. When the driver wants to accelerate, he does so with authority; when it is time to decelerate, he lets off the throttle and coasts before pushing the brakes. The next point to look at is the length of time that passes between letting off the throttle and stepping on the brakes. Driver 1 shows plenty of time between stepping off the throttle and stepping on the brakes for both coached and un-coached runs. There are more braking events with the un-coached runs, and larger braking events for un-coached runs. The information helps link the fuel economy results shown above. Figure 4-8 shows the powertrain performance for the same two runs in Figure 4-7. Driver 1 makes good use of the hybrid powertrain whether being coached or un-coached. Figure 4-9 shows a histogram of the throttle use. Driver 1 coached throttle use is centered around 14% and the un-coached throttle use is centered around 16-17%. The coached run contains less events after 19%. Figure 4-10 contains a histogram of the braking events for all of driver 1 runs. When coached driver 1 uses most brake force of 500nm. The un-coached runs use 750 to 850 nm braking torque. The increase in throttle use and braking force contribute to the increased fuel consumption when un-coached. When un-coached Driver 1 demonstrates that drivers with a moderate driving style can see fuel consumption reductions while being coached.

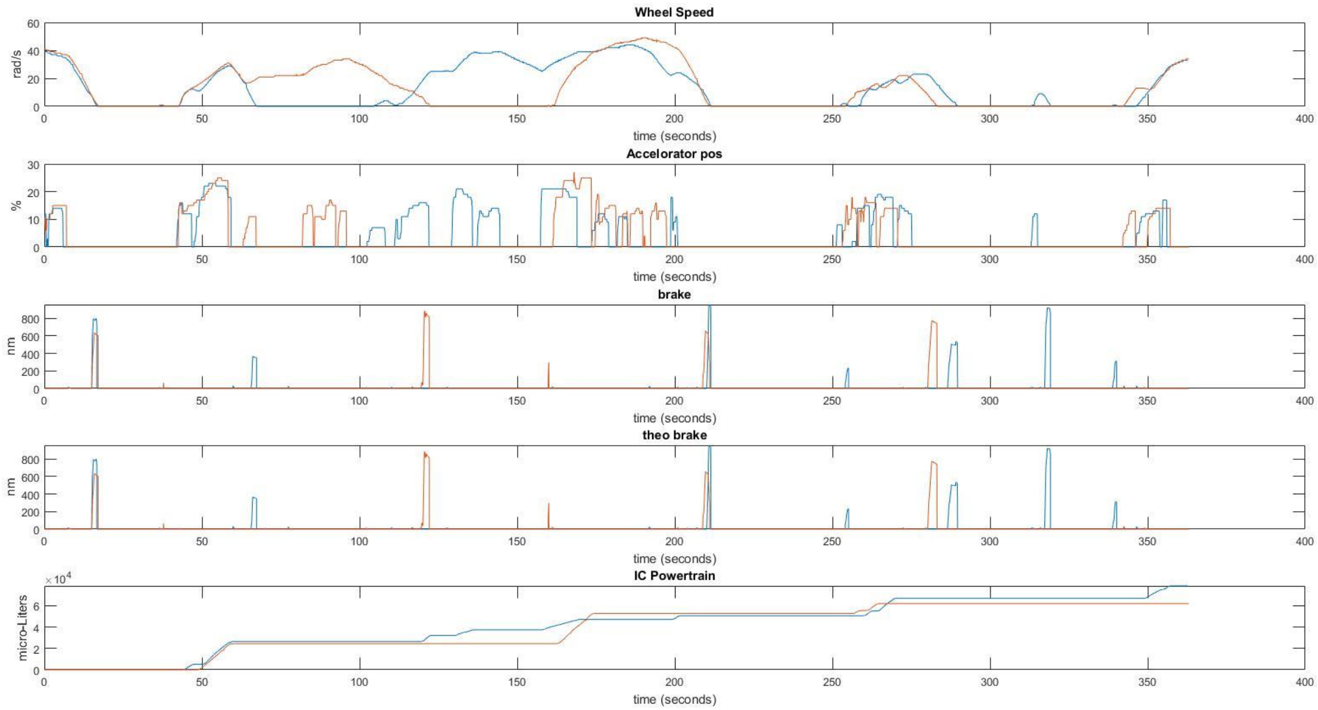


Figure 4-7: Driver 1 Day 3 Un-coached Run 2 and Coached Run 3 Throttle and Brake Perfromacne

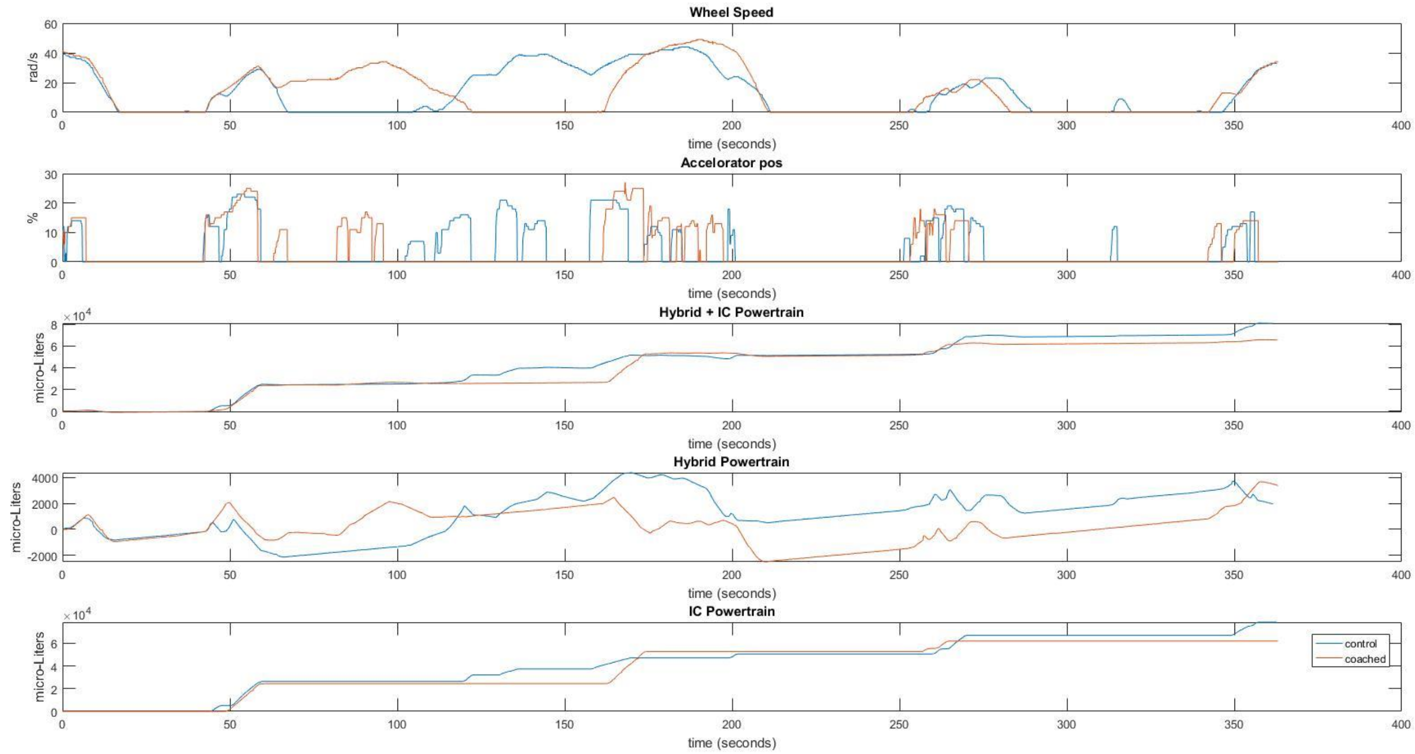


Figure 4-8:Driver 1 Day 3 Un-coached run 2 and Coached run 3 Power Train Performance

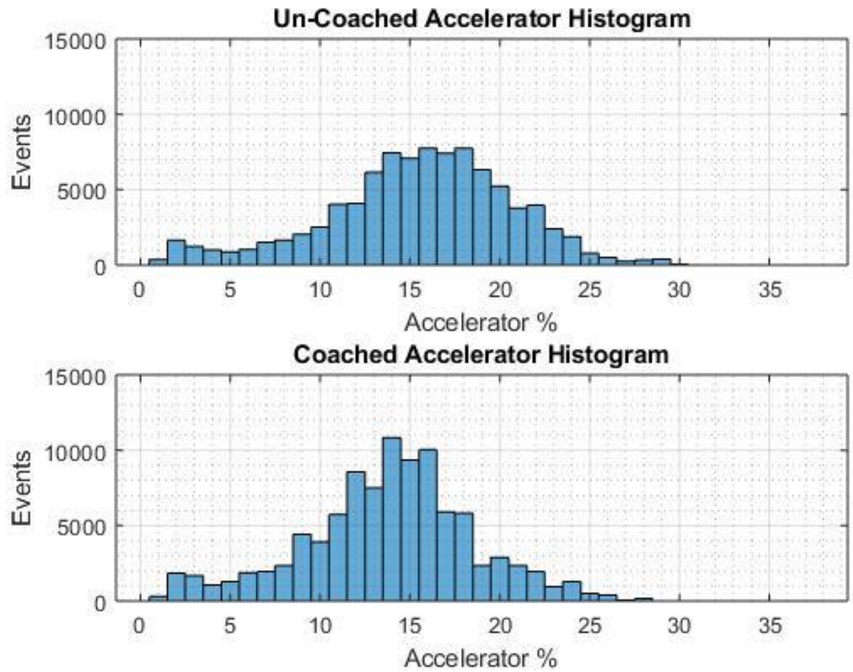


Figure 4-9: Driver 1 Accelerator Histogram

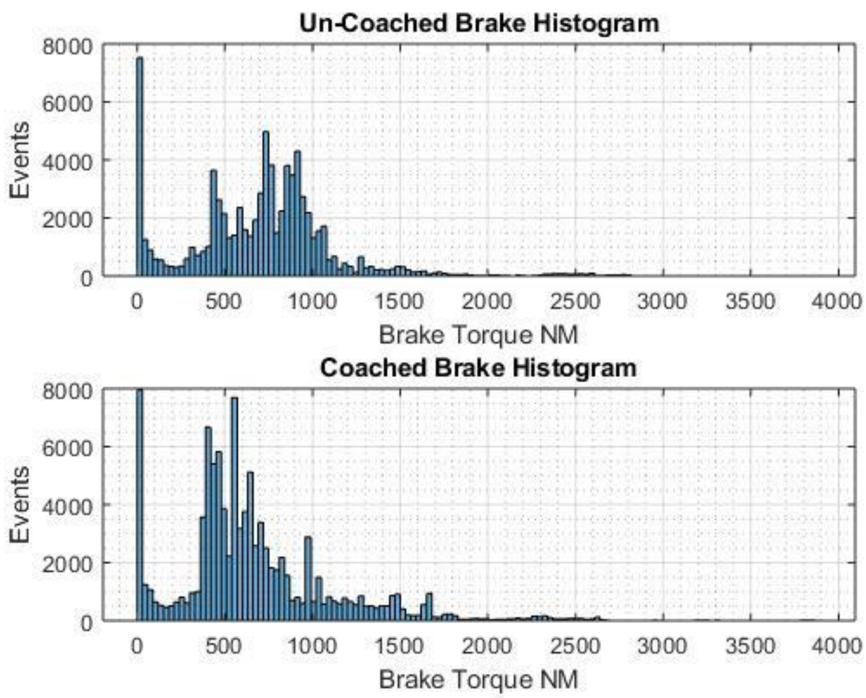


Figure 4-10: Driver 1 Brake Histogram

4.5 Driver 2 Test Observations

Driver 2 is a 20-year-old male. Driver 2 has had a driver's license for less than a month prior to starting the study. The lack of experience provides the unique opportunity to analyze ways in which a new driver might react to coaching. Driver 2 does not demonstrate advanced control over the vehicle in terms of predicting future events that seemed obvious to the observer in the passenger seat. Driver 2 struggled to leave large stopping distances when traffic in front of the vehicle is dense. The lack of time headway increased frequency and magnitude of braking events. Driver 2 did not react as soon to the traffic light coaching application as Driver 1 had been able to react to the coaching. For example, the Driver 2 continued accelerating when the traffic light was a few seconds from changing, and the intersection is not going to be cleared as shown on the leader-follower traffic light prediction coaching. On day 1 of testing, during the un-coached runs there was a field trip at the Fox Theatre and busses blocked intersections a few times during un-coached run 1 and un-coached run 2. Driver 2 did not noticeably change the driving style between coached and un-coached runs, providing an opportunity to view how the coaching affects the driver with little adaptation to driving style. Driver 2 results are in the next section.

4.6 Driver 2 Results and Discussion

Table 4-3 shows Driver 2's statistics. Driver 2's 30 test run's fuel consumption are shown in Figure 4-11. The average fuel consumption for Driver 2 is 90850 microliters for un-coached, and 78752 microliters for coached runs. The average fuel consumption per day is shown in Figure 4-12.

