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Run-Time HEV Engine-Generator Power-Speed Optimization for Fuel Consumption and Emissions Reduction

Chester Paul Rowe II

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A Thesis Submitted to the College of Engineering Department of Mechanical Engineering in Partial Fulfillment of the Requirements for the Degree of Master of Science in Mechanical Engineering

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This thesis was prepared under the direction of the candidate's Thesis Committee Chair, Dr. Patrick N. Currier, Professor, Daytona Beach Campus, and Thesis Committee Members Dr. Marc D. Compere, Professor, Daytona Beach Campus, and Dr. Darris L. White, Professor, Daytona Beach Campus, and has been approved by the Thesis Committee. It was submitted to the Department of Mechanical Engineering in partial fulfillment of the requirements for the degree of Master of Science in Mechanical Engineering

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Abstract

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As fuel economy and emissions standards become more stringent, Plug-in Hybrid Electric Vehicles (PHEV) using series architectures are being increasingly explored. Due to the decoupling of the Internal Combustion Engine (ICE) from the road, the primary control challenge in this architecture is the optimization of an ICE control law. A run-time Genset speed controller is presented for use during the charge-sustaining mode in a Series PHEV to find the optimal operating parameters for a conventional diesel engine coupled to an electric generator in terms of minimized fuel consumption and emissions generation. On board vehicle sensors provide real time data to the controller allowing for this method of optimization to be valid regardless of environment or operating conditions. The controller is validated through computer simulations using data from the Embry-Riddle EcoCAR 2 vehicle platform. Compared to the existing static Genset speed controller, the run-time controller resulted in a 40% reduction in fuel consumption and a 45% reduction in NO_X production.

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Chapter I

Introduction

Current vehicles cannot meet the future requirements of the Corporate Average Fuel Economy (CAFE) standards implemented by the National Highway Traffic Safety Administration (NHTSA) [1]. This is forcing the development of new technologies that present themselves in many forms, the most prevalent of which being Hybrid Electric Vehicles (HEVs). HEVs combine conventional Internal Combustion Engines (ICE) with electrical propulsion. When a method of charging from the electric grid is added to the vehicle, it is then referred to as a Plug-In Hybrid Electric Vehicle (PHEV). Plug-In charging allows the Energy Storage System (ESS) to be charged at both lower monetary cost and emissions production than if it were charged with an ICE.

In order to train new engineers in the technologies required to meet the CAFÉ standards, the United States Department of Energy (DOE) through Argonne National Labs (ANL) has partnered with General Motors (GM) in hosting Advance Vehicle Technology Competitions (AVTCs). The latest AVTC to be completed is EcoCAR 2. EcoCAR 2 is the premiere North American Automotive Competition where students are challenged to design a new powertrain for a 2013 Chevrolet Malibu. The goals in redesigning the powertrain are:

- Reduce fuel consumption
- Reduce well-to-wheel greenhouse emissions
- Reduce criteria tailpipe emissions
- Maintain consumer acceptability in the areas of performance, utility, and safety [2]

All fifteen teams created a PHEV, in varying forms, to meet the competition requirements. The vehicles included both parallel and series architectures with fuels ranging from hydrogen to E85 to B20. Most of the HEVs and PHEVs within the USA today use gasoline as the fuel source for the Internal Combustion Engine (ICE). Diesel is a more efficient fuel source than gasoline; however, it comes with some challenges including a higher upfront cost and difficulty in meeting emissions regulations [3].

Since diesel is a more efficient fuel than gasoline and cost was not a factor of the competition, it was chosen as the fuel to be used in the previously built Embry-Riddle EcoCAR 2 vehicle platform. This leaves the main drawback of the diesel engine to be that of emissions. Emissions reduction can occur at multiple points within the cycle: pre-combustion, during combustion, and post-combustion. Pre-combustion emissions reduction is performed by injecting the diesel fuel into the cylinder at high pressures to ensure better mixing and a more complete combustion [4]. During the combustion process emissions can be controlled by the operating point of the engine, as different operating points allow for a more complete combustion [4]. Post-combustion involves the treatment of the exhaust which typically includes a combination of a Diesel Particulate Filter (DPF), Catalytic Converters (CAT), Selective Catalytic Reduction (SCR), and a Diesel Oxidation Catalyst (DOC) [4]. Most of the work that has been done so far has dealt with Pre and Post-combustion as the diesel engine is coupled to the road therefore defining the operating points by the vehicle speed and gear ratios. In contrast, the ICE in a series PHEV is not coupled to the road, but instead is coupled to an electric generator. The coupling of the ICE to an electric generator forms what is referred to as a Genset. A Genset allows for two degrees of freedom, torque and speed, whereas a conventional vehicle's ICE only has a single degree of freedom, torque. This work takes advantage of the 2 degrees of freedom found in the Genset of a series PHEV focusing on the run-time optimization of the ICE operating points to reduce both fuel consumptions and emissions production.

Vehicle Architecture

The Embry-Riddle EcoCAR 2 vehicle platform is based on a 2013 Chevrolet Malibu that was converted to a series PHEV. A series PHEV is essentially a full Electric Vehicle (EV) with a generator on board capable of creating electricity on-demand regardless of the vehicle's velocity. The ERAU Series PHEV is the ideal platform for this optimization problem as it is it is available and has the ability for control strategies to be quickly modified. The major components of the vehicle are:

Table 1 – Major Vehicle Components

Description	**Manufacturer**	**Model #**
Electric Traction Motor	Remy Motor in an AM Racing Housing	HVH250-090-P
Transmission	GKN	eTransmission (9.59:1 ratio)
Energy Storage System (ESS)	A123	Lithium-Ion, 15s3p, 292V nominal, 16.2 kWh
Electric Generator	Remy Motor in an AM Racing Housing	HVH250-090-S
1.7L Diesel ICE	Opel	LUD (A17DTS)

The front wheels are mechanically connected to a single speed GKN eTransmission through conventional half shafts. The GKN eTransmission is directly coupled to the Traction Motor through a splined shaft. The Traction Motor is powered off of the High Voltage (HV) bus. The ESS is the primary electrical source for the HV bus and can be charged by plugging it in to an outlet through a J1772 connector, by the Genset, or through regen from the Traction Motor. The Electric Generator is coupled to the ICE with a Polyurethane Lovejoy coupler and is not used for vehicle propulsion, only for electrical power generation. The vehicle layout and energy flow diagram is shown in Figure 1.

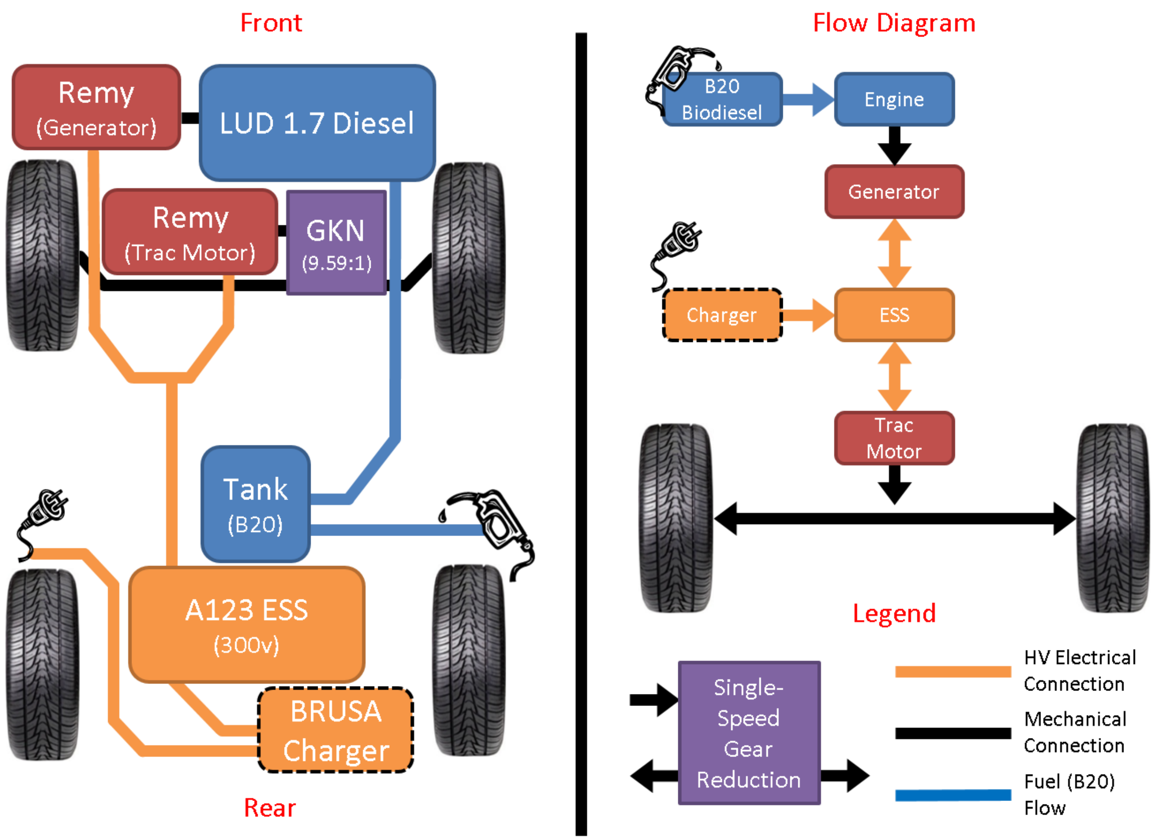

Figure 1 – Embry-Riddle EcoCAR 2 Vehicle Architecture – Series PHEV

Previous Work

This work is a continuation of work performed by the Embry-Riddle Aeronautical University EcoCAR 2 team (the EcoEagles). Two individuals on the team, Brian Harries and Derek Bonderczuk, provided the most notable contributions to the team's control system development.

In 2012 Harries developed and tested the initial vehicle controller in both SIL and HIL environments. Part of this work was the development of a Charge Sustaining (CS) mode which would turn the Genset on when more power was required than the ESS could provide. Two different controllers were developed for this scenario, the first being a Bang-Bang controller and the second being a Power-tracking controller. [5]

A Bang-Bang controller turns the Genset on at a predetermined minimum ESS SOC level, operates the Genset at a single operating point then shuts it off when a predetermined desired ESS SOC level is reached. The single operating point chosen was the point of minimum Brake Specific Fuel Consumption (BSFC) in order to reduce fuel consumption while maximizing power output. The data used to make the BSFC map shown in Figure 2 was used to determine the point of minimum BSFC, which was determined to be 206.1606 g/kWhr. The point of minimum BSFC is defined by the operating points of 2,200 rpm and 60% Throttle Position producing 59kW of power from the ICE. [5]

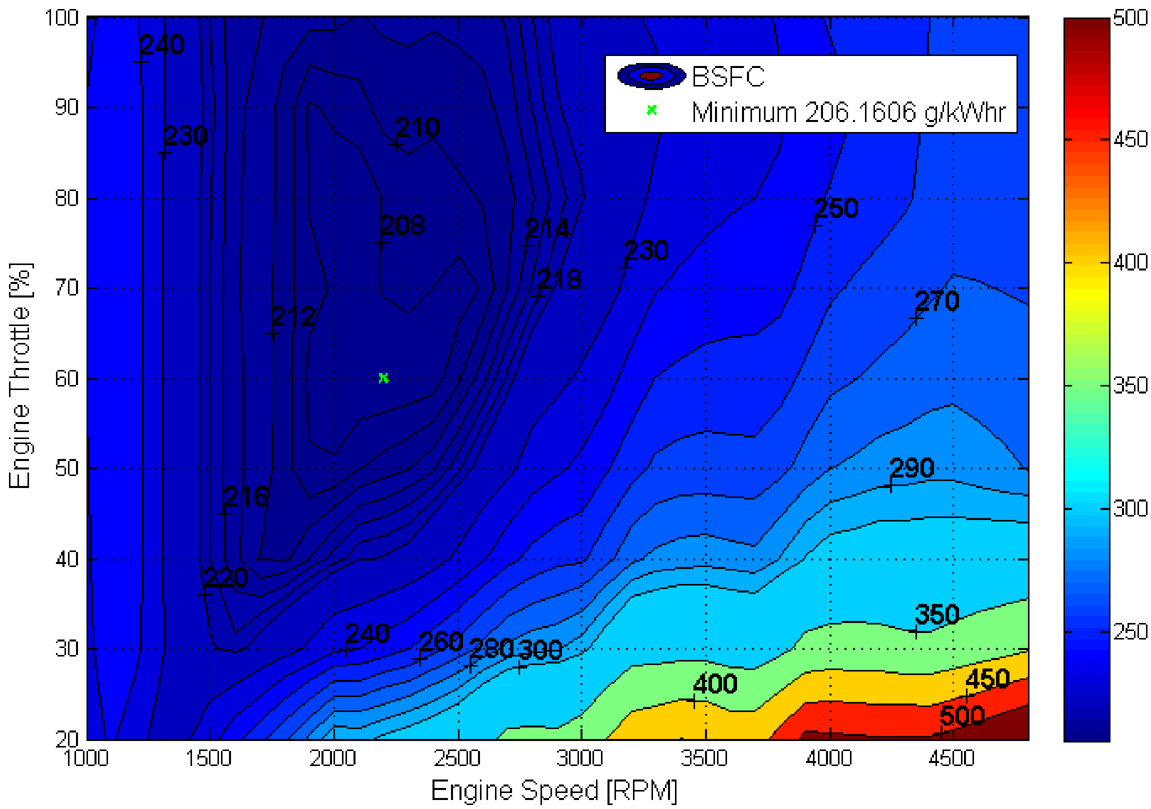

Figure 2 – BSFC Map with Minimum BSFC Operating Point [5]

The Bang-Bang Controller was tested in both SIL and HIL drive cycle simulations. Figure 3 shows the operating points of the Genset during a simulated US06 drive cycle. Except for during start-up and shut-down of the Genset, the Minimum BSFC operating point was maintained. [5]

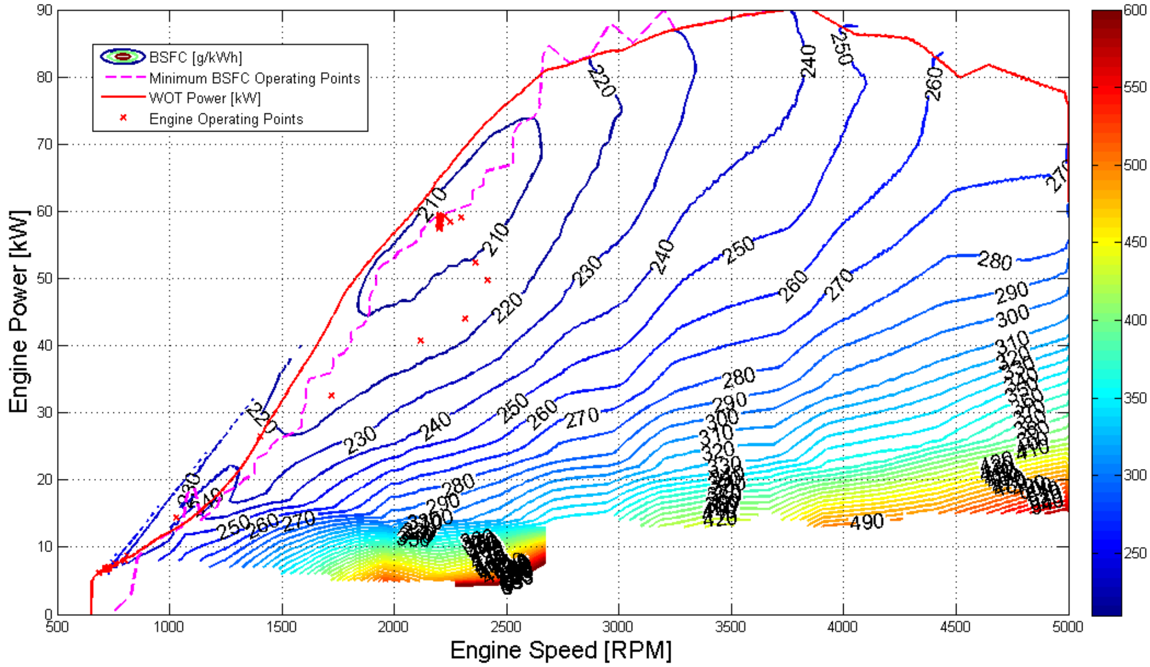

Figure 3 – Bang-Bang Controller Operating Points on US06 Drive Cycle [5]

An average of 35 kW is consumed during the US06 drive cycle. Considering 59 kW is produced by the Genset with a Bang-Bang controller at the minimum BSFC, there is an average surplus of 24 kW. After an analysis of vehicle limitations was performed, it was found that the ESS is limited to 18 kW power input during charging. Harries then explored the use of a Power-tracking controller instead of a Bang-Bang controller that would automatically account for this limitation. [5]

Harries analyzed the full power range of 0 – 90 kW and found the minimum BSFC as a function of power and speed. The resulting curve is shown in Figure 4. [5]

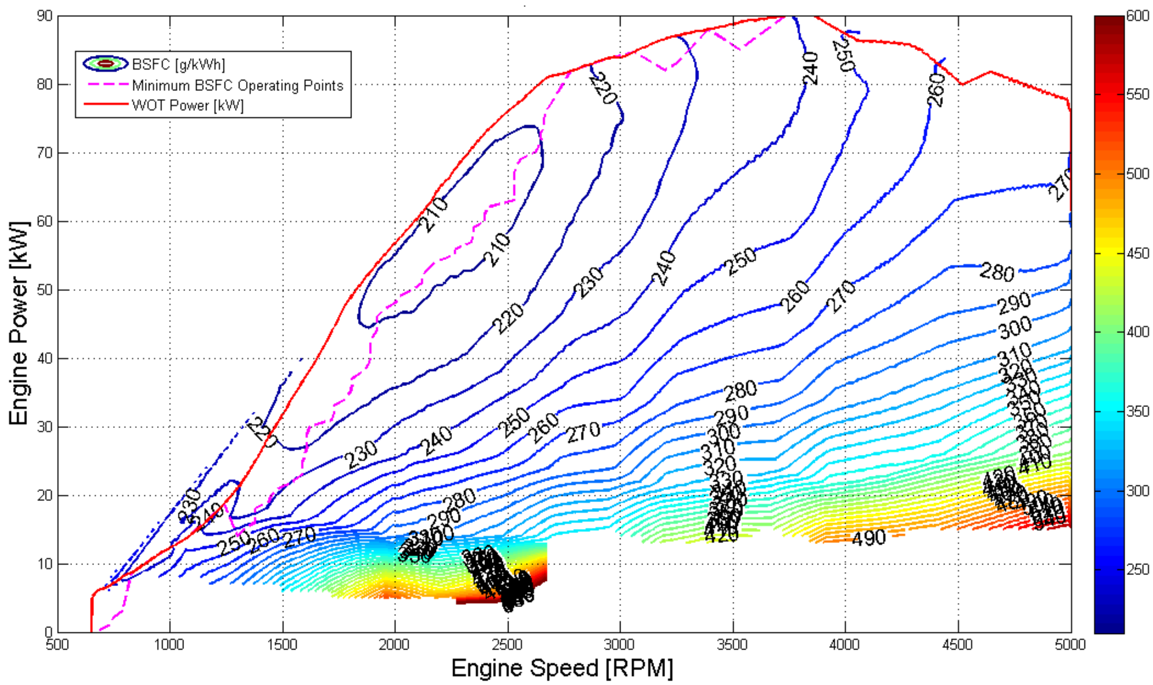

Figure 4 – Minimum BSFC Curve in terms of Power and Speed [5]

