

Modeling and Simulation of a Series Hybrid CNG Vehicle

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ABSTRACT

Predicting fuel economy during early stages of concept development or feasibility study for a new type of powertrain configuration is an important key factor that might affect the powertrain configuration decision to meet CAFE standards. In this paper an efficient model has been built in order to evaluate the fuel economy for a new type of charge sustaining series hybrid vehicle that uses a Genset assembly (small 2 cylinders CNG fueled engine coupled with a generator). A first order mathematical model for a Li-Ion polymer battery is presented based on actual charging /discharging datasheet. Since the Genset performance data is not available, normalized engine variables method is used to create powertrain performance maps. An Equivalent Consumption Minimization Strategy (ECMS) has been implemented to determine how much power is supplied to the electric motor from the battery and the Genset. Finally the simulator has been tested for different driving cycles and the results which include fuel consumption, battery state of charge and the vehicle drivability performance are shown.

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INTRODUCTION

During the early stages of concept development process for the Deep Orange project, which is taking place at Clemson University International Center for Automotive Research, it is required to build a complete vehicle model that would be used to evaluate the fuel economy of the concept vehicle with the proposed powertrain configuration. Due to the lack of complete powertrain data, this paper will present a method for creating (with minimal available test data) a forward vehicle simulator for a charge-sustaining series hybrid vehicle with an electric motor to drive the rear axle and a Genset assembly running on compressed natural gas (CNG) providing power directly to the electric motor and to charge the batteries. The simulator is capable of estimating the fuel consumption under different driving conditions and control strategies. The considered vehicle configuration is not a range extender concept where the ICE charges the battery. The battery needs to be sized for peak power (acceleration, road grade, overtaking) and needs to be minimal in size/capacity. During normal driving, a very limited usage of the battery is considered (as for HEVs) and will be charged through regenerative braking (or if needed via the ICE). The vehicle does not have a requirement for all-electric mode but it can have All-Electric-Range if the component sizes allow. Below are the assumed vehicle parameters and the vehicle targets:

- Wheelbase: 2900 mm
- Rolling Resistance Coefficient: 0.008
- Aerodynamic Drag Coefficient: 0.27
- Air Density (Rho): 1.225 kg/m³
- Frontal Area: 2.27 m²
- Curb Weight: 1100 kg
- GVWR: 1475 kg (5 seats with 100 kg extra load in trunk)
- Weight Distribution: 50 %/50% (Front/Rear)
- Tire Size: 175/60 R19
- Dynamic Rolling Radius: 0.345 m

Vehicle Targets

- Target Fuel Economy: Should meet CAFE 2020 for 43.1 ft² footprint (47.0 MPG).
- Overall Range: 250 Miles (EPA Combined)
- Brake Energy Recovery: Yes
- Plug-in: No
- 0-60 mph time with (75 kg driver): Less than 10 sec

SYSTEM ARCHITECTURE

The Simulink model is designed as a forward vehicle simulation of the series-hybrid powertrain. The high-level overview of the model consists of a driver model, a powertrain model, and a vehicle model. A driver block compares current vehicle velocity against the desired velocity profile of the

Vehicle Parameters

- Length / Width / Height: 4250/1800/1500 mm

driving cycle, and a simple PID controller outputs accelerator and brake pedal position signals to match the desired velocity profile. The powertrain model takes these signals as inputs, and outputs a traction force at the wheels. The vehicle model converts the torque to a speed, and sends this value back to the powertrain model.

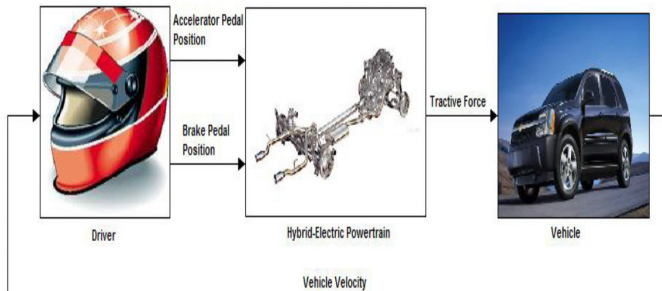


Figure 1. Model Architecture, higher model level showing Driver, Powertrain and Vehicle models.

The powertrain model starts with the controller block (blue block in Fig 2). This block takes accelerator and brake pedal position as inputs, and determines electric motor torque that is sent forward to the wheels through a gearbox and brakes. The controller block also calculates the power split that is supplied to the electric motor. Electric power is supplied to the electric motor via either a battery or a Genset, and the controller calculates the most efficient way to split the power delivered. Battery power is then passed back to the battery model. Genset power, torque, and speed is then passed to the Genset model.

