SCHOOL OF MECHANICAL, INDUSTRIAL & AERONAUTICAL ENGINEERING

Reduction of Fuel Consumption and CO_2 Emissions using a Hybrid Drive Train in a Truck Logistics Operation

MECN4006 - Research Project

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A project report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Bachelor of Science in Engineering.

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University of the Witwatersrand, Johannesburg

School of Mechanical, Industrial & Aeronautical Engineering

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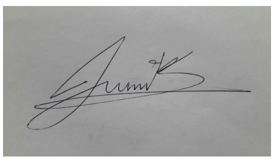

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Abstract

An investigation is conducted on the fuel consumption and CO_2 emission implications of various drive trains for a semi truck trailer logistics operation. Three drive trains in particular are under consideration, namely the conventional internal combustion engine (ICE), plug-in (series) hybrid and full hybrid (parallel).

The three drive trains are developed as quasistatic systems on Matlab and Simulink and are each simulated on three different logistics routes between major port cities and the economic hub of South Africa. The starting locations of the operations are Durban, Cape Town and Port Elizabeth, which then terminate in Johannesburg. In addition to the logistics operations described previously, the Heavy Heavy-Duty Diesel Truck (HHDDT) drive cycles are also simulated.

It is found that a quasistatic approach is inadequate for predicting the transient behaviour of a vehicle due to the extreme deviations from the expected fuel economy of the ICE on the HHDDT drive cycles. An average velocity on the logistics routes yields a more realistic estimate of the fuel consumption of the ICE, with an average deviation of 10% from the expected fuel economy of 37 litres per 100km.

The full hybrid leads to roughly 50% savings on the truck fuel economy, bringing it down to average of 21 litres per 100km. The plug in hybrid yields by far the best fuel economy of the three drive trains with more than 60% fuel savings.

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1 BACKGROUND AND LITERATURE REVIEW

1.1 Background and Motivation

Human induced climate change is becoming an increasingly popular topic of discussion both among scientists and the general population alike. Greenhouse gas (GHG) emissions from human activity are believed to drive climate change at increasingly alarming rates as unpredictable weather patterns cause natural human suffering on scales that have never been seen before.

The transport sector contributes approximately 14% of the global carbon emissons according to a Edenhofer et al [1]. Although transport emissions only increased by 0.6% year on year in 2018 as opposed to the average 1.6% annually in the past decade due to improved tehnology, truck CO_2 emissions have grown by 2.2% annually since 2000 [2, 3]. This leaves a lot to be desired and Secretary-General of the United Nations, António Guterres, has called for all nations in the Paris Climate Accord to reduce carbon emissions by 45% within the next decade, as will be discussed at the 2019 UN Climate Action Summit [4]. Improvements in trucking technology in this regard will be critical to meeting the carbon emissions goals set out by organisatons such as the UN and Paris Accord.

Truck logistics are an integral part of human society for the distribution of consumer and capital goods. Their involvement in the supply chain cannot be reduced so it is critical that solutions are developed that reduce the GHG emissions that harm the planet.

The burning of liquid fuels for energy provides a dilemma where unexpectedly large quantities of GHG's are emitted from a seemingly small amount of fuel. This occurs due to the addition of oxygen to the reactants during the burning process. The Natural Resources Centre of Canada found that burning a litre of diesel releases 2.66kg of carbon into the atmosphere [5]. Current semi truck trailers can achieve a fuel economy of about 6.4 miles per gallon (36.75 litres per 100km) [6], which translates to roughly 97.755 kg of carbon dioxide (CO_2) per 100km.

1.2 Literature review

1.2.1 Standard Drive Cycles

Standard drive cycles are widely used to determine fuel consumption and GHG emissions of vehicles. These cycles can either be done by simulation or chasis dynamometer testing. The velocity profile is imposed on the vehicle as a function of time with the engine speed and torque being computed such that they meet the imposed driving conditions [7]. The HHDDT drive cycle parameters are shown in Table 1.

Standardised driving cycles allow for different vehicles to be compared with relative certainty. For light commercial vehicles these drive cycle methods tend to underestimate actual fuel consumption and GHG emissions as found by Chindamo and Gadola[9]. These variations in measured data and

Table 1: Heavy Heavy Duty Diesel Truck (HHDDT) Drive Cycle Data [8]

Parameter	**Creep**	**Transient**	**Cruise**
Duration (s)	253	668	2083
Distance (km)	0.2	4.59	37.12
Average Speed (km/h)	2.85	24.78	64.21
Stops/km	15.01	1.12	0.16
Max Speed (km/h)	13.26	76.44	95.43
Max Acceleration (km/h/s^2)	3.70	4.83	3.70
Max Deceleration (km/h/s^2)	-4.07	-4.51	-4.02
Percent Idle	42.29	16.3	8

drive cycle data can be attributed to dynamics that are not recognised by drive cycles such as traffic, incline starts and turning.

1.2.2 Previous Work on Fuel Consumption Modelling and Reduction

Vehicle fuel consumption depends on a multitude of factors that can vary significantly from vehicle to vehicle. These factors can range from the engine size, wheel specifications, aerodynamic properties, load carried, route driven and driver skill. For this reason, standardising the study to a single truck thus keeping many variables constant is necessary to ensure consistency of results when comparing the performance of different drive trains.

Previous research was conducted by Yacoob, alongside Kienhoffer, studied the fuel consumption implications of varying base parameters such as the drag, rolling resistance and weight reduction on fuel consumption [10]. A truck presented by Genta was used as the basis for Yacoob's work and is thus deemed an appropriate model to base the current study on [11]. The truck used is shown in Figure 1 and has the gearbox characteristics presented in Table 2.

The truck under consideration is used for long haul, heavy duty logistics operations. The payload has a mass of 32000kg and the truck itself has a mass of 7150kg.

The internal combustion engine used by Genta does not have appropriate data that can be used when modelling. Specifically, the specific fuel consumption data as a function of torque and rpm. Additionally, most manufacturers do not make the performance specifications of their engines available to the public. Guzella provides a novel way to create a generic fuel consumption map that only depends on the torque and angular velocity (i.e mechanical power) demanded by the engine. An example of this is shown in Figure 13. This formulation of the fuel map is not an entirely accurate representation as other factors can contribute to the fuel consumption map such as the friction between components, the exact number of pistons and the wear and tear of engine components. These factors are deemed negligible in this study.

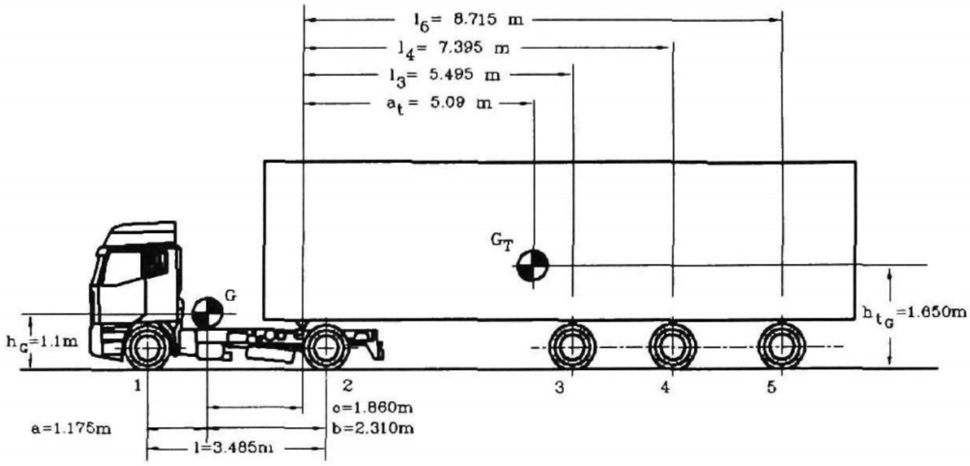


Figure 1: Semi truck trailer developed by Genta [11]

Table 2: Gearbox and differential gear ratios and efficiencies [11]

Gear	**Gear Ratio**	**Gear Efficiency**
1	12.5	0.81
2	8.35	0.84
3	6.12	0.84
4	4.56	0.84
5	3.38	0.89
6	2.47	0.87
7	2.14	0.84
8	1.81	0.87
9	1.57	0.84
10	1.35	0.87
11	1.17	0.84
12	1.00	0.93
13	0.87	0.89
Differential	4.263	1.00

An internal combustion engine's overall efficiency typically varies, depending on a number of conditions. In this study it is deemed appropriate to keep the efficiency as a constant, which Khoobbakh et al found to be roughly 37% in their study on the effects of various types of diesel on the performance of a diesel engine [13].

1.2.3 Cost of fuel and electricity

The cost of fuel is one of the greatest expenses for trucking companies thus the recent price hikes have been of great contention as these costs tend to be offloaded onto the consumer [14]. According to the AA, a litre of diesel costs R14.33 at the time of writing [15]. This cost quickly adds up when running a fleet of vehicles that run on hundreds of litres of fuel for long haul trips.

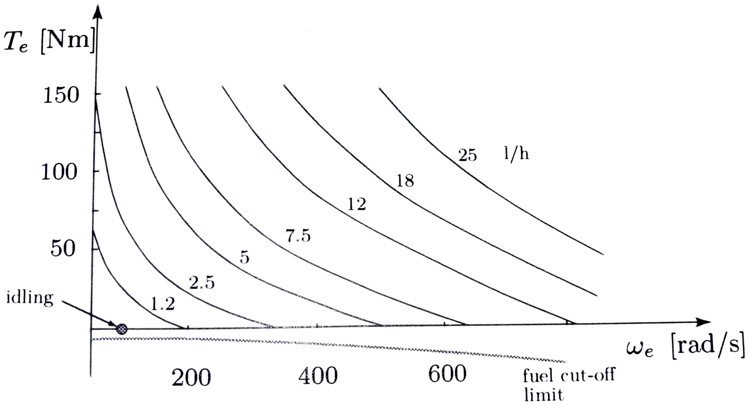


Figure 2: A generic fuel map of an internal combustion engine [12]

Although electricity costs have been rising in recent times, it is still significantly cheaper per unit than gasoline and diesel. According to Eskom, the major electricity generator and distributor in South Africa, it costs commercial businesses R1.50 per kWh [16]. Depending on the fuel consumption requirement of the engine, it can be seen that a fleet of electric or hybrid vehicles has the potential of being much cheaper to run.

1.2.4 Hybrid Drive Trains

Hybrid electric drive trains can yield between 30 and 50% of fuel savings and are great for stop-start applications such as city driving, as motors operate well under conditions of low speed and high torque [14, 17]. The benefit of this arrangement is allowing the internal combustion engien to operate at its peak effectiveness, which is at the high speeds and low torques.

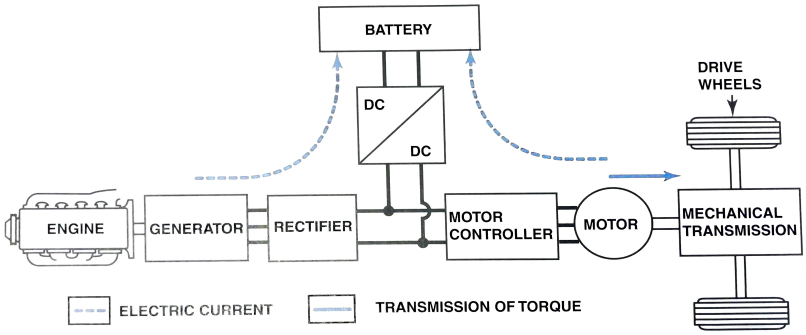
Hybrid electric drive trains typically have two configurations, namely series and parallel, which are shown schematically in Figure 3 [12, 17].

Combinantions of the two can also be used. These combination configurations can vary greatly thus are not considered in the current study. The former allows the electric motor to be the exclusive drive element, with the internal combustion engine only recharges the battery during the journey in order to ensure that the vehicle can travel uninterrupted until the destination is reached. The latter uses both the internal combustion engine and electric motor to drive the vehicle, while simultaneously allowing the IC engine to operate beyond its required operation point to recharge the battery [17].

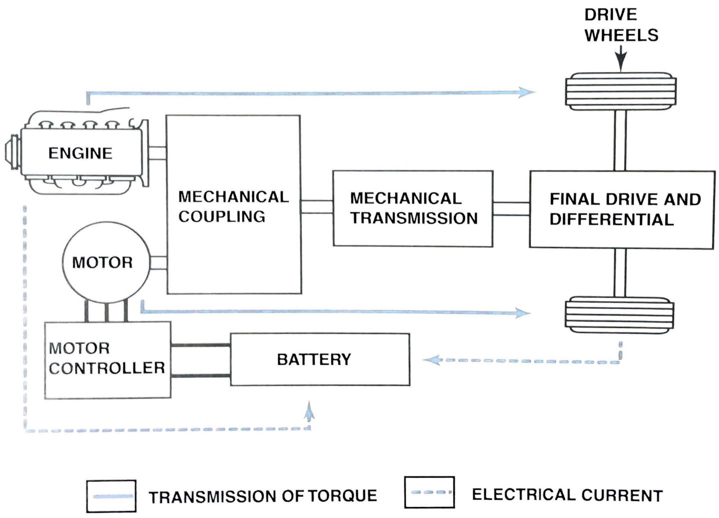
1.2.5 The Quasistatic Approach

The quasistatic approach is a causality based method of computing parameters of interest. Essentially it is a way of working "backwards" from the desired outputs back to the inputs [12].