A Power-tracking controller was developed and tested in the same manner as the Bang-Bang controller. A diagram of the Power-tracking controller developed by Harries is shown in Figure 5. [5]

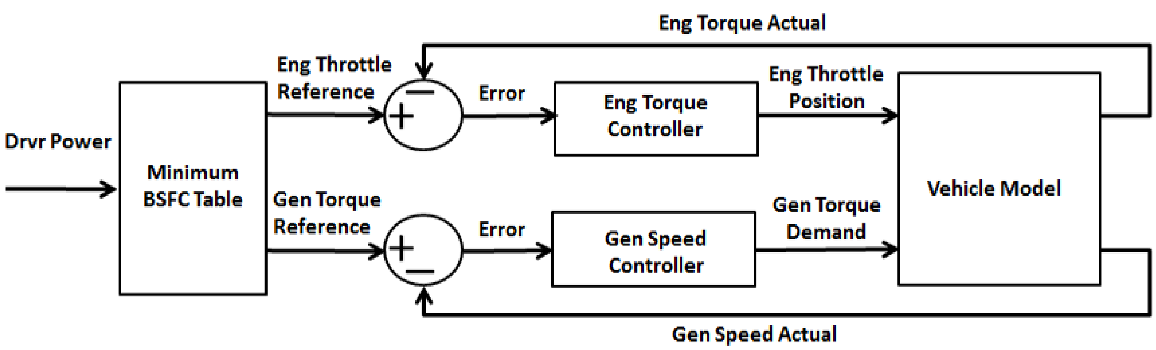

Figure 5 – Power-Tracking Controller Diagram [5]

Except for during start-up/shut-down and some transient conditions, the engine operating points closely followed the minimum BSFC curve as shown in Figure 6. The shift in the WOT curve from Figure 5 to Figure 6 is due to a change in the engine friction model. [5]

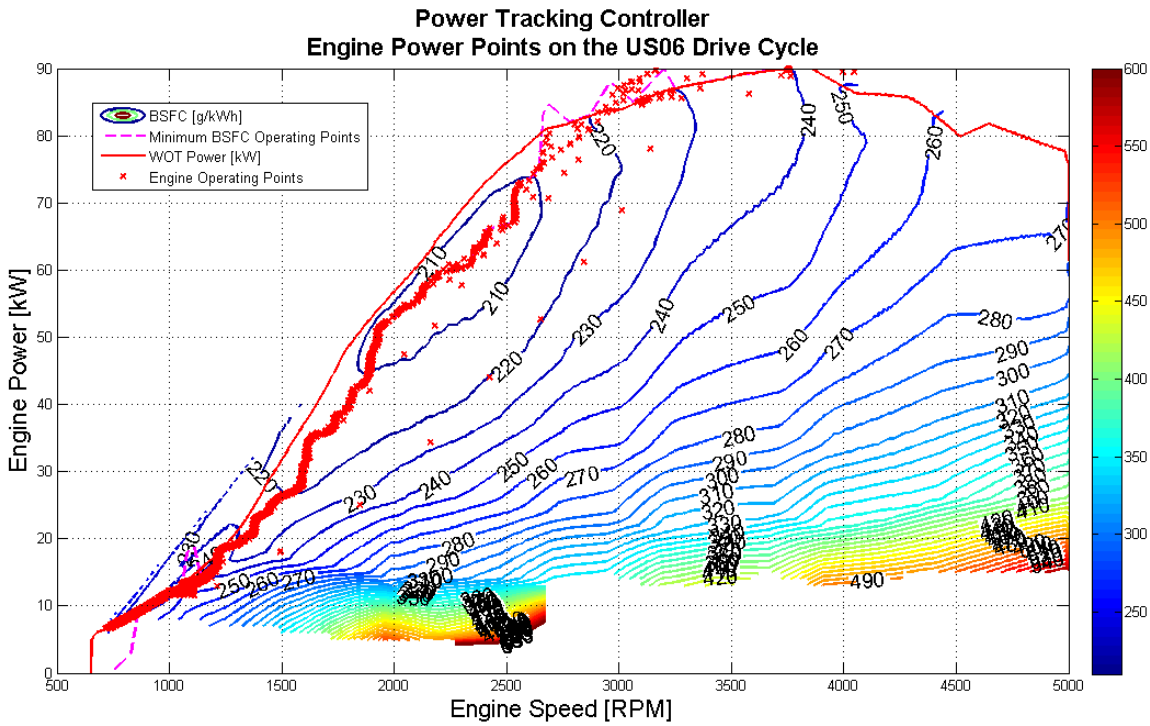

Figure 6 – Power-Tracking Genset Operating Points on the US06 Drive Cycle with Filtered Driver Power Demand [5]

Due to time constraints on the team before competition, a 1-D lookup table was used in order to determine the appropriate speed for the Genset to operate at in order to maintain the desired State of Charge (SOC) in the Energy Storage System (ESS). The controller used during competition is shown in Figure 7.

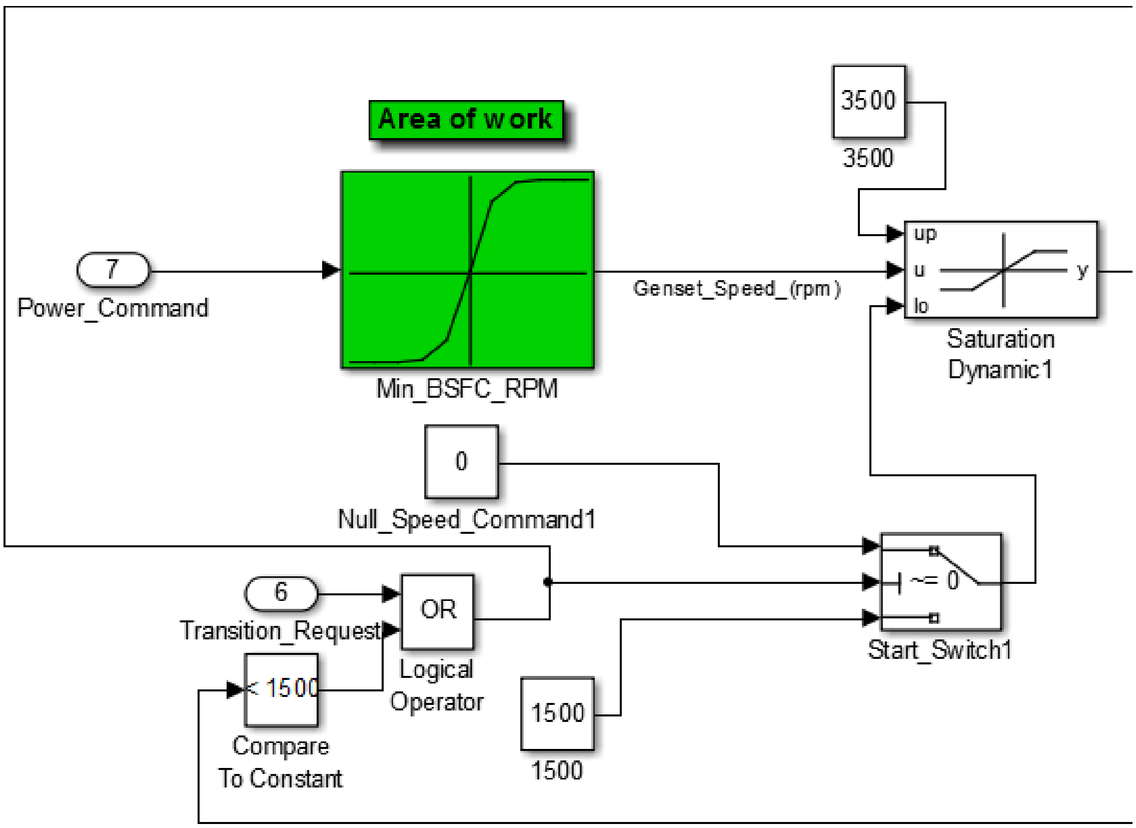

Figure 7 – Section of Current Embry-Riddle EcoCAR 2 Genset Speed Controller with the Scope of This Work Highlighted in Green

Thesis Scope

The scope of this work limited specifically to the 1-D lookup table currently used to determine the Genset operating speed, as shown in Figure 7. The output of the new controller is to be maintained as the Genset speed (rpm). Additional inputs may be used; however, no vehicle modifications are permitted, whether physical or software based (outside of the subsystem shown in Figure 7). The goal of this work is to create a run-time Genset speed controller in place of the current static 1-D lookup table. The new controller should be able to automatically adapt to new operating environments and conditions, selecting the optimal operating points based off of a predefined objective function and data collected from the vehicle's sensors, with no user input. The objective function should take both fuel economy and emissions into account when determining the appropriate Genset operating points.

Thesis Statement

A run-time Genset speed controller relying on operating maps updated in real time with vehicle sensor data will reduce fuel consumption and emissions production when compared to the current steady state Genset speed controller.

Limitations and Assumptions

For the purposes of this work, it is being assumed that all data recorded at a specific time took place at that time. For instance, it is assumed that the emissions recorded multiple feet down the exhaust at a certain time are the result fuel consumption and Genset operating points at that same time. In reality, the emissions produced are from fuel burnt multiple time steps before the emissions are recorded.

A single emission type is being used as a representation of all emissions. For this work, the particular emission type is that of NOx. NOx however, is affected by SCR systems whereas Particular Matter (PM), for example, is affected by a Diesel Particulate Filter (DPF) instead. Therefore, NOx is not always a good representation for all emissions types.

In the simulation of the results, it is being assumed that each of the controllers would experience the same power dynamics and overshoots as were seen on the vehicle during testing. Due to the difference in operating points these dynamics and overshoots would not be consistent between controllers.

List of Acronyms

BSFC	Brake Specific Fuel Consumption
CAFÉ	Corporate Average Fuel Economy
CAT	CATalytic converter
CS	Charge Sustaining
DOC	Diesel Oxidation Catalyst
DPF	Diesel Particulate Filter
E&EC	Emissions and Energy Consumption
EMS	Energy Management Strategy
ESS	Energy Storage System (high voltage battery pack)
EV	Electric Vehicle
HIL	Hardware In the Loop
ICE	Internal Combustion Engine
MPG	Miles Per Gallon
MY	Model Year
NHTSA	National Highway Traffic Safety Administration
NOx	Nitrogen Oxide
PHEV	Plug-in Hybrid Electric Vehicle
RDE	Real-Driving Emissions
RPM	Revolutions Per Minute
RTCS	Real-Time Control Strategy
SCR	Selective Catalytic Reduction
SIL	Software In the Loop

SOC	State of Charge
WOT	Wide Open Throttle

Chapter II

Review of the Relevant Literature

Future Regulatory Compliance Issues

As of MY 2012, vehicle manufacturers are not in full compliance with the CAFE standards. In terms of all vehicles, independent of manufacturer, Table 2 shows that although Passenger Cars were able to exceed the CAFE standard, Light Trucks were not able to meet the standard [6]. For MY 2012 alone, a total of $14,962,381.50 were paid in fines for not meeting the CAFE standards. Volvo Cars of North America paid $5,143,380.00 total, $4,609,000.00 was for Passenger Cars while the remaining $534, 380.00 was for Light Trucks. Jaguar Land Rover NA, LLC paid $9,819,001.50 for Light Trucks [7].

Table 2 – MY 2012 Summary of Fuel Economy Performance (MPG) [6]

	Passenger Cars			Light Trucks
CAFE	**Combined**	**Domestic**	**Import**	**Combined**
Standards*	33.0	32.7	33.3	25.3
Summary	35.3	34.7	36.3	25.0

(*) – MY 2012 projected required average fuel economy standard values are based on EPA & MMY reports.

By MY 2025 vehicle manufacturers must meet even more stringent CO_2 and fuel economy targets than for MY 2012, as shown in Table 3. Comparing the data, in a favorable manner to the automotive companies, the 35.3 mpg of a MY 2012 combined passenger car is 12.7 mpg less than the required 48 mpg of a MY 2025 full size car. A similar comparison for light trucks shows the 25.0 mpg of a MY 2012 light truck is 8 mpg less than the required 33.0 mpg of a MY 2025 Large pickup truck. In only 13 years, vehicle manufacturers as a whole must increase the average passenger car's mpg by over 36% and the average light-duty truck's mpg by over 32% to stay in compliance with the CAFE standards. [1]

Table 3 – Model Year 2025 CO_2 and Fuel Economy Targets For Various MY 2012 Vehicle Types [1, p. 62648]

Vehicle type	Example models	Example model footprint (sq. ft.)	CO_2 Emissions target (g/mi) [a]	Fuel economy target (mpg) [b]
Example Passenger Cars				
Compact car	Honda Fit	40	131	61.1
Midsize car	Ford Fusion	46	147	54.9
Full size car	Chrysler 300	53	170	48.0
Example Light-duty Trucks				
Small SUV	4WD Ford Escape	43	170	47.5
Midsize crossover	Nissan Murano	49	188	43.4
Minivan	Toyota Sienna	56	209	39.2
Large pickup truck	Chevy Silverado (extended cab, 6.5 foot bed).	67	252	33.0

[a,b] Real-world CO_2 is typically 25 percent higher and real-world fuel economy is typically 20 percent lower than the CO_2 and fuel economy target values presented here.

Diesel Emissions

Diesel engines produce 20% less CO_2 than gasoline engines making them an attractive alternative to meet new regulations [4]. However, The US EPA, California, and Europe are all tightening down on diesel emissions. The US EPA is calling for a 75% reduction in NMOG+NO_x resulting in a 30 mg/mile combined allowance [8]. Europe is tightening down on NOx emissions by using a new testing procedure called Real-Driving Emissions (RDE) designed to simulate actual NOx emissions during real world driving [8]. California has put a test program in place to determine the feasibility of achieving 0.020 g/bhp-hr NO_x emissions for compliance with tightening HD truck NO_x regulations [8].

As a result of increasing crude oil costs due to the depleting of reserves alternative fuel sources are being explored with the goals of reducing cost and emissions. Biodiesel has had a particular emphasis on it due to its renewability and the multiple feed stocks it can be made from. Twenty years of published data is used to determine the effect of biodiesel, produced from multiple feed stocks, on regulated emissions from multiple engines during transient conditions. In general, an increase in the biodiesel ratio in the fuel blend results in an increasing trend in NO_x emissions and a decreasing trend in PM, HC and CO emissions. More aggressive driving patterns result in an exacerbation of the effects on both NO_x and PM emissions. In addition to this, unsaturated feed stocks further increase NO_x emissions. [9]

In addition to exploring alternative fuels, alternative combustion concepts are also being explored in an effort to comply with emissions regulations. A new concept, Modulated Kinematics (MK), uses low temperature and premixed combustion characteristics to simultaneously reduce NO_x and smoke without increasing fuel consumption. In everyday driving a potential 90% NOx reduction was confirmed with no increase in fuel consumption or smoke production on the second generation of the MK combustion system. [3]

Hybrid Electric Vehicle Technologies

Hybrid Electric Vehicles is a good general reference providing practical knowledge on many vehicle architectures including that of PHEV. Components used in the production of power and tractive force are detailed along with the control strategies used for them. System level control strategies used to manage the power and energy are also discussed. In addition to the detailed descriptions MATLAB simulation case studies are also given. [10]

Hybrid Electric Vehicle Control

Introduction to Hybrid Vehicle System Modeling and Control covers all major aspects of modeling, control, simulation, performance analysis and design of hybrid vehicles. Vehicle architecture and component characteristics / mathematical models are detailed with a systematic approach to develop models, controls and algorithms. [11]

Optimal Control of Hybrid Vehicles compiles results of studies on hybrid vehicles centered around optimizing energy management through controls. The scope is based on energy management of the vehicle system and does not delve into optimizations such as gear shifting, velocities, or routes. In addition to presenting actual studies performed the book details the formation and execution of control systems optimizations. In order to help the reader understand the content, background information is also given on vehicle components / architectures. [12]

Chen, et al, developed a control system for use in an off-road series hybrid electric vehicle. The controller was designed with multiple predefined operating points for the Genset in which two modes were employed. One mode, constant engine speed control mode, was designed with the main objective of minimizing speed overshoot. A secondary mode, change speed control mode, was designed with the main objective of minimizing settling time. Good dynamic response characteristics while maintaining a stable output voltage was observed in both bench testing of the Genset and road testing of the vehicle. [13]

Harries detailed the development of a supervisory control unit for a series PHEV in which both Bang-Bang and Power tracking controllers were developed to determine the operating points of the Genset, as discussed in the Previous Work section of this text. In his concluding remarks Harries noted that further development of the controllers should be performed in order to account for both fuel consumption and emissions instead of fuel consumption alone. [5] The work presented in this paper is a continuation of Harries work on the Power tracking controller with the addition of emissions to the objective function.

Johnson, et al, developed a Real Time Control Strategy (RTCS) for a parallel HEV that accounted for both fuel consumption and emissions when selecting the operating points of the vehicle’s engine and motor. When compared to an optimized static control strategy the RTCS successfully reduced NO_x emissions by 23% and PM emissions by 13%. In order to achieve this reduction in emissions the tradeoff was in fuel economy which increased by 1.4% compared to the optimized static control strategy designed for the same vehicle. [14]

Optimization Methods

Nash, et al, describes and provides examples of the theory, algorithms, and applications of linear and nonlinear programming. Emphasis is given to practical aspects, the importance of algorithmic design, and extensive examples to familiarize the reader with modern algorithms that can be readily applied to a number of applications as well as the latest ideas in barrier methods for nonlinear programming. [15]

As the objective function is planned to be a linear function, the focus is on linear programming algorithms. The majority of Nash, et al’s, discussion of linear programming is on variations of the Simplex Method. [15]

Throughout the years there have been many variations of the simplex method starting with George Dantzig’s work starting in 1947 [16] to Spendley, Hext, and Himsworth in the early 60’s to Nelder-Mead in the mid to late 60’s and beyond. Some of these methods have been adapted off of each other for specific problem sets while others aren’t based on each other at all. Out of all of the different simplex methods, the Nelder Mead method has gained the most notability. By the late 70’s their paper on the method qualified as a “Science Citation Classic” and in the context of unconstrained optimization has become called “the” simplex method. [17]

The Nelder-Mead Simplex Method evaluates system outputs in order to determine optimal system inputs [18]. It is a simplex-based direct search method that performs a sequence of transformations on the simplex aimed at decreasing the function values at its vertices. The process is terminated when the working simplex meets a convergence criterion or when the function values become sufficiently close [19]. The unique aspect to the Nelder-Mead Simplex method is that it can vary shape from iteration to iteration which allows it to adjust its shape to local contours [20]. Running such a method in real time will allow for any environment, grade of fuel, or other variables to be taken into account without having to model or predict them beforehand.

The simplex method is compact so that it is not resource intensive and is estimated to solve a problem similar to this in only 94 iterations [18]. This will allow the method to be run on the vehicle's on-board controller in real time while being fast enough to respond to the systems changes.

Both Mckinnon [20] and Nelder and Mead [18] have demonstrated the ability of the simplex method to reliably converge with multiple variables. The simplex method has generally proved to be robust and reliable in practice, yet it was developed heuristically with no proof of convergence. Due to this engineers typically love the method, because it often works, while mathematicians generally hate it, because convergence can't be proven. [17]

Although the Nelder-Mead Simplex is quite reliable there have been instances where convergence is not reached. In such an instance end users of the algorithm have been known to modify it or move to another method. [17] The only method that can guarantee convergence is a brute force method in which all possibilities are solved and compared. The main drawback to such a method in comparison to the Simplex Method is that more resources are required to solve the same problem. Due to the resource requirements associated with a brute force method, it is not practical for problems with more than 3 or 4 variables. [21]

Chapter III

Methodology

The purpose of creating a run-time Genset speed controller is to operate at the speed corresponding to the minimum fuel consumption and emissions production for a given power requirement in any operating condition or environment.