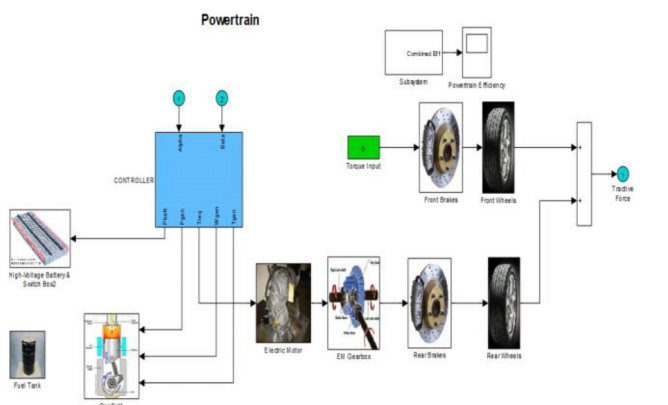


Figure 2. Powertrain model consists of controller, battery pack, Genset, electric motor and brakes models.

BATTERY MODEL

Lithium Ion Polymer (LiFePO₄ based cathode, Carbon-based anode) is the battery type used in this model with specifications shown in Table 1.

The battery model consists of an electrical model, which is implemented as simple model with no dynamic behavior. The model has a series connection between resistor (R) and voltage source (E_0). The mathematical representation for the charging and discharging phases for the battery is obtained after fitting the charging and discharge curves for the battery [1].

Table 1. Battery Specifications

Description	Assumption
Single battery capacity	7.5 Ah (per cell)
Maximum current charging and discharging	Charge: 3C / Discharge: 30 C for 10 seconds
Max Power	0.758 kW per cell
Nominal voltage	3.2 Volt per cell
Battery cell weight	237 gram per cell
Battery pack specific density	60 Wh/kg, 40 Wh/liter

For the discharge curves, the normalized state of charge (SOC) is calculated using Peukart effect, equation (1):

$$\Delta SOC_I \% = - \left(\int \frac{I}{C_I} dt \right) \times 100 \quad (1)$$

The fitting is done using equation (2), where the battery voltage depends on the temperature, resistance and SOC.

$$V = E_0 - IR$$

$$V = \alpha_0 + \alpha_1 \times SOC + \alpha_2 \times T - I(\beta_0 + \beta_1 \times SOC + \beta_2 \times T) \quad (2)$$

Where $\alpha_i, \beta_i, i=0, \dots, 2$, are parameters to be found by curve fitting. Figure 3 shows the R and E_0 for discharging curves versus the fitting results. Figures 4 and 5 show the E_0 and R versus SOC.

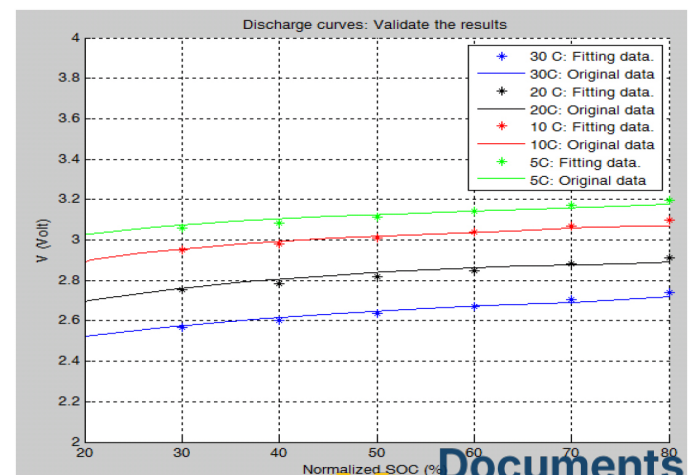
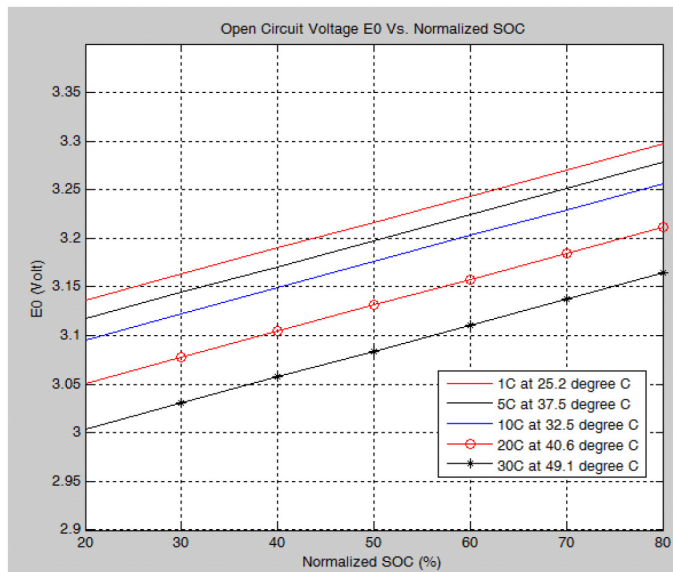