In the case of a truck, the vehicle's behaviour is modelled for an instantaneous time h, over which its behaviour is constant given the inputs. At time $h+1$ the vehicles behaviour is computed for the



(a) Series



(b) Parallel

Figure 3: Hybrid Electric Drive Train Configurations [17]

inputs at that particular time step. In order to make the model more realistic, a smaller sample time can be used, however at some point there is a trade off between accuracy and computing time. This trade off is problem specific and must be carefully considered on a case by case basis.

2 OBJECTIVES

The current study aims to fulfill the following objectives:

1. Determine the reduction in fuel consumption, costs and CO_2 emissions when using the series and parallel hybrid drive train configurations for various drive cycles, including that proposed by Yacoob in 2018 [10].
2. Create a control logic and transmission that can achieve objective 1 while maintaining the speed requirements of the drive cycle.

3 APPARATUS

Matlab R2018b v9.5.0.1049112 is used in this study. Additional installations and are as follow:

- Simulink 9.2 (R2018b)
- Stateflow 9.2 (R2018b)
- DSP Toolbox 9.2 (R2018b)

Stateflow is a graphical language that makes use of state transition diagrams, flow charts, state transition tables and truth tables [18]. Use of this extension makes it more efficient to model and debug elements that have clearly defined states and transitions between them, such as gear shifts without the need for nested loops within a Matlab script. At the time of writing, Stateflow can be found in the Add-Ons section on the "Home" tab in Matlab.

The DSP System Toolbox simply adds signal handling capabilities to Simulink. These capabilities are useful when statistics blocks such as mean, variance, etc are required. At the time of writing, the DSP Toolbox can also be found in the Add-Ons section on the "Home" tab in Matlab.

Additional Simulink libraries are required for the models developed. These additional libraries are as follow:

- Powertrain Blockset by Mathworks
- Powertrain Blockset Drive Cycle Data extension

The powertrain blockset is a powerful library that allows for simple development of power train elements such as differentials, engines, batteries, motors, and even driver controllers for dynamic modelling of vehicle behaviour.

4 EXPERIMENTAL METHODOLOGY

Prediction of a semi-truck trailer is the primary focus of this study. The fuel consumption of a vehicle depends on a number of factors, such as the vehicle mass, aerodynamic characteristics, rolling resistance properties, transmission and engine characteristics, among other factors. For the purposes of the current study, many of these factors are modelled at a high level. The models are developed using Matlab and Simulink with a number of additional packages and libraries to simplify the development process section 3.

The quasistatic approach is the basis for the model development phase and is presented by Guzzella and Sciarretta [12] for a two axle passenger vehicle. Broadly speaking, this is a multi-input-multi-output (MIMO) system with the drving profile as the input, namely the velocity, acceleration and road grade. The outputs are the fuel and electricity consumption over the duration of the drive cycle.

The quasistatic approach is a causality approach that assumes that the truck and its subsystems are able to fulfill the torque and power demands of the drive cycle. This is not the most physcally accurate approach to use when trying to determine dynamic behaviour of the vehicle, especially when considering velocity reduction when climbing an incline. However, for the purposes of determining fuel consumption behaviour, this approach can give a good first approximation without any need for complex dynamic behaviour.

The quasistatic models are subdivided into a number of key subsystems, namely the drive cycle, truck dynamic behaviour, transmission system, internal combustion engine, electric motor, battery pack and power link [12]. Each of these subsystems can independently be modified in order to achieve more realistic results, given the limitations of the quasistatic approach.

Once the conventional IC, series and parallel drivetrain models are developed, their fuel and electricity consumption can be compared for a number of different initial conditions and drive cycles. The conventional IC engine model is used as the control for these comparisons and is validated through literature and the work of Yacoob [10].

The data that is analysed on is the fuel consumption, CO_2 emission and electricity consumption of each drive train. Each configuration is then compared and conclusions are then drawn in order to fulful the objectives set out in section 2.

5 MODELLING AND SIMULATION

The model developed for further study is a combination of components and parameters from various sources due to the lack of information available from individual manufacturers on the entire specification of their trucks. The engine, truck, motor and batteries are all from different manufacturers. The model is designed in a way that allows for easy variation of parameters to test for more complete drive trains.

The modelling of the drive trains focuses on three primary configurations, namely the conventional internal combustion engine, series hybrid and parallel hybrid. These three models and their subsystems are detailed further in the following section. The Matlab script used to run this program can be found in Appendix C.

5.1 Drive Train Assembly

5.1.1 Conventional Internal Combustion Engine (ICE) Model

The ICE is modelled as a quasistatic system as shown in Figure 4. The velocity profile is the input and the fuel consumed is the output. The conventional IC engine is used as the control state of this study on each of the drive cycles.

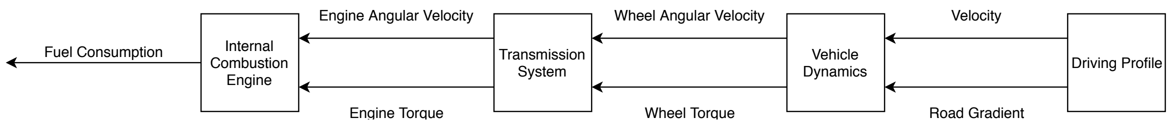


Figure 4: Quasistatic Internal Combustion Engine block diagram [12]

5.1.2 Series Hybrid Model

The series drive train is modelled as a quasistatic system as shown in Figure 5. Similar to the conventional ICE, the the fuel consumption is the output to an input of the drive cycle. An additional output of the electrical energy consumed is given in order to compare to the final drive train configuration.

Essentially, the motor is the exclusive source of drive power while the ICE is used as a method of recharging the battery on demand throughout the vehicle's journey. The engine only ever operates at its peak torque when recharging, as this is one of its most efficient modes of operation.

5.1.3 Parallel Hybrid Model

The final drive train under cosideration is the parallel configuration, shown schematically in Figure 6. The inputs and outputs are the same as those for the conventional and series configurations.

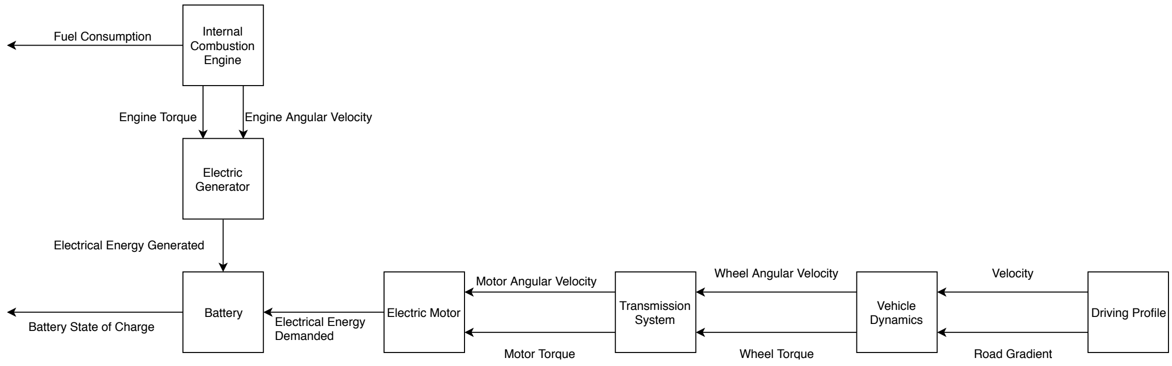


Figure 5: Quasistatic Series Hybrid Drive Train block diagram [12]

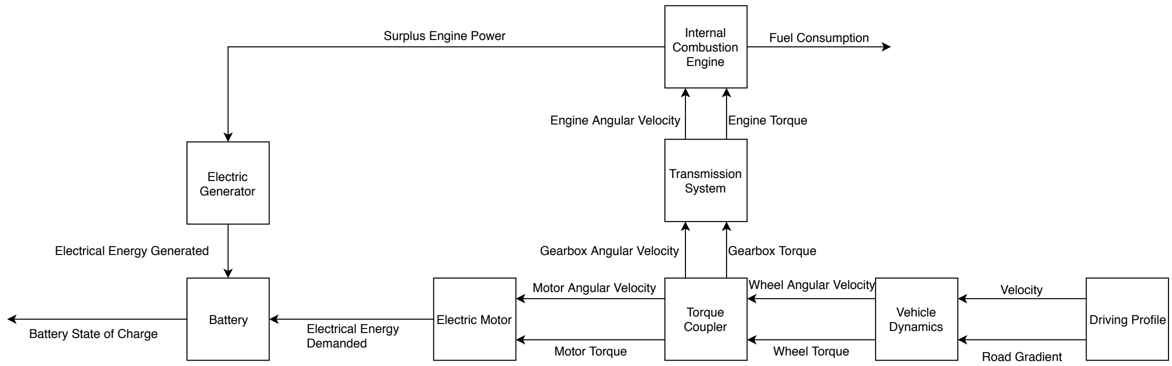


Figure 6: Quasistatic Parallel Hybrid Drive Train block diagram [12]

The motor and ICE both drive the vehicle in this configuration. Each of their contribution is dependent on the drive cycle demands, where each subsystem is designed to operate at its peak efficiency at all times. In the case of an ICE this is at high angular velocities and moderate torques and high torques and low angular velocities for the electric motor.

5.2 Subsystem Elements

The drivetrains of interest are divided into a number of subsystems. These subsystems are developed independently and allow for various levels of complexity, as required.

The complexity of each individual subsystem is modelled at a high level in this study, with more attention paid to their behaviour as part of the wider drive train. The complete drivetrains are then assembled in such a way that it is compatible for variation of test conditions, vehicle parameters, etc. Greater detail of the Matlab and Simulink models used in this study can be found in Appendix C.

5.2.1 Drive Cycle

Two types of drive cycles are used in this study to estimate the vehicle fuel consumption. The two drive cycles of interest are:

1. Heavy-Heavy Duty Diesel Truck (HHDDT) standard drive cycles as presented in subsubsection 1.2.1

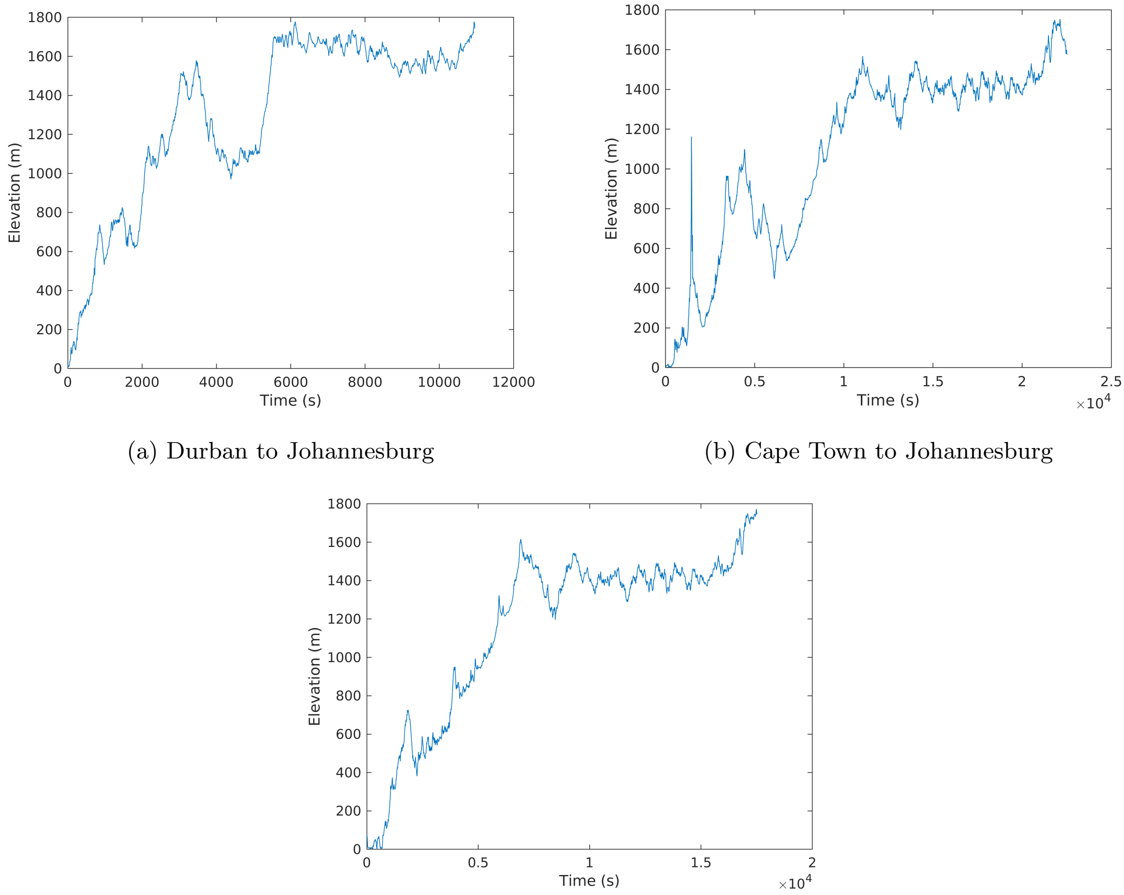
2. Constant velocity transit along a variable gradient route between two cities:

   (a) Durban to Johannesburg

   (b) Cape Town to Johannesburg

   (c) Port Elizabeth to Johannesburg

The logistics routes of interest represent trips from three of some of South Africa's busiest ports (Durban, Cape Town and Port Elizabeth) to the economic hub of the country in Johannesburg. The altitude variations of each route are generated with Doogal.co.uk and are shown in Figure 7. Appendix B details how the required data was extracted.