Controller Block Diagram

Figure 8 shows a high level block diagram of both the existing Genset speed controller and the new run-time Genset speed controller. The development of the run-time Genset speed controller will be discussed in the following sections.

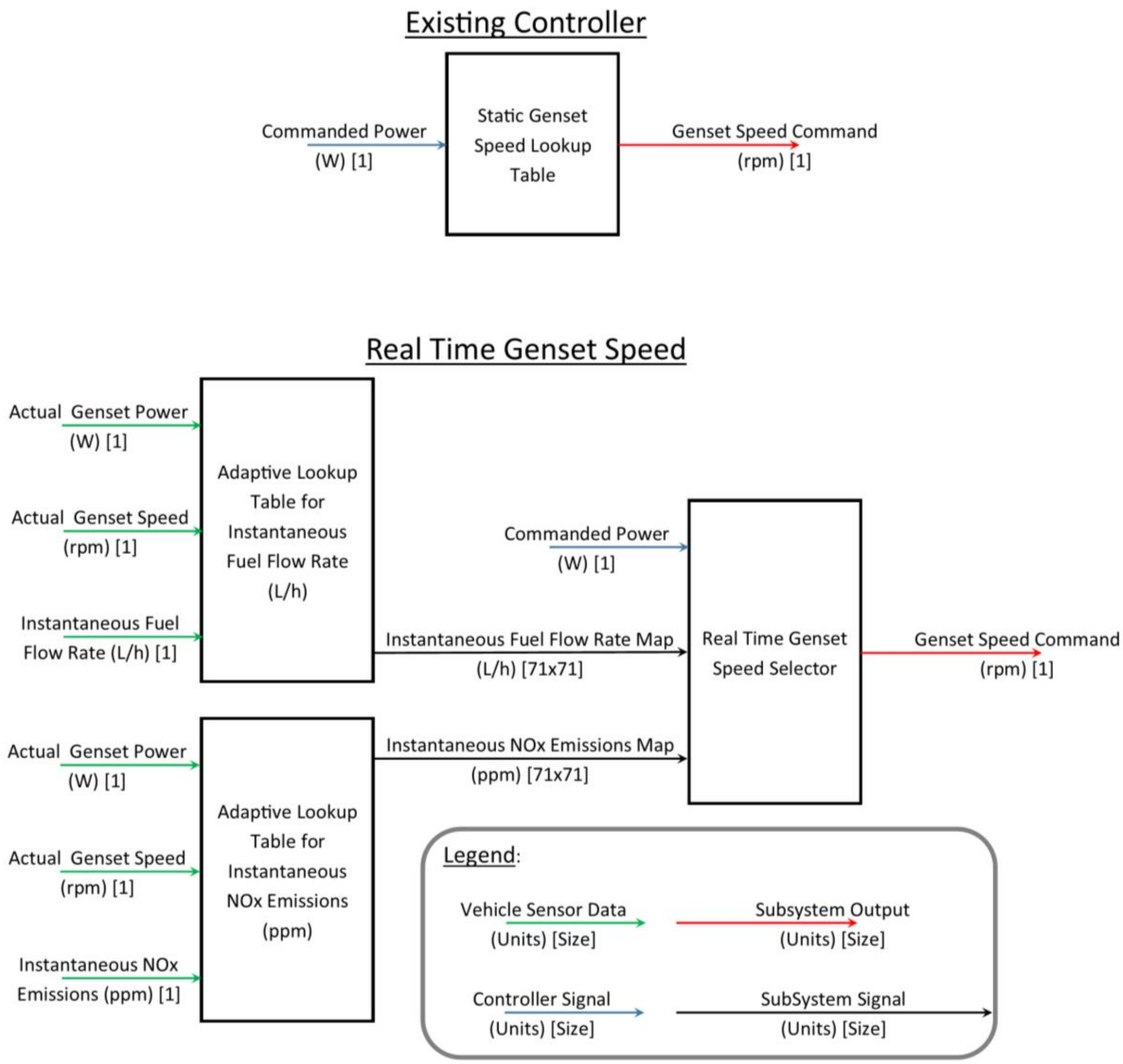

Figure 8 – Controller Block Diagram

System Inputs and Outputs

In order to replace a single 1D lookup table, a run-time data collection and analysis process had to be constructed. The first step in constructing this is to define the inputs and outputs of the system. The original 1D lookup table had an input of Power Commanded in Watts. This input was the amount of power the controller determined was required in order to maintain the proper State of Charge (SOC) while providing the required power to the rest of the vehicle. The output of the original system was

Generator Speed in Revolutions Per Minute (rpm). This was the command that set the operating speed of the Genset required to maintain the proper SOC. The original 1D lookup table with the input and output can be seen in Figure 9.

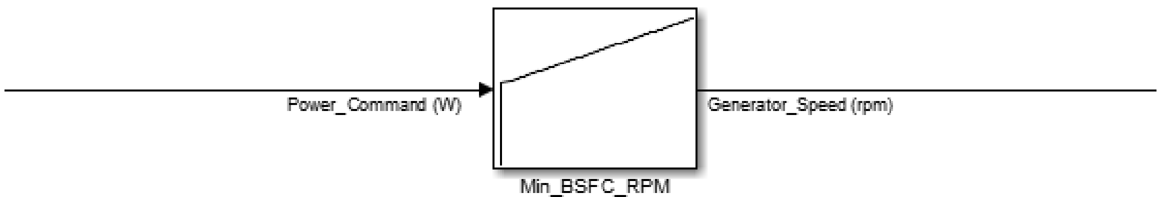

Figure 9 – Original Genset Speed Controller

The table was developed by manual engine characterization techniques and in-vehicle testing. A plot of the data for the 1D lookup table can be seen in Figure 10.

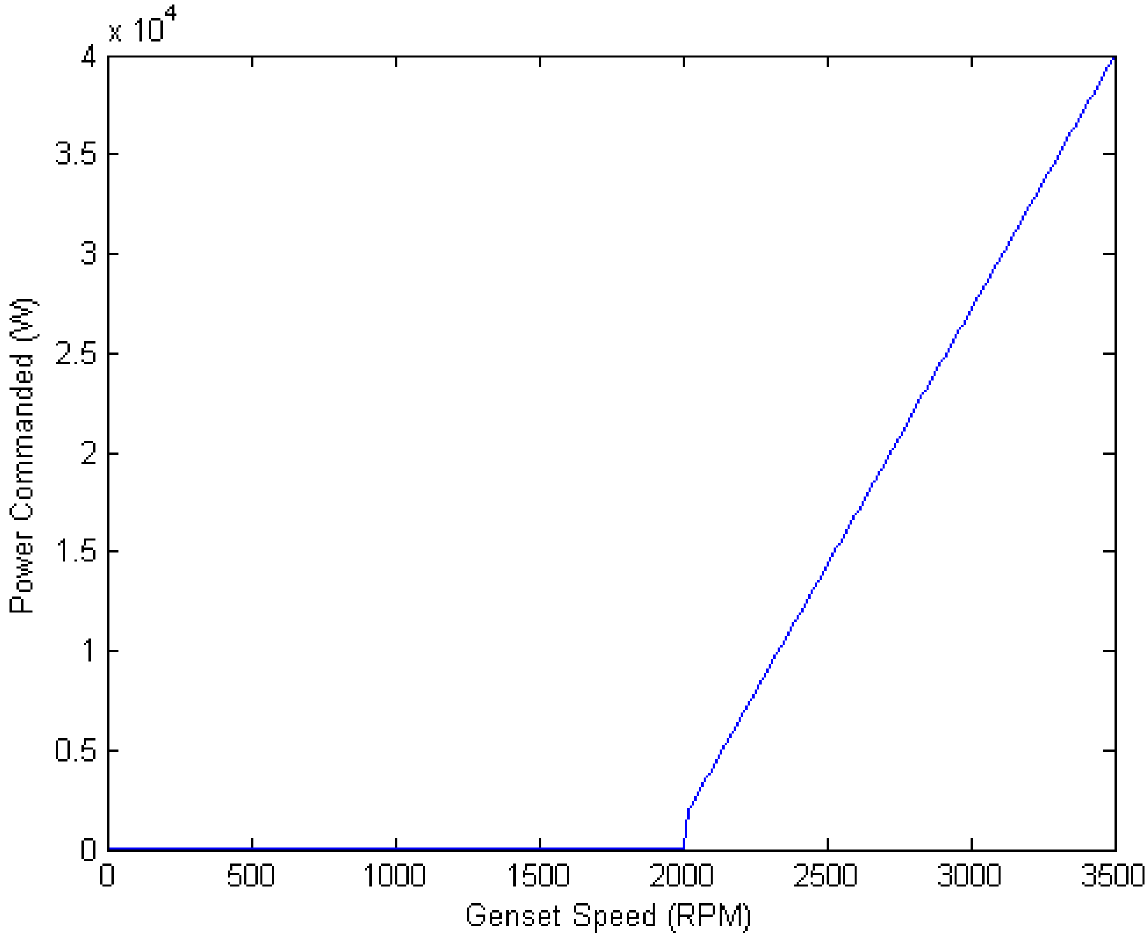

Figure 10 – Original 1D Lookup Table Map

As the scope of this work is to upgrade this table to a run-time system while minimizing the impact on the rest of the vehicle's controller, the original input and output must remain. Additional inputs may be added, in order to reduce the impact of this change to the rest of the vehicle controller, any additional inputs are being limited to those already available on the controller. As the goal is to reduce both fuel consumption and emissions, an input for each of these will be required. In order to relate the fuel consumption and emissions data to operating points of the vehicle both the Genset power production and Genset speed will have to be recorded for each record of the fuel and emissions data. Finally, to ensure that this controller only operates while the Genset is on, a control signal must be used to determine whether the system is on or off. After analyzing all the vehicle signals, those shown in Table 4 were found to be possible signals to meet the aforementioned goals.

Table 4 – List of possible Controller Signals Already Available on the Vehicle

Signal Name	**Units**	**Min Value**	**Max Value**	**Purpose**
D1_Commanded_Torque_PM100	Nm			Operating Points
EngCntrlRunCrnkTrmSt	N/A	0	1	On/Off Signal
EngSpd	RPM			Operating Points
InstFuelConsmpRate		0		Fuel Data
NO2_Concentration				Emissions Data
NOxConcEngOut				Emissions Data
NOxConcPostCat				Emissions Data
Power_Actual	Watts			Operating Points

With the possible signals already present in the vehicle's controller identified, the signal list for this work must be selected. The first set of signals to define are the operating points to relate the fuel consumption and emissions data to. The possible signals for this are: D1_Commanded_Torque_PM100, EngSpd, and Power_Actual. With any two of these signals the third could be calculated. Referring back to the original 1D lookup table, Genset power and speed are used; therefore, power and speed will be used here for consistency. The signals to define to Genset operating points are then EngSpd and Power_Actual. With the operating points defined, the other signals can be looked at. Both the On/Off Signal and fuel data only have one signal to choose from; therefore, no further decision must be made. Emissions Data has three choices: NO2_Concentration, NOxConcEngOut and NOxConcPostCat. $C0_2$ is not included in the choices for two reasons:

1. CO_2 emissions in diesel engines are 20% less than that of gasoline engines [4].
2. CO_2 emissions data is not currently in the vehicle signals.

Between NO_2 and NO_x, NO_x is a more suitable choice for this work for two reasons:

1. NO_x is a generic term encompassing 7 different compounds; NO, NO_2, N_2O, N_2O_2, N_2O_3, N_2O_4, and N_2O_5 [22].
2. Regulations are being written around NO_x; therefore, specifically measuring and minimizing NO_x is advantageous [4] [8].

There are two signals listed for NO_x emissions: NOxConcEngOut and NOxConcPostCat. The main difference between these two signals is that NOxConcEngOut is the NO_x concentration measured before the SCR while NOxConcPostCat is the NO_x concentration measured after the SCR. NOxConcPostCat would be a more direct comparison to the regulated NO_x values; however, if the SCR system did not function properly and cycled on and off (which has been noticed during testing), the new controller will be constantly adapting to the changing values. This could cause it to determine non-optimum points as optimum until all the old data is cleared out of its memory. Although NOxConcEngOut would not allow for a direct comparison to regulations, it would allow for the data to be consistent no matter the condition of the SCR system. Due to the issues currently surrounding the SCR system, the decision was made to use the NOxConcEngOut signal that is not affected by whether or not the SCR system is working properly or not. The final list of system input and output signals is shown in Table 5 where input signal 1 and output signal 1 are the same as the original 1D lookup table.

Table 5 – Finalized Input / Output Signals

	Input Signals	**Output Signals**
1	Power_Commanded	Eng_Spd_Output
2	Power_Actual	
3	EngSpd	
4	InstFuelConsmpRate	
5	NOxConcEngOut	

Adaptive Lookup Tables

In order for this controller to work, it must collect, store, and be able to access data on the fuel consumption and emissions production corresponding to the Genset operating points. Simulink has a built-in block within the Simulink Design Optimization Library called an Adaptive Lookup Table (2D Stair-Fit). With this block, a two dimensional adaptive lookup table is created by dynamically updating the underlying lookup table which can be used to model time-varying systems with two inputs [23]. In the case of this controller, the two inputs (or breakpoint sets for the table data) are Power_Actual and EngSpd. These two inputs define the cell in the table data that will be updated with the new measurements. Because the Adaptive lookup table can only have one set of table data, two tables will be required, one for fuel consumption data and one for emissions data, an example configuration is shown in Table 6.

Table 6 – Configuration of 2D Adaptive Lookup Table

	Power_Actual (1x71)
EngSpd (71x1)	Table Data (71x71)

As the name implies, the table adapts the table data to account for the incoming values, this can be done through one of two methods. The first method is “Sample mean” which uses the value of the mean or average of the all the values for a cell. The second method is “Sample mean (with forgetting)” which like “Sample mean” uses the mean or average value of the values for a cell. The key difference is that not all values are used in “Sample mean (with forgetting)”. An “Adaptation Gain” variable is used to determine how much weight is given to new data. It ranges in value from 0 to 1 where would mean that no averaging is performed, the last value input into the cell is the current cell value where 1 means that the average of all values is taken which would be the same as “Sample mean” [23]. This allows for the adaptation of the table to be tuned for a quicker or slower response to changes, depending on the situation.

Although an adaptive lookup table is considered a lookup table it does not perform like a normal lookup table in that a value or values can be input and the corresponding value in the table will be exported. With an adaptive lookup table there are two ways of retrieving data from it. The first option, which cannot be disabled, is that when it updates the value of a cell the new value and the cell number are output from the adaptive lookup table as two separate outputs. The second, optional, way of getting data from the table is by exporting the entire table each time a value is updated. For simplicity of use in the MATLAB function block, the second options is used here where the entire table is output each time a change is made to it.

Specifically with the NO_x data, there are times when the sensor reads -100 ppm, as this is not a realistic value the NO_x data is saturated from 0 to infinity. This saturation, along with the setup of the Adaptive lookup table within Simulink is shown in Figure 11.

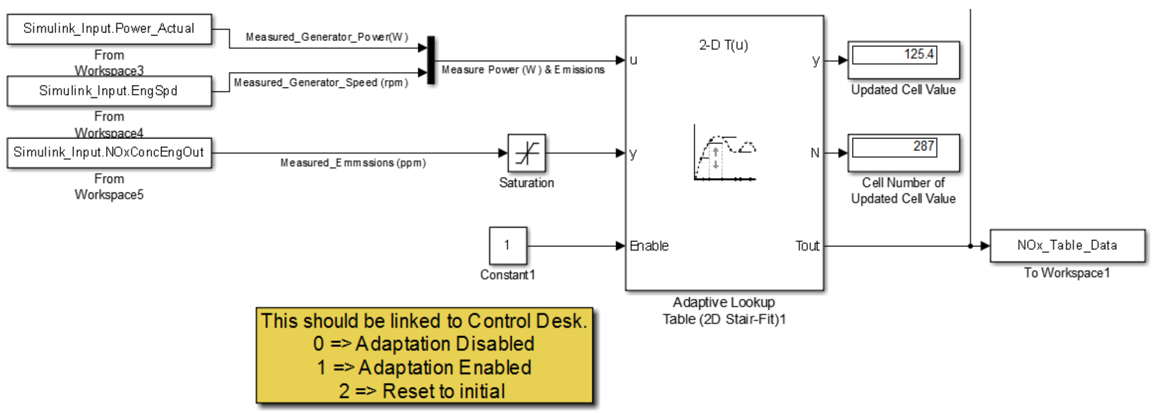

Figure 11 – Adaptive Lookup Table Setup within the Simulink Environment

Figure 12 shows the function block parameters that are used in this controller. The only difference between the fuel consumption and emissions adaptive lookup tables is in the table data itself. This allows for easy future expansion to monitor additional variables as desired.

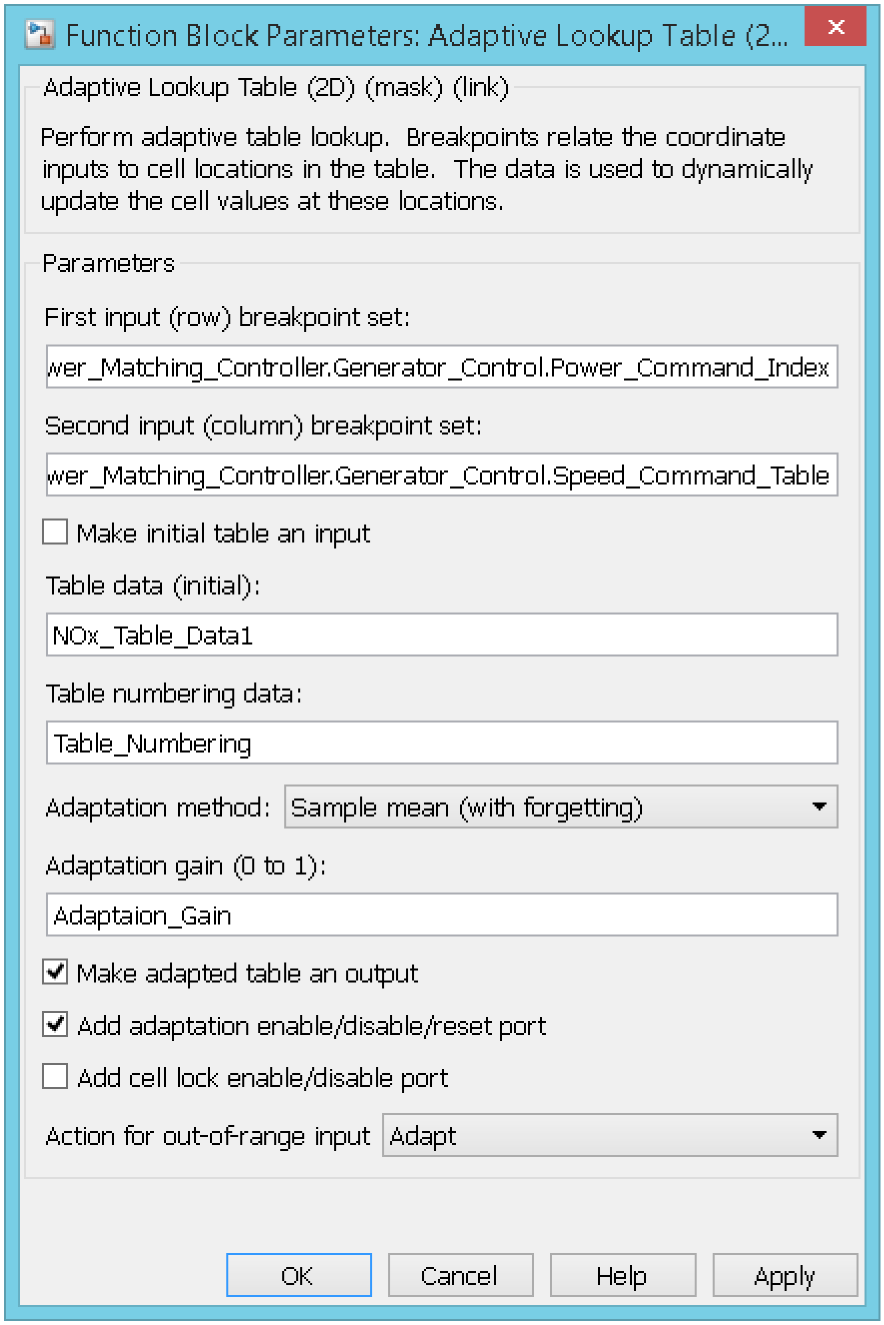

Figure 12 – Adaptive Lookup Table Block Parameters

MATLAB Function Block

The next block after the Adaptive Lookup Tables is that of the MATLAB Function Block. Simulink does not have the built-in blocks required to do all tasks; there, a MATLAB Function Block can be used to utilize MATLAB code within Simulink itself. Although the MATLAB function block does not have all of the functionality found in MATLAB if is quite capable in its own right. [24] In this case, the purpose of this block is to find the Genset Speed (rpm) that minimizes both the fuel consumption and emissions production for the desired power output (W).