Table 4-3: Driver 2 Performance

	Un-Coached	Coached	Percent Improvement	Two Tail P Value
Avg. Fuel Consumption (microliters)	90,850	78,752	13.3	1.33E-01
Corrected Fuel Consumption (microliters)	90,338	77,487	14.2	6.60E-02
Avg. Run Time(seconds)	396	384	3.2	5.34E-01
Normalized Avg. Fuel Recovery (microliters)	18.0	23.2	22.5	

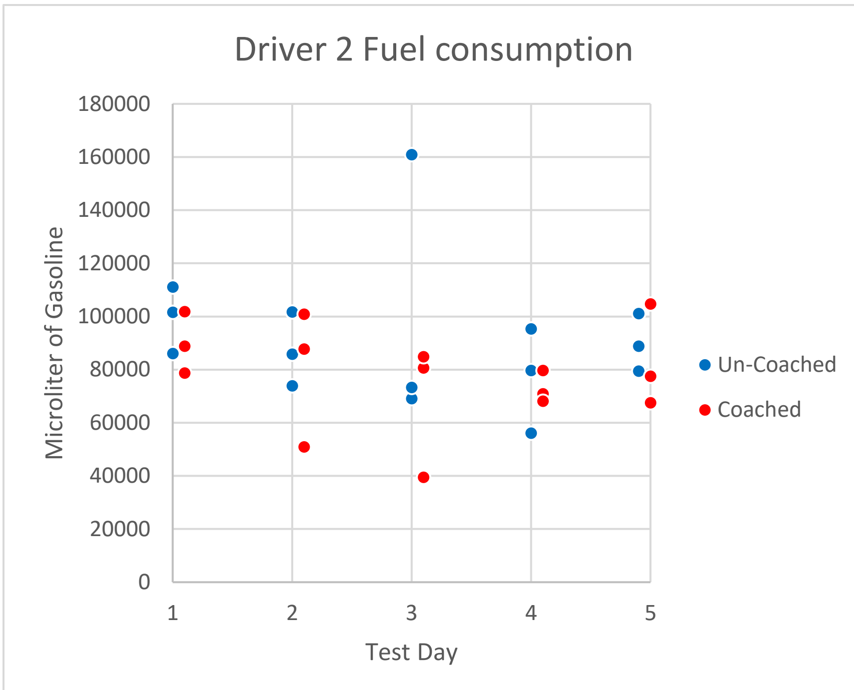


Figure 4-11: Driver 2 Fuel Consumption

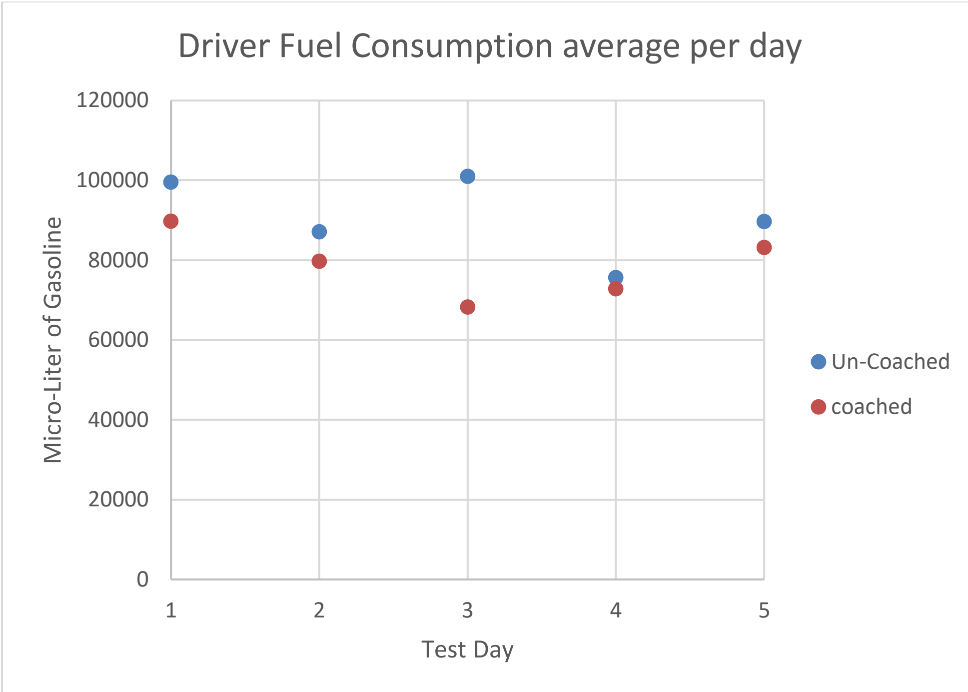


Figure 4-12: Driver 2 Average Daily Fuel Consumption

The average fuel consumption reduction is a 13.3% fuel reduction while being coached. The two-tail p value for Driver 2 is 0.133 resulting in Driver 2's fuel consumption not being statistically significant. The corrected fuel consumption reduction is 14.2%. A possible reason for the lack of statistical significance is because Driver 2 is a new driver and is not as consistent as drivers who have driven for longer. Driver 2's un-coached standard of deviation is 24276 microliters and the coached standard of deviation is 18006. As with Driver 1, Driver 2 shows more consistency while being coached. The reduction is not over a factor of 2, as with Driver 1, but the standard of deviation is 25.8% smaller with the coached runs. Figure 4-13 shows the time that each run took to complete in seconds.

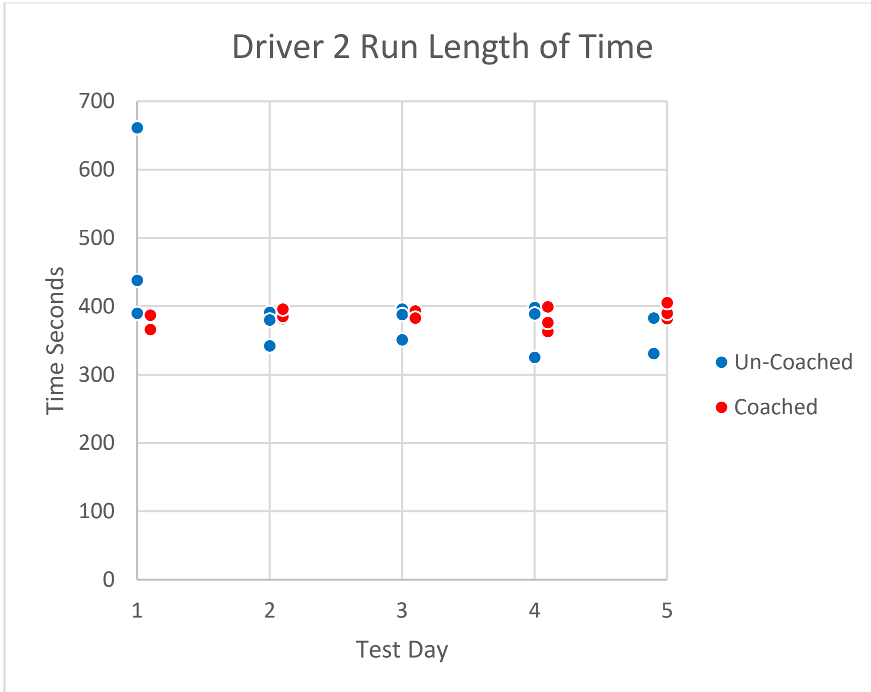


Figure 4-13: Driver 2 Length of Time per Test Run

There are two outliers on day 1. Un-coached run 1 and 3 had times of 438 and 661 respectively. Un-coached run 1, traffic light 2 was not able to be traversed because of busses blocking the intersection for one cycle. On un-coached run 3, traffic light 2 was again blocked for multiple cycles by busses. Driver 2 is 3.06% faster while being coached when the outliers are used. When run 3 is removed the coached runs are 1.79% percent slower than the control runs. Figure 4-14 shows the average time per day for un-coached and coached performance.

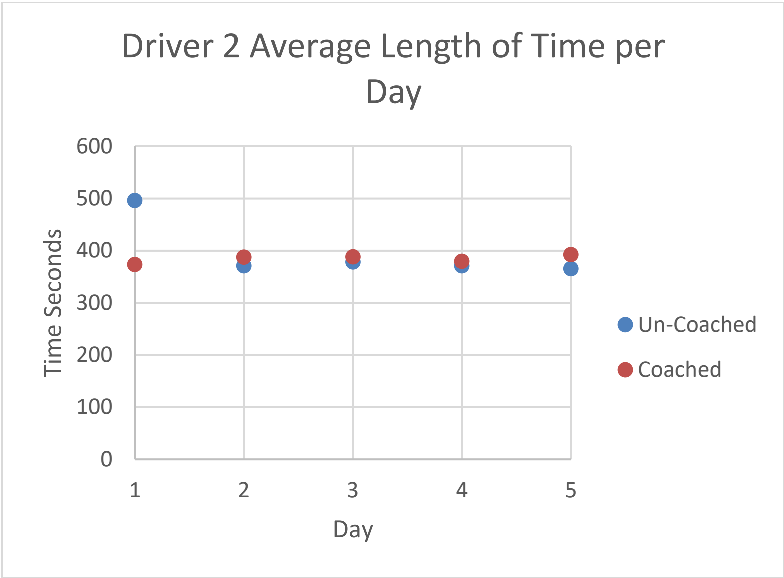


Figure 4-14: Driver 2 Averge Length of Time per Day

The average is consistent and equal on almost every day, but the first day for the reasons already mentioned. The traffic lights dictate the time required to complete the run not the drivers driving style. Faster driving does not equate to shorter run times. Figure 4-15 shows how much energy is stored during the run by the hybrid powertrain. As with Driver 1, Driver 2 stores more energy in the hybrid powertrain when un-coached, but when normalizing for the fuel used during the run, Driver 2 recovered more energy per energy spent as shown in Figure 4-16.

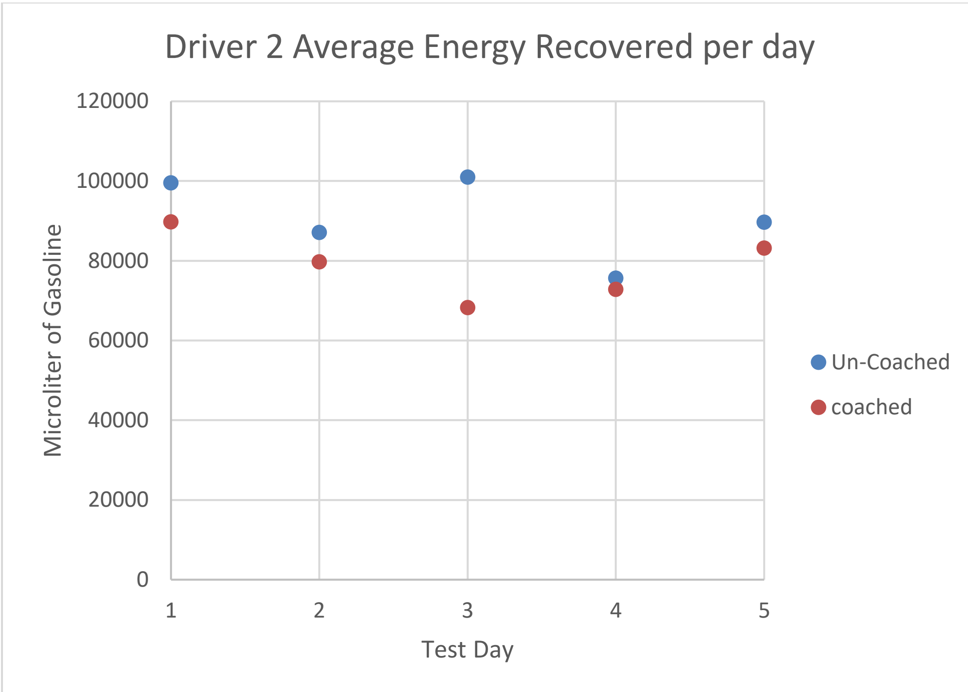


Figure 4-15: Driver 2 Average Energy Recovered per Day

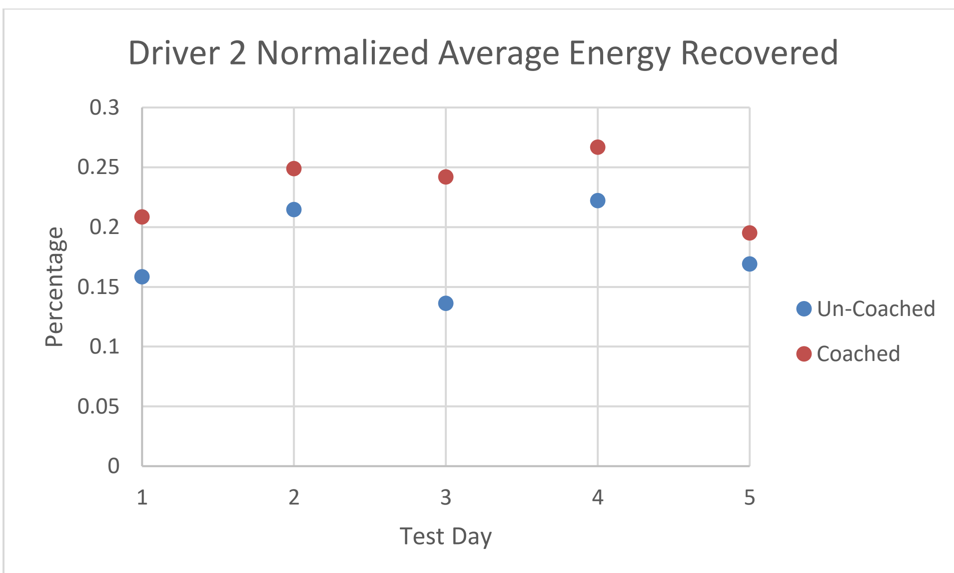


Figure 4-16: Driver 2 Normalized Average Energy Recovered per Day

The normalized energy recovered during each run shows how well each driver uses the hybrid powertrain. The coached runs recover 29.0% more energy than the un-coached runs. Figure 4-17 shows how Driver 2 used the vehicle on day 5. Figure 4-17 shows the 1st coached and un-coached run on that day. Both of those runs were consistent with the coached and un-coached average fuel consumption. Driver 2's driving style is confirmed to be much more oscillatory than Driver 1's driving style, but Driver 2 accelerated and decelerated with authority when being coached. Driver 2 uses more throttle frequency when un-coached. The throttle is rapidly cycled between 0 and high throttle positions when un-coached, even when the vehicle is up to speed. These accelerations events are quickly followed by braking events when un-coached. When Driver 2 is coached, his use of the brake and throttle changes. The throttle is used largely toward the beginning of accelerations events, and then it is followed by long pauses of not braking or accelerating. The length of time between using the throttle followed by the brake increases with the coached runs. The length of time is important for hybrid electric vehicles as it leaves more time for regenerative braking, instead of using the friction braking system. As with Driver 1, the throttle and braking performance shows the link between coaching the driver and the driver using the throttle and brake in more productive ways. Figure 4-18 shows the hybrid and IC performance during the same two runs as Figure 4-17. The first two plots are the same as Figure 4-17. The third plot is the combined hybrid and IC powertrain fuel consumption through the run in seconds. The fourth plot is the hybrid powertrain performance. It is important to note that the y-axis on the hybrid powertrain plot is an order of magnitude less than the IC powertrain performed plot. The fifth plot shows the IC powertrain performance. The hybrid powertrain shows the user being unable to use all of the recovered energy through the un-coached run. When driving on the road, a user accelerates to a certain speed limit and then begins to coast or maintain speed. If the IC powertrain is providing a large percentage of that acceleration, there is less opportunity for the hybrid powertrain to use its stored energy to accelerate the vehicle. The un-coached run had an excess of 2888 microliters of gasoline recovered and the coached run ended with a deficit of 1788 microliters of fuel. The un-coached run is not able to spend its stored energy fast enough. Figure 4-19 contains a brake histogram for driver 2. Driver 2 shows consistence in his braking histogram, but has an increase in number of braking events when un-coached. Figure 4-20 shows a deceleration histogram fro driver 2. Driver 2 has an increase of -0.9 rad/s^2 when un-coached. When coached driver 2 has more braking events at -0.6 rad/s^2. Lower accelerations allow for more regenerative braking to occur and more energy to be recovered. This shows an impact the presence of coaching has on the drivers operation of the vehicle.