(a) Durban to Johannesburg

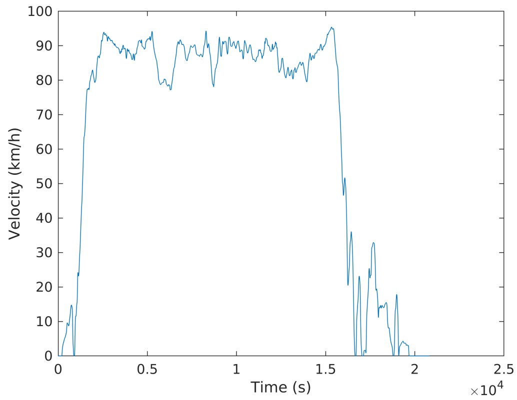
(b) Cape Town to Johannesburg

(c) Port Elizabeth to Johannesburg

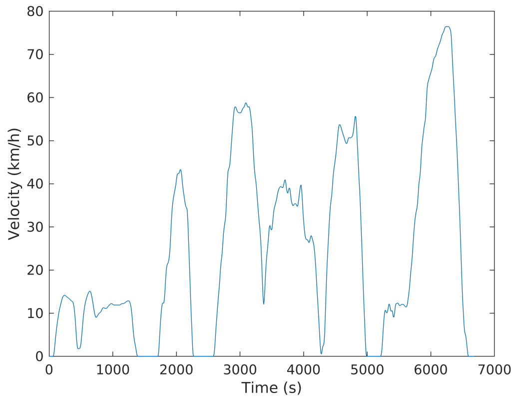
Figure 7: Route elevations between three major ports and the economic hub of South Africa [19]

The HHDDT standard drive cycles can be found in the Powertrain Drive Cycles blockset. The drive cycles used in this study are shown in Figure 8.

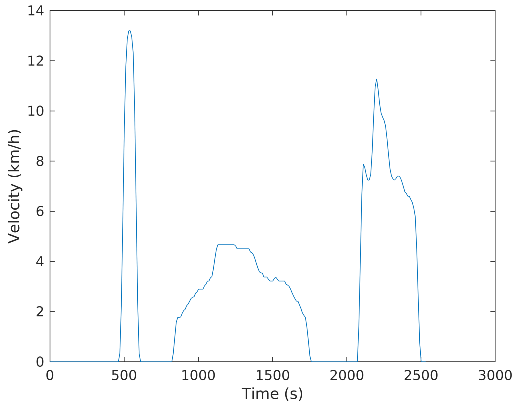
The route module has no inputs and outputs the road gradient, desired velocity and acceleration profiles.



(a) HHDDT Cruise



(b) HHDDT Transient



(c) HHDDT Creep

Figure 8: Heavy Heavy-Duty Diesel Truck Drive (HHDDT) cycles

5.2.2 Mechanical Force Demand

The truck's dynamic behaviour is modelled as longitudinal motion throughout its drive cycle, similar to the technique presented by Guzella [12]. This subsystem is commmon for all of the drive train configurations.

The force balance requires the rolling resistance, drag force, gravitational component and the torque applied at the wheels. The force balance in Figure 9 shows a generic way of determining the longitudinal loads on a vehicle. Equation 1 is the result of the application of Newton's laws of motion to this free body diagram. F_t, F_a, F_r and F_g are the applied force, aerodynamic drag force, rolling resistance force and the gravitational force component respectively. F_d are resistances that are assumed to be negligible.

$$T_w = r_w(m_e a + F_a + F_r + F_g) \tag{1}$$

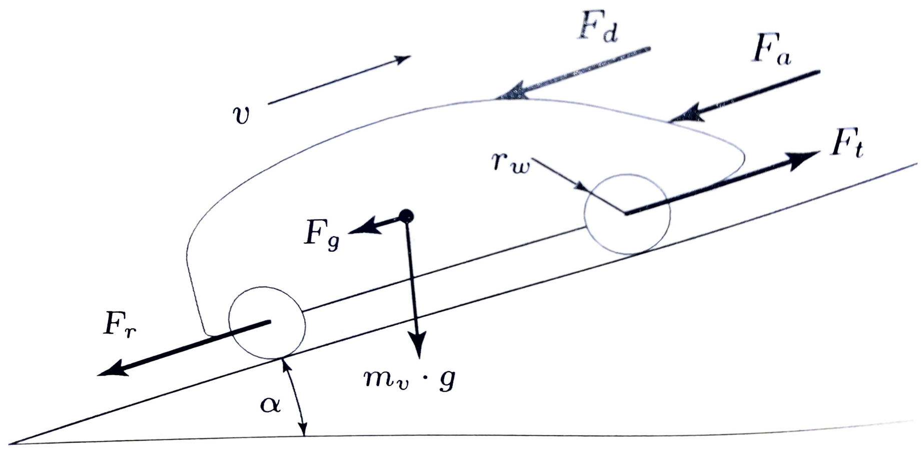


Figure 9: Free body diagram of a generic vehicle's longitudinal motion [12]

Expansion of each term in Equation 1 and applying the small angle approximation leads to Equation 2. The small angle approximation holds as the largest gradient expected on any trip is roughly 0.22rad.

$$T_w = r_w \left(m_e a + \frac{1}{2}\rho_a A_f V^2 C_d + m_e g C_r + m_e g \alpha \right) \tag{2}$$

The variables used in Equation 2 are as follow:

- T_w is the applied torque at the wheels $[N \cdot m]$
- r_w is the wheel radius $[m]$
- ρ_a is the air density at the truck's current altitude $[kg/m^3]$
- A_f is the frontal area of the truck $[m^2]$
- V is the velocity of the truck $[m/s]$
- C_d is the longitudinal drag coefficient $[-]$
- m_e is the equivalent mass of the vehicle $[kg]$
- C_r is the net average rolling resistance coefficient of the vehicle wheels $[-]$
- g is the gravitational acceleration which is assumed as $9.81 m/s$ for this study
- α is the gradient of the road being traversed $[rad]$

The equivalent mass of the vehicle (m_e) takes the inertia of rotational loads into consideration, which create fictitious d'Alembert forces. D'Alembert's principle fundamentally reduces these inertias from dynamic quantities to static ones [20].

The equivelent mass is determined by Equation 3 [12], where m_v is the vehicle's mass and m_r is the equivalent mass of the rotating components, defined in Equation 4. The subscripts w and e represent the wheel and engine respectively while Θ, γ and r_w are the moments of inertia, gear ratio and wheel radius respectively.

$$m_e = m_v + m_r \tag{3}$$

$$m_r = \frac{1}{r_w^2} \cdot \Theta_w + \frac{\gamma^2}{r_w^2} \cdot \Theta_e \tag{4}$$

The air density used in Equation 2 varies with the altitude as derived by Yacoob, following the linear relation in Equation 5, where z is the altitude in meters [10].

$$\rho_a = -1.4497 \times 10^{-4} z + 1.225 \tag{5}$$

Given that the model developed is a causality based quasistatic model, the inputs for this module are the velocity, air density, current gear ratio, acceleration and road grade. The wheel torque, angular velocity and accelleration are the outputs of this module.

The Simulink vehicle subsystem is shown in Figure 10. This subsystem encapsulates the inputs and outputs shown in **??**.

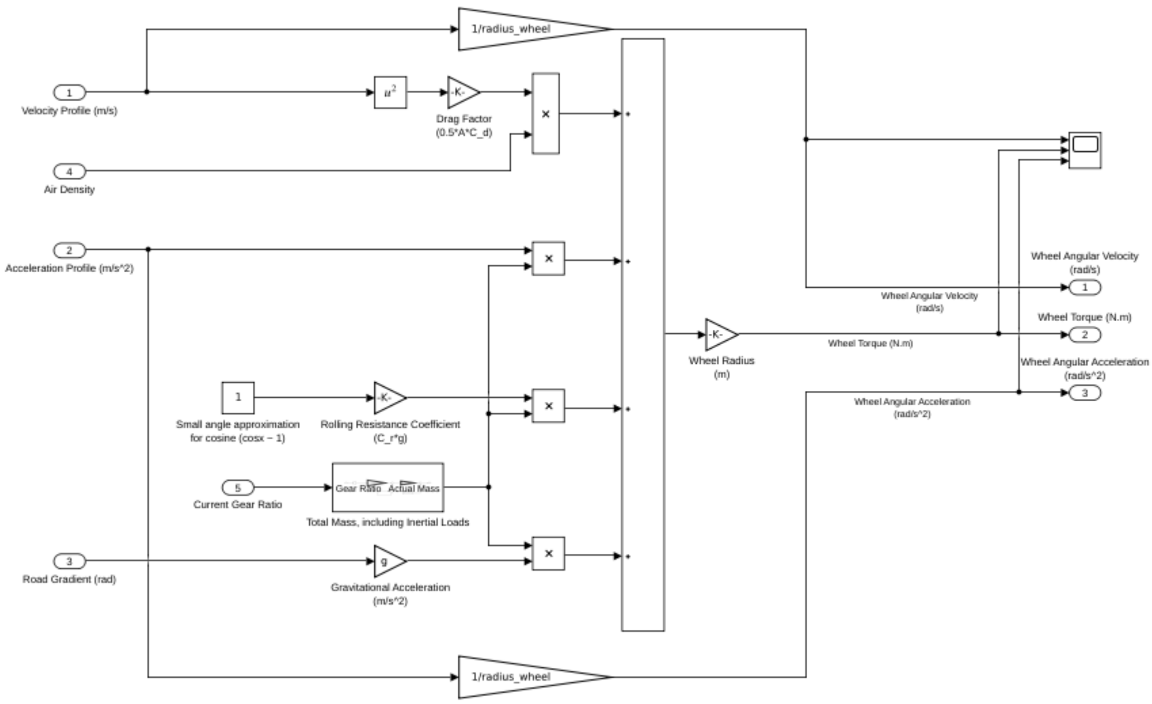


Figure 10: Vehicle Simulink Subsystem

5.2.3 Transmission

The vehicle's transmission system varies slightly for each drive train. The common feature in all of the transmission systems is a differential and 13 speed gearbox. The series drivetrain does not have a transmission system at all and similarly the motor in the parallel drive train connects directly to the drive shaft via the differential, as electric motors are able to generate high torques at low speeds unlike internal combustion engines.

The gearbox data used in this model is the same as that presented in subsubsection 1.2.2 (Table 2). Since the current study is based on a causality model, the differential simply reduces the torque when going from the wheels to the gearbox while simultaneously increasing the angular velocity and acceleration. The differential gear ratio is constant and thus requires no special analysis.

The gearbox model is more complex than the differential as it has 13 possible states (gear ratios) that depend on the driving conditions that the truck experiences throughout its drive cycle. In order to develop the appropriate gear change logic, it is deemed fit to use Stateflow, which is a graphical programming language that allows for simple debugging and formulation of various types of logic.

The gear change logic is done such that there is a gear change up if the engine angular velocity goes above a predetermined threshold. The gear shift down has two possible conditions; either the engine angular velocity must dip below a predetermined lower threshold or the torque demanded of the engine exceeds the maximum possible torque the engine can deliver.

Techniques that can potentially increase fuel economy such as gear skipping are omitted from this study in order to reduce the number of variables in the system. The gearshift logic is shown as a Stateflow chart in **??**.

The mechanical transmission subsystem is shown in Figure 11. The inputs are the wheel torque, angular velocity and acceleration. The outputs are the outlet torque, angular velocity and accelerations of the internal combustion engine.