Input and Outputs

The inputs and outputs of this block are all custom defined by the user. In this case, there are 3 inputs and one output. The three inputs are Power_Command (the same signal input into the lookup table that is being replaced, reference Figure 9), the Fuel_Table_Data (from the fuel consumption adaptive lookup table) and the NO_x_Table_Data (from the emissions adaptive lookup table). The single output of this block is the Generator Speed (the same signal output from the lookup table that is being replaced, reference Figure 9). The inputs and outputs of the MATLAB function block can be seen in the Simulink environment in Figure 13.

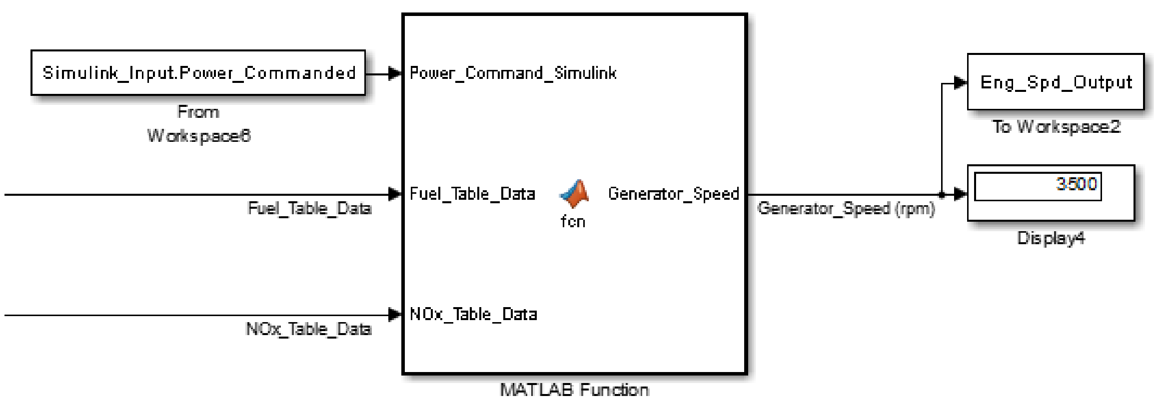

Figure 13 – MATLAB Function Block Inputs and Outputs

Power Command Location

The first step of the optimization is to determine the location of the Power_Comanded value in terms of the available power values. There are 71 power values in watts, the first being 10 watts then 70 evenly spaced values starting at 2,000 and ending at 40,000. The Power_Comanded value is in increments of 200 up to 40,000. The chances the Power_Comanded value matching one of the 71 breakpoints is very low; therefore, an estimation must be made. If the exact power can't be produced, the choices available are to produce less power or more power. As CS mode is in place to ensure that the batteries do not drain too low causing damage to them, a lower power value could create an unfavorable situation. With this in mind, the breakpoint equal to or the first one greater than the Power_Comanded is located. Using this location, the data sets imported from the adaptive lookup tables can be reduced.

Data Set Reduction

Since the whole table from the adaptive lookup table blocks had to be imported and not just a section of them, the first task is to remove all unnecessary parts of the tables. In this case, only the columns associated with the Power_Comanded are required. This allows a reduction from two 71x71 matrixes to two 2x71 arrays, two for fuel consumption and two for emissions data. This is because at this point the power value is known and bounded by two values, hence the two rows, while all Genset speeds (all 71) are still available.

Optimum Generator Speed

The next step is to determine the optimal speed to operate the Genset at. In this situation, the optimal speed is being defined as the Genset speed (rpm) that results in the lowest fuel consumption and emissions production. In reviewing data from an E&EC

event performed by the ERAU EcoCAR 2 Malibu at Year 3 Final Competition at the Milford Proving Grounds the data shown in Table 7 was found.

Table 7 – Fuel Consumption and Emissions Signal Information from EcoCAR 2 Year 3 Final Competition E&EC Event

Signal Name	Minimum Value	Maximum Value
InstFuelConsmpRate	0	14.0250
NOxConcEngOut	-100	2,891.6

The maximum values for the two signals are orders of magnitude different; therefore, a direct comparison can't be made. To further complicate the issue, the range of fuel consumption data is within the range of the emissions data. As the relationship between one of the signal values to the rest is what is important, i.e. which value is the minimum data point, and not the actual value of the minimum data point, each of the arrays can be normalized on a scale from 0 to 1. This allows for a direct comparison between the two signals without losing the relations within the signals themselves. An objective function can now be written as:

$$Genset\ Speed = \min[(1 * Fuel\ Consumption) + (1 * Emissions)]$$

The simplex method was originally intended to be used to solve the objective function. Due to difficulties with all MATLAB functions not being available in the Simulink MATLAB Function Block [24] and a discrete solution set provided in table format, a brute force method [21] is opted for instead. In this method, the objective function is solved for at each Genset Speed point for both of the power levels that bound the Power_Comanded. The Genset Speed (rpm) associated with the minimum objective function value for each of the bounding power levels is recorded and linearly interpolated in order to find the appropriate Genset Speed (rpm) for the given Power_Comanded value.

Controller Training

For initial training purposes, the operating data is input into the adaptive lookup table with the adaptation method set to “Sample mean with forgetting” and an adaptation gain of 1. In this setting, the value of any cell is determined by the mean or average value of all the numbers input into that cell. As the initial table is 0, if no values are input into a cell the value of that cell remains at 0. If values are input into a cell, the value of that cell then becomes the mean of all values.

Controller Testing

Once all of the training is complete the initial table data for both the fuel consumption and emissions adaptive lookup tables is replaced with the table data produced during training. The training data is used as a starting point; however, it is not intended to be kept due to the distinct possibility of different operating conditions seen between the training data and the current operation. Therefore, the adaptation gain would be lower than 1. As stated previously in the Adaptive Lookup Tables section, the lower the adaptation gain, the faster old data is forgotten allowing the table to adapt to the new conditions quicker. Care must be taken in choosing the adaptation gain, if it is set too low and a bad data set is received it could then cause the controller to choose a non-optimum operating speed. If however, the adaptation gain is set too high it will not adapt to the current conditions fast enough and could again cause the controller to operate at a non-optimum point until it has adapted to current conditions.

Adaptation Gain Selections

For the purpose of this work, there are three different instances in which the adaptation gain (see Adaptive Lookup Tables for additional information) is used and can be adjusted. The first instance is during the training of the model, the second is in the generation of the post processing data and the third instance is in the simulation of the controller.

Selection for Training Data Generation

The first instance, training of the model, is using an adaptation gain of 1. During the training of the model the goal is to find an average of all of the training data. This ensures that the training data is as well rounded as possible. As stated in Adaptive Lookup Tables, an adaptation gain value of 1 provides an average of all of the values.

Selection for Post Processing Data Generation

The second instance, generation of the post processing data, is used to generate the data used to evaluate the controllers. Adaptation gain values from 0 to 1 in increments of 0.25 were evaluated. Figure 14 and Figure 15 show the evaluation in terms of both Total Diesel Fuel Consumption (gal) and Average NOx Production (ppm), respectively. All 5 of the adaptation gain values produces similar curves for the Total Diesel Fuel Consumption (gal). While the 5 different adaptation gains produced different curves for the Average NOx Production (ppm). This indicates a difference in the data between the training and testing data which validates the need for a run-time controller that can adapt to each driving condition, as has been developed here. It should be noted that the maximum values for the Total Diesel Fuel Consumption (gal) are seen with an adaptation gain value of 0 while the minimum values are seen with an adaptation gain of

1. Average NOx Production (ppm) is the reverse of this where the maximum values are found with an adaptation gain value of 1 and the minimum with an adaptation gain value of 0. Based off of that alone, an adaptation gain value of 0.5 would have been chosen in order to use a midline value for both Total Diesel Fuel Consumption (gal) and Average NOx Production (ppm) instead of a maximum for one and a minimum for the other. However, due to the change of shape in the Average NOx Production (ppm) curves, an adaptation gain value of 1 is being chosen instead for the Post Processing Adaptation Gain. This ensures that all of the training and testing data is represented in the evaluation of the controllers and that one set of data is not favored over the other.

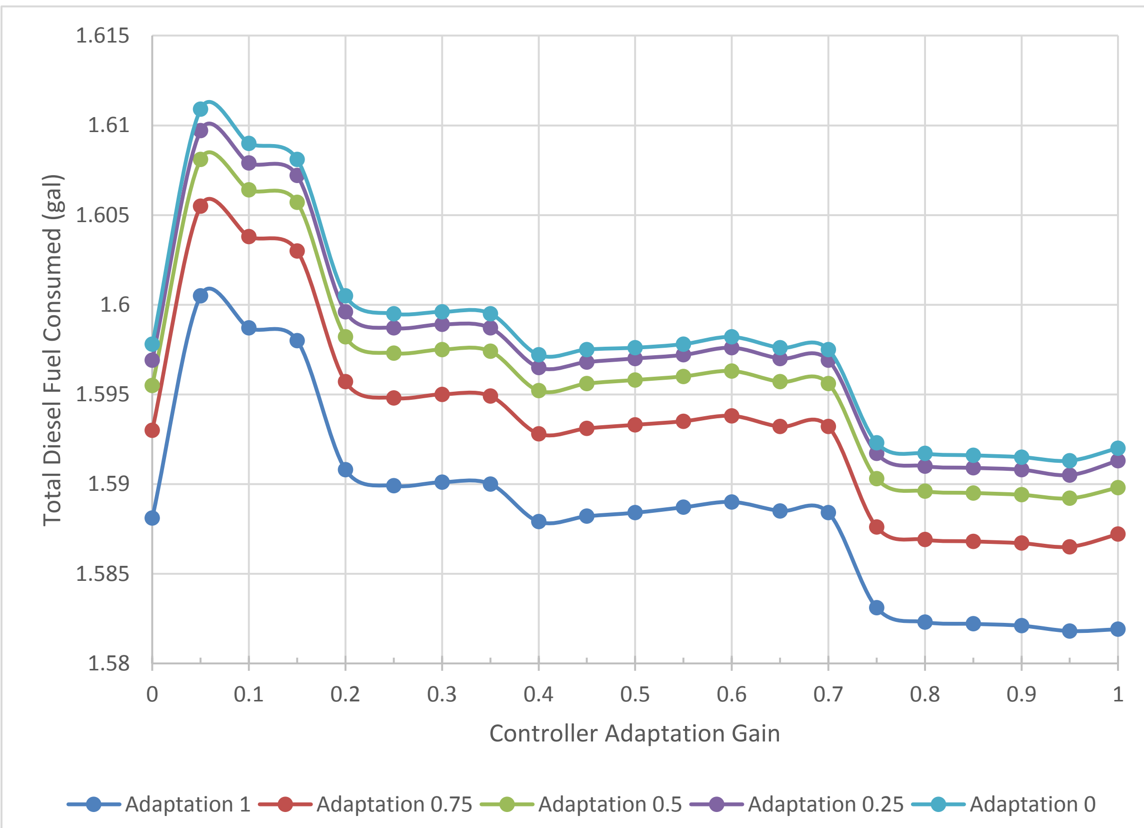

Figure 14 – Post Processing Adaptation Gain Selection for Total Diesel Fuel Consumption (gal)

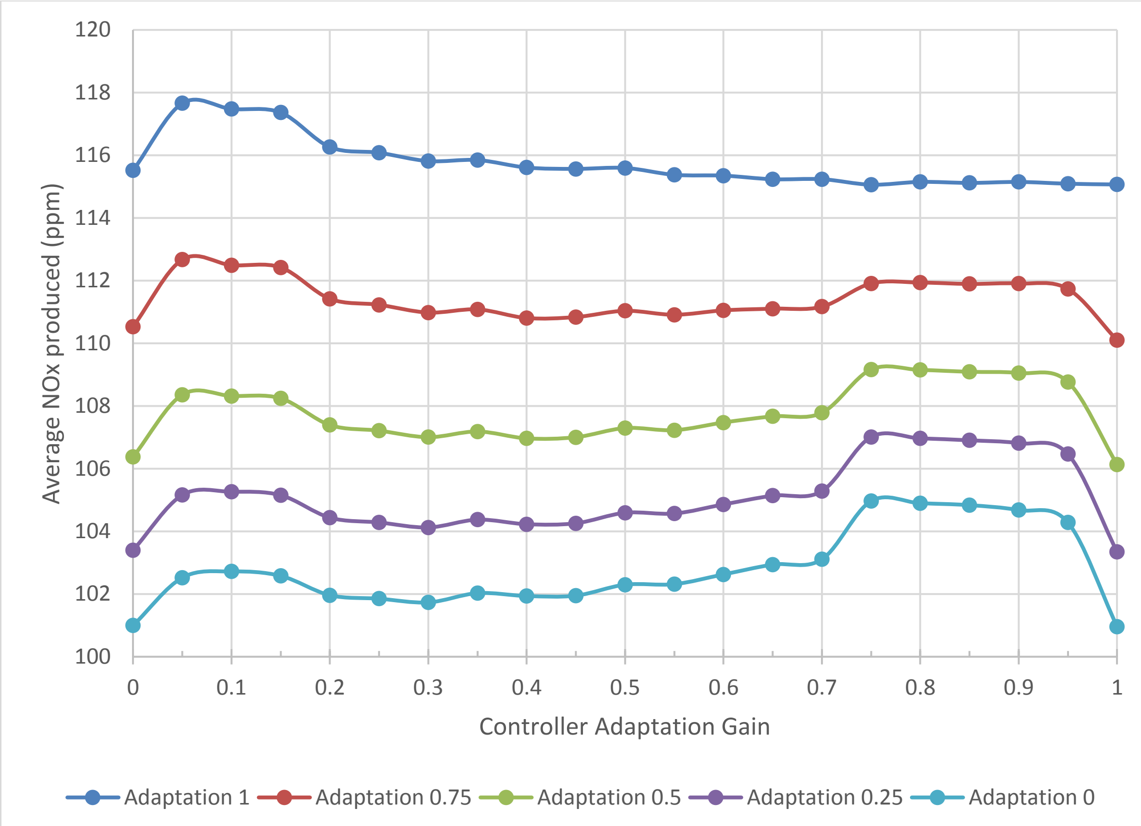

Figure 15 – Post Processing Adaptation Gain Selection for Average NOx Production (ppm)

Selection for use in Genset Speed Controller

The third instance of the adaptation gain value, simulation of the Genset Speed Controller, is used in the controller itself. This is the 1 instance of the 3 that would be used on the vehicle in the future application of this work. In order to compare each of the controller adaptation gains against each other the results of each value, with a post processing adaptation gain of 1, has been normalized and plotted in Figure 16. The maximum value for both the Diesel Fuel Consumption and NOx Production occurs at a controller adaptation gain value of 0.05. The minimum Diesel Fuel Consumption occurs at 0.95 and the minimum NOx Production occurs at 0.75 while the combined minimum occurs at 1. For this work, the combined minimum is the value of interest as it corresponds to the minimum objective function value across the controller adaptation gains. It should be noted that even though a value of 1 was chosen, there is only a small variation in results from one Controller Adaptation Gain to another. In NOx Production there is a maximum variation of 2.2% while Diesel Fuel Consumption has a maximum variation of 1.2%.

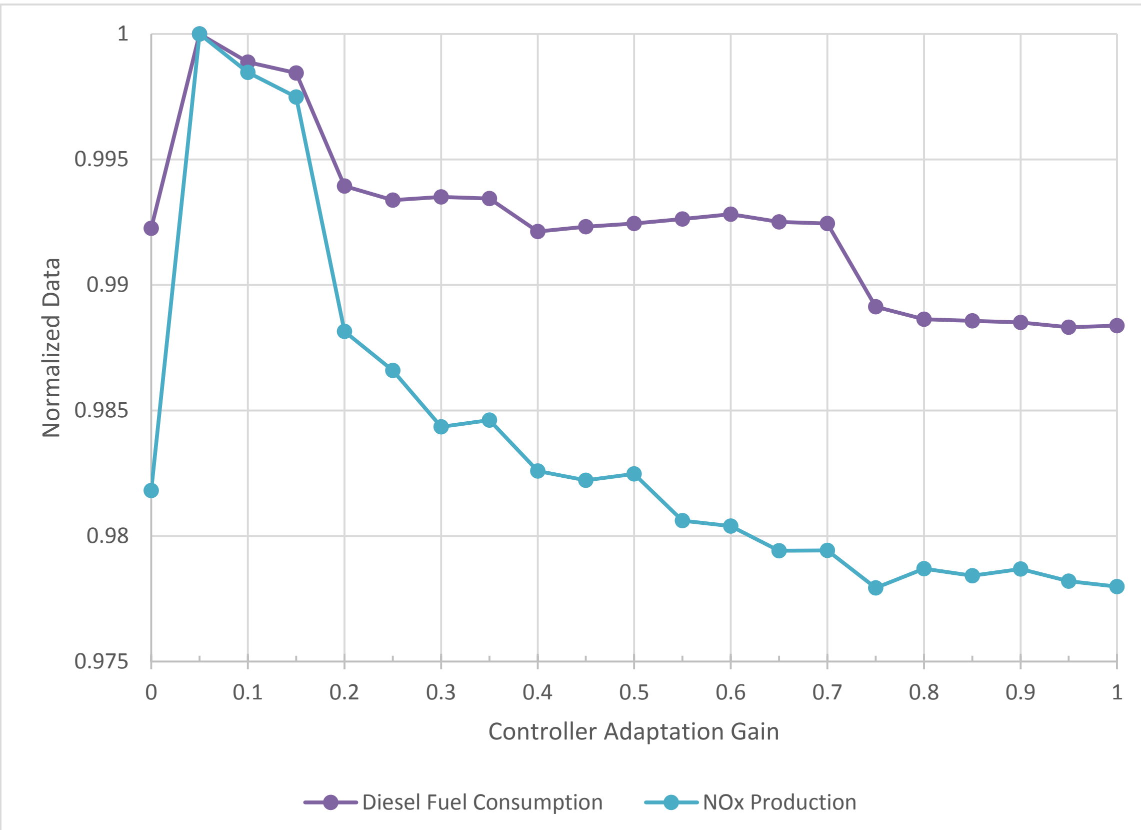

Figure 16 – Effect of Controller Adaptation Gains on Diesel Fuel Consumption and NOx Production with a Post Processing Adaption Gain of 1

Adaptation Gain Selection Summary

The Adaptation Gains to be used in this work are summarized in Table 8. An adaptation gain value of 1 was expected to be used for both the Training Data Generation and Post Processing Data Generation; however, a lower value was expected to be used for the Genset Speed Controller. An adaptation gain value of 1 in the Genset Speed Controller results in all of the training and testing data being used to determine the Genset Speed (rpm). As more data is added, especially data from different operating conditions, the adaptation value should decrease some so that only the most relevant data is used in the controller. The value is never expected to reach 0 as this would mean only the single latest data values would be used and could cause large changes in the Genset Speed (rpm) selection for the same power point. Additional testing with more data will be required to find the optimal Genset Speed Controller Adaptation Gain Value for on vehicle use.