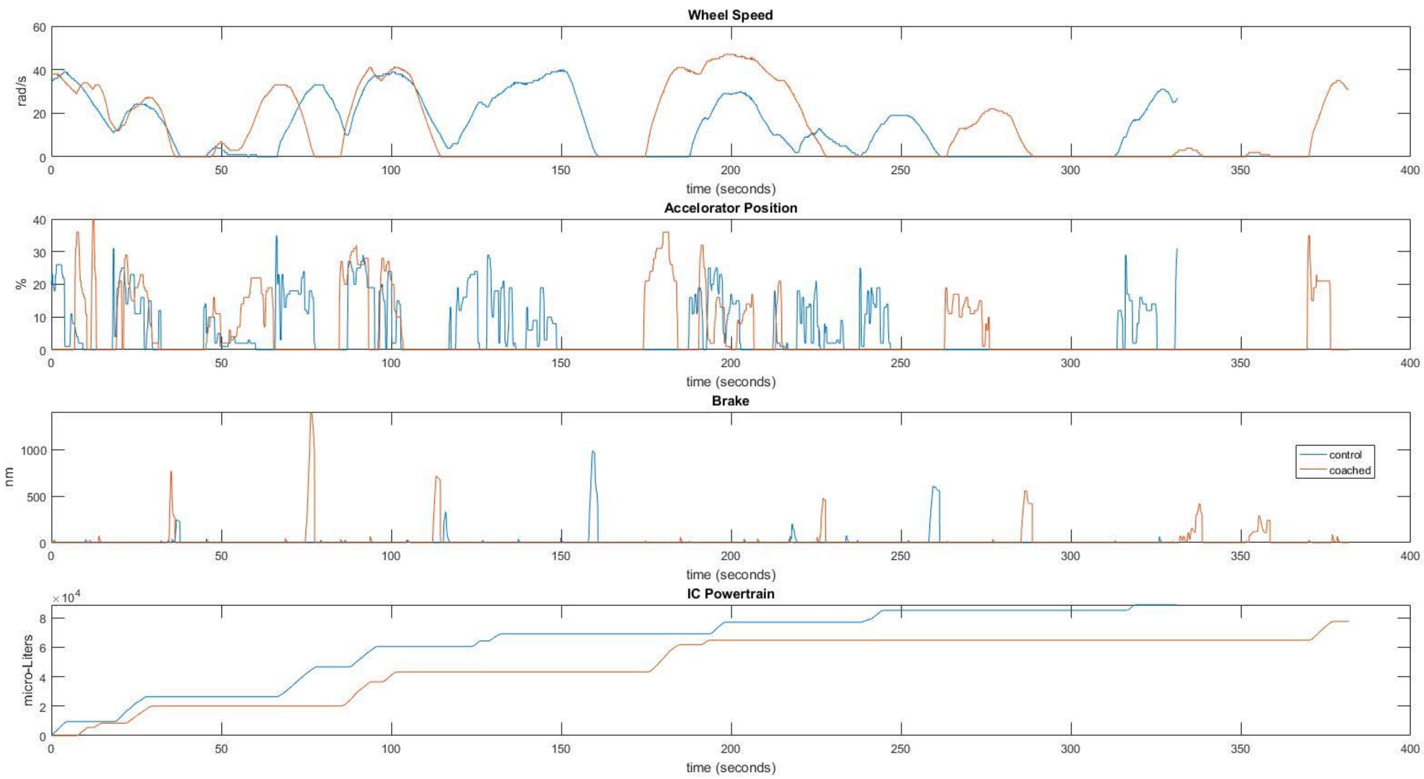


Figure 4-17: Driver 2 Day 5 Un-Coached Run 1 and Coached Run 1 Throttle and Brake Performance

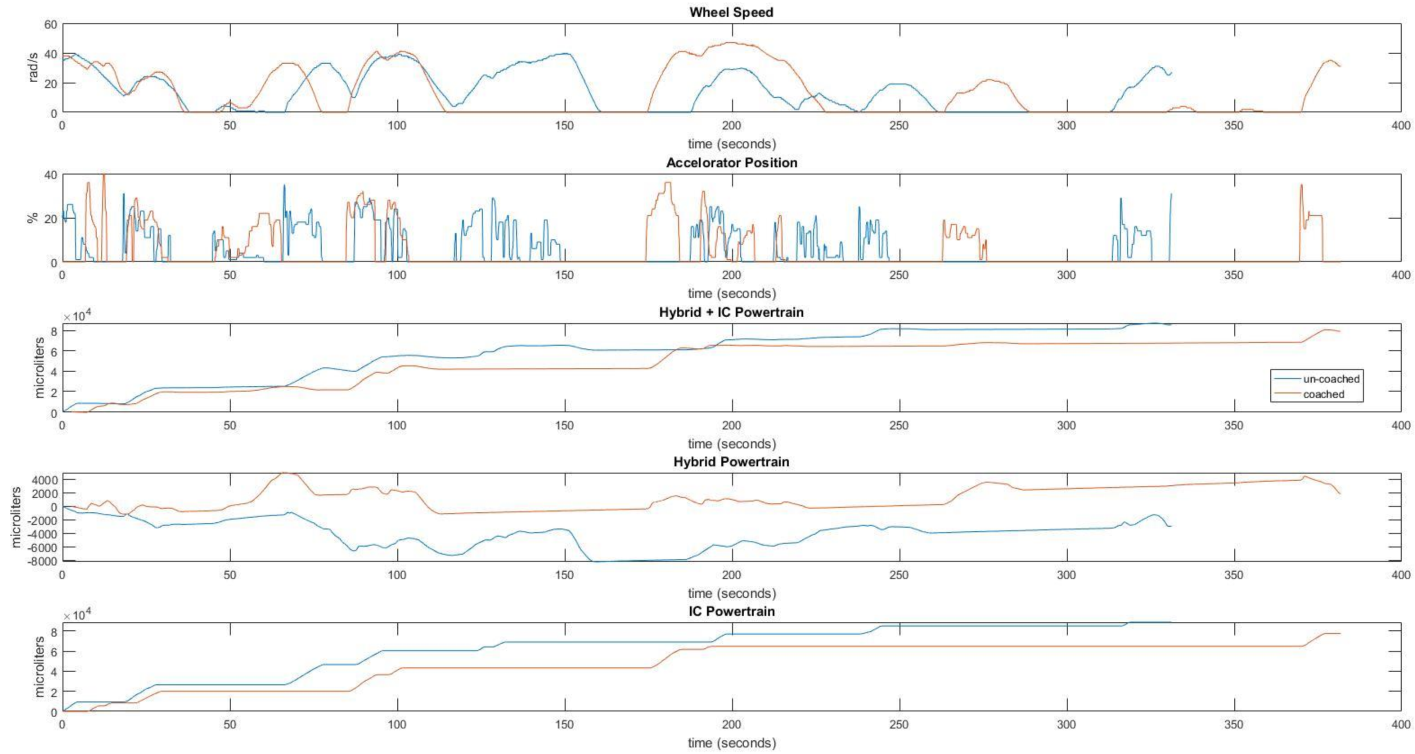


Figure 4-18: Driver 2 Day 5 Un-Coached Run 1 and Coached Run 1 Powertrain Performance

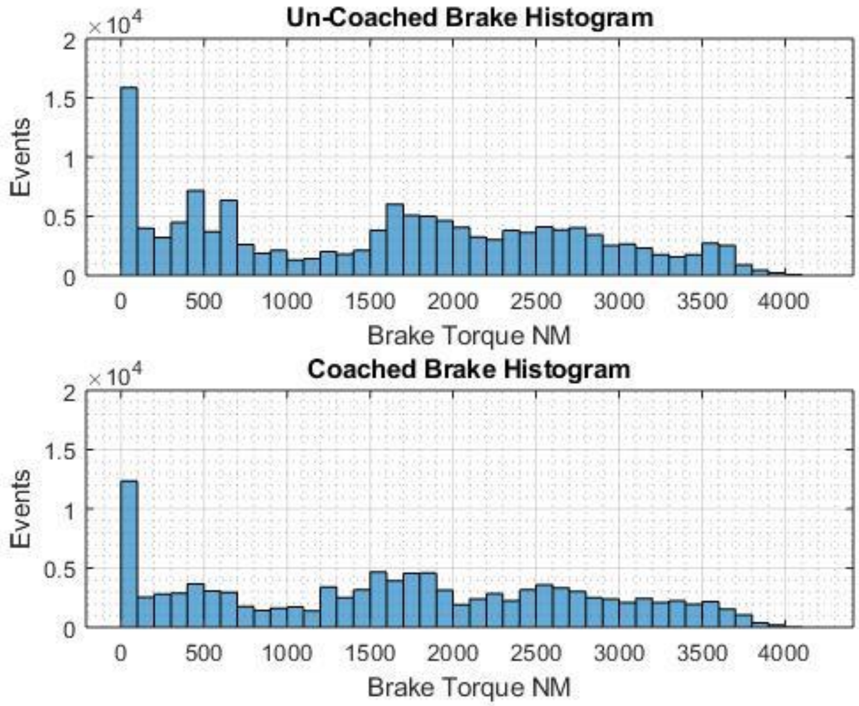


Figure 4-19: Driver 2 Brake Histogram

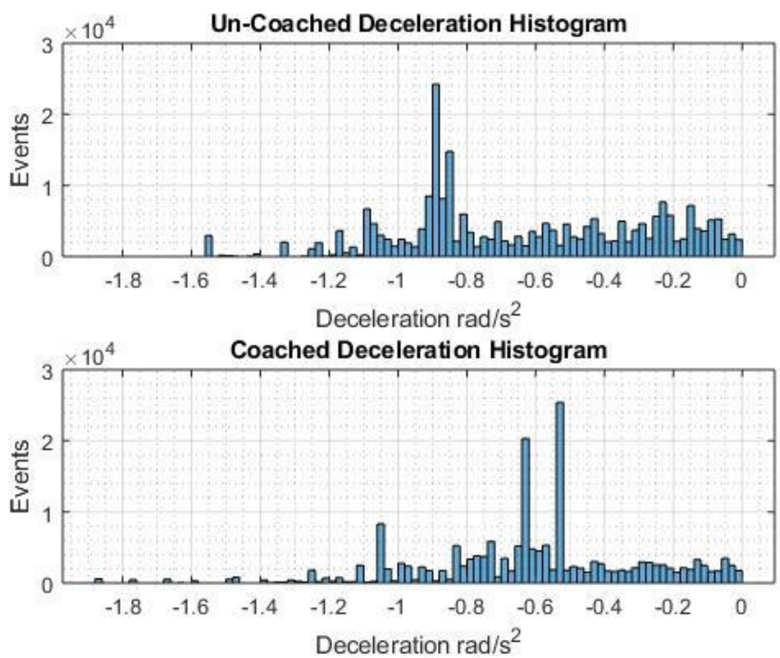


Figure 4-20: Driver 2 Deceleration Histogram

4.7 Driver 3 Test Observations

Driver 3 is a 23-year-old male. Driver 3 is an aggressive driver that uses the full acceleration and deceleration ability of the vehicle. When Driver 3 is coached he tries to take his foot off the accelerator as soon as he determines he will not clear the intersection. Coaching causes the most dramatic change in driving style. The driving style change should result in the most extreme fuel economy numbers between un-coached and coached. On day 2 of testing, he informed the operator in the passenger seat that he had memorized the traffic lights from day 1. The driver prediction shows in the results on day 2. However, Driver 3 resumed his normal un-coached driving style for the other un-coached runs on later days. Driver 3 results are in the next section.

4.8 Driver 3 Results and Conclusions

Table 4-4 shows Driver 3's statistics. Driver 3's 30 test runs' fuel consumption is shown in Figure 4-21. The test day is shown on the x-axis and the y-axis shows the fuel usage in microliter of fuel. Figure 4-22 shows the average fuel consumption per day for coached and un-coached runs.

Table 4-4: Driver 3 Performance

	Un-Coached	Coached	percent improvement	Two Tail P Value
Avg. Fuel Consumption (microliters)	97,970	64,357	34.3	1.38E-04
Corrected Fuel Consumption (microliters)	95,142	66,928	29.7	2.53E-05
Avg. Run Time(seconds)	373	375	-0.6	4.71E-01
Normalized Avg. Fuel Recovery (microliters)	16.3	16.0	-1.5	