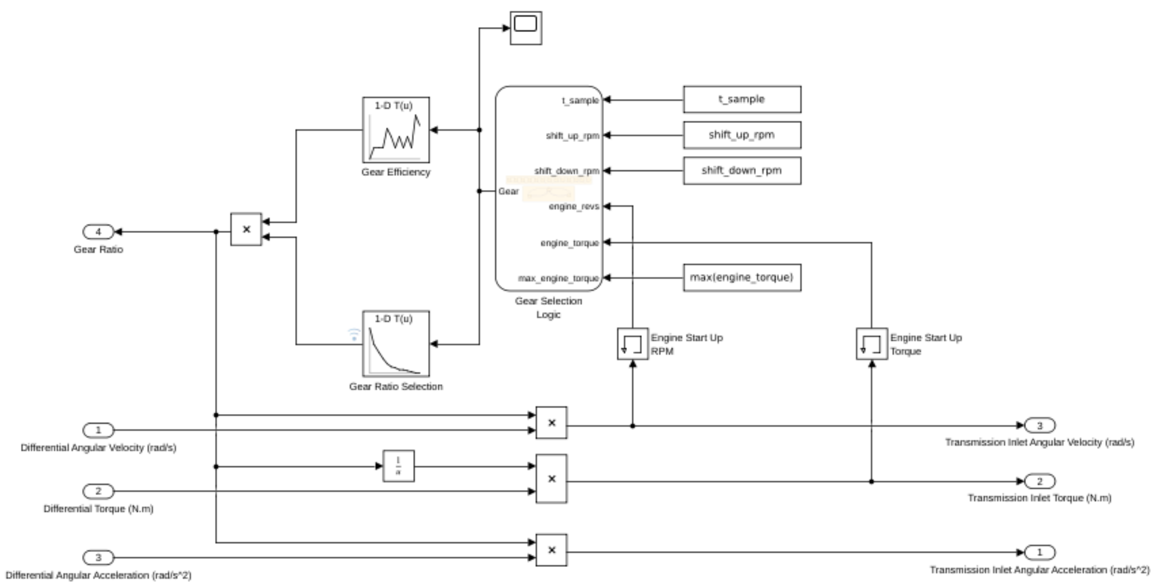
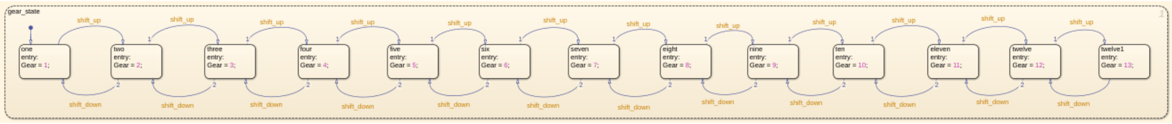
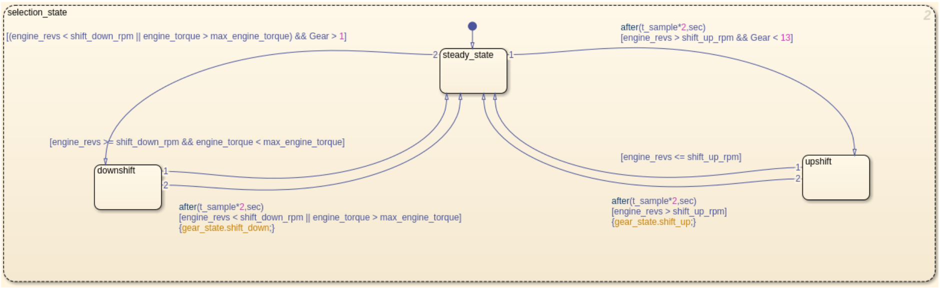


Figure 11: Simulink model of the mechanical transmission subsystem



(a) Gear state



(b) Selection state

Figure 12: Stateflow gear shift logic

5.2.4 Internal Combustion Engine

The engine model developed is a simple conversion of the torque-angular velocity curve into a map of the power demand at each torque and rpm value, such as that presented in subsubsection 1.2.2 (Figure 13). In order to create a generic fuel consumption map of this nature, the mechanical power demanded of the engine is calculated by Equation 6 where P_e, T_e and ω_e are the mechanical power, torque and angular velocity demanded by the engine.

$$P_e = T_e \omega_e \tag{6}$$

In order to determine the fuel consumption of the engine a correlation between the fuel energy available and the power demanded is established. The relationship between these quantities can be made by the overall efficiency relation in Equation 7, where η_{th} and P_c are the engine overall efficiency and fuel available power respectively.

$$\eta_{th} = \frac{P_e}{P_c} \tag{7}$$

The engine's thermal efficiency is assumed to be constant as presented in Table 3, which allows for the available fuel power to be determined. The fuel mass flow rate is defined by Guzella by Equation 8 [12], where H_l is the lower heating value of the fuel used, which is diesel in this study.

$$\dot{m}_{fuel} = \frac{P_c}{H_l} \tag{8}$$

The mass flow rate can be converted into a volumetric flow rate by applying the mass-density relation

Table 3: Fuel and engine characteristics as presented by Khoobbakht et al [13]

Engine thermal efficiency (%)	37
Fuel density (kg/m^3)	837
Fuel lower heating value (MJ/kg)	42.72

shown in Equation 9, where $\dot{V}_{fuel}$ and ρ_{fuel} are the fuel volumetric flow rate and density respectively.

$$\dot{V}_{fuel} = \frac{\dot{m}_{fuel}}{\rho_{fuel}} \tag{9}$$

This volumetric flow rate can be related directly to the torque and angular velocity demanded by the engine by manupulating Equation 6 to Equation 9. Converting the volumetric flow rate from m^3/s to l/h requires a scaling of $3.6 \times 10^6 l/m^3$, leading to a volumetric flow rate equation that can be related to a given torque and angular velocity pair in Equation 10.

$$\dot{V}_{fuel} = \frac{3.6 \times 10^6}{\eta_{th} H_l \rho_{fuel}} \vec{T}_e \cdot \vec{\omega}_e \tag{10}$$

Plotting the fuel map created by Equation 10 leads to Figure 13. The contours in this figure represent the expected fuel consumption in litres per hour, which is a generic formulation as described in subsubsection 1.2.2. The engine data used as for this study is the Mack Trucks MP8 505HP engine,

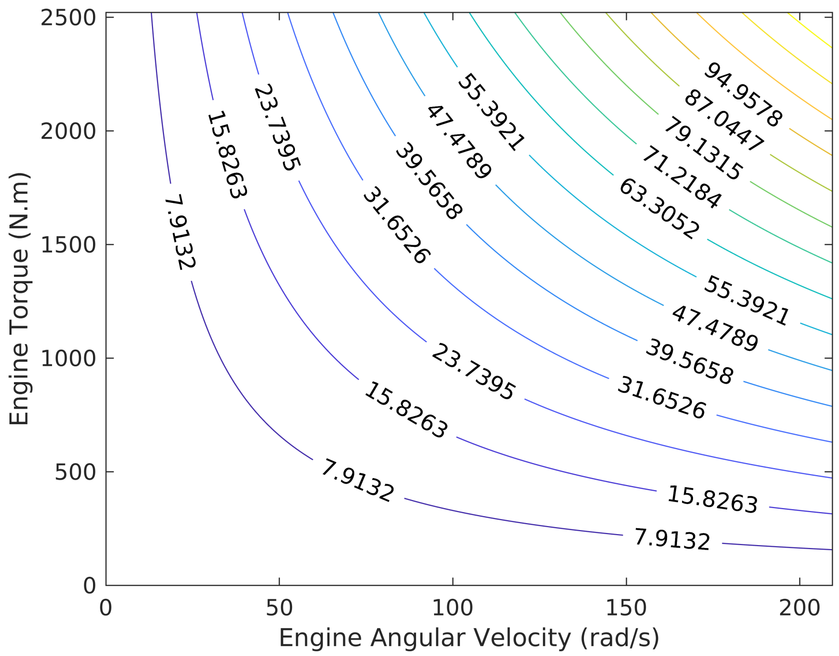


Figure 13: Fuel consumption contours in litres per hour as generated by Equation 10

the torque-rpm graph for which is shown in Figure 14. This is a 6 cylinder, in line diesel injection engine that idles at approximately 600rpm. At a low power demands the efficiency is expected to reduce significantly thus could lead to deviations from the actual fuel consumption [13]. For the purposes of this study the lower limit of the engine performance is kept at the idle condition in order to ensure that the reduction in efficiency is not as pertinent.

All three configurations are tested with the 505HP as the baseline. The hybrid models are tested with the Mack MP8 Econodyne 445HP and 415HP engines in order to further reduce the engine fuel consumption.

The engine subsystem has inputs of demanded angular velocity and torque and outputs the fuel consumption in litres per hour and in total litres consumed throughout the drive cycle. The complete Simulink subsystem of the internal combustion engine is shown in Figure 15.

It must be noted that the internal combustion engine model varies slightly from one drive train to another as its operation is not the same in each case. In the series model the IC engine only has

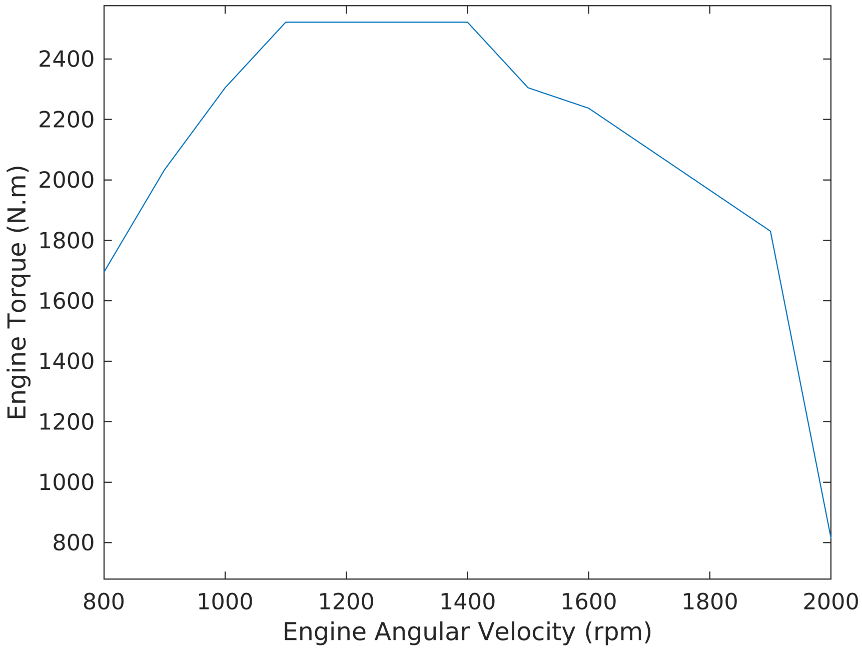


Figure 14: Torque vs rpm graph for the Mack Trucks MP8 Econodyne 505HP diesel injection engine [21]

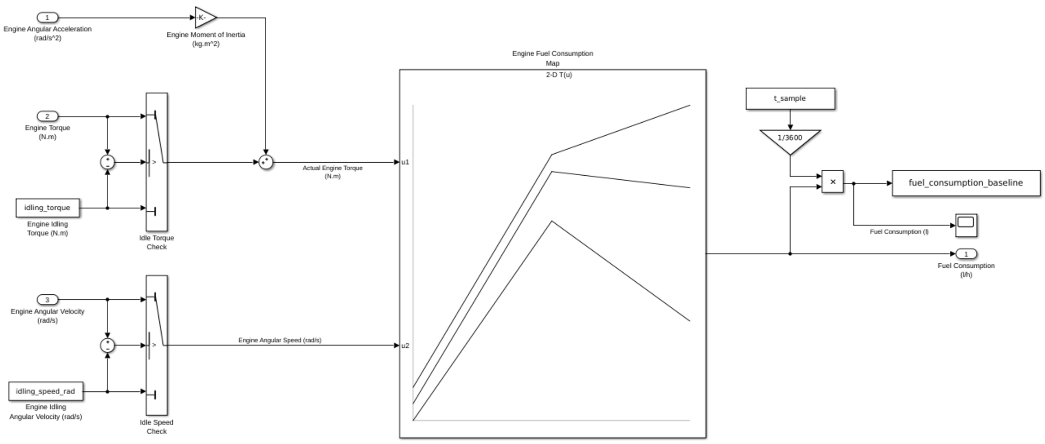


Figure 15: Simulink model of the conventional drive train's ICE subsystem

one operating state, at its peak performance (i.e maximum torque condition) when commanded to charge the battery pack. In the parallel case there are a multitude of different operating conditions, depending on the drive cycle demands in a simialar way to the conventional ICE. When the battery needs to be recharged rapidly the engine operates at its peak performance, fulfilling the demands of the drive cycle and diverting the excess energy to the generator. The series and parallel internal combustion engines are shown in Figure 16 and Figure 17 respectively.