Table 8 – Adaptation Gain Value Summary

Instance #	Area of Use	Adaptation Gain Value
1	Training Data Generation	1
2	Post Processing Data Generation	1
3	Genset Speed Controller	1

Chapter IV

Results

Post Processing Data Generation

The training and testing data sets were imported into the adaptive lookup tables for both the diesel fuel consumption and NOx production with an adaptation gain of 1. The resulting data is shown in Figure 17 and Figure 18. The Post Processing Data is utilized in 2-D lookup tables to evaluate the results of the controllers' Genset Speed (rpm) selection based on the fuel flow rate and the NOx production.

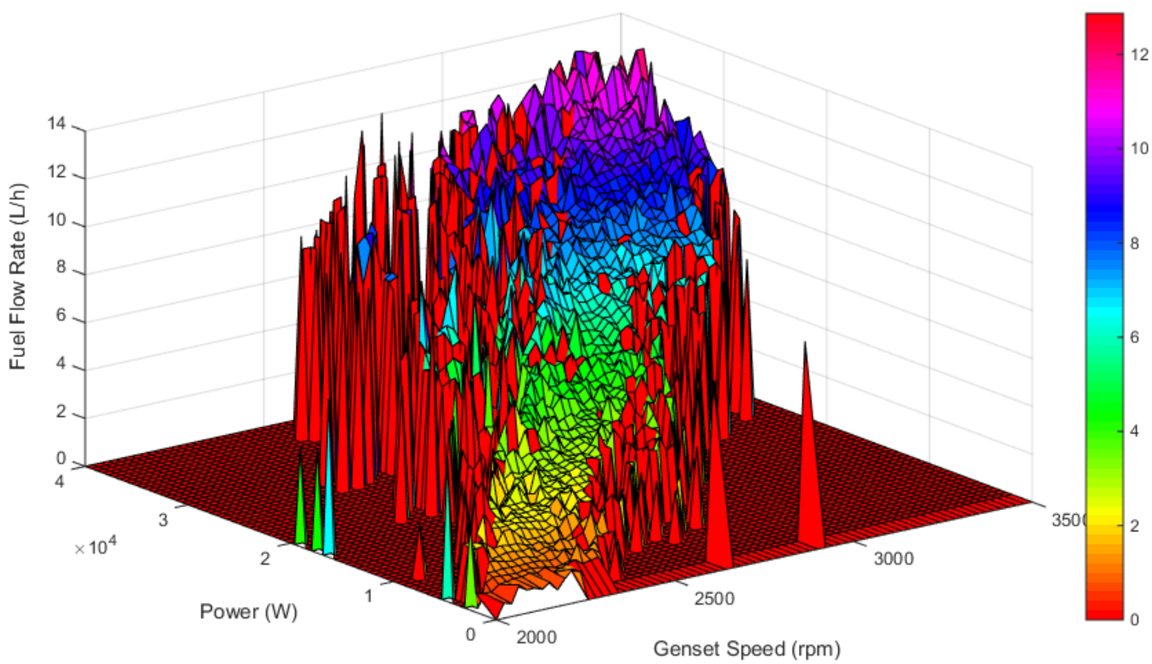

Figure 17 – Instantaneous Diesel Fuel Flow Rate Post Processing Data

Figure 18 shows one relatively large spike in NOx Production at approximately 3200 rpm and 36kW. One benefit of this controller is that when using an adaptation gain of less than 1 for the Genset Speed Controller, older data will be dropped. This helps to guard against single points of erroneous data.

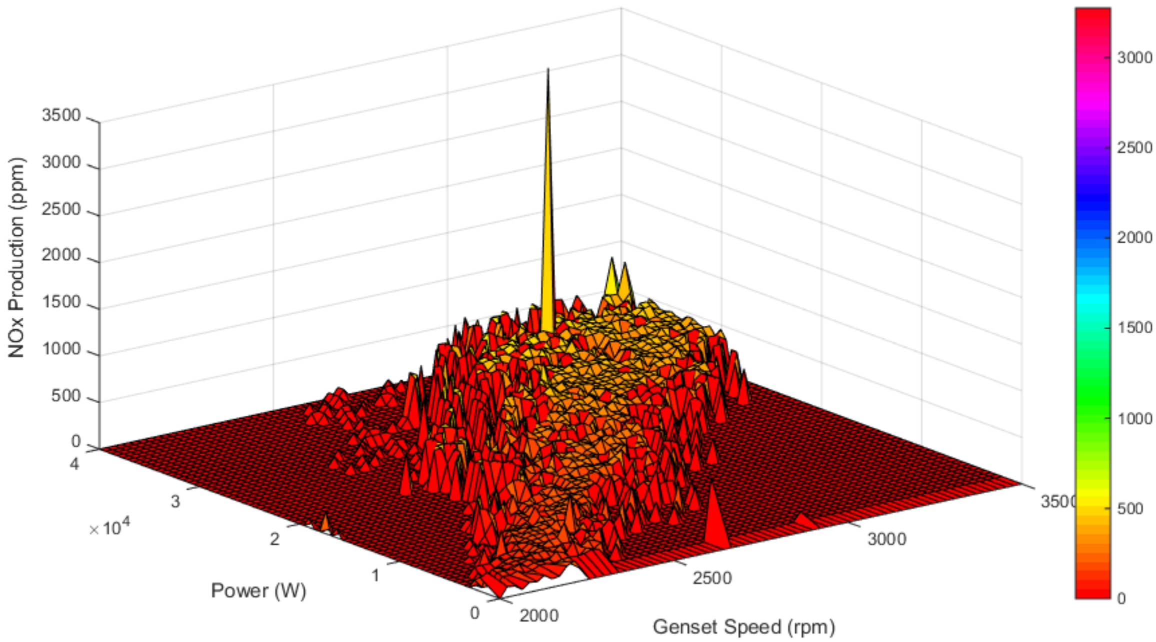

Figure 18 – NOx Production Post Processing Data

Evaluation of Results

In order to compare the actual vehicle performance to that of the simulated vehicle performance, a total of 4 evaluations were completed. Evaluation 1, Actual Log, used the results directly from the vehicle log recorded during testing. Evaluation 2, Actual, used the vehicle log data evaluated with the Post Processing Data. Evaluation 3, Existing Controller, used data from simulating the existing controller evaluated with the Post Processing Data. Evaluation 4, New Controller, used data from simulating the new controller evaluated with the Post Processing Data.

Evaluation 1 – Actual Log

Evaluation 1, Actual Log, used the recorded Fuel Flow Rate (L/h) and the recorded NOx Production (ppm) directly from the testing log. The Fuel Flow Rate was converted from liters per hour to gallons per timestamp, then integrated within Simulink to find the total gallons of diesel used during the testing session, as shown in Figure 19.

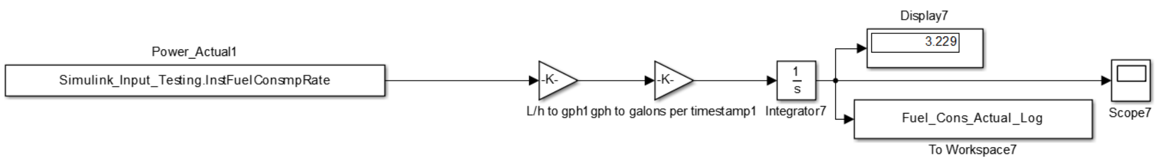

Figure 19 – Evaluation 1, Actual Log, Diesel Fuel Consumption (gal) Calculation

The Average NOx Production (ppm) was read directly into the model and recorded. Once recorded, the average of all the values was found by using the mean command in MATLAB.

Figure 20 – Evaluation 1, Actual Log, Average NOx Production (ppm) Calculation

Evaluation 2 – Actual

Evaluation 2, Actual, used the recorded Power Produced (kW) and the Genset Speed (rpm) from the testing log input into a 2-D Lookup Table populated with the Diesel Fuel Consumption Post Processing Data. The instantaneous fuel

consumption (L/hr) is output from the 2-D Lookup with the total gallons consumed calculated the same way as in

Evaluation 1 – Actual Log.

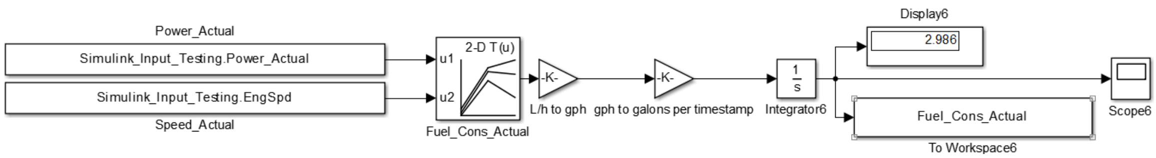

Figure 21 – Evaluation 2, Actual, Diesel Fuel Consumption (gal) Calculation

In order to determine the Average NOx Production (ppm), Evaluation 2 – actual, used the same input signals as used to determine the Diesel Fuel Consumption. These signals were the recorded Power Produced (kW) and the Genset Speed (rpm) from the testing log which was then input into a 2-D Lookup Table populated with NOx Production Post Processing Data. The NOx Production (ppm) was output from the 2-D Lookup Table with the Average NOx Production (ppm) being calculated in the same way as in

Evaluation 1 – Actual Log.

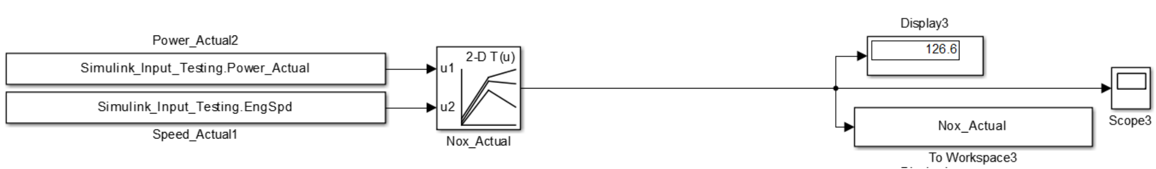

Figure 22 – Evaluation 2, Actual, Average NOx Production (ppm) Calculation

Evaluation 3 – Existing Controller

Evaluation 3 was the same as in Evaluation 2 – Actual, for both the Diesel Fuel Consumption (gal) and Average NOx Production (ppm) calculations, except for the speed signal input into the 2-D Lookup Table. The speed signal in this case was determined by inputting the Power Commanded (kW) into the existing controller which then determined the appropriate Genset Speed (rpm). This speed was then input into the 2-D Lookup Tables as in Evaluation 2 – Actual.

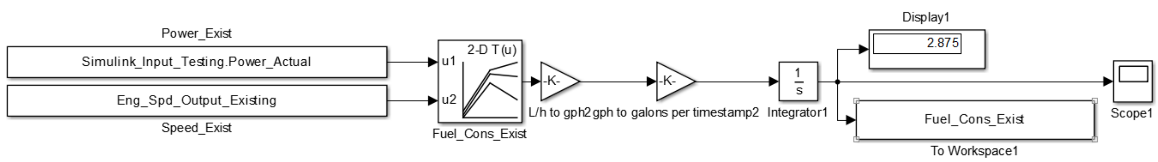

Figure 23 – Evaluation 3, Existing Controller, Diesel Fuel Consumption (gal) Calculation

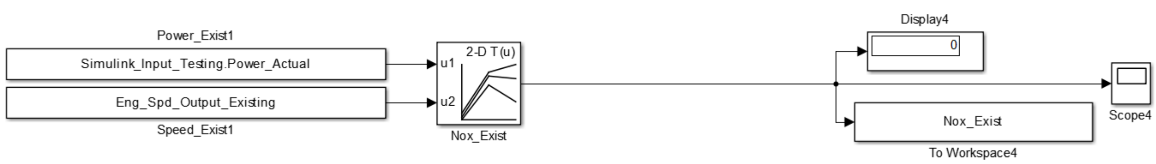

Figure 24 – Evaluation 3, Existing Controller, Average NOx Production (ppm) Calculation

Evaluation 4 – New Controller

Evaluation 4 was the same as in Evaluation 2 – Actual and Evaluation 3 – Existing Controller, for both the Diesel Fuel Consumption (gal) and Average NOx Production (ppm) calculations, except for the speed signal input into the 2-D Lookup Table. The speed signal in this case was determined by inputting the Power Commanded (kW) into the new controller which then determined the appropriate Genset Speed (rpm).

This speed was then input into the 2-D Lookup Tables as in Evaluation 2 – Actual and Evaluation 3 – Existing Controller.

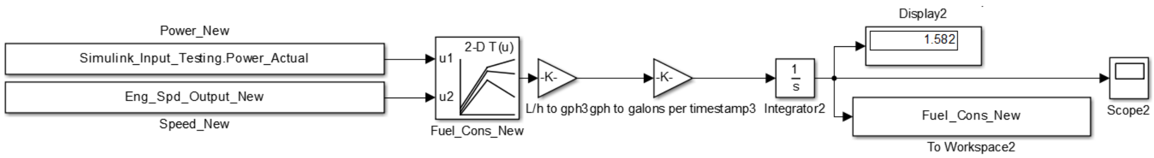

Figure 25 – Evaluation 4, New Controller, Diesel Fuel Consumption (gal) Calculation

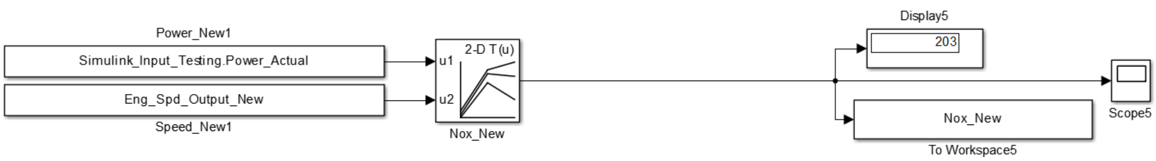

Figure 26 – Evaluation 4, New Controller, Average NOx Production (ppm) Calculation

Genset Speed Curve

As discussed in the MATLAB Function Block section, the new controller evolves the Genset Speed (rpm) curve as new Power Commands (kW) are given based on the actual operating data of the vehicle. Figure 27 shows the evolution of the Genset Speed (rpm) curve during the testing section of the controller.

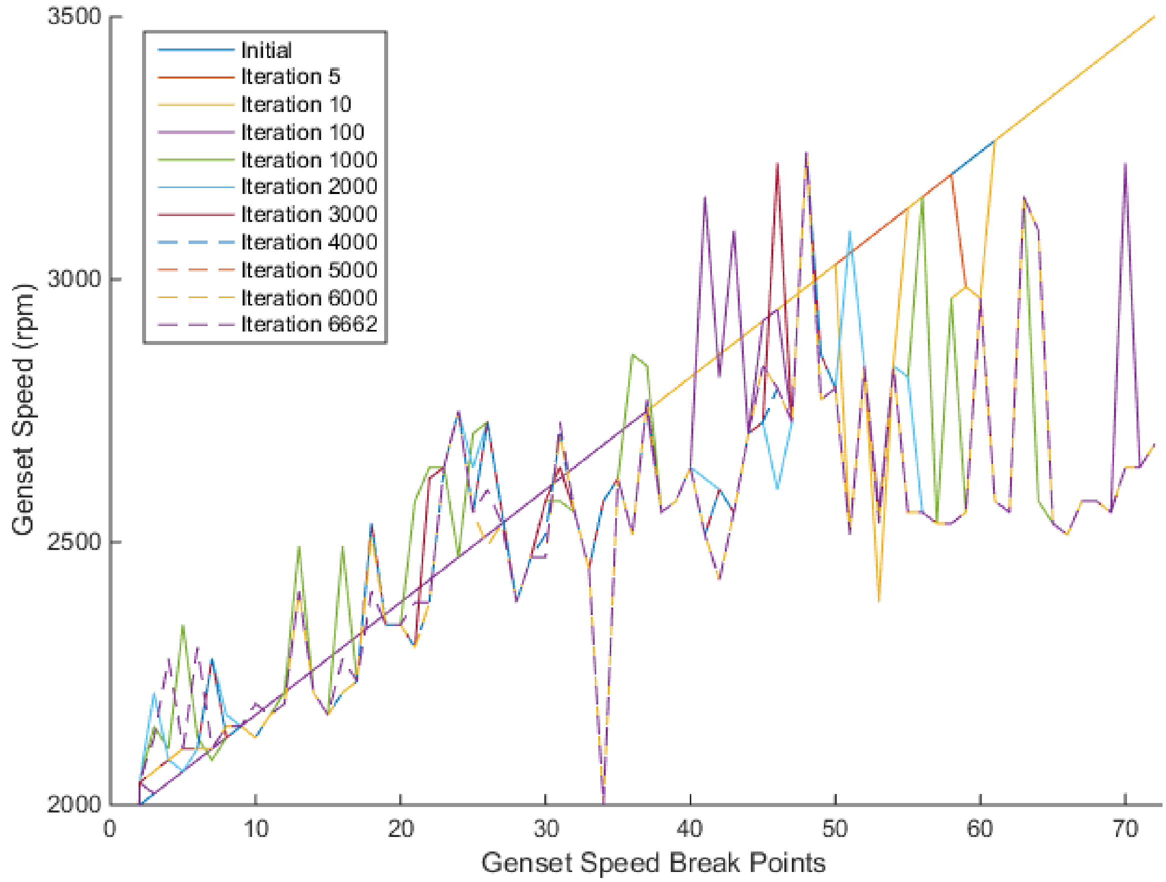

Figure 27 – Evolution of Genset Speed (rpm) Curve

Figure 28 shows the Genset Speed (rpm) curve used on the existing controller versus the final curve found during testing of the new controller. The figure also shows the points that have data to ensure that all of the new operating points are on points with data.