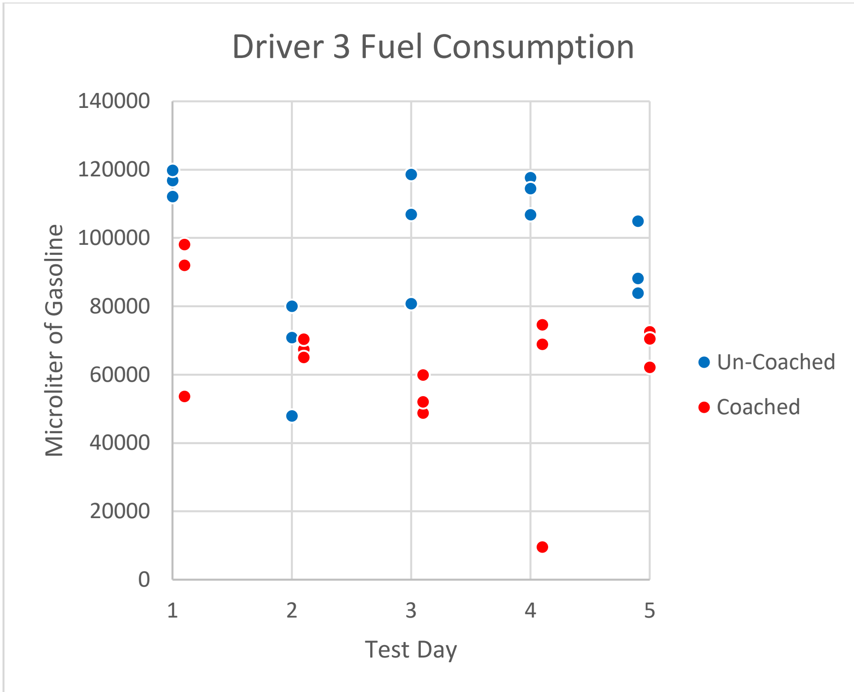


Figure 4-21: Driver 3 Fuel Consumption

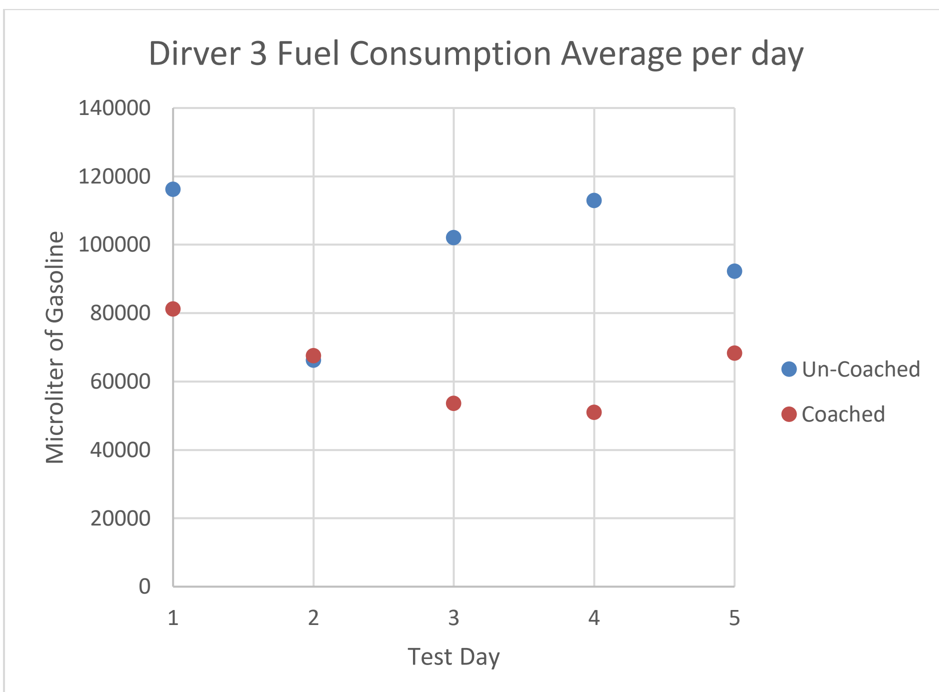


Figure 4-22: Driver 3 Average Fuel Consumption per day

In Figure 4-22, the axis is labelled the same way as Figure 4-21. Day 2 is particularly interesting as the driver said he could remember which lights would be green or red based on the previous day's coaching. Driver 3 has similar results to the coaching on day 2 because of his knowledge from the previous day. Driver 2's prediction shows that understanding what the traffic lights will do can have a big impact of fuel economy. However, he continued to drive normally for the other days. Driver 3 averages 34.3% less fuel then being coached. Driver 3's fuel consumption improvement is highly statistically significant with a two-tail p-value of .00014. The standard of deviation is 21,500 microliters for un-coached runs and 20,197 microliters. The standard of deviations between un-coached and coached runs is small. The standard of deviation from Driver 1 differed where his coached runs had a difference of more than a factor of two. The corrected fuel consumption reduction is 29.7%. The first coaching run on day 4 showed approximately 10,000 microliters of fuel being used, but the hybrid powertrain did another 20,000 microliters of work resulting in a total hybrid plus IC powertrain fuel consumption of 30,000 microliters of fuel consumption. 30,000 microliters is still a very low amount of energy for a 1-mile run, but realistic. The run resulted in a 33 mpg effective fuel economy but averages 100 mpg when just looking at the gasoline used during the test. Figure 4-23 shows the outlier run gasoline usage.

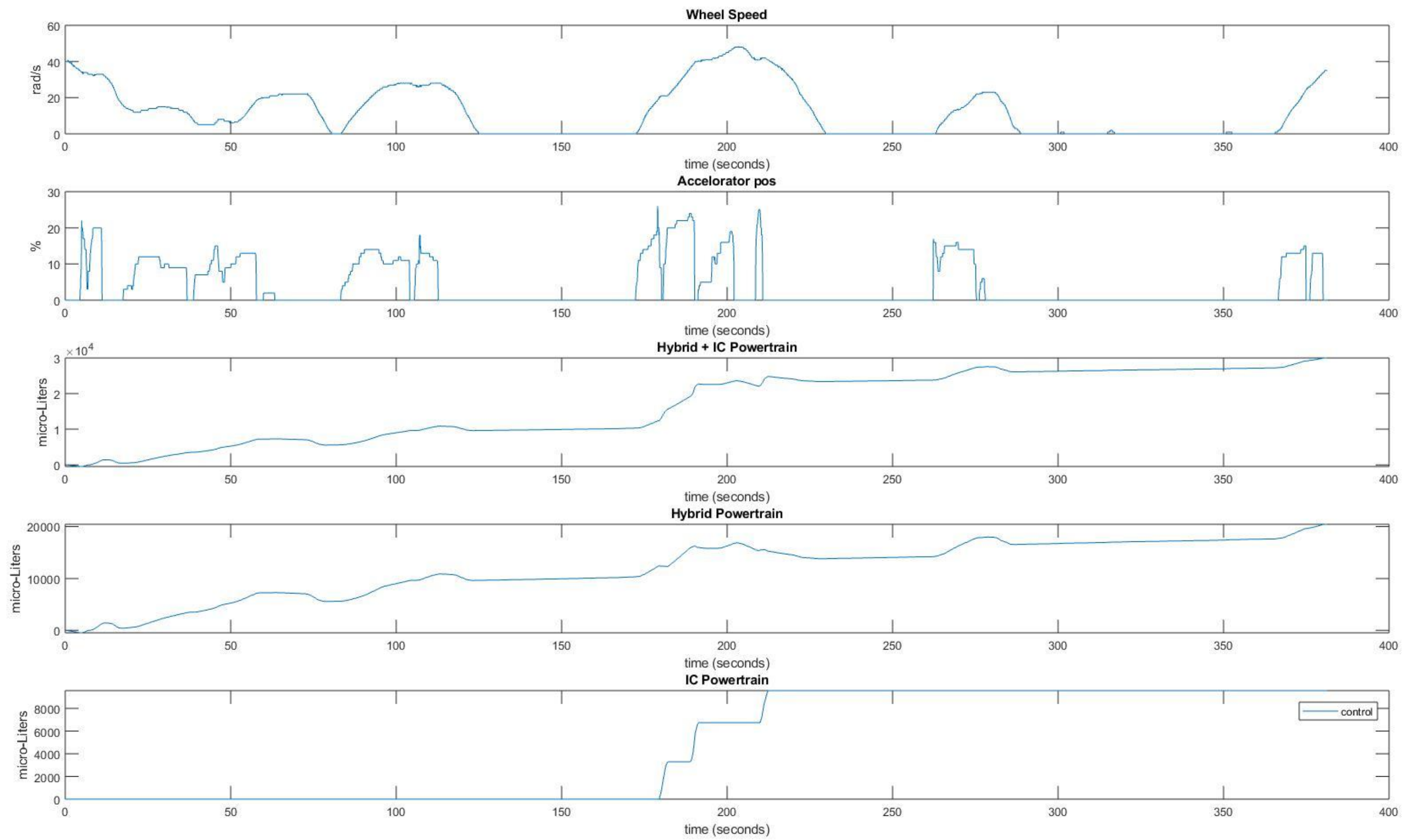


Figure 4-23: Driver 3 Day 4 Coached Run 1

Figure 4-23 shows there are very few stopping events. The length of time the vehicle is stopped does not matter as much as the frequency of the stops, because the vehicle has start-stop technology where the IC engine turns off while not moving. The vehicle's IC engine only turns on while the vehicle is accelerating through lights 4 through 9, which has a green wave associated with it. An average energy recovered un-coached and coached run is shown in Figure 4-24 for Driver 3. The normalized energy recovered shown in Figure 4-25. The normalized energy refers to the energy recovered over the fuel used during the run.

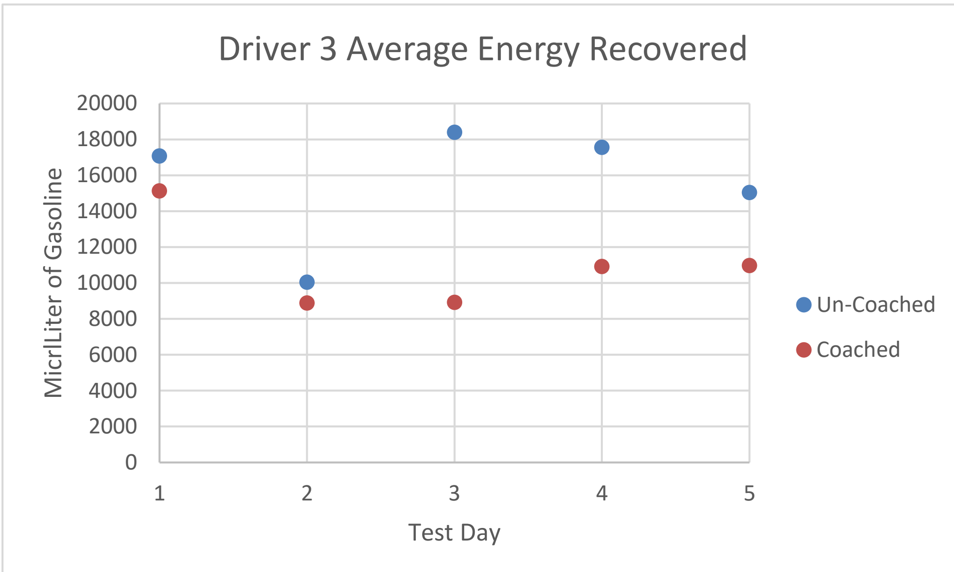


Figure 4-24: Driver 3 Average Energy Recovered per day

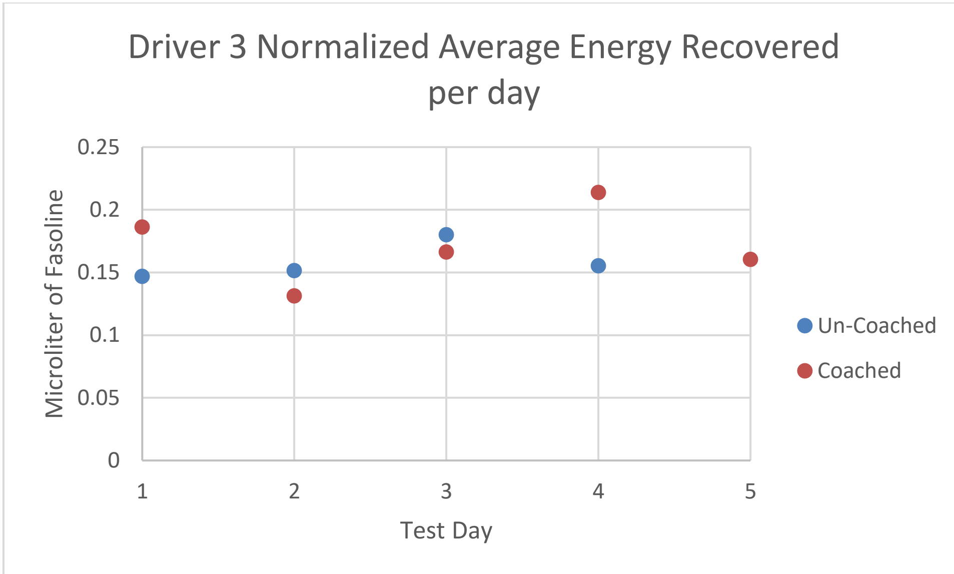


Figure 4-25: Driver 3 Normalized average Energy Recovered per day

The fuel that was recovered and stored is shown in Figure 4-24. Figure 4-24 shows more fuel was recovered in un-coached runs than the coached runs. However, Figure 4-25 shows that sometimes coached runs recover a higher percentage of the energy that was used during the run. The un-coached runs recovered 15.9% of the fuel that was used, while the coached runs recovered 17.2% of the fuel that was used. The difference in fuel recovered shows that the coached driver is making better use of the hybrid powertrain. Figure 4-26 is related to the time that the run took to complete. Figure 4-26 shows the average time that a coached an un-coached run took to complete per day. Figure 4-27 shows each test run time to complete.

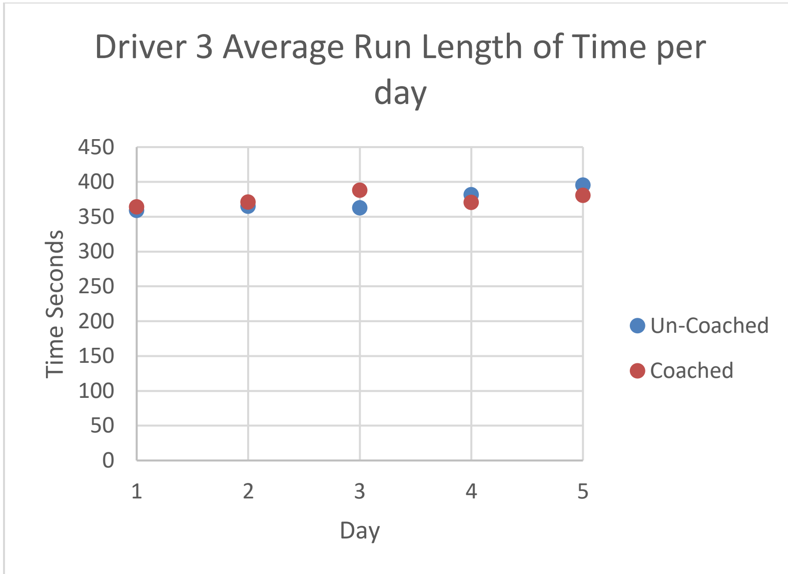


Figure 4-26: Driver 3 Average Run Length of Time per day

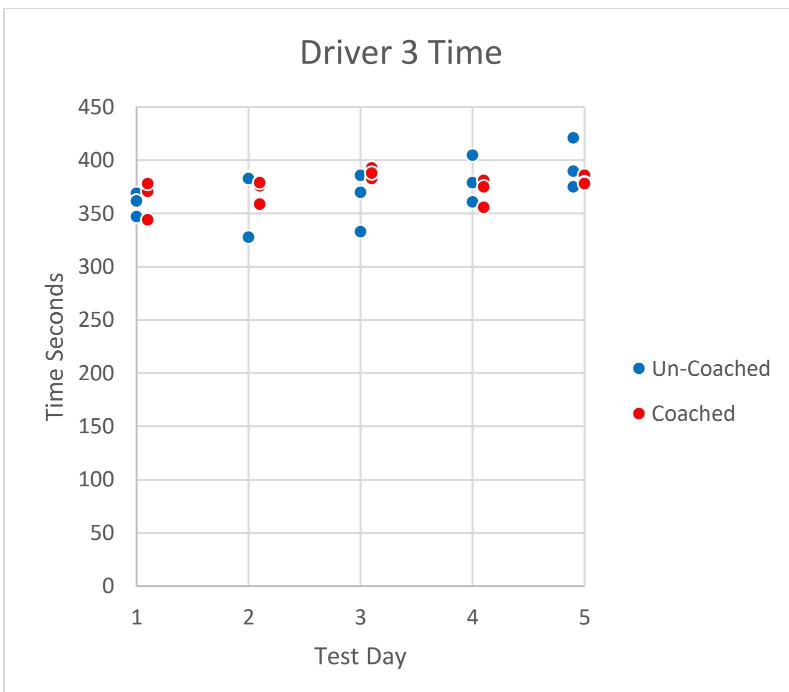


Figure 4-27: Driver 3 Run Length of Time

Driver 3 shows no time penalty for being coached. He suffers only 0.59% time increase when being coached. Figure 4-27 shows that the runs have a range of 88 seconds. 88 seconds is 24% of the average length of time that the run took to complete. There is less time variation than fuel consumption variation. Figure 4-28 shows Driver 3's use of the throttle and brake, and their relationship to vehicle speed and fuel consumption. The runs chosen closely corresponds to the average fuel consumption for Driver 3. Both runs come from day 4: un-coached run 2 and coached run 2. Driver 3's aggressive driving style still shows in both of his coached and un-coached runs. However, Driver 3 is much more conservative with the throttle during the first 150 seconds of the coached run. The driver uses less than 20% throttle for much of the coached run, while the un-coached runs use more than 20% throttle. The coached runs throttle reduction corresponds with coaching where the traffic lights encountered through traffic light 4 are red as the user drives up to them. The second half of the run corresponds to a green wave; Driver 3 still uses the acceleration of the car when he is confident of crossing the intersection. The un-coached runs show more percentage of the throttle being used, and large throttle use is followed by rapid decelerations. An example of this behaviour is shown at the 220 second point during the un-coached run. The large speed achieved at the 220 second point is unnecessary because the traffic light that caused the stoppage was predictable. Figure 4-29 shows the same runs as the Figure 4-28, but shows the hybrid powertrain performance. The first plot shows the wheel speed in radians per second. The second plot shows the throttle position. The third plot shows the combined hybrid and IC powertrain performance energy use in microliters of gasoline. The fourth plot shows hybrid powertrain energy use in microliters of gasoline. The last plot shows the IC engine energy use in microliters of gasoline. Figure 4-28 shows how Driver 3's use of the throttle affects the hybrid powertrains ability to help in acceleration. A similar hybrid performance is shows with Driver 2. The driver ends the route with excess energy inside of the hybrid system, instead of trying to use all that is available. Plot 4 shows this behaviour because the un-coached run is not able to use about

9,075 microliters of fuel. However, the coached run uses an excess of 4,100 microliters of fuel from the battery. The difference in net energy use by the hybrid powertrains shows the difference in demand of the hybrid powertrain. The coached run makes more efficient use of the stored energy in the hybrid powertrain. Driver 3 is a more extreme case of what Driver 2 showed. Most of the energy is used during accelerations, and if the IC engine is providing that energy, there is less opportunity for the hybrid powertrain to accelerate the vehicle.Figure 4-30 contains a histogram of driver 3's throttle use for both coached and un-coached runs. Driver 3 uses more throttle above 30% when un-coached. The coached run throttle use is centred around 12% and the un-coached throttle use is centred around 17%. The presence of coaching changed how driver 3 operated the acceleration of the vehicle. Aggressive drivers can expect to see large fuel consumption improvements from coaching.