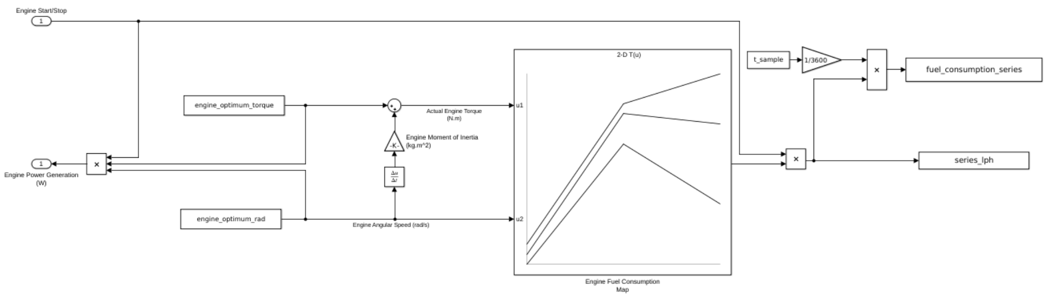


Figure 16: Simulink model of the series drive train's ICE subsystem

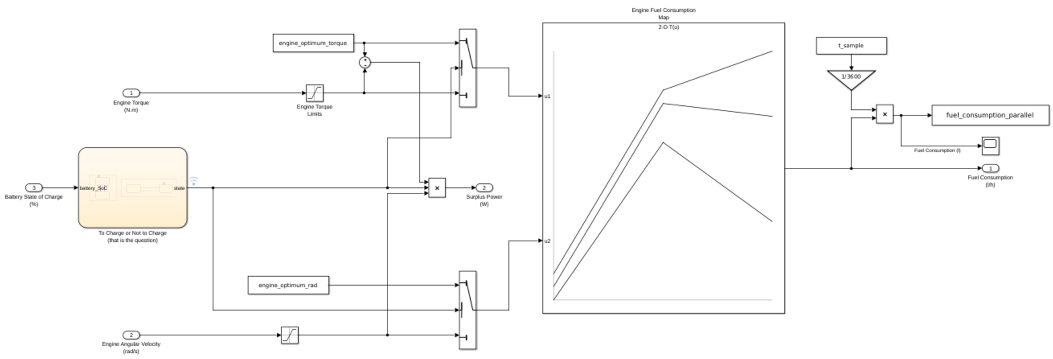


Figure 17: Simulink model of the parallel drive train's ICE subsystem

5.2.5 Electric Motor and Generator

The electric motor and generator are both modelled as alternating current (AC) machines. These machines are not accurately modelled due to the limited information on motors and generators that are used in automotive applications. The AC machines are modelled as simple power converters that can then be used to size the appropriate motor or generator for the vehicle.

The AC Induction Machine (ACIM) has inputs of the torque and angular velocity at the gearbox inlet. The ACIM converts these inputs into a power by Equation 11 and Equation 12 for the motor and generator respectively.

$$P_m = \frac{T_m \cdot \omega_m}{\eta_m}, \qquad T_m \cdot \omega_m > 0 \tag{11}$$

$$P_m = T_m \cdot \omega_m \cdot \eta_m, \qquad T_m \cdot \omega_m < 0 \tag{12}$$

These equations are implemented in tandem as a negative torque would tend to reduce velocity (i.e. braking) while a positive torque signifies an increase in velocity (i.e. throttle application). When in motor mode the ACIM consumes battery power, while when in generator mode the ACIM produces battery electrical power, which corresponds to the regenerative braking condition.

These systems are much more complex than the model that is presented, however the results from this subsystem can be used to size the appropriate ACIM in future works. The Simulink model of the ACIM is shown in Figure 18.

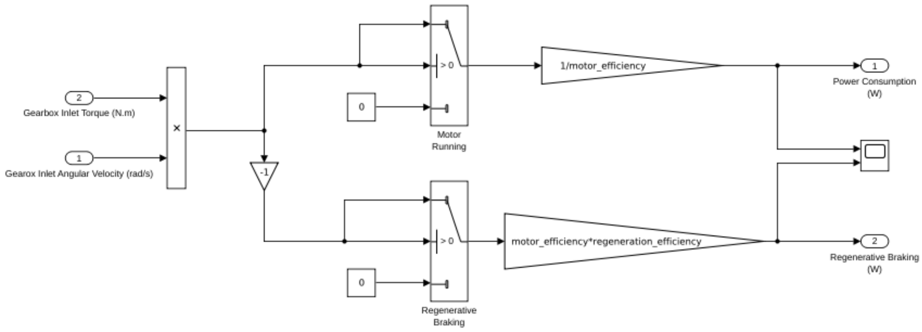


Figure 18: Simulink subsystem representing the alternating current induction machine

When in either of the hybrid configurations a dedicated generator is connected to the internal combustion engine such that the drive shaft motor can drive the vehicle completely independently of the engine's task of recharging the battery. The ACIM that is connected to the drive shaft purely recharges the battery by regenerative braking.

5.2.6 Battery Pack

The battery pack is divided into a number of submodules. In quasistatic analysis the battery subsystem has inputs of the power demand from the electric motor and the power regenerated throught braking and the internal combustion engine's contribution. The only output of the battery subsystem is the battery's state of charge (SoC), which is then used to regulate the operation of other subsystems in the vehicle. The battery has many submodules in order to meet the current limitation demands of individual battery modules.

In this study battery modules sourced from Enedel are used. The specifications of each battery module are given in Table 4. From this data, it can be deduced that the maximum power carrying capabilities (either charging or discharging) are $22.88kW$. Taking into consideration the maximum demanded power of the vehicle is roughly $350kW$, it can be concluded that approximately 15 battery modules are required in either drive train. This adjustment to the battery subsystem allows for much longer discharge times in simulations and would prevent real batteries from short circuiting.

Table 4: Battery make and model [22]

Maximum Current (A)	160
Nominal Voltage (V)	143
Nominal Charge (kWh)	24.5

The battery modelled for this study simply integrates the net power dissipated over time, which yields the battery's energy usage over time. This is then divided by the battery's energy capacity, which then yields the battery module's state of charge as shown in Equation 13. P_{net}, ζ and $E_{battery}$ are the net power consumed by the electric motor in kW, battery state of charge and the battery's nominal energy in kWh.

$$\zeta(t) = \frac{0.001}{3600} \cdot \frac{1}{E_{battery}} \int P_{net}(t)dt \tag{13}$$

The battery module Simulink block diagram is shown in Figure 19 while the complete battery pack is shown in Figure 20.

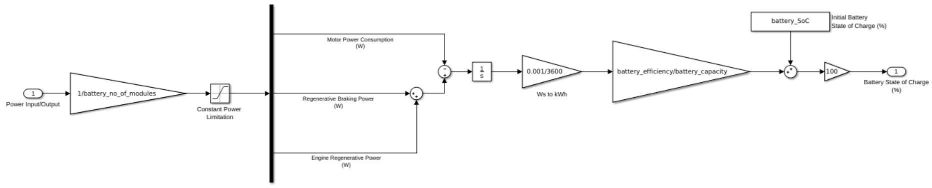


Figure 19: Simulink model of the battery module used in the battery pack subsystem

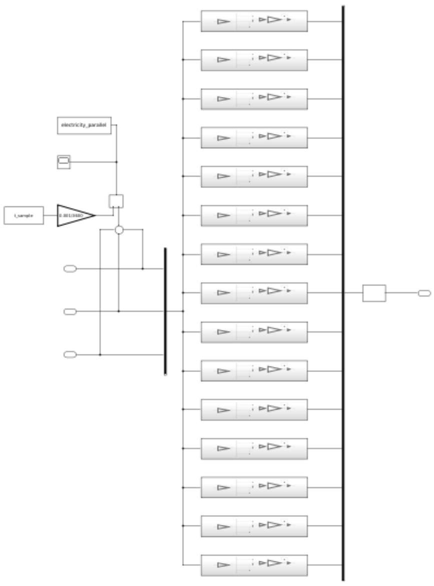


Figure 20: Simulink model of the battery pack used in the hybrid drive train models

5.2.7 Battery Recharge Controller

A simple controller activates the internal combustion engine to rapidly drive the generator when the battery's state of charge is below a predetermined amount and stops the engine when the battery has been satisfactorily recharged. This controller is designed with Stateflow and is shown in Figure 21 and Figure 22.

Halderman and Martin state that hybrid vehicle batteries tend to overhead when under or over charged. These conditions are 20% and 80% state of charge respectively [17].Given this information it is seen necessary to begin engine recharging at 25% and cut off all recharging, including regenerative braking, when the battery state of charge is 79%.

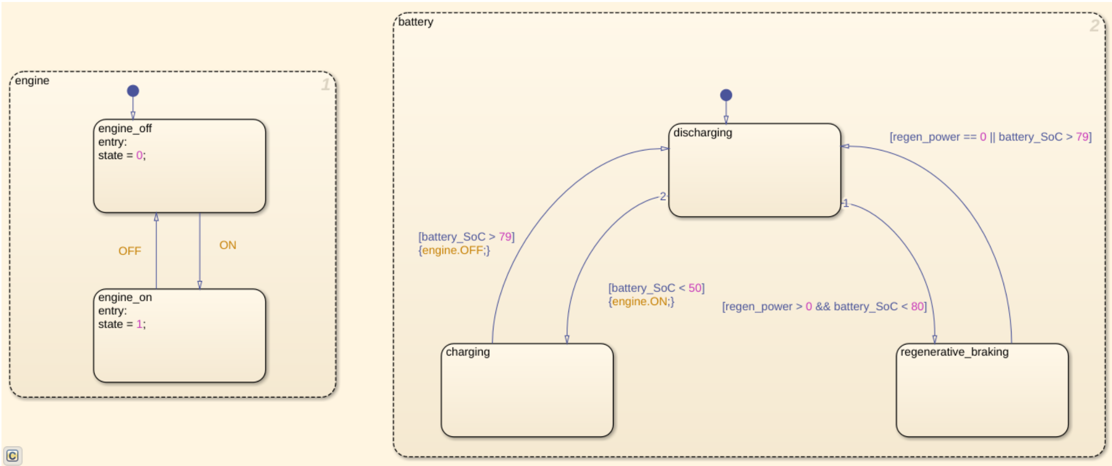


Figure 21: Engine controller for the series drive train configuration

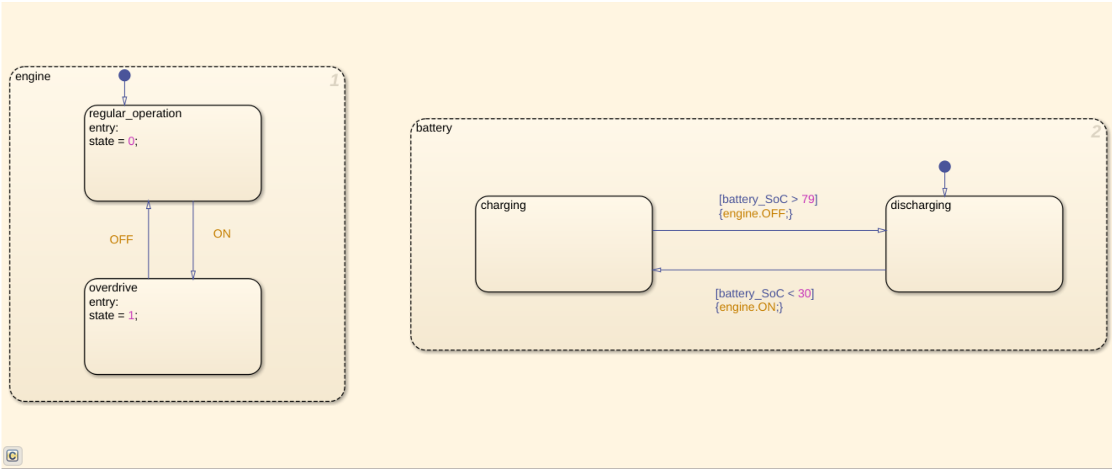


Figure 22: Engine controller for the parallel drive train configuration

5.2.8 Torque Coupler

The parallel drive train requires a torque splitter that uses the internal combustion engine and electric motor in differing percentages, depending on the drive cycle conditions. The torque splitter developed in this study is simply a controller that focuses on the drive cycle demands, with no consideration of the mechanical functionality of this subsystem.