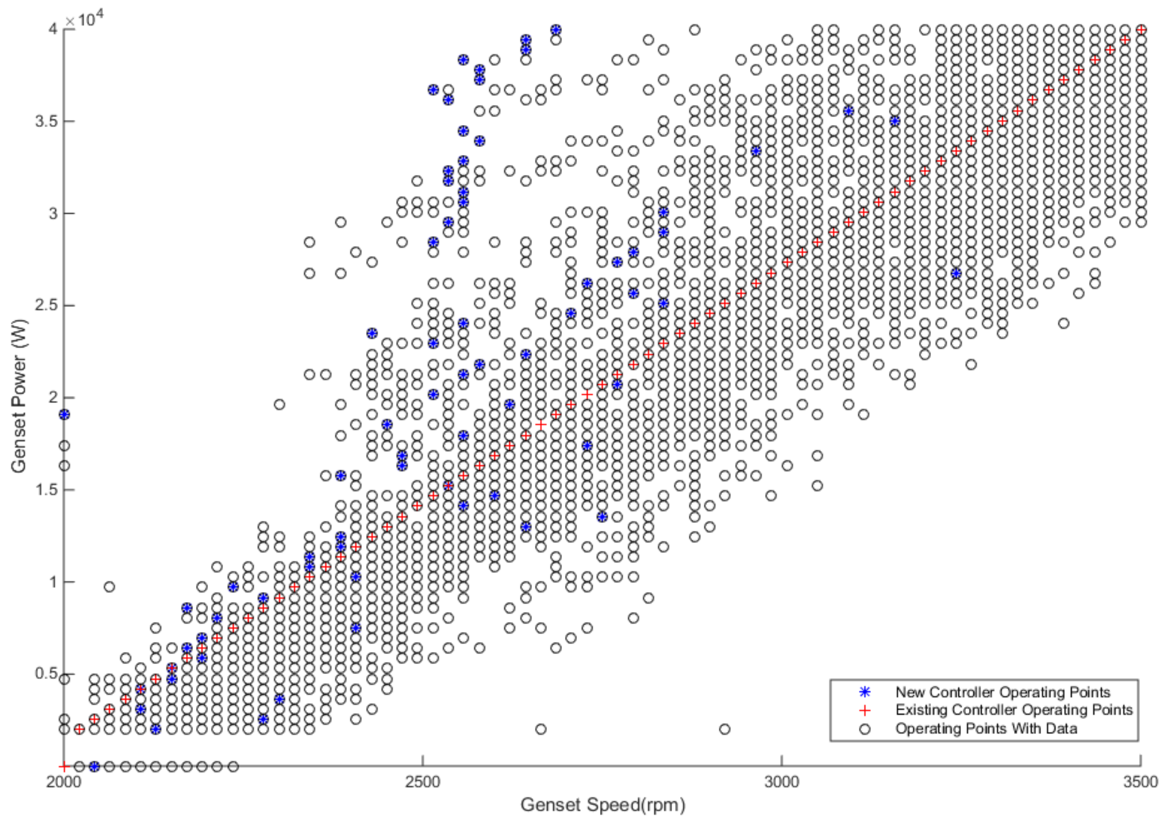

Figure 28 – New Vs Existing Operating Points Plotted Over Points with Data

Figure 29 and Figure 30 show the new controller operating points plotted over the instantaneous diesel fuel flow map (L/h) and NOx production map (ppm), respectively. As seen in both figures, the areas of high fuel flow rate / NOx production are avoided by the controller whereas areas of low fuel flow rate / NOx production are favored by the controller.

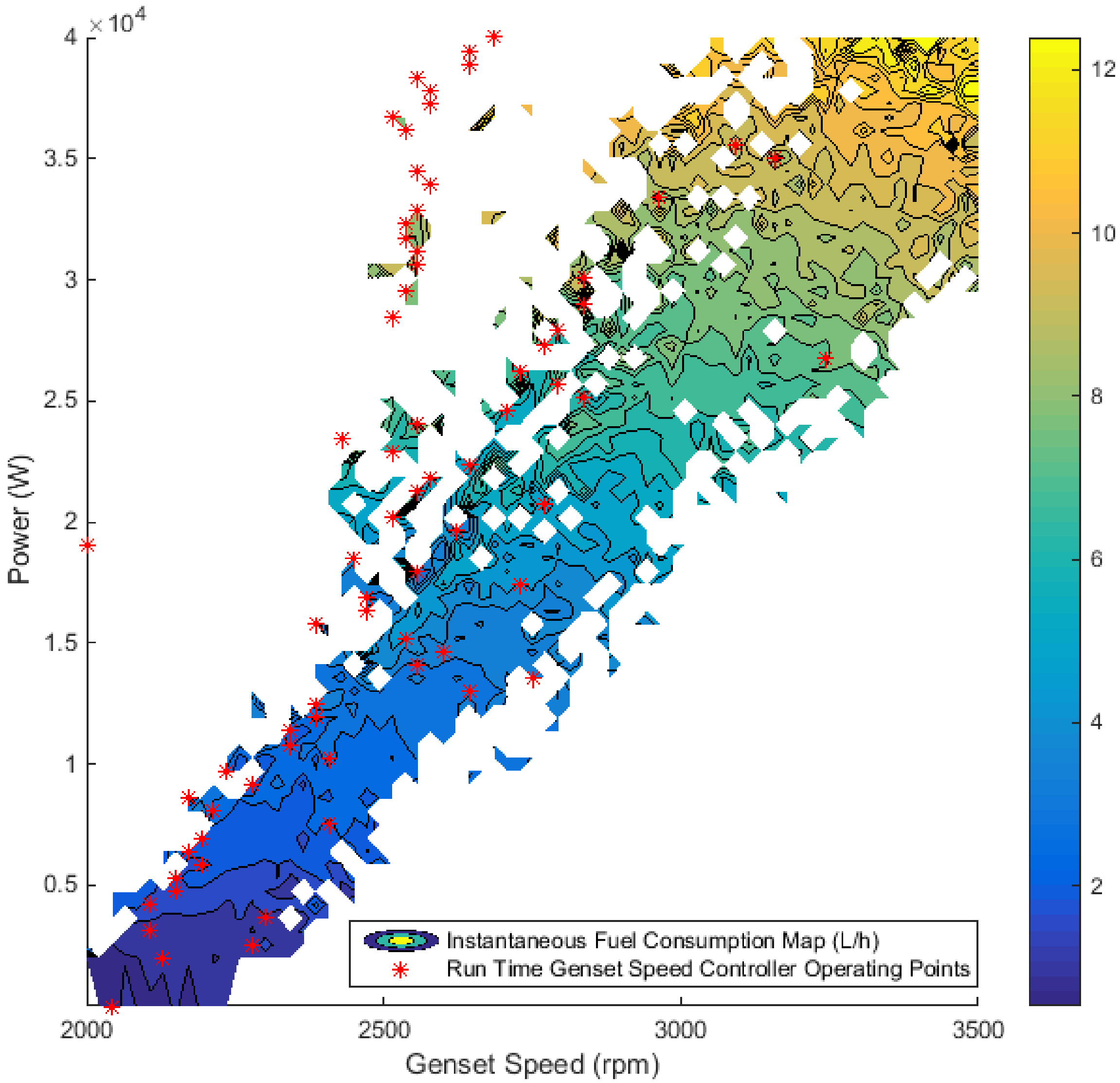

Figure 29 – New Controller Operating Points Plotted Over the Instantaneous Diesel Fuel Flow Map (L/h)

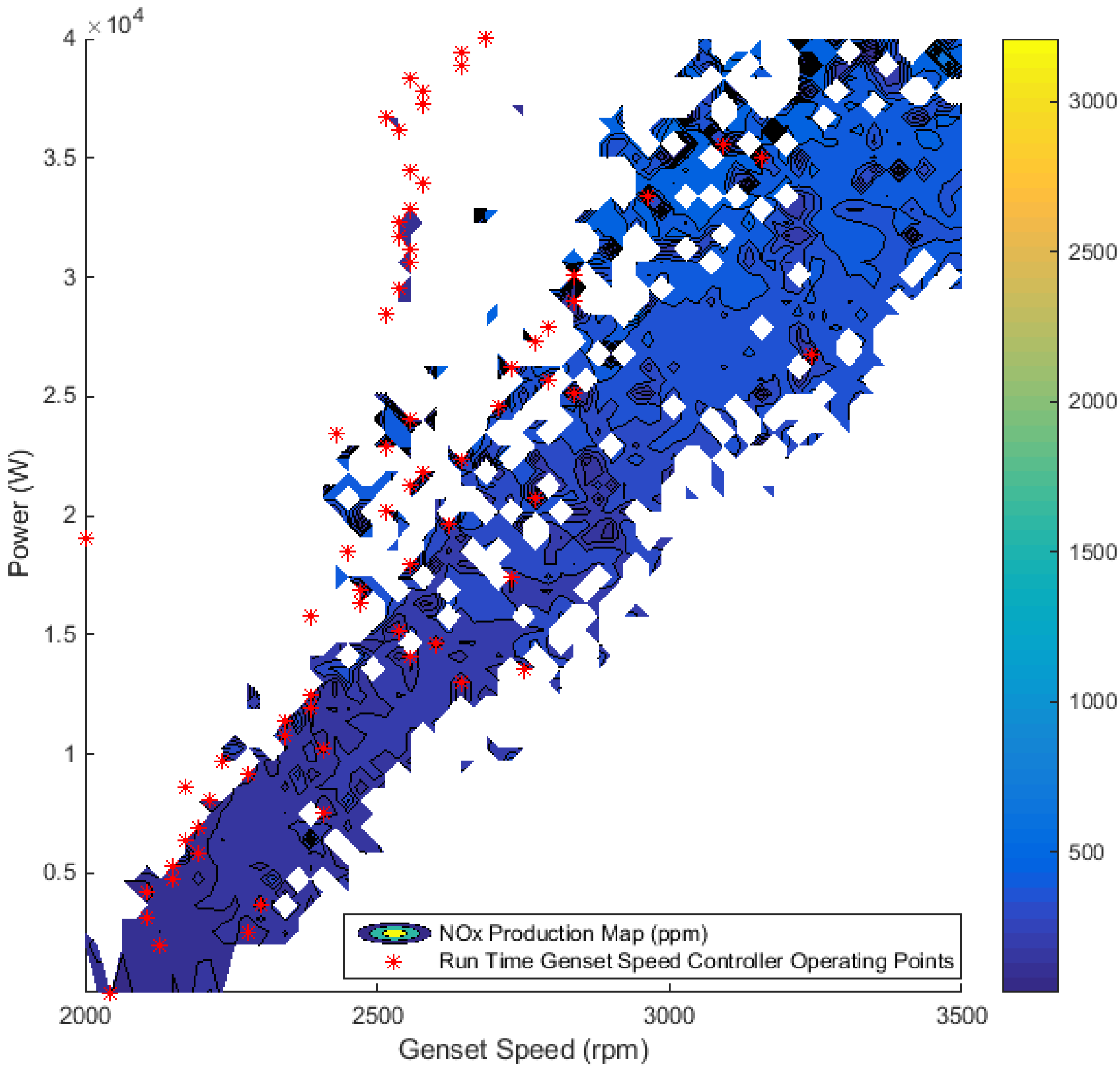

Figure 30 – New Controller Operating Points Plotted Over the NOx Production Map (ppm)

Table of Results

Table 9 shows the results from Evaluations 1 – 4 using the adaptation gains shown in Table 8. Evaluations 2 and 3 are both designed to validate the simulation as a proper method of comparison between the real world data, Evaluation 1, and the simulated data, Evaluations 2 - 4. Table 10 shows the Percent the simulated values are reduced from that of the real world values in Evaluation 1. Between Evaluation 1 and

Evaluations 2 & 3, which should all be equal, the largest step of percentage decrease was seen between Evaluation 1 and Evaluation 2 for both the diesel fuel consumed and the average NOx produced. The only change from Evaluation 1 to Evaluation 2 was that the instantaneous fuel map and NOx production map shown in Figure 29 and Figure 30 were used in the calculation. Thus, the largest point of error between Evaluation 1, the real world evaluation, and Evaluations 2 and 3, the simulated evaluations, are the maps used. With additional training data, this issue could be resolved. The difference between Evaluation 3 and Evaluation 2 is less than half of the difference between Evaluation 1 and 2. The only change from Evaluation 2 to Evaluation 3 is that the existing controller was simulated in Evaluation 3. It can therefore be concluded that the error due to the simulation of the existing controller has a significantly lower effect than the error due to the maps being used which then validates the simulation method for Evaluation 3 which is identical to that used for Evaluation 4, only with the new controller.

In terms of diesel fuel consumed, Evaluation 1 shows that the vehicle actually consumed 3.2 gallons of fuel during the testing event. Simulating the existing controller and utilizing the diesel fuel flow map shown in Figure 29, a total diesel fuel consumption of 2.9 gallons was found which is almost an 11% reduction. Simulating the new controller, a total diesel fuel consumption of 1.6 gallons was found which is a 51% reduction from Evaluation 1 and a 40% reduction from Evaluation 3.

In terms of NO_X production, Evaluation 1 shows that the vehicle actually produced an average of 324 ppm of NO_X during the testing event. Simulating the existing controller and utilizing the NOx production map shown in Figure 30, an average NO_X production of 262 ppm was found which is almost a 19% reduction. Simulating the new controller, an average NO_X production of 115 ppm was found which is a 65% reduction from Evaluation 1 and a 45% reduction from Evaluation 3.

Table 9 – Comparison of Actual Vehicle Performance to Simulated Vehicle Performance

Evaluation #	**Evaluation Name**	**Diesel Fuel Consumed (gal)**	**Average NO_X Emissions (ppm)**
1	Actual Log	3.2290	324.1862
2	Actual	2.9863	281.5909
3	Existing Controller	2.8754	261.5284
4	New Controller	1.5819	115.0649

Table 10 – Percent Reduction of Simulated Vehicle Performance Values to Actual Vehicle Performance Values

Evaluation #	**Evaluation Name**	**Diesel Fuel Consumed (% reduction)**	**Average NO_X Emissions (% reduction)**
1	Actual Log	0.00%	0.00%
2	Actual	7.52%	13.14%
3	Existing Controller	10.95%	19.33%
4	New Controller	51.01%	64.51%

As shown by the differences between Evaluation 1 and Evaluations 2 and 3, the simulated values are lower than real life values. However, the reduction from Evaluation 3 to Evaluation 4 is so great that even when accounting for this, the new controller is expected to reduce both the diesel fuel consumed and the NOx produced when implemented in real life.

Analysis of Results

Figure 31 shows the vehicle speed and SOC for the entire duration of the test. The testing data shown here is part of a much larger test which included operation with the Genset on and off. The testing data is only comprised of the data where the Genset was on; hence the test starting at over 70 mph.

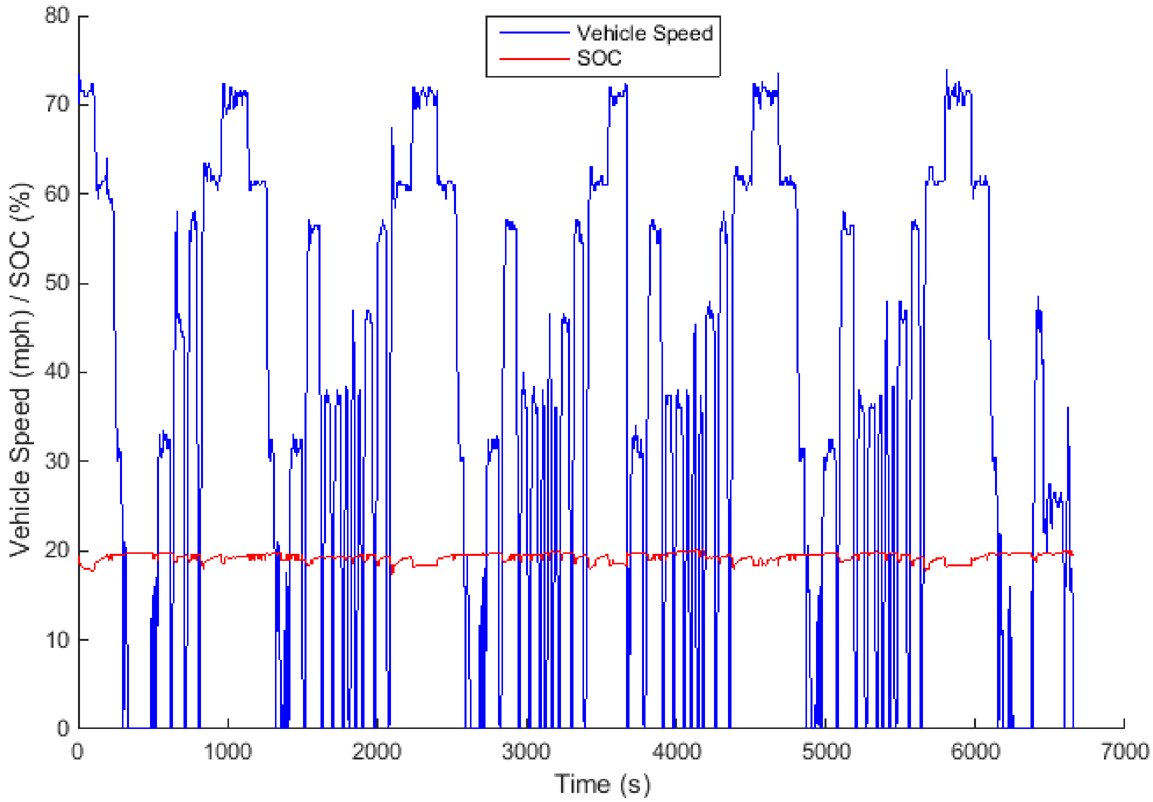

Figure 31 – Vehicle Speed (mph) & SOC (%) During Testing

In order to better show the differences between the controller performances and Evaluations 1 through 4, a 200 second range from 4500 to 4700s has been selected to analyze in more detail. The vehicle speed and SOC for this section is shown in Figure 32. During this 200s segment, the speed is over 60 mph the entire time and over 70 mph most of the time. The SOC if below 20% during the entire during. This results in a high power output from the Genset.

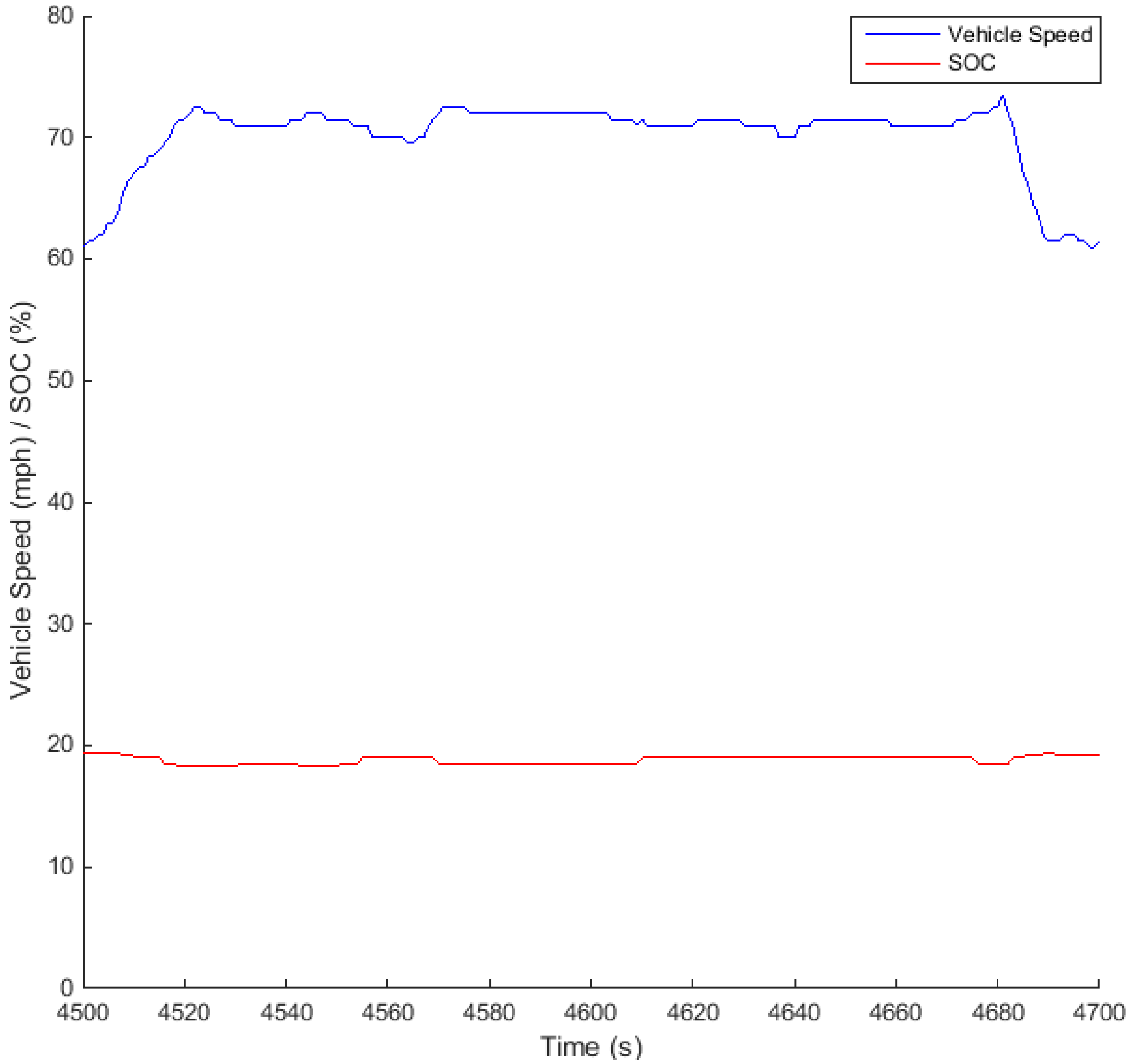

Figure 32 – Vehicle Speed (mph) & SOC (%) During Testing (4500 – 4700s)

The Genset power commanded (W) and the Genset speed (rpm) for each evaluation is shown in Figure 33. There are multiple segments of the test in which the Genset produces the maximum allowed power of 40kW yet there are many variations in the power commanded during most of the test. In terms of the Genset speed (rpm), the actual testing data (Evaluation 2) is normally at a higher rpm than the simulated data from Evaluations 3 and 4. Evaluation 4 typically operates at a lower rpm than the other two, which is especially apparent during steady state operation at approximately 40kW.