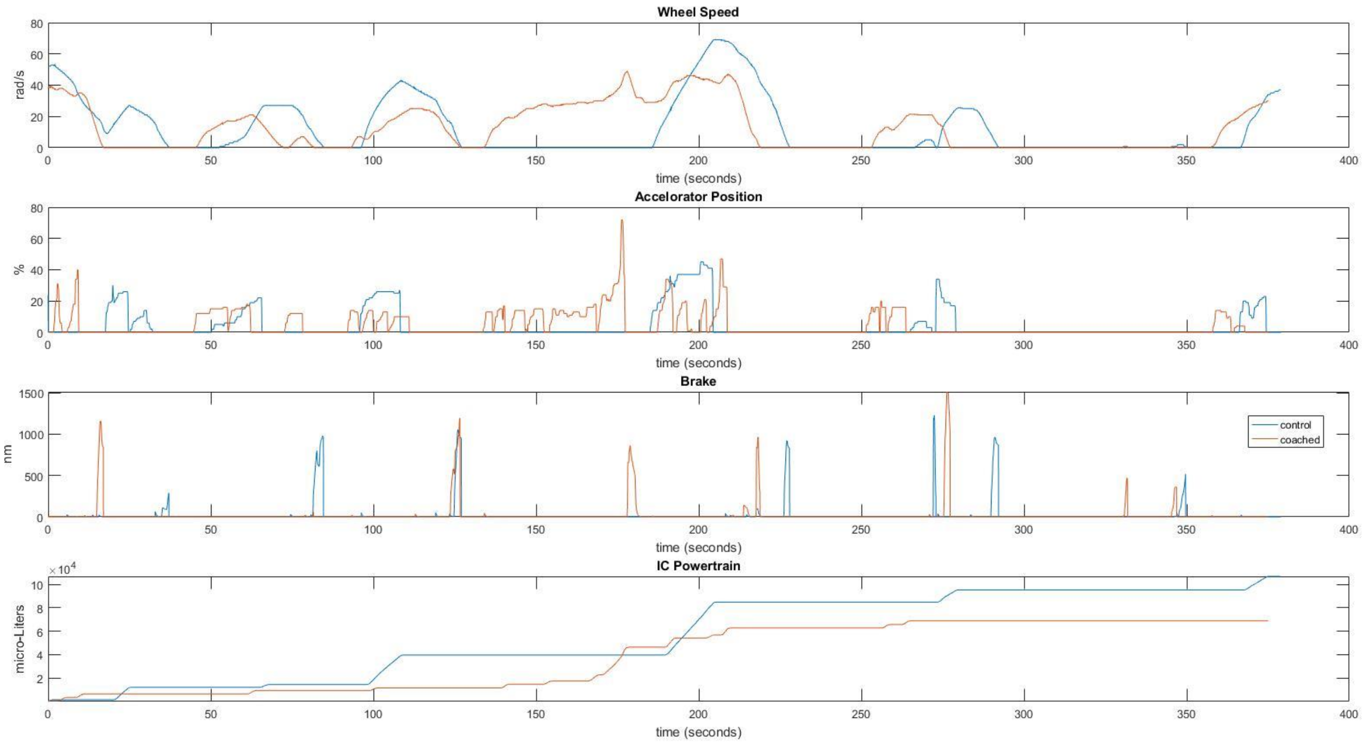


Figure 4-28: Driver 3 Day 4 Un-Coached Run 2 and Coached Run 2 Throttle and Brake

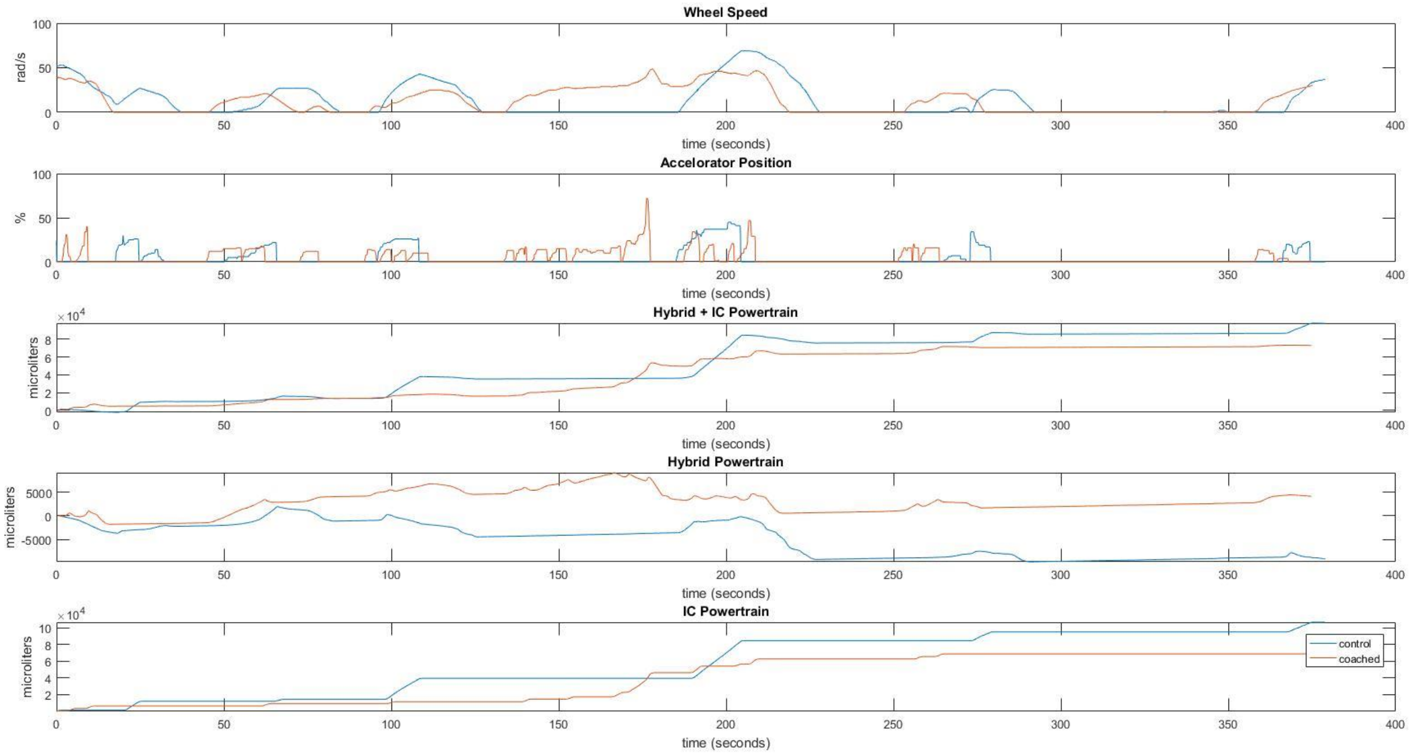


Figure 4-29: Driver 3 Day 4 Un-Coached Run 2 and Coached Run 2 Powertrain Fuel Use

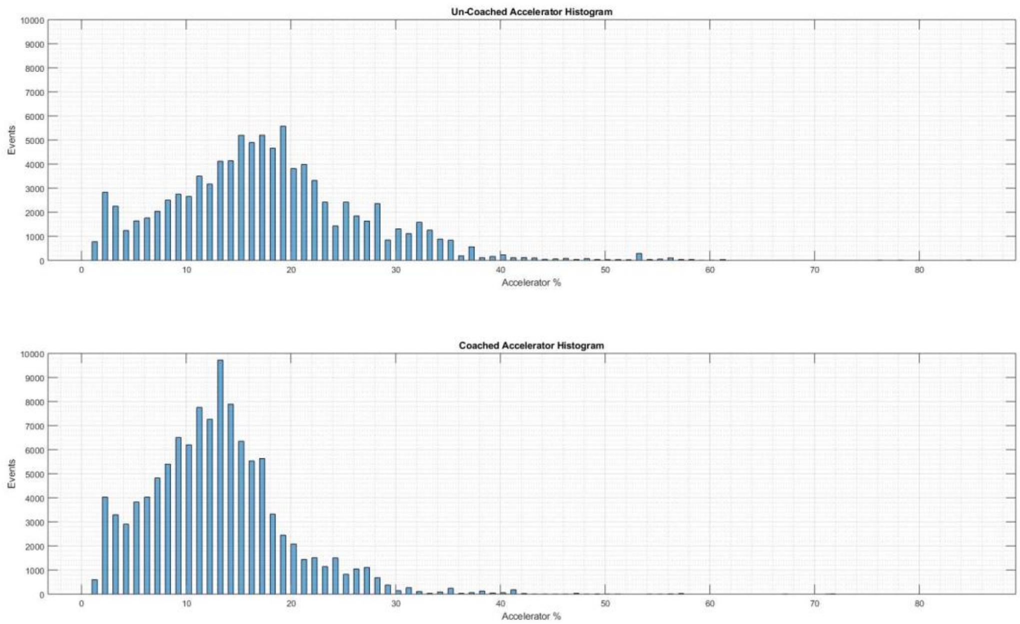


Figure 4-30: Driver 3 Throttle Histogram

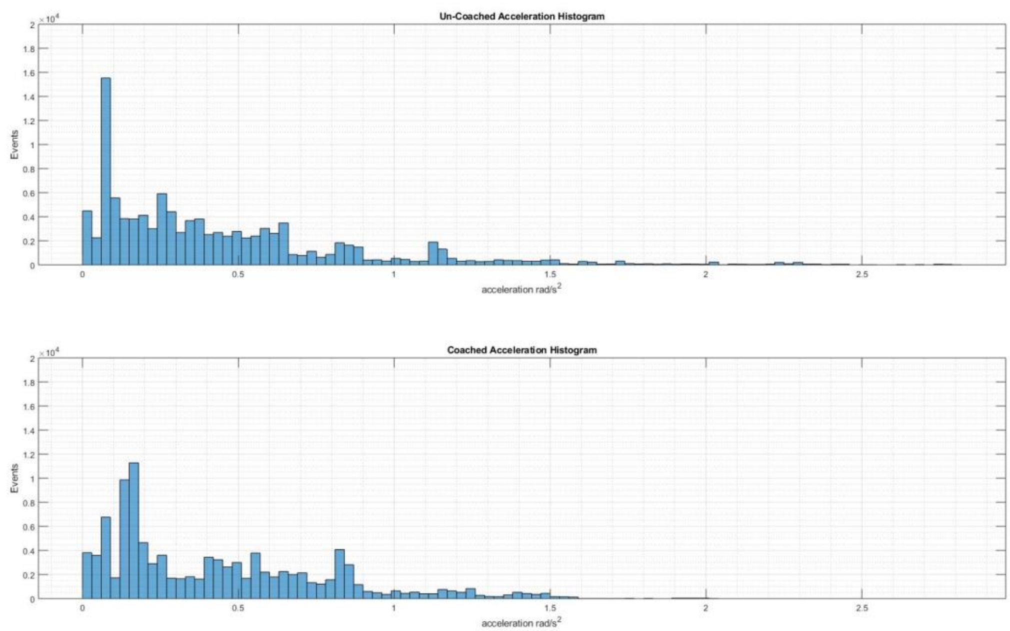


Figure 4-31: Driver 3 Acceleration Histogram

4.9 Driver 4 Test Observations

Driver 4 is a 23-year-old female. She has a conservative driving style leaving safe distances between vehicles and large stopping distances. Driver 4 is smooth with her use of the throttle and brake. The observer could not tell any differences in driving style between coached and un-coached runs. Because of her driving style, the results should show realistic fuel consumption reductions that should translate well to other drivers not contained in the study. On day 1, there was a power outage that affected traffic lights 2 and 3 on the route; the approach to traffic light 1 was shortened due to a detour for repairs. The beginning part of the run on Spring Street started about half of the distance between Ponce de Leon and 3rd Street. The start position started from a parking lot with an initial velocity of 0, whereas most other runs started with a running start. On day 2, a heavy rainstorm started on the last coaching run forcing more braking than usual through the run and lower travel speeds. Driver 4 results are in the next section.

4.10 Driver 4 Results and Discussion

Table 4-5 shows Driver 4's statistics. Driver 4's 30 test run fuel consumption results are shown in Figure 4-32. Driver 4's average daily fuel consumption is shown in Figure 4-33.