A novel approach to splitting the drive shaft torque between the motor and engine is developed along with the torque coupler presented by Guzella and Sciarretta [12]. The approach uses a power split ratio defined by Equation 14, where u, P_m and P_{driven} are the power split ratio, motor power and drive shaft power respectively. It can be seen that a power split ratio of 1 corresponds to full electric drive while 0 corresponds to full internal combustion engine drive.

$$u = \frac{P_m}{P_{driven}} \tag{14}$$

The electric motor is used for greater torque demands, typically at lower speeds while the internal combustion engine is used for more steady, low torque portions of the drive cycle. These uses of the two drive elements maximises their operating ranges. The torque split is defined by Equation 15 and

Equation 16 for the motor and engine respectively, as defined by Guzella and Sciarretta [12].

$$T_m = \frac{u}{\gamma_m} T_{drive} \tag{15}$$

$$T_e = \frac{1-u}{\gamma_e} T_{drive} \tag{16}$$

In this study the motor has no mechanical transmission before the drive shaft, as such γ_m is unity. γ_e is the mechanical transmission of the gearbox and operates as with the conventional internal combustion engine.

The power split ratio is determined by creating two straight line graphs with u as the output and velocity and road gradient as the inputs. This relation creates a surface defined by Equation 17. Complete development of this relationship is presented in Appendix A.

$$u(\alpha, v) = \frac{1}{\alpha_{max}}\alpha - \frac{1}{v_B - v_A}v + \frac{v_B}{v_B - v_A} \tag{17}$$

v_B and v_A are the cruise velocity and maximum velocity required of the motor respectively. The relationship developed describes the power split as a function only of the velocity and grade. Plotting this equation for varying inputs leads to the surface shown in Figure 23.

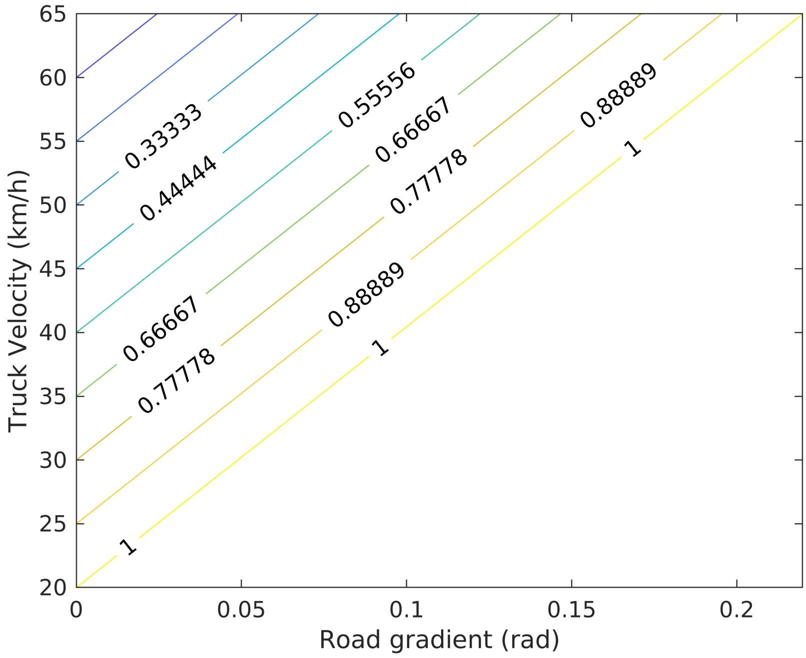


Figure 23: Contours desctibing the power split ratio as a function of the velocity (v) and the road gradient (α)

5.3 Simulation Parameters

The Simulink simulations are run at fixed time-step of 0.1 seconds with an unconstrained periodic sample time. The Euler (ode1) solver, which is a first order of accuracy method, is selected for this application [23]. The logic behind this selection comes from following the flow chart shown in Figure 24.

There are no Simulink physical modelling components in the models developed. Additionally, there are no stiff equations present in the modelling phase. There is no precise definition for stiff equations available, however it is generally accepted that these are equations that cannot be solved with numerical methods or includes terms that can lead to solution instability unless the time step is very small [24].

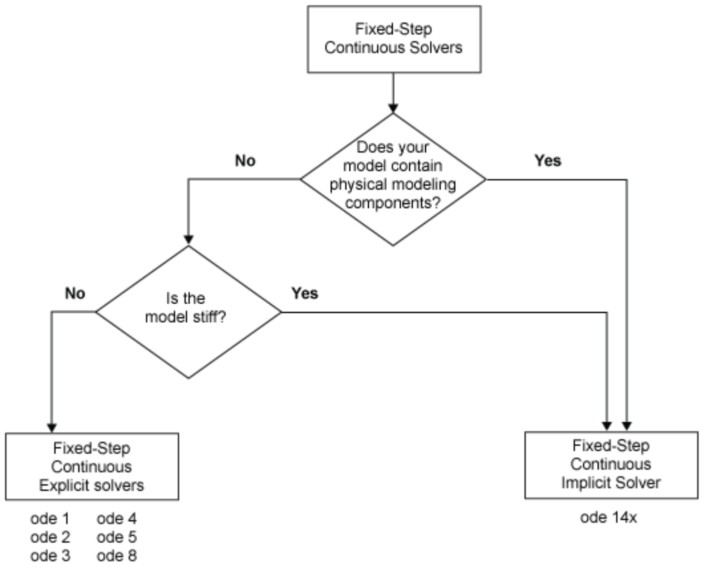


Figure 24: Flowchart detailing the logic flow when choosing a fixed time step solver [23]

A comparison between the results of the different fixed time step solvers (ode1 to 8) shows that there is no significant deviation in the fuel consumption results. The selection of the Euler method is due to the fact that only a first order of accuracy is required for the fuel consumption prediction model. If more realistic elements are added to the models such as detailed development of the required motor, internal combustion engine, etc are developed there may be scope to use more complex solvers and maybe even those of the variable step size type.

6 MODEL VALIDATION

The conventional IC engine model is validated with respect to the model developed by Yacoob on a journey between Durban and Johannesburg along the N3 highway [10]. The results of interest are the fuel consumption per 100km on the logistics operation for differing 'Green Truck' vehicle modifications, namely the drag, rolling resistance and mass adjustments. These modifications are tested at average velocities ranging from 60km/h to 90km/h in 10km/h increments. The Pearson's correlation coefficient is used to determine the correlation between the results of the two studies.

Figure 25 shows a scatter plot of the data generated by the current study's IC engine model and that of Yacoob for various configurations at various velocities. A Pearson's correlation coefficient of 0.6784 is found, which suggests a strong positive correlation between the two sets of data. This finding confirms the validity of the model.

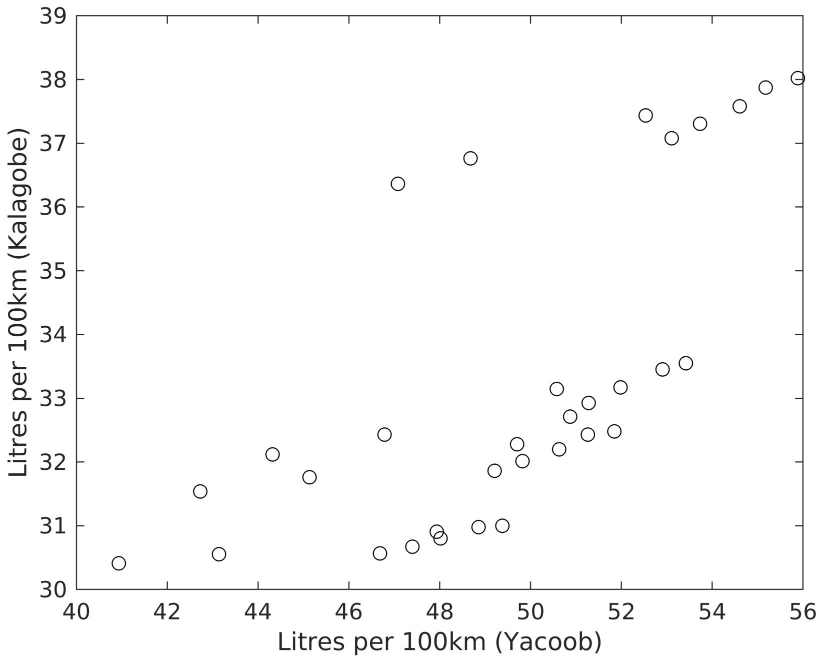


Figure 25: A scatter plot used to determine the correlation between the data produced in this study and the work of Yacoob [10]

The model developed in this study closely matches the average semi-truck trailer fuel consumption of 36.75 litres per 100km eluded to by ZumMallen [6], suggesting that the fuel consumption determined by Yacoob deviates by roughly +26% while that of this paper deviates by about -10%.

It is identified Yacoob's model does not take idling fuel consumption into consideration due to the fact that the fuel consumption of the vehicle is inherintly linked to the throttle application. The application of throttle is done incrementally as required as a proportional controller but due to the small simulation time steps (0.1 seconds) there is a high probability of overshooting the throttle thus consuming more fuel than expected. Additionally, the fuel consumption map used is not entirely accurate, which can lead to poor predictions of the actual fuel consumption of the vehicle.

Modelling the drive train as a quasistatic system neglects the effects of vehicle dynamics such as the inherent velocity variations when going up an incline. Neglecting these effects has the risk of underestimating the fuel consumption, as the engine may be working below its required performance to match the drive cycle under realistic conditions. In the case of the logistics operations between two cities, the route gradient is sampled as the input, independent of the exact distance covered. This leads to the distance and time of travel covered being underestimated, however, this deviation is deemed acceptable for the purposes of predicting the fuel consumption behaviour of the vehicle.

For the purposes of this analysis a deviation of 10% from the average expected fuel consumption of 36.75 litres per 100km is considered acceptable as there are many factors that affect that statistic and could exasperate or reduce this error, depending on the conditions. The results of these simulations must thus be carefully considered before any design decisions are made.

7 RESULTS AND DISCUSSION

A quasistatic representation of three drive trains is produced in this paper in order to determine the fuel consumption, greenhouse gas emission and, by implication, cost savings that can be achieved by hybridizing a conventional internal combustion engine drive train. The hybrid configurations under consideration are of the series and parallel nature as described in subsubsection 1.2.4.

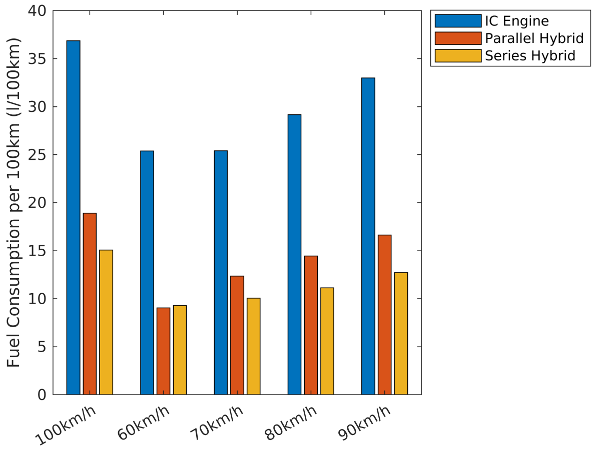
The quasistatic approach is selected for it simplicity of modelling and flexibility of alterations. Each subsystem is modelled as a stand alone subsystem in Simulink, systematically starting from the drive cycle, to the vehicle dynamics, transmission systems and finally the drive systems. This approach has allowed for systematic validation of each subsystem as part of the overall system throughout the modelling and simulation phases, reducing the risk of inherent quasistatic assumptions leading to model inaccuracies.

Although there are advantages to the quasistatic approach, it does have some notable drawbacks. The causality approach, which imposes a drive cycle on the vehicle and then working backwards to the drive train, does not lend itself to understanding how exactly the drive elements affect each other. For this reason, only one internal combustion engine is modelled for all of the simulations as downsizing the engine does not have a direct effect on the behaviour of the drive cycle. The key assumption at this stage is that the vehicle and all of its components can fulfill the loads demanded of them.

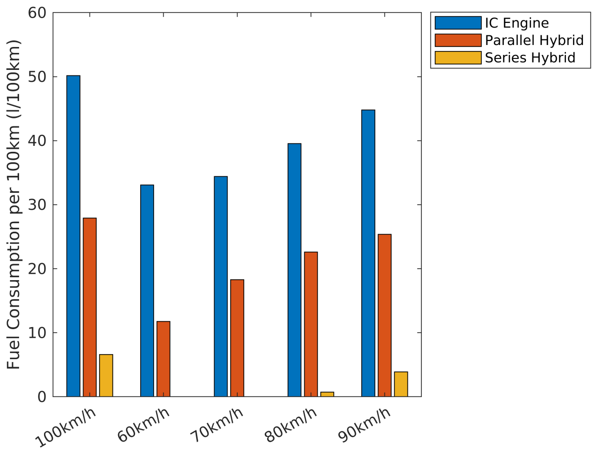
The motor drive element in the hybrid drive trains is modelled as a simple system that simply extracts or adds electrical energy to the battery pack. A controller monitors the battery via a generator as required. Modelling in this way does not allow for the load carrying capabilities of the motor to be accurately assessed, however, it does present an opportunity to have a first pass estimate for the design of an appropriate, realistic motor for the given drive the battery's state of charge then commands the engine to charge conditions.