Genset Speed and Power

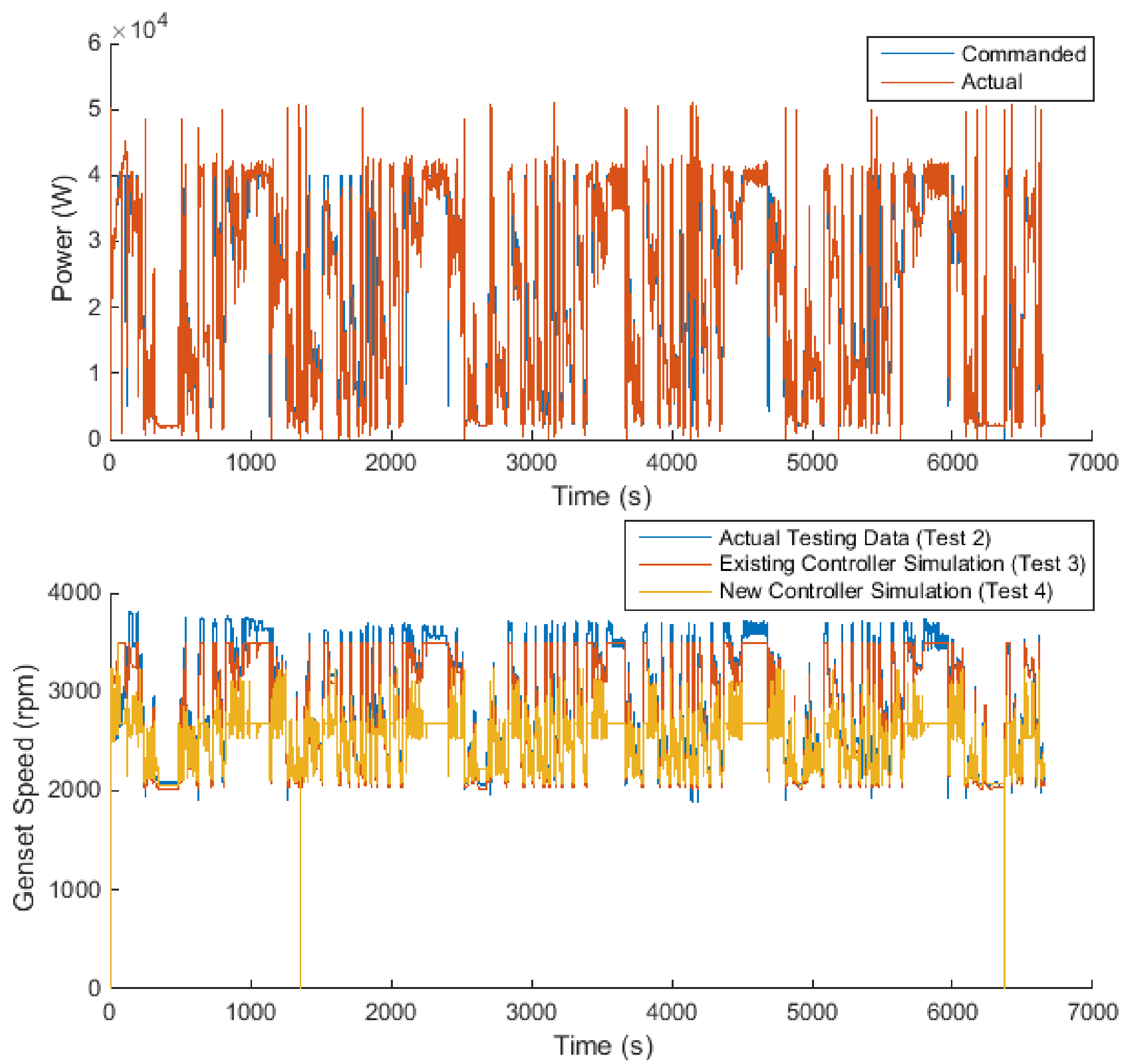

Figure 33 – Genset Speed Comparison and Power Commanded

Figure 34 shows an example of one such instance that occurs within the window of 4500 to 4700s. In order to aid discussion, the data at 4580s will be used as representative values of the steady power command between 4500 – 4700s. At 4580s, the power commanded is at 40kW and the actual power generated is at 40.4kW while the Genset speeds vary from 2,686 to 3,685 rpm between Evaluations 4 and 2, respectively. The run-time Genset speed controller selected a speed 999 rpm less than recorded and 814 rpm less than the simulated existing controller for the same power output.

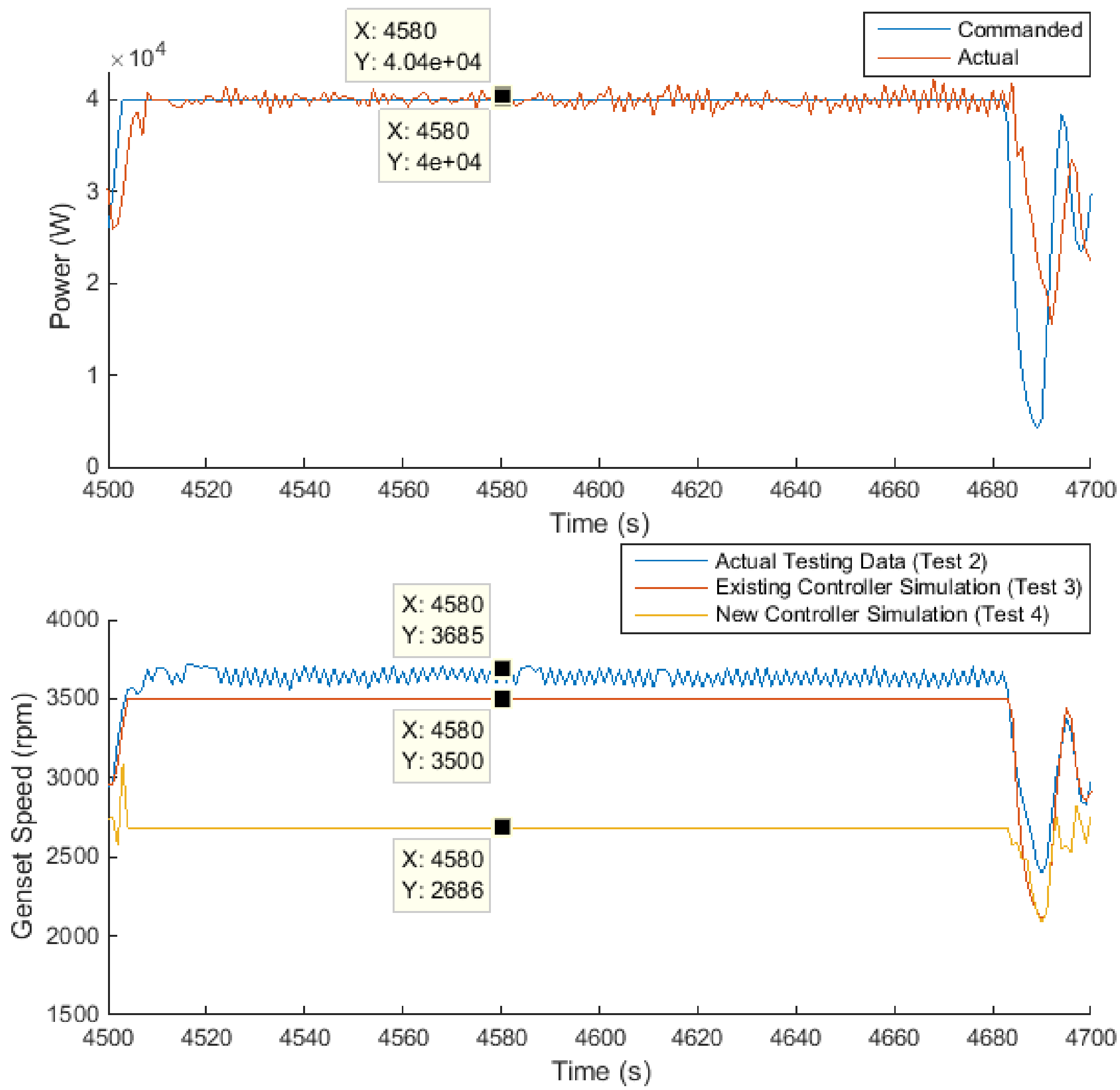

Figure 34 – Genset Speed Comparison and Power Commanded (4500 – 4700s)

Cumulative Fuel Consumption

Figure 35 shows the cumulative fuel consumption in gallons during the entire test. Throughout the majority of the run, Evaluations 1 – 3 had a similar slope while Evaluation 4 (the run-time Genset speed controller) had a slope approximately half that of the others. In addition to a lower slope, Evaluation 4 also evened out the slope overall whereas Evaluations 1 – 3 had deviations of higher slopes. Higher slopes equate to higher instantaneous fuel consumption rates.

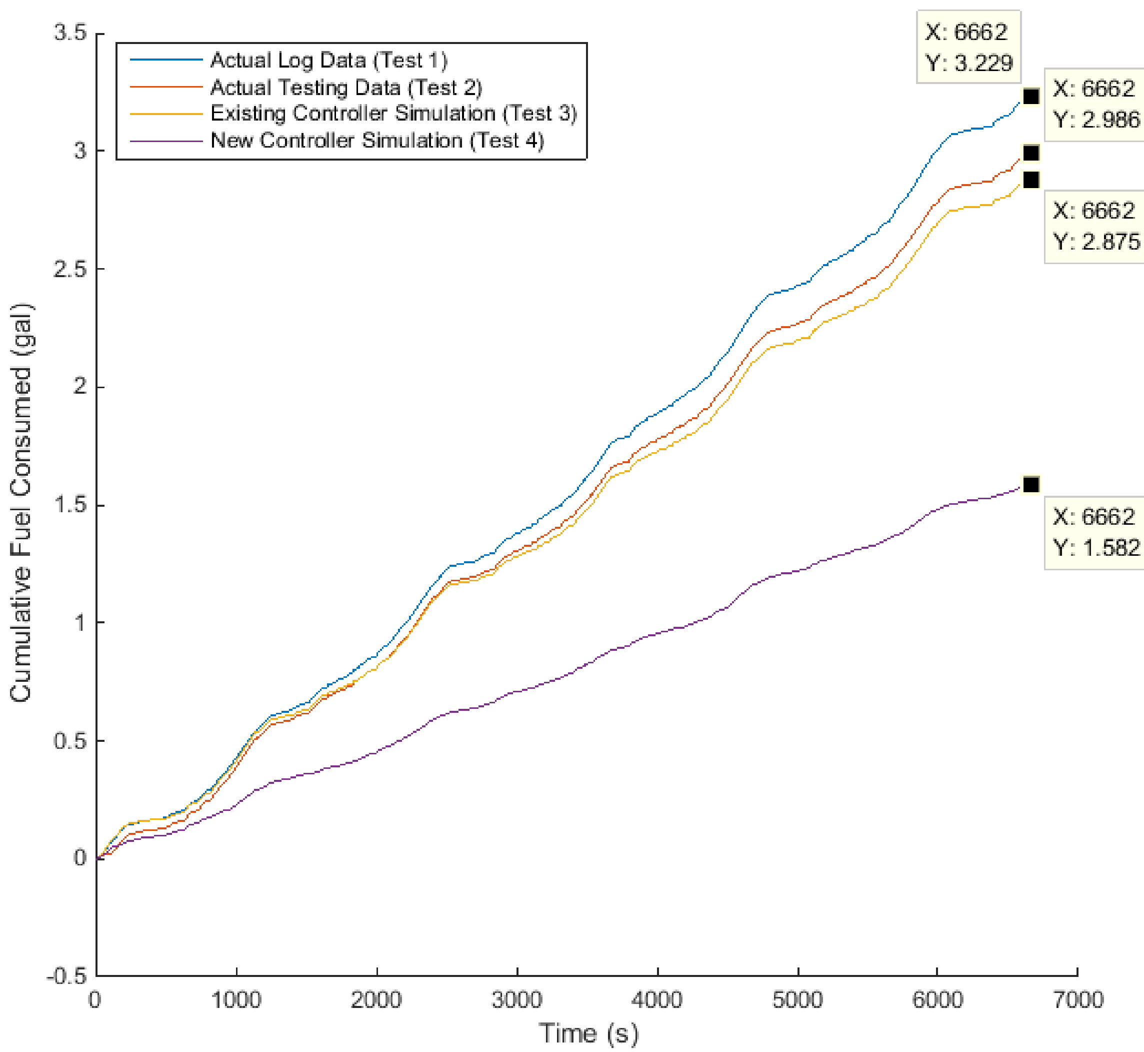

Figure 35 – Cumulative Fuel Consumed

Figure 36 shows the cumulative fuel consumption from 4500 – 4700s with Table 11 being a summary of the information. At 40kW, the real run Genset speed controller consumes 37% less fuel than the next closest evaluation (Evaluation 3). This accounts for a significant fuel savings.

Table 11 – Summary of Cumulative Fuel Consumed from 4500 – 4700s

Evaluation #	**Cumulative Fuel Consumption at**		**Fuel Consumed From 4500 – 4700s (gal)**	**Average Fuel Consumption from 4500 – 4700s (Gal/h)**
	4500s	**4700s**		
1	2.146	2.329	0.183	3.294
2	2.011	2.177	0.166	2.988
3	1.947	2.109	0.162	2.916
4	1.063	1.165	0.102	1.836

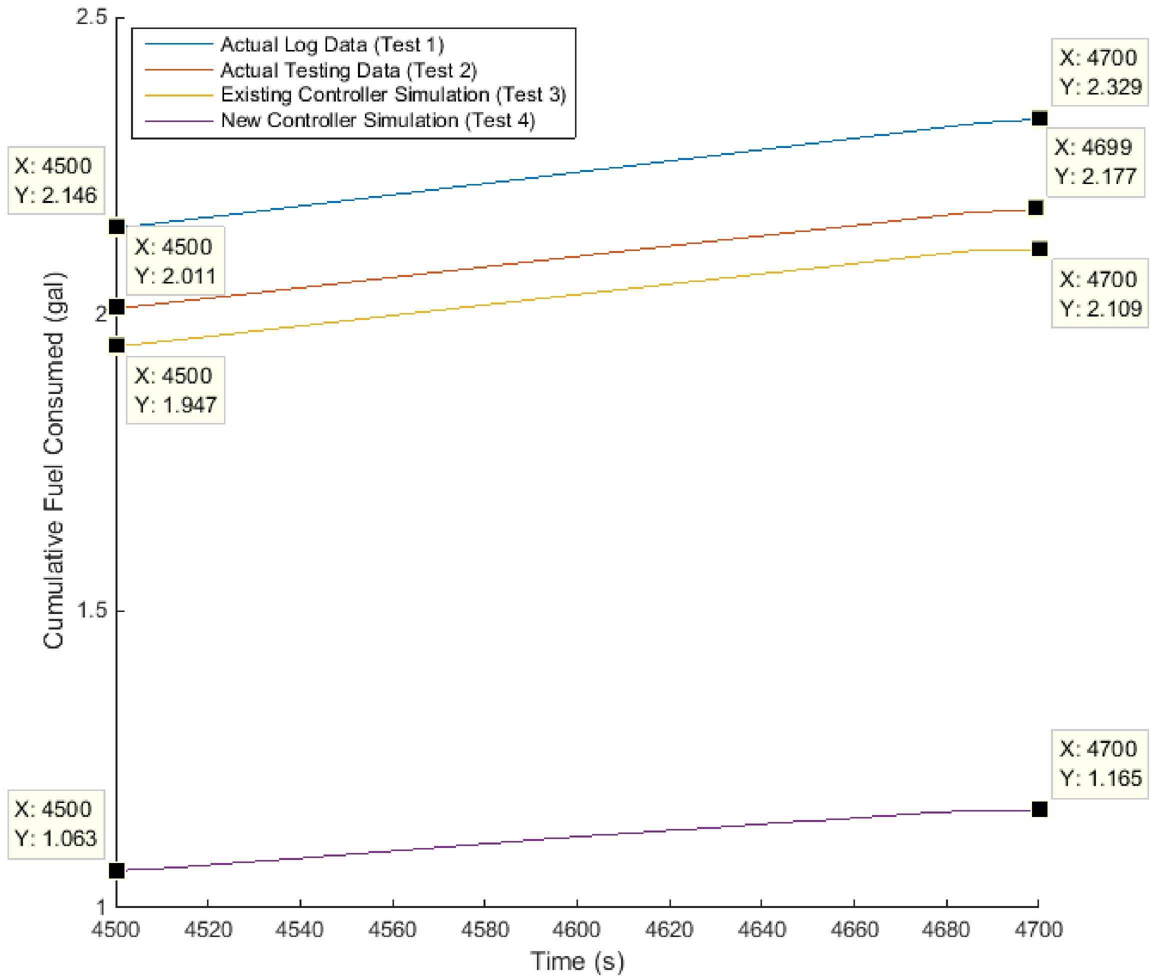

Figure 36 – Cumulative Fuel Consumed (4500 – 4700s)

NOx Production

Figure 37 and Figure 38 show the NOx produced during the entire length of all 4 evaluations. As with the instantaneous fuel consumption, the NOx production is greatly reduced during the 40 kW steady state periods. In addition to this, the NOx emissions for Evaluation 4 overall are lower than the other evaluations. Evaluation 4 was the only evaluation to not encounter a large spike in NOx at any point.