Table 4-5: Driver 4 Performance

	Un-Coached	Coached	percent Improvement	Two Tail P Value
Avg. Fuel Consumption (microliters)	88,320	82,822	6.2	1.37E-01
Corrected Fuel Consumption (microliters)	84,565	79,938	5.5	1.59E-01
Avg. Run Time(seconds)	378	383	-1.3	5.54E-01
Normalized Avg. Fuel Recovery (microliters)	14.1	13.8	-2.1	

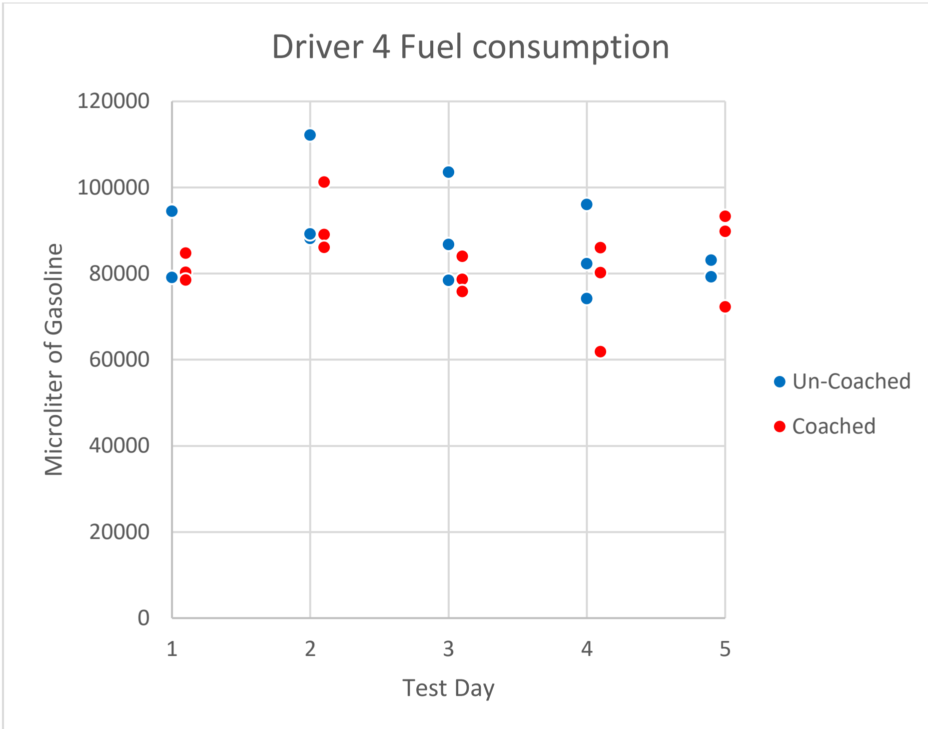


Figure 4-32: Driver 4 Fuel Consumption

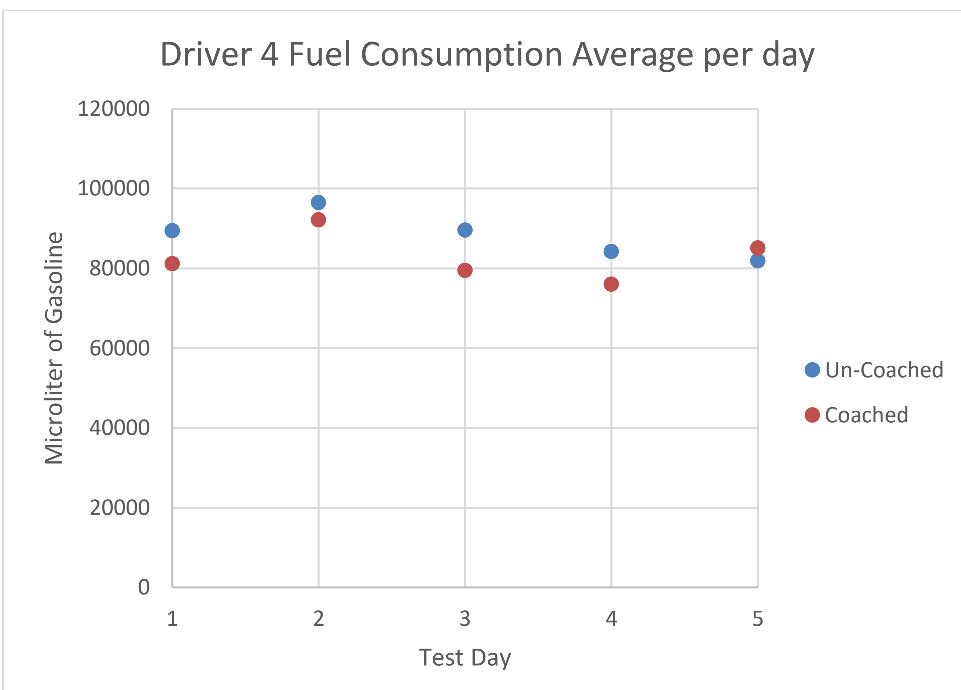


Figure 4-33: Driver 4 Average Fuel Consumption per day

Driver 4's average fuel consumption improvement from coaching is 6.22%. The average fuel consumption reduction has a p-value of 13.7% meaning it is not statistically significant on its own. The corrected fuel consumption reduction is 5.5%. Driver 4 is consistent with her driving style between coached and un-coached runs and does not have any outliers in Figure 4-32. Figure 4-34 shows the fuel recovered by the hybrid powertrain on the vehicle. Driver 4 recovers more energy while un-coached except for day 3. Figure 4-35 shows the normalized performance of the energy recovered over the fuel used during the run.

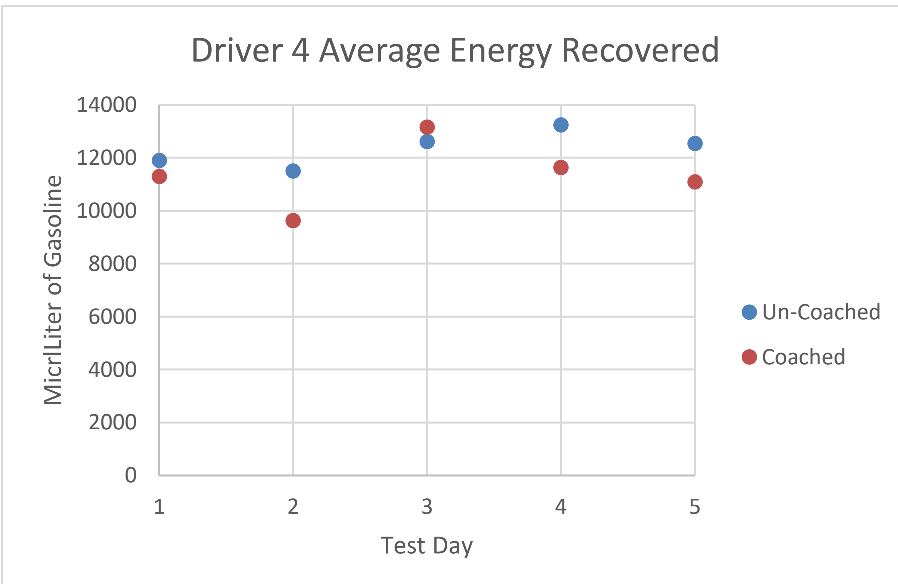


Figure 4-34: Driver 4 Average Energy Recovered per day

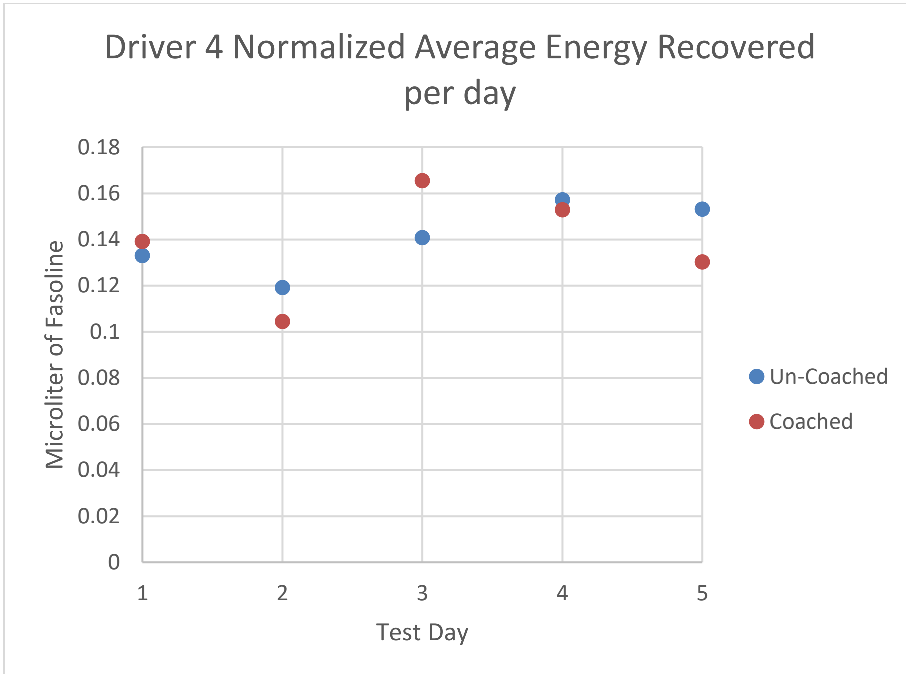


Figure 4-35: Driver 4 Normalized average Energy Recovered per day

The normalized energy recovery shows a 1.59% decrease for the coached run. The coached runs only outperformed the un-coached runs on day 3. This performance shows that Driver 4 used the hybrid powertrain effectively weather coached or un-coached. Figure 4-36 shows the time that each of the 30 runs took to complete. Figure 4-37shows the average time each run took to complete per day.

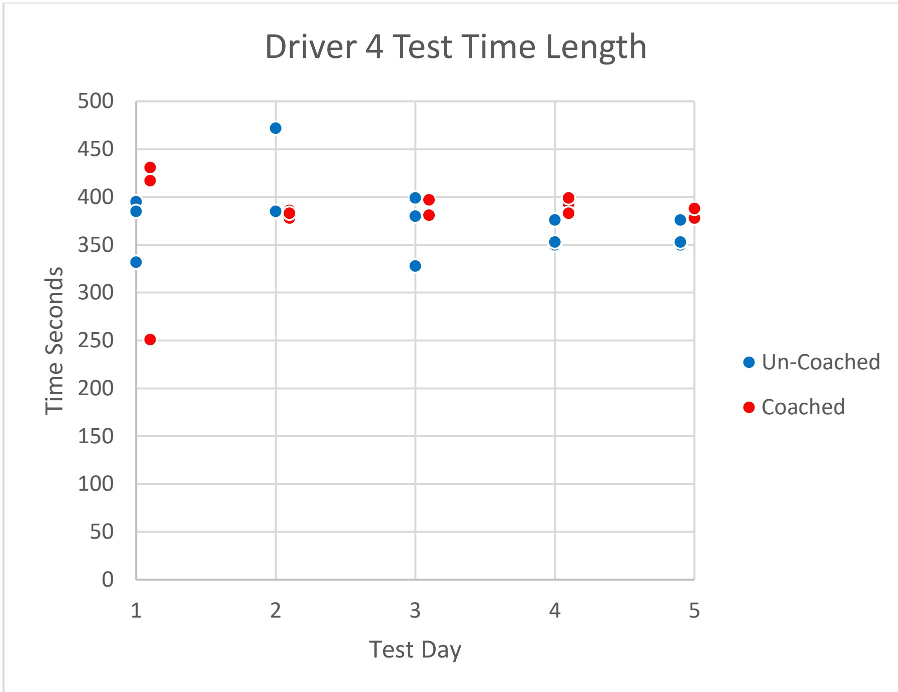


Figure 4-36: Driver 4 Run Length of Time

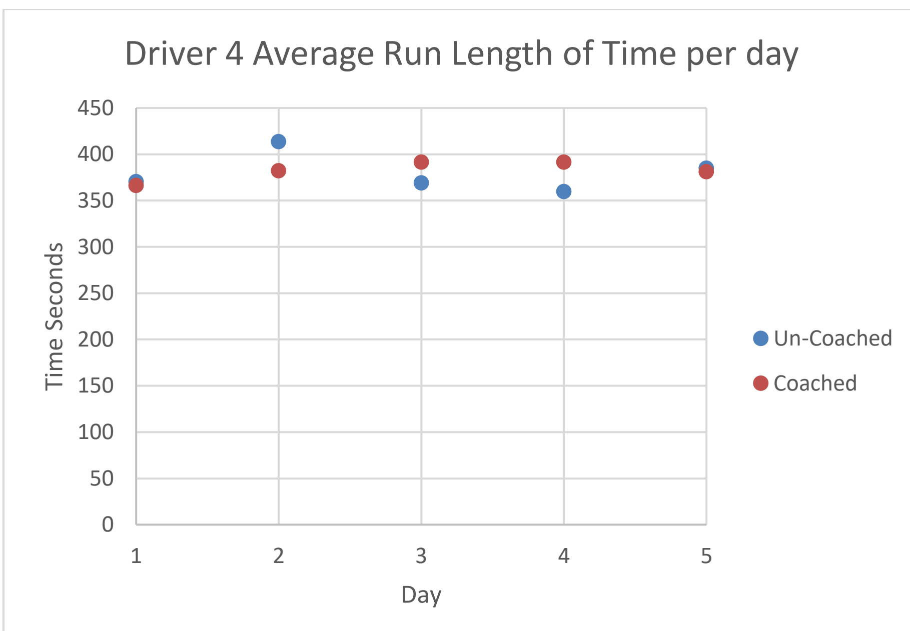


Figure 4-37: Driver 4 Average Run Length of Time per day

Driver 4 took 1.30% longer when coached to complete the runs. These runs are far from statically significant with a two-tail p-value of 55.4%. There is minimal time penalty observed for Driver 4 when being coached. Figure 4-38 shows two of Driver 4's runs. The two runs were chosen because they correspond to the fuel usage average for the coached and un-coached runs. The coached run consumed 88,175 microliters of gasoline and the un-coached run consumed 80,250 microliters of gasoline. The plot configuration is the same as Figure 4-28. The wheel speed plot shows a unique behavior to Driver 4. Driver 4's un-coached runs tended to get stopped at traffic light 7. That stop is seen in the coached run at 225 seconds. Many of the other drivers were able to drive fast enough through this portion to get to traffic light 9 without stopping. Driver 4's coached runs gave confidence and she drove fast enough to make traffic light 7 and 8 when not traffic limited. Driver 4 uses the brake harsher and more often when not coached and leaves more time between letting off the throttle and stepping on the brake. Figure 4-39 shows the performance of the different powertrain systems with the same two runs as Figure 4-38. Figure 4-39 is organized the same way Figure 4-29 is organized. Unlike Driver 3, Driver 4 makes better use of the hybrid powertrain whether she is coached or un-coached. Plot 4 shows that Driver 4 recovers more of energy from regenerative braking when coached and un-coached. Figure 4-40 contains a histogram of driver 4's throttle use. Driver 4 is so consistent with throttle use. It is difficult to see exactly where the 5-6% fuel consumption improvement is coming from. With little change in driving style, Driver 4 shows that measurable fuel consumption improvements are possible for drivers with little change in driving style.