Figure 26 shows results from simulating the truck model moving at constant velocity over routes of variable gradients between the port cities selected in subsubsection 5.2.1 and Johannesburg. Only the forward routes (i.e ports to Johannesburg) are considered for this study as this is when the most fuel is consumed due to the high altitude difference. The conventional IC engine is used as a baseline fuel consumption metric for all of the routes under investigation and it is found that the Durban to Johannesurg route consumes roughly 22 to 26% more fuel per 100km than the Cape Town and Port Elizabeth routes. This deviance can be attributed to the steep roads found in the KwaZulu-Natal inland region, which would almost certainly require greater power to climb. Even taking this deviance into account, the results for the internal combuston engine closely correlate with those presented by ZumMallen and Yacoob as determined in section 6 [6, 10].

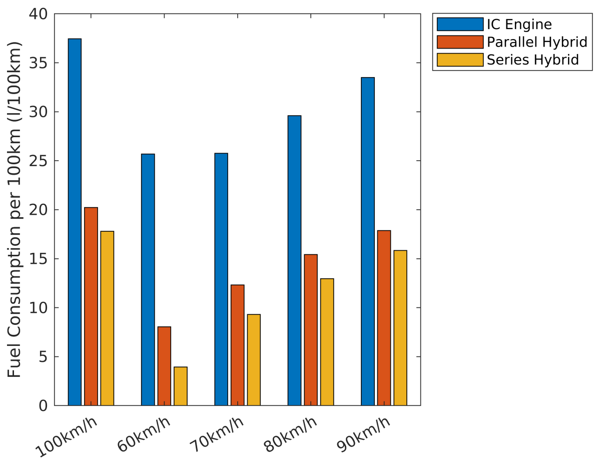
The fuel consumption rates in Figure 26 appear to increase exponentially, which can be attributed to the quadratic term in Equation 2 as all other equations in the modelling phase are linear. The quadratic nature of the fuel consumption cannot be taken as fact at higher speeds because dynamic effects would come into play in actual trucking applications. In a real trip the truck would struggle to maintain high speeds when going up an incline due to the extreme torque requirements. Conversely, going down inclines at high velocities with large loads is extremely hazardous as the vehicle would be difficult to control due to its high momentum.



(a) Cape Town to Johannesburg



(b) Durban to Johannesburg



(c) Port Elizabeth to Johannesburg

Figure 26: Fuel consumption in litres per 100km for the various drive trains on journeys between the major ports and economic hub of South Africa

The CO_2 emitted can be determined by multiplying the fuel consumption by 2.66kg per litre. The shape of the carbon emission graph would thus be the same as that shown in Figure 26, simply scaled up by a factor of 2.66 kg per litre. Using the average fuel consumption of heavy duty semi-trucks of approximately 36 litres per 100km, this translates to CO_2 emissions ranging from 87.78kg/100km to 133kg/100km for the conventional drive train proposed in this study.

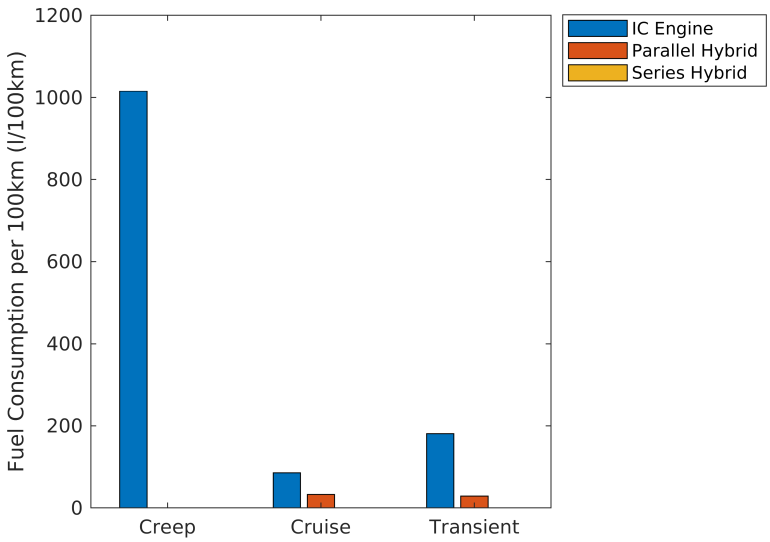
Introducing the parallel hybrid drive train reduces the fuel consumption by up to 50% for all of the routes as showwn in Figure 26. This reduction coincides with the fuel savings of 30 to 50% suggested by Whistler [14]. Halderman and Martin also state that a full hybrid is expected to achieve 30 to 50% fuel economy savings [17]. A full hybrid is one that incorporates idle stop regenerative braking and is able to propel the vehicle exclusively by the electric motor, much like the parallel hybrid that has been developed. Fuel economy savings would thus bring the truck to within the specified limit of 23 litres per 100km stated by the US EPA, as it would average about 21.2 litres per 100km across all velocities [25]. Due to the linear relationship between carbon emissions and fuel consumption, this translates to CO_2 emission savings of up to 43.89-66.5kg/100km.

The torque splitting logic used in the parallel model follows that which is described by Guzella and Sciaretta [12]. A torque split ratio dictates how much of the load is carried by the engine and motor with a ratio of 0 representing full load carrying by the former and 1 representing the latter. A linear equation that is related to the vehicle velocity and road gradient determines the torque split ratio that is used for the given driving conditions. The linear assumption applied to this controller leaves a lot of room for optimisation as it does not take into consideration acceleration, tire slip, engine start up and turning. Including these factors would lead to a control method that is more in tune with actual driving conditions.

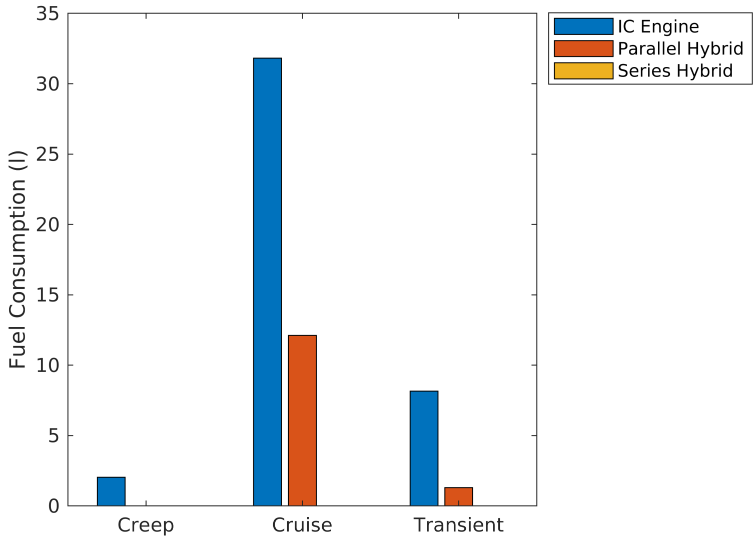
The series drive train presents the lowest fuel consumption characteristics of all three drive trains, having begun with a battery state of charge of 95%. It displays no fuel consumption on the trip from Durban to Johannesburg when travelling at 60km/h. For other trips the fuel consumption increases in a linear fashion, contradictory to the quadratic velocity term as seen in the case of the conventional engine. The engine only ever operates at a single torque and rpm when charging the battery. Furthermore, the battery depleats faster when travelling at greater velocities which necessitates a recharge sooner in the journey. This phenomenom explains the linear fashion of fuel consumption increment.

The fuel consumption statistics of the Heavy Heavy-Duty Diesel Truck drive cycles are presented in Figure 27. Each drive cycle tests the limits of the truck in differing ways, simulating a range of drive conditions.

The fuel economy of the conventional drive train is the best when on the cruise drive cycle and diminishes on the transient and creep cycles as shown in Figure 27a. This result shows the weakness of the quasistatic approach to modelling dynamic systems such as vehicle behaviour. The cruise cycle has the least stops per kilometer as presented in subsubsection 1.2.1 (Table 1), which limits the need for constant stops and accelerations from zero velocity. The fuel economy of the cruise cycle itself is still much higher than the expected amount, with a staggering deviation of 131% from 37 litres per 100km. Although a much better estimate than the transient and creep cycles, this shows that the model created cannot be used for varying velocity profiles of any nature. The inability of the model to predict transient behaviours for the conventional drive train gives no illusions that the hybrid drive trains would have better predictions and thus the results thereof are ignored.



(a) Fuel Economy



(b) Total Fuel Consumption

Figure 27: Fuel consumption results for the Heavy Heavy-Duty Diesel Truck (HHDDT) Drive Cycles

The quasistatic approach provides a simple way of estimating the fuel consumption characteristics of reasonably steady systems and leads to extreme deviations when transient behaviour is introduced. For this reason, it is recommended that dynamic models are used for realistic predictions of fuel consumption. If a quasistatic model must be used then it is recommended that the average velocity of the operation be used as a constant velocity input with other parameters such as the road gradient used as variable inputs. This measure ensures that the model works at its optimal level throughout and limits over or underestimations of the fuel consumption and economy. High average velocity applications must be avoided as the quadratic velocity term can lead to inaccuracies in the fuel consumption prediction.

8 CONCLUSIONS

The following conclusions are drawn from the results produced during the analysis of various drive train configurations in a semi-truck trailer that undergoes various drive cycles:

- Quasistatic models are not accurate when attempting to predict the fuel consumption behaviour of vehicles for drive cycles that have variable velocities and non-zero accelerations.
- When a constant velocity over the duration of a drive cycle is used in a quasistatic model the fuel consumption prediction deviates by at most 10% from the average fuel economy of 37 litres per 100km.
- The model accurately predicts the fuel savings of 30 to 50% expected for a full (parallel) hybrid drive train configiuration.
- The plug in (series) drive train's fuel economy follows an expected linear increment with increasing velocity.
- The series drive train is a more cost effective and carbon netral model to use for short trips that have frequent stops and starts as it seldom requires the engine recharge. If longer trips are required then opting for velocities below 65km/h would reduce the IC engine run time and by implication the fuel consumption and carbon emissions.

9 RECOMMENDATIONS FOR FUTURE WORK

The following recommendations are made for future work:

1. Greater detail can be added to the subsystems developed in section 5 in order to create a more realistic model and achieve a more accurate representation of each drive train's fuel consumption behaviour.
2. A dynamic model can be developed in order to better understand how the transient behaviour of the drive trains affects fuel and battery energy consumption.
3. A dynamic model would allow for accurate fuel consumption predictions to be made for transient drive cycles such as the HHDDT.
4. When developing the hybrid models take auxilliary electrical components such as electric windows, air conditioner refrigerant pumps, etc into consideration for a more accurate prediction of the battery consumption.

5. The torque split logic for the full hybrid model is done in a simplistic manner and does not take into consideration the complete drive cycle behaviour. Optimisation of the control logic must include dynamic effects such as acceleration, cornering, etc.

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A TORQUE SPLIT RATIO DEVELOPMENT

The torque split ratio (u) is an essential parameter for the regulation of the motor-engine balance in the parallel hybrid configuration. Development thereof works on the assumption that there is a linear relationship between the power split, velocity and road gradient. This assumption neglects many of the dynamics at play that affect the drive profile, however it is deemed adequate for this aapplication.

To establish a relationship between the velocity and torque split ratio, it must be stated that the motor only drives the vehicle at low velocities if all other factors are kept constant. When the velocity required is below a particular value (v_A) then the motor is the sole driver of the vehicle and the torque split ratio is unity. When the velocity is above a predetermined cruise velocity (v_B) then the internal combustion engine is the sole driver of the vehicle abd the torque split ratio is zero. The relationship between the two can thus be plotted as a straight line with a negative slope as seen in Figure 28 in order to define the region between the cruise and max motor velocity.

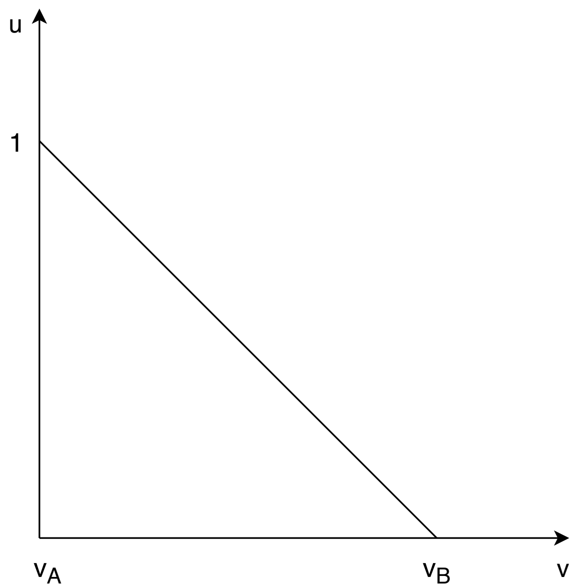

Figure 28: Representation of the relationship between the torque split ratio and velocity

The road angle and torque split ratio relationship is similar in many ways to that of the velocity. The motor takes on the full load of the vehicle when at the maximum slope (α_{max}) and thus the torque split ratio is unity. Conversely, the torque split ratio is zero when the slope is a zero. The relationship between the two parameters are thus related by the straight line with positive slope shown in Figure 29.