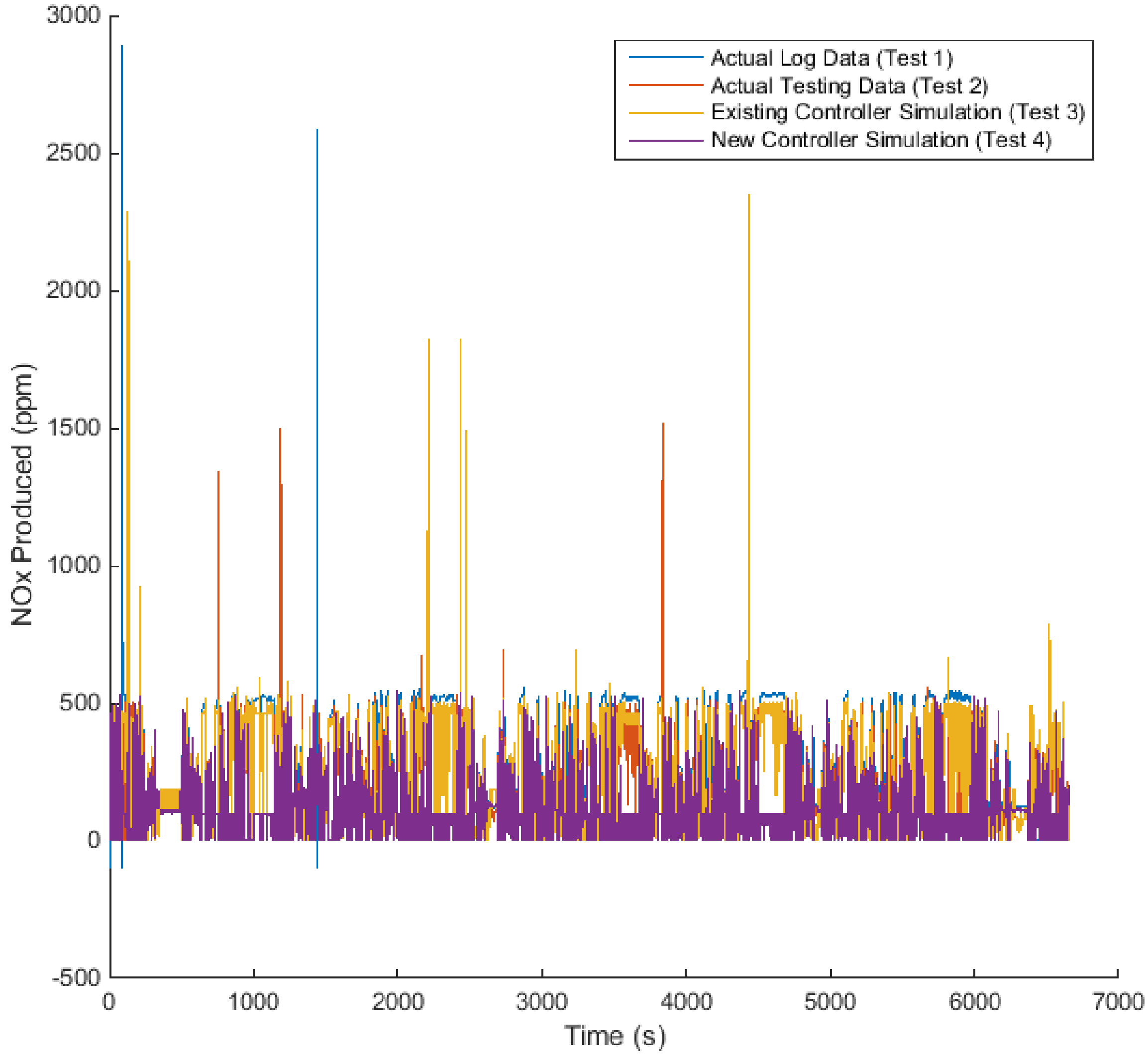

Figure 37 – NOx Production

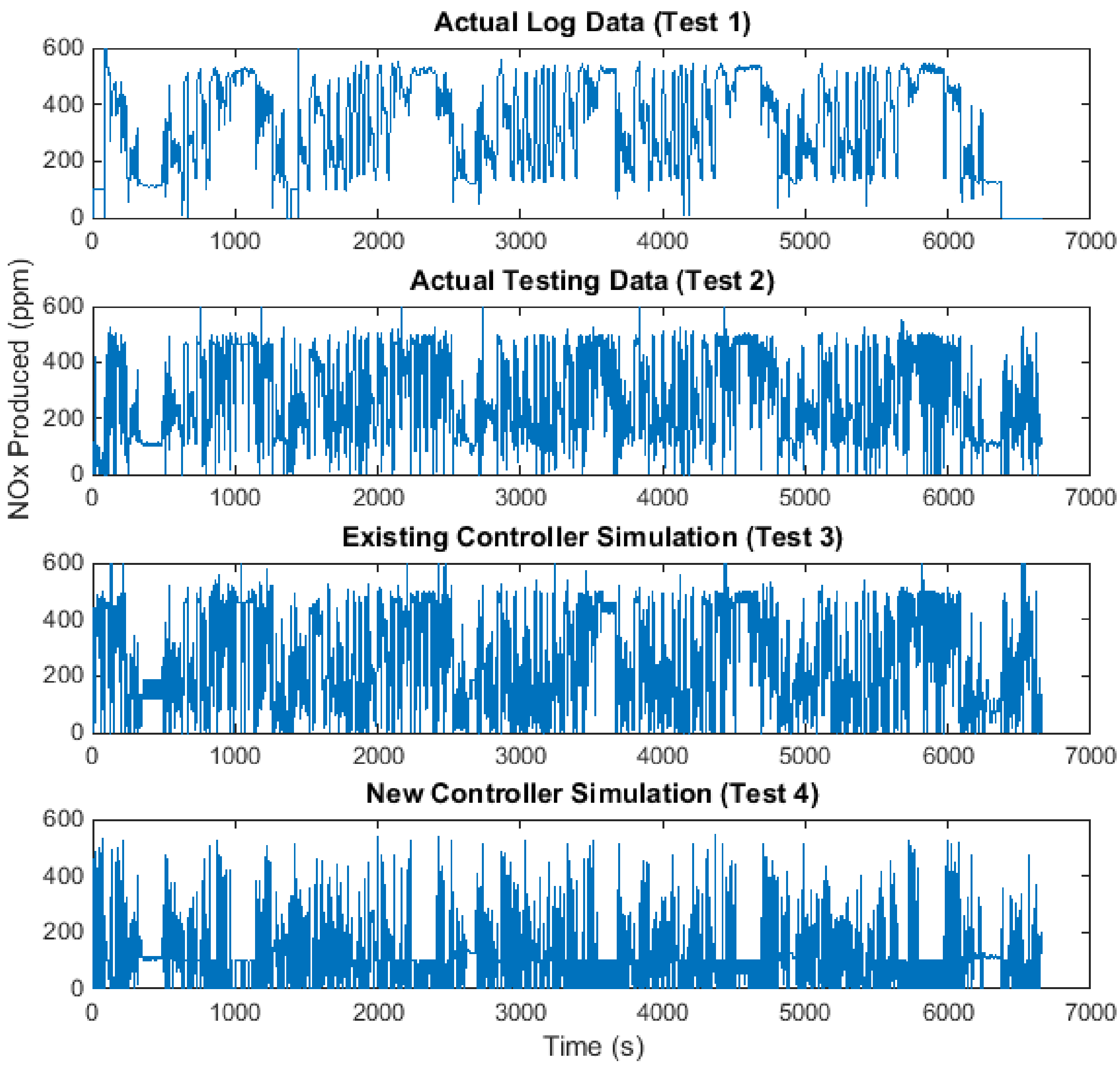

Figure 38 – NOx Production, Multi-plot

Figure 39 and Figure 40 show the NOx production for Evaluations 1 – 4 between 4500 – 4700s. During steady state operation at 40kW, the data from Evaluation 1 was the highest of all. Both Evaluations 2 and 3 produced very similar results while the run-time Genset speed controller was the lowest of all by a factor of almost 5.

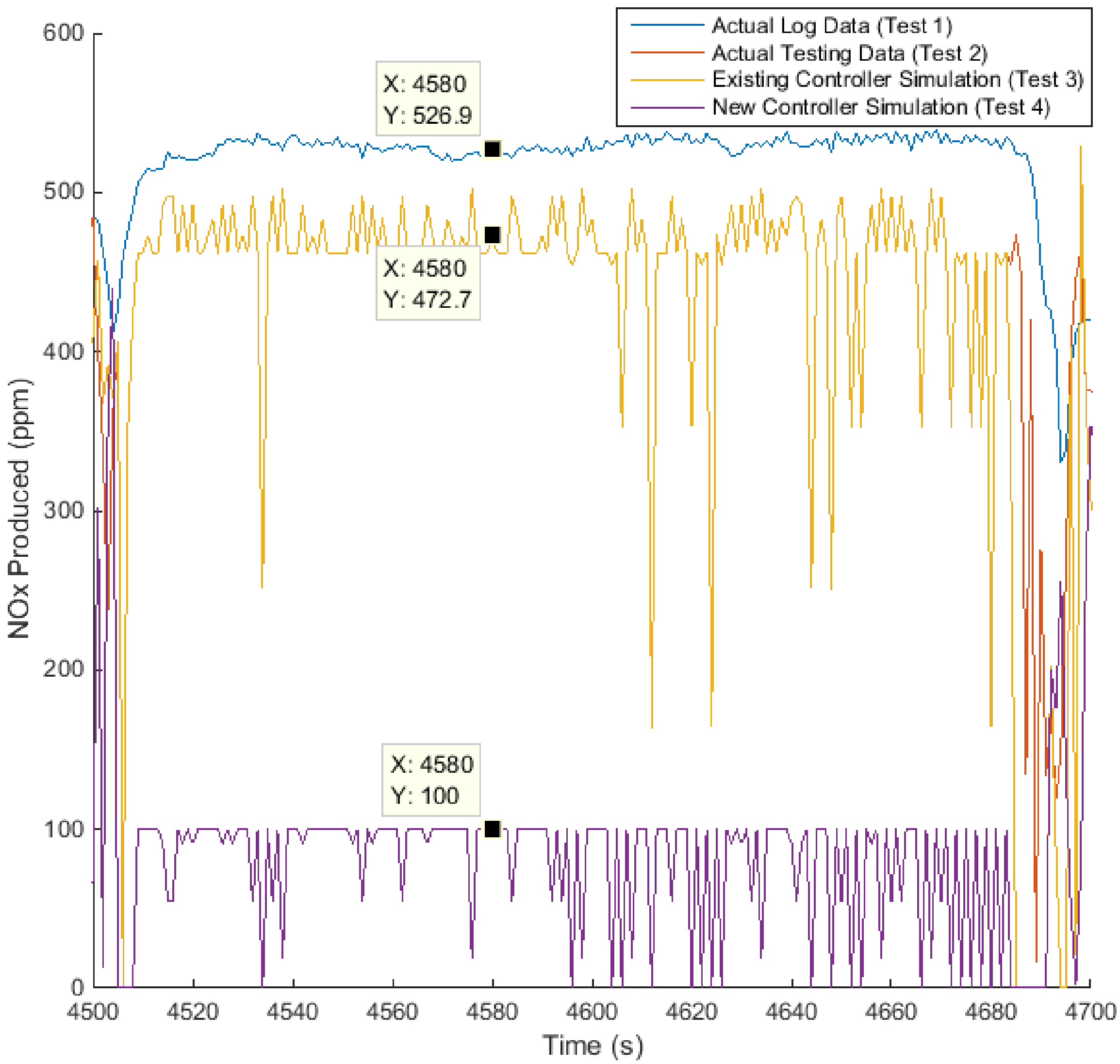

Figure 39 – NOx Production (4500 – 4700s)

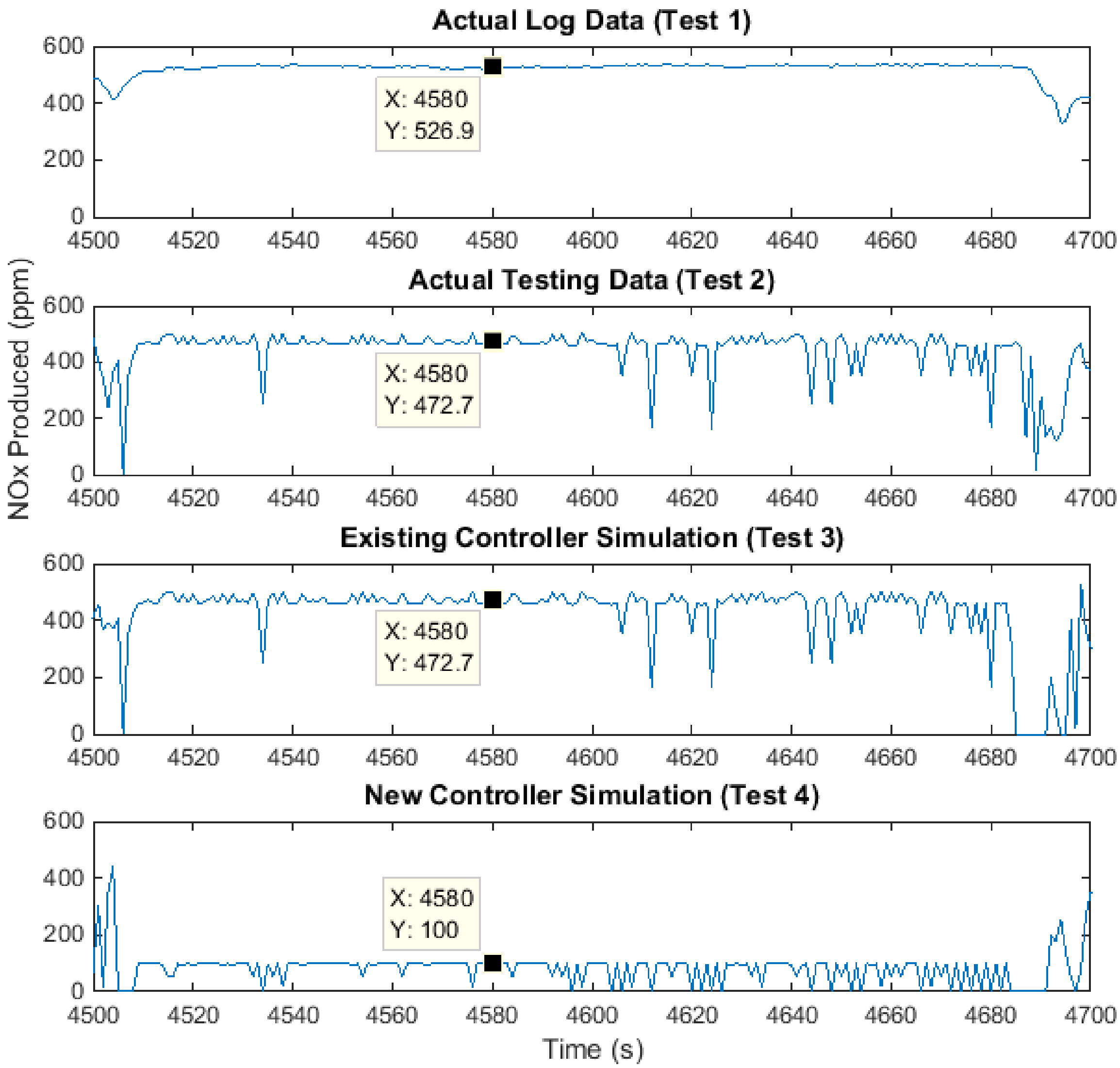

Figure 40 – NOx Production (4500 – 4700s), Multi-plot

Chapter V

Discussion, Conclusions, and Recommendations

Future Work

The next steps for this project, in the following order, are the creation of a complete baseline map / Genset speed curve, implementation of the run-time Genset speed controller on a vehicle, implementation of a maximum emissions limit and implementation of a CAT light-off strategy.

Creation of a Complete Baseline Map / Genset Speed Curve

As shown in Figure 28, Figure 29 and Figure 30, the training and testing data currently available does not create a full map of the Genset operating points. The Genset should be fully characterized so that a complete map can be produced. The map should ideally be created for the operating conditions the vehicle will normally operate in. This map would then become the initial or baseline operating map that the vehicle could would use when it starts for the first time. While the Genset is operating the run-time Genset speed controller would continually update the map, saving the latest version to memory for use upon restart. Along with the complete map, a Genset speed curve should be created as in Figure 28 for the vehicle to use when it starts for the first time with a run-time Genset speed controller. As with the map, the Genset speed curve would continually update while the Genset is operating, saving the latest version to memory for use upon restart. This makes the assumption that conditions will be similar between shutdown and restart; however, if they aren't the controller will be able to adapt if the controller adaptation gain is properly selected.

Implementation of the Run-Time Genset Speed Controller on a Vehicle

After the creation of a complete baseline map / Genset speed curve the controller should be implemented on a vehicle. Once implemented the controller adaptation gain can be adjusted so that only the most recent data is used in the controller. Care must be taken when doing this, a value too close to 1 would result in the controller not adapting to the current environment quick enough to ensure best performance in terms of reduced fuel consumption and reduced NOx emissions. A value too close to 0 would result in a controller that rapidly adapts to new environments. Data however, is not perfect and if a series of bad values were recorded they could greatly skew the maps which in turn could affect the Genset performance.

Implementation of a Maximum Emissions Limit

The run-time Genset speed controller has been built in such a manner that it is easily scalable for additional control variables. The controller is currently using only two variables, instantaneous diesel fuel flow rate and NOx production with equal weighting. All regulated emissions, instead of just NOx, could be monitored with the addition of sensors to the vehicle. As reduced fuel consumption is typically more important to the consumer than reduced emissions, the objective function could be adjusted to reflect this. Instead of all variables being equally weighted in the objective function, the emissions variables could be changed to the maximum allowable values permitted in order to ensure compliance with regulatory / competition rules (this maximum value would be lower than the regulated values in case of overshoot due to system dynamics or sensor error). With the emissions limits satisfied, the lowest fuel flow rate while maintaining emissions compliance could then be determined instead of a weighted 1:1 compromise.

This would also adapt very well to markets with different regulations as the emissions limits could simply be tuned for each individual market while utilizing the same controller. This would allow savings in the fact that a new controller with new operating points would not have to be developed for each of the markets. The run-time Genset speed controller developed here, would automatically adjust the operating points to comply with the input emissions regulations.

Implementation of a CAT Light-Off Strategy

The emissions during the initial startup until CAT light-off are much higher than found during normal at temperature operation. Currently, the maps being used contain data from both of these distinct periods of operation. In order to achieve lower fuel consumption and emissions production during both periods, a strategy needs to be developed and researched.

The first strategy to be considered is that of the adaptation gain value. If the adaptation gain value were low enough, the map would update itself fast enough to account for this change. With this solution, the initial maps should be based solely on pre-CAT light-off conditions.

A second strategy to be considered would be to implement two sets of maps, one map for pre-CAT light-off and a second set for post-CAT light-off.

Concluding Remarks

The beneficial potential of a run-time Genset speed controller over the existing static controller has been proven. Without changing any hardware on the vehicle great gains in both increased fuel economy and reduced emissions can be observed at the same time. After estimating and accounting for simulation error then comparing the new run-time Genset speed controller to that of the existing static Genset speed controller, a 40% reduction in fuel consumption and 45% reduction in NOx production was found. Based off of these results, a run-time Genset speed controller to optimize both fuel consumption and emission production is recommended over for use over a static Genset speed controller. In order to implement this strategy a less resource intensive optimization method than the brute force method currently used may have to be employed, depending on the hardware used.

The controller is not specific to any Genset combination but can be trained to work on any Genset. This opens up any vehicle application with an engine-generator combination and 2 degrees of freedom which includes most series hybrids and some series-parallel hybrids. The controller also has application outside of automotive. Many locomotives are diesel-electric, and all stand-alone generators are an engine-generator combination and 2 degrees of freedom.

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