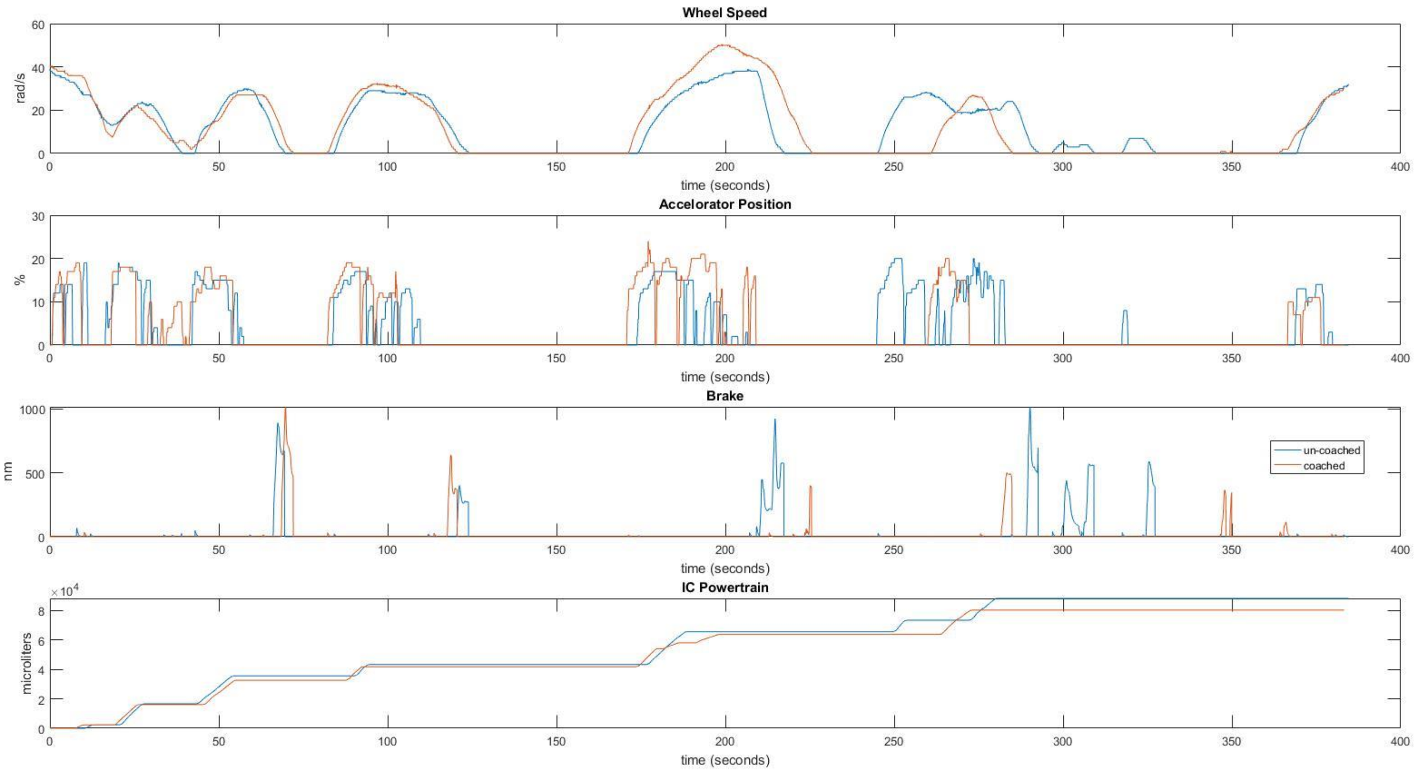


Figure 4-38: Driver 4 Day 2 Un-Coached run 2 and Day 4 Coached run 2 Throttle and Brake Performance

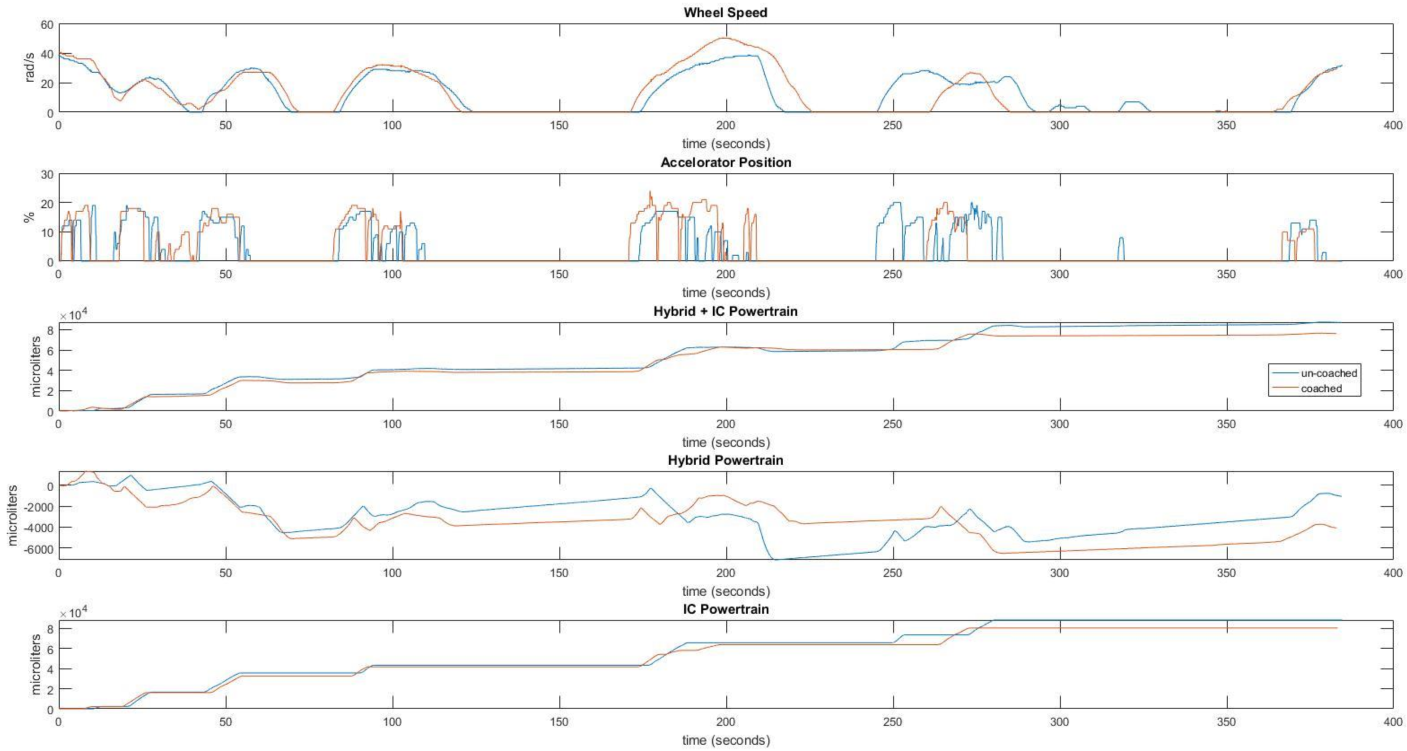


Figure 4-39: Driver 4 Day 2 Un-Coached run 2 and Day 4 Coached run 2 Throttle and Brake Performance

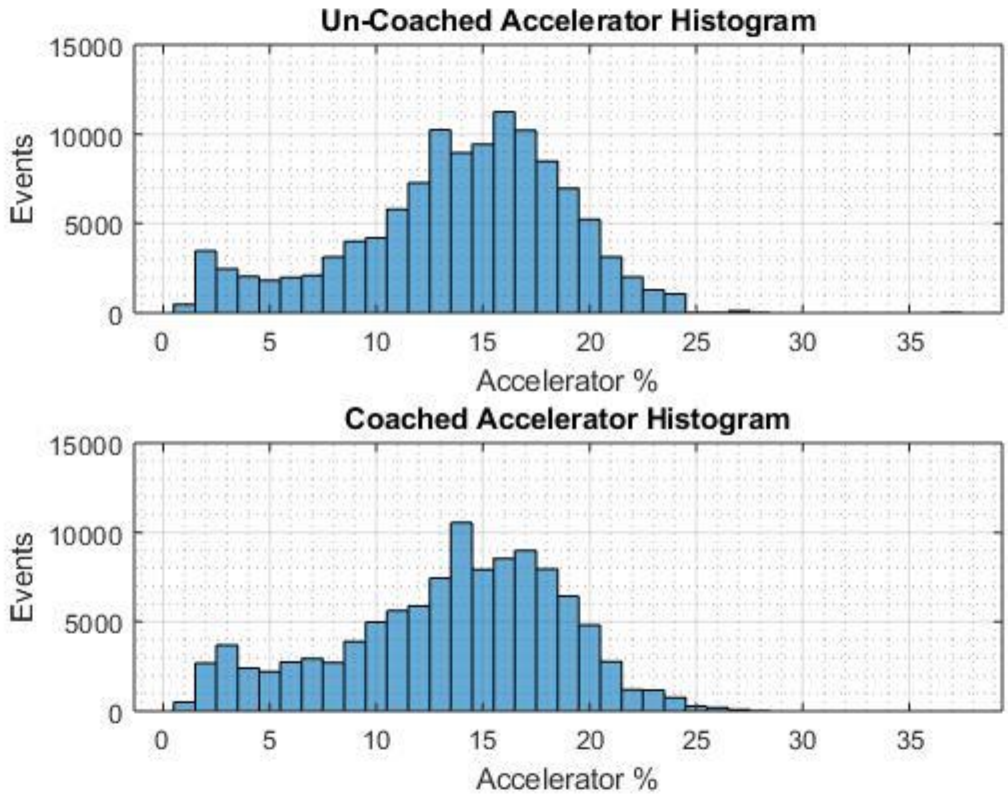


Figure 4-40: Driver 4 Throttle Usage

4.11 All 4 Drivers Combined Results

Between all 4 drivers there was a total of 120 test runs. 60 runs are coached, and 60 runs are un-coached. The combined fuel consumption reduction from coaching is 18.7%. The two-tail p-value is 5.6ppm. The p-value makes the total fuel consumption reduction for all 4 drivers highly statistically significant. The corrected fuel consumption reduction is 16.7%. Figure 4-41 shows all 4 drivers' fuel consumptions relative to each other with error bars. Driver 1 consumes the least fuel when coached and un-coached. Driver 3 consumes the most fuel when un-coached and consumes slightly more fuel than the most efficient driver when coached. Driver 4 shows small error bars compared to the other drivers. The time required to complete a route is not statistically significant. The coached runs averaged 1.99% longer to complete, but the p-value is 41.5%. There is no strong correlation between the time required to complete the route and whether the driver is being coached. Figure 4-42 shows the average time each driver took to complete their coached and un-coached runs. The time is approximately the same between coaching and drivers unlike the fuel consumption results. These 4 drivers show that there are fuel economy improvements from the leader-follower traffic light prediction method.