The straight lines generated by the preceding development are then considered as a linear combination, which yields Equation 17, which is given below for convenience:

$$u(\alpha, v) = \frac{1}{\alpha_{max}}\alpha - \frac{1}{v_B - v_A}v + \frac{v_B}{v_B - v_A}$$

It is apparent that this formulation does not guarantee that $u\epsilon[0, 1]$ so in the Simulink development a saturation block is used to limit the ratio to either zero or unity if it exceeds these bounds.

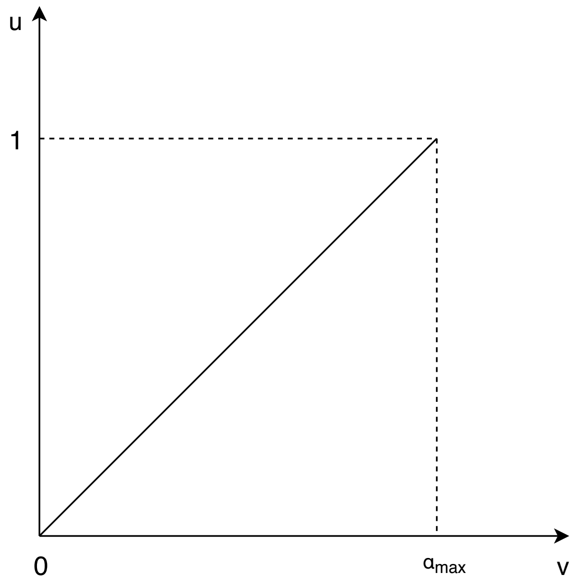

Figure 29: Representation of the relationship between the torque split ratio and road gradient

B DOUGAL ROUTE DATA EXTRACTION GUIDE

There is some set up required in order to use the route elevation code developed by Bell in Doogal.co.uk [19]. A Google API key must be created in order to successfully use the elevation code. The procedure is adapted from the one provided by Bell and is as follows:

1. A Google Maps API key must be retrieved from this link: https://developers.google.com/maps/documentation/javascript/get-api-key
2. Click on 'Get Started'.
3. Choose Routes and Places when selecting products during the setup process.
4. Create a project.
5. Enable billing. Google now require billing to be enabled on your account, so beware of how much you'll be charged - at the time of writing the service is free for th first year of usage and then USD100 thereafter. The service can be terminated before the end of the trial period if it will no longer be used.
6. An API key should get generated.
7. Click 'Secure Credentials'.
8. Under 'Applications restrictions' select 'HTTP referers (websites)'.
9. In the field that appears type https://www.doogal.co.uk.
10. Click 'Save'.
11. The API key generated in step 5 can now be used on doogal.co.uk

If an API key has already been retrieved then ensure that the following APIs are enabled in the project:

- Google Maps Geocoding
- Google Maps JavaScript
- Google Maps Directions
- Google Maps Distance Matrix

Finally in order to get the elevation details of a route the procedure is as follows:

1. Paste the API key into the 'Your Google Maps API Key' tab on https://www.doogal.co.uk/RouteElevation.php.
2. Press 'Use Key'.
3. A map should load where the user must select two locations as desired.
4. Press 'Get Elevation'.
5. Patiently allow the code to run. *Do not refresh the page until the operation is complete.*
6. Download the file in the preferred format.

After the API key is successfully generated and/or modified paste it into the 'Your Google Maps API Key' tab and click 'Use Key'. A map should be loaded which allows the user to select any two locations.

C MATLAB SCRIPT

The script used to initialise and silently run the simulink models.

Contents


```
clc; clear;
%{
Author          :   Tumisang Kalagobe (800363)
Supervisor      :   Professor Frank Kienhoffer
Date finalised  :   27/08/2019
Matlab Version  :   R2018b v9.5.0.1049112
Course          :   Mechanical Engineering Research Project (MECN4006)
Description     :   Quasistatic Fuel Consumption Prediction of Various
Drive Trains for a Semi Truck Trailer Logistics
Operation. More Information on how the models were
developed can be found in "800363.pdf"
%}

tic
```

Simulation parameters and required files

```
n = 100;                                 % no. of data points for maps
[elevation, gradients, t_stop, distance, selection, txt_file] ...
= cycle_time();

% Data files %
engine_file = 'Drive_Train_Data/Mack_MP8_505HP.txt';        % engine data
gearbox_file = 'Drive_Train_Data/Genta_Example.txt';        % gearbox data
```

```
motor_file = 'Drive_Train_Data/Siemens_Simotics_8288.txt';  % motor data

% Model files %
ic_engine_model = 'truck.slx';           % ic engine
parallel_model = 'parallel.slx';         % parallel
series_model = 'series.slx';             % series
```

Conversion factors

```
unitToKilo = 1/1000;                     % unit to kilo
mpsToKPH = 3.6;                          % m/s to km/h
rpsToRPM = 60/(2*pi);                    % radians per second to rpm
lbftToNm = 1.35581795;                   % N.m = ft-lb * lb_ftToN_m
```

Gearbox Data

```
gearbox = importdata(gearbox_file);
gear_ratios = gearbox.data;              %  data for the selected gearbox
shift_up_rpm = 1600/rpsToRPM;            %  rad/s for gear shift up
shift_down_rpm = 850/rpsToRPM;           %  rad/s for gear shift down
gearRatio_differential = 4.263;          %  differential gear ratio (WH:GB)

series_gear_ratio = 4.263;               %  series single gear ratio
```

Fuel and environment data

```
fuel_density = 837;                      % kg/m^3
fuel_LHV = 42.72e6;                      % J/kg
g = 9.81;                                % m/s^2
air_density_sea_level = 1.225;           % kg/m^3
```

Truck data

```
mass_truck = 7150;                       % kg
mass_trailor = 32000;                    % kg
total_mass = mass_truck + mass_trailor;  % kg
frontal_area = 5.14;                     % m^2

momentOfInertia_wheel = 2.5;             % kg.m^2
momentOfInertia_transmission = 1.1;      % kg.m^2
```

```
momentOfInertia_engine = 2.55;          % kg.m^2

wheels_truck = 4;
wheels_trailor = 12;
wheels = wheels_truck + wheels_trailor; % total number of wheels
radius_wheel = 0.46; % m

rolling_resistance = 0.008;             % rolling resistance coefficient
drag_coeff = 0.65;                      % drag coefficient
```

Electric Motor data

```
motor_data = importdata(motor_file);
motor = motor_data.data;
motor_efficiency = motor(1);            % -
motor_rated_torque = motor(2);          % N.m
motor_rated_rpm = motor(3);             % rpm
motor_rated_power = motor(4);           % kW
regeneration_efficiency = 0.75;         % kinetic energy recovery eff.
```

Battery data

```
battery_SoC = 0.95;                     % initial state of charge (%)
battery_efficiency = 0.8;               % -             % sec
battery_capacity = 24.5;                % kWh
battery_v = 144;                        % Volts
battery_max_i = 160;                    % Amps (maximum recharge current)
battery_max_power_flow = battery_v*battery_max_i; % Watts
battery_no_of_modules = 15;             % number of battery modules
```

IC engine data

```
engine_efficiency = 0.37;               % -

engine = importdata(engine_file);
engine_torque = lbftToNm.*engine.data(:,1); % N.m
engine_rpm = engine.data(:,2);          % rpm
engine_rad = engine_rpm./rpsToRPM;

idling_speed = 600;                     % rpm
idling_speed_rad = idling_speed/rpsToRPM;
```

```
idling_torque = interp1(engine_rpm(1:2),engine_torque(1:2),idling_speed,...
'linear','extrap'); % extrapolated torque at idling speed

% Engine torque and rpm for max fuel efficiency %
engine_optimum_torque = max(engine_torque);
engine_optimum_index = find(engine_torque==engine_optimum_torque,1);
engine_optimum_rad = engine_rad(engine_optimum_index);

% Engine fuel consumption map %
torque_axes = linspace(min(engine_torque),max(engine_torque),n);
rps_axes = linspace(min(engine_rad),max(engine_rad),n);
fuel_map = (3.6e6/(engine_efficiency*fuel_LHV*fuel_density))*...
(rps_axes'*torque_axes);% litres per hour
```

Power Split for Parallel

```
v_motor_max = 20; % Max velocity supplied exclusively by motor (km/h)
v_cruise = 65; % Cruise velocity - ie when IC drive only (km/h)

slopes = ones(n,n).*linspace(0,max(gradients),n);
velocities = ones(n,n).*linspace(v_motor_max,v_cruise,n);

m_v = 1/(v_motor_max - v_cruise);
m_a = 1/(max(gradients));

u = m_a.*slopes + m_v.*(velocities' - v_cruise); % power split ratio map
```

Simulink Executions

```
t_sample = 0.1;                            % simulation sample time (s)
constant_velocity = 60;                    % constant velocity (km/h)

if selection > 3
fuel_cons = zeros(5,3);
fuel_cons_per100km = zeros(5,3);
i = 1;
for constant_velocity = 60:10:100
% Conventional IC Engine %
disp('Running IC Engine...')
sim(ic_engine_model);
fuel_baseline = sum(fuel_consumption_baseline);
baseline_per100km = 100*fuel_baseline/max(distance);
```

```
disp('IC Engine Complete. Running Parallel...')

% Parallel Hybrid %
sim(parallel_model);
fuel_parallel = sum(fuel_consumption_parallel);
parallel_per100km = 100*fuel_parallel/max(distance);
disp('Parallel Complete. Running Series...')

% Series Hybrid %
sim(series_model);
fuel_series = sum(fuel_consumption_series);
series_per100km = 100*fuel_series/max(distance);
disp('Series Complete.')
clc;

fuel_cons(i,:) = [fuel_baseline, fuel_parallel, fuel_series];
fuel_cons_per100km(i,:) = [baseline_per100km,parallel_per100km,...
series_per100km];

i = i + 1;

disp(constant_velocity + "km/h run complete.")
end

else
% Conventional IC Engine %
disp('Running IC Engine...')
sim(ic_engine_model);
fuel_baseline = sum(fuel_consumption_baseline);
baseline_per100km = 100*fuel_baseline/max(distance);
disp('IC Engine Complete. Running Parallel...')

% Parallel Hybrid %
sim(parallel_model);
fuel_parallel = sum(fuel_consumption_parallel);
parallel_per100km = 100*fuel_parallel/max(distance);
disp('Parallel Complete. Running Series...')

% Series Hybrid %
sim(series_model);
fuel_series = sum(fuel_consumption_series);
series_per100km = 100*fuel_series/max(distance);
disp('Series Complete.')
end
```

```
disp('Simulation Complete!')
toc
```

Functions

```
function [elevation, gradients, t_stop, distance, selection, fuel_file]...
= cycle_time()
%{
Function that requests a user input for the desired drive cycle. If the
desired cycle is "Creep", "Transient" or "Cruise" then the user must ensure
that the drive cycle source in "{truck/series/parallel}.slx > Driving
Profile > Standard Drie Cycle on flat terrain" matches the selected drive
cycle.
%}

drive_cycle = {'Cruise', 'Transient', 'Creep', 'DBN-JHB', 'PE-JHB',...
'CPT-JHB'};
selection = listdlg('ListString', drive_cycle);
if selection > 3
if selection == 4
geo_file = 'Elevation Matrices/DBN-JHB.txt';
fuel_file = "DBN-JHB.txt";
elseif selection == 5
geo_file = 'Elevation Matrices/PE-JHB.txt';
fuel_file = "PE-JHB.txt";
else
geo_file = 'Elevation Matrices/CPT-JHB.txt';
fuel_file = "CPT-JHB.txt";
end
else
geo_file = 'Elevation Matrices/DBN-JHB.txt';
fuel_file = 0;
end

route = importdata(geo_file);
elevation = route.data(:,3); % m
distance = route.data(:,4); % km
gradients = (pi/400).*route.data(:,5); % rad
for i=1:length(gradients)
if isnan(gradients(i)) || gradients(i) == Inf
gradients(i) = 0;
end
```

```
end

% setting simulation times and distances
if selection == 1
t_stop = 2083;
distance = 37.12;% km
elseif selection == 2
t_stop = 668;
distance = 4.51;% km
elseif selection == 3
t_stop = 253;
distance = 0.20;% km
else
t_stop = length(distance);
end
end
```