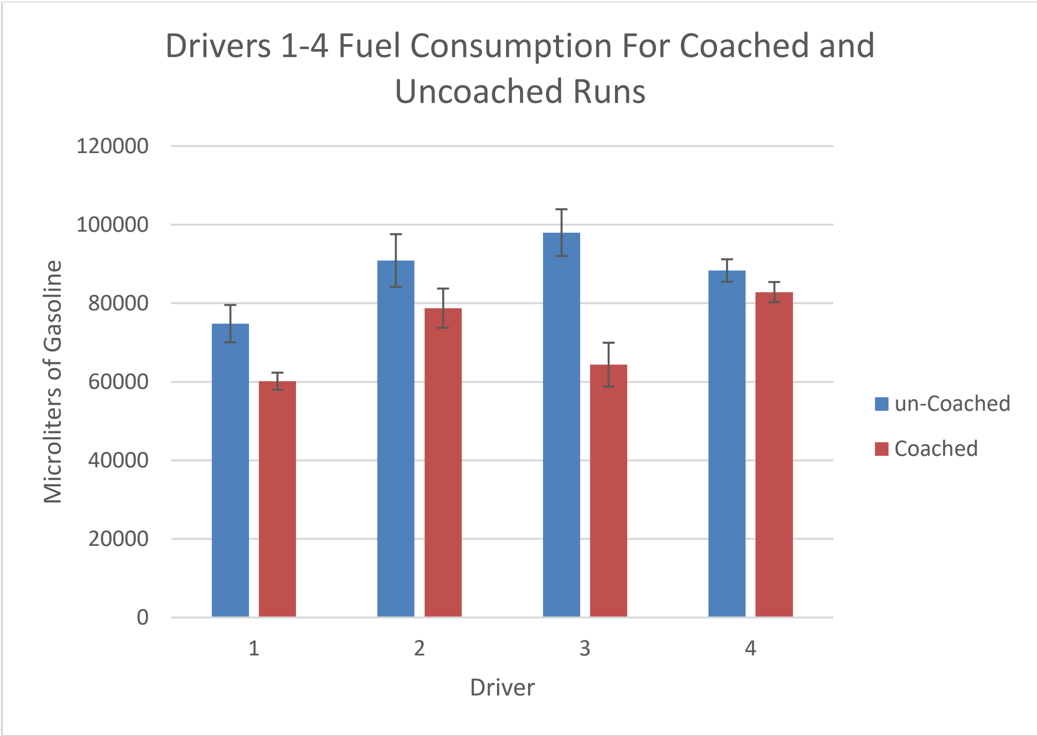


Figure 4-41: Drivers 1-4 Fuel Consumption with Error Bars

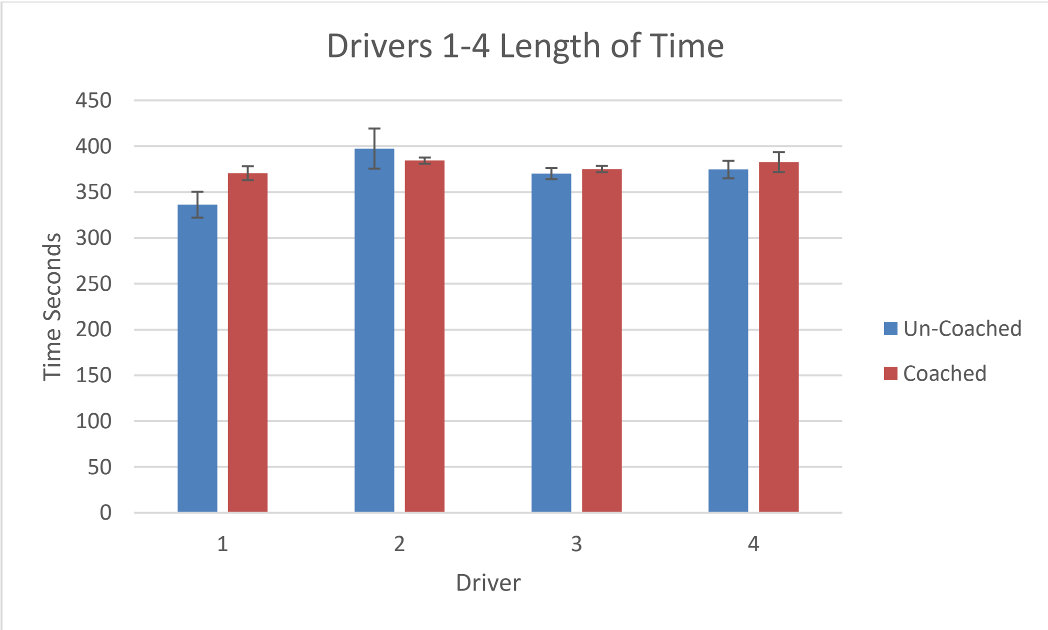


Figure 4-42: Drivers 1-4 Time per Run with Error Bars

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

5.1 Conclusion

This thesis set out to propose and develop a system for new driver coaching devices and methods. The developed coaching methods resulted in a method for accurate prediction of fixed-time traffic lights that can be implemented for a driver aid. Real world fuel consumption improvements are seen from coaching drivers on traffic light timings. A test is developed that is a 1 mile long with 10 traffic lights on the route. Drivers 1 through 4 showed a coached fuel usage range from of 66% to 94%of the un-coached fuel usage. The average fuel consumption reduction is 18.7% for all the drivers runs combined. The corrected fuel consumption reduction is 16.7% for all drivers. Driver behaviour has a big impact on the performance from traffic light coaching. Driver 3 shows a fuel reduction of 34.3%. The fuel consumption reduction resulted in a large part from a massive change in driving style. However, drivers 1, 2, and 4 showed smaller changes in driving styles while being coached, and still showed 6% to 19% fuel economy improvement. The impact of the coaching on the time required to complete the route is small because the route is dominated by the traffic light timings. The route is very traffic light dense with 10 traffic lights in one mile. The coaching shows little to no time impact with coaching. While Driver 1 shows 10% longer to complete the runs when coached, Driver 2 shows completing the runs 1.79% faster while coached. The coaching application reduces fuel consumption by reduce the number of braking events and increasing the time between accelerating and braking events. Depending on the driver the coaching influenced driving behaviour to produce fuel consumption reduction of 34% in the case of Driver 2. For large fuel consumption reductions to occur, the driver must have started with an inefficient and aggressive driving style. These results are only possible with a route that contains traffic lights. If the driver is on the interstate, there is no possibility for traffic light coaching because there are no traffic lights. The route is an extreme case of city driving that has 10 traffic lights in 1 mile. The fuel economy results would likely decrease with a decrease in traffic light density, but this is difficult to definitively conclude based on the experiment in Chapter 4. With a lower traffic light density, traffic lights could be coached with larger distances. Larger coaching distances could result in more gains per traffic light. To see fuel consumption reductions on roads with few or no traffic lights, other methods such as those discussed in Chapter 2. Fuel consumption is only one part of driver coaching. Fuel consumption might be a motivating factor for adoption of such coaching systems. Drivers expressed satisfaction during the testing of less anxiety and appreciation of being coached while stopped at a red light. It allowed the drivers to relax while waiting for a traffic light to change, yet still be ready when the traffic light does change. Driver feedback systems and driver coaching has more potential with the increase in sensors around the vehicles.

5.2 Future Work

For the coaching system to be implemented on a large scale there is is room for futher development. Automation of the leader-follower traffic light prediction method would allow the system to be implemented on a large scale. The test prototype focuses on the follower functionality. Leading and Lerning still needs more automation. Automation of the traffic light selection system, automation of the learning phase, and automation of the following phases would allow the system to function without an operator in the passenger seat. Automation could be done with a traffic light computer vision system. The learning data base needs to quickly estimate traffic light cycles with historical traffic light infromatoin. Prediction for other fixed time cycle traffic lights can be done with the leader-follower method with more inputs and more case statement in the following phase.

The leader-follower coaching needs to be tested with other types and classes of vehicles to see how its performance varies with traditional IC vehicles and larger semi-trucks.

APPENDIX

A. Appendix A

The data for all the driver's tests runs is shown in Appendix A. For each driver the first table contains the fuel consumption results. The fuel consumption is the sum of the fuel that is measured being injected to the IC engine. The second table contains the run time results. The time is measured by taking the time stamp off of the last CAN bus signal and subtracting off the time of the first CAN bus signal. The third table contains the energy recovered through the run. The energy recovered is calculated by summing up any energy amount that decreases from the previous energy state for the hybrid powertrain.

A.1 Driver 1 Test Results Data

Table A-1: Driver 1 Fuel Consumption

Day	Run	Un-Coached(microliters)	Coached(microliters)
1	1	113,225	70,975
1	2	86,550	72,425
1	3	56,950	63,625
2	1	83,750	55,075
2	2	79,375	51,050
2	3	92,725	60,900
3	1	72,525	51,525
3	2	78,625	66,625
3	3	88,800	62,025
4	1	75,275	54,463
4	2	58,575	64,000
4	3	59,925	43,675
5	1	71,350	58,475
5	2	48,200	63,750
5	3	56,075	63,825

Table A-2: Driver 1 Run Time

Day	Run	Un-Coached(seconds)	Coached(seconds)
1	1	269	376
1	2	337	384
1	3	372	362
2	1	360	380
2	2	370	382
2	3	386	382
3	1	314	363
3	2	363	378
3	3	376	363
4	1	418	276
4	2	266	386
4	3	271	378
5	1	306	386
5	2	375	386
5	3	261	375

Table A -3: Driver 1 Energy Recovered

Day	Run	Un-Coached(microliters)	Coached(microliters)
1	1	11,544	11,226
1	2	11,902	11,384
1	3	16,554	11,659
2	1	12,269	9,513
2	2	12,498	10,499
2	3	12,793	7,458
3	1	6,300	9,513
3	2	8,701	10,499
3	3	13,516	7,458
4	1	11,824	11,954
4	2	12,658	12003
4	3	13,634	13827
5	1	10,664	10664
5	2	9,989	9989
5	3	12,031	12031

A.2 Driver 2 data

Table A-4: Driver 2 Fuel Consumption

Day	Run	Control(microliters)	Coached(microliters)
1	1	101,500	101,750
1	2	86,000	78,700
1	3	111,050	88,800
2	1	73,850	87,625
2	2	101,650	50,850
2	3	85,750	100,775
3	1	160,775	39,375
3	2	69,075	80,525
3	3	73,250	84,825
4	1	95,200	79,575
4	2	55,975	70,875
4	3	79,575	68,075
5	1	88,725	77,475
5	2	100,975	67,425
5	3	79,400	104,625

Table A-5: Driver 2 Run Time in seconds

Day	Run	Un-Coached(seconds)	Coached(seconds)
1	1	438	368
1	2	390	366
1	3	661	387
2	1	342	382
2	2	391	385
2	3	380	396
3	1	351	389
3	2	396	393
3	3	388	383
4	1	325	363
4	2	398	376
4	3	389	399
5	1	325	382
5	2	398	390
5	3	389	405

Table A-6: Driver 2 Energy Recovered

Day	Run	Un-Coached(microliters)	Coached(microliters)
1	1	14,382	20,546
1	2	16,412	16,718
1	3	16,490	18,834
2	1	11,269	20,994
2	2	24,496	18,290
2	3	20,340	20,275
3	1	9,885	13,470
3	2	14,805	18,513
3	3	16,571	17,566
4	1	15,782	20,774
4	2	14,994	17,993
4	3	19,621	19,556
5	1	15,016	15,582
5	2	17,008	14,575
5	3	13,463	18,551

A.3 Driver 3 data

Table A-7: Driver 3 Fuel Consumption

Day	Run	Un-Coached (microliters)	Coached(microliters)
1	1	112,150	53,600
1	2	116,775	98,100
1	3	119,800	92,000
2	1	47,950	67,375
2	2	80,025	65,050
2	3	70,800	70,400
3	1	106,900	48,800
3	2	118,575	59,900
3	3	80,775	52,075
4	1	117,600	95,75
4	2	106,825	68,875
4	3	114,425	74,575
5	1	88,175	72,500
5	2	83,850	62,100
5	3	104,925	70,425

Table A-8:Driver 3 Run Time

Day	Run	Un-Coached(seconds)	Coached(seconds)
1	1	347	344
1	2	369	371
1	3	362	378
2	1	328	376
2	2	384	359
2	3	383	379
3	1	333	393
3	2	370	383
3	3	386	388
4	1	361	381
4	2	379	375
4	3	405	356
5	1	361	386
5	2	379	379
5	3	405	378

Table A-9: Driver 3 Energy Recovered

Day	Run	Un-Coached(microliters)	Coached(microliters)
1	1	16,560	16,704
1	2	15,344	14,591
1	3	19,289	14,088
2	1	11,252	9,682
2	2	9,637	9,425
2	3	9,214	7,515
3	1	21,756	8,616
3	2	17,805	10,186
3	3	15,603	7,922
4	1	13,117	9,089
4	2	20,144	14,152
4	3	19,360	9,498
5	1	13,140	12,705
5	2	14,879	11,282
5	3	17,081	8,916

A.4 Driver 4 data

Table A-10: Driver 4 Fuel Consumption

Day	Run	Un-Coached(microliters)	Coached (microliters)
1	1	94,575	80,325
1	2	79,150	84,800
1	3	94,500	78,525
2	1	112,200	89,075
2	2	88,175	86,150
2	3	89,225	101,300
3	1	86,800	78,700
3	2	103,550	75,825
3	3	78,425	84,050
4	1	82,300	61,875
4	2	74,200	80,250
4	3	96,100	86,025
5	1	83,150	89,800
5	2	79,275	93,350
5	3	83,175	72,275

Table A-11: Driver 4 Run Time

Day	Run	Un-Coached(seconds)	Coached(seconds)
1	1	395	251
1	2	332	431
1	3	385	417
2	1	472	386
2	2	384	378
2	3	385	383
3	1	328	381
3	2	380	397
3	3	399	397
4	1	350	393
4	2	376	383
4	3	353	399
5	1	350	378
5	2	376	378
5	3	353	388

Table A-12: Driver 4 Energy Recovered
Table 0-13

Day	Run	Un-Coached(microliters)	Coached(microliters)
1	1	12,125	11,091
1	2	10,723	9,672
1	3	12,843	13,130
2	1	13,086	8,496
2	2	10,228	9,452
2	3	11,183	10,934
3	1	9,610	13,611
3	2	14,341	12,497
3	3	13,875	13,365
4	1	13,323	11,335
4	2	13,068	11,132
4	3	13,323	12,415
5	1	11,924	10,039
5	2	13,905	11,342
5	3	11,797	11,889

B. Appendix B

Appendix B shows the calculations used for the analysis of the data. Section B.1 contains the method for calculation of the two-tail p value, and the variance calculation.

B.1 Two-tail p value with unequal variances, and variance calculation

The analysis calculated the p value and variance to determine the statistical significance of results. This section shows how the p value and variance are calculated using excel. The Data Analysis Tool is used in excel for these calculations. Figure B-1 shows the Driver 2's data set. Figure B-2 shows the data analysis tool in excel. Figure B-3 shows the input into the t-test two sample assuming unequal variances window. Figure B-4 shows the output of the t-test two sample assuming unequal variances. The box in the variable 1 column and the 9^{th} row shows the two-tail p value. If the p value is less than 0.05 this experiment is statically significant. The p value is 13.3%. The square root of the variance is the standard of deviation.

	A	B	C	D
1	Day	Run	Un-Coached(microliters)	Coached(Microliters)
2	1	1	101500	101750
3	1	2	86000	78700
4	1	3	111050	88800
5	2	1	73850	87625
6	2	2	101650	50850
7	2	3	85750	100775
8	3	1	160775	39375
9	3	2	69075	80525
10	3	3	73250	84825
11	4	1	95200	79575
12	4	2	55975	70875
13	4	3	79575	68075
14	5	1	88725	77475
15	5	2	100975	67425
16	5	3	79400	104625

Figure B-1: Driver 2 Fuel Consumption Data Excel

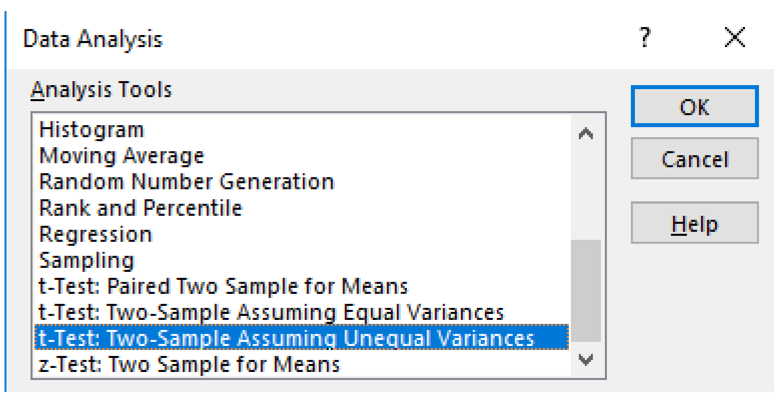


Figure B-2: Data Analysis Tool Excel

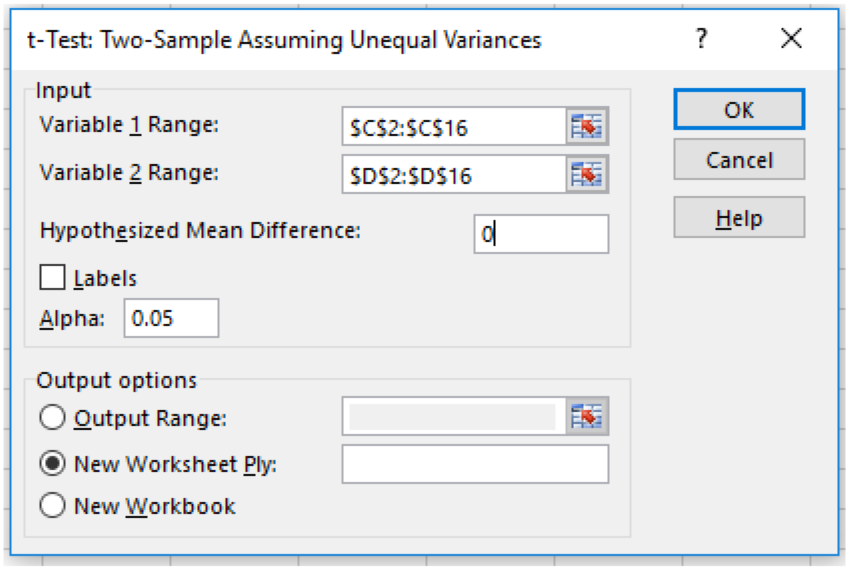


Figure B-3: t-Test: Two-Sample Assuming Unequal Variance

	Variable 1	*Variable 2*
Mean	90850	78751.67
Variance	5.89E+08	3.24E+08
Observati	15	15
Hypothesi	0	
df	26	
t Stat	1.550287	
P(T<=t) or	0.06658	
t Critical o	1.705618	
P(T<=t) tw	0.133161	
t Critical t	2.055529	

Figure B-4: t-Test: Two-Sample Assuming Unequal Variance Output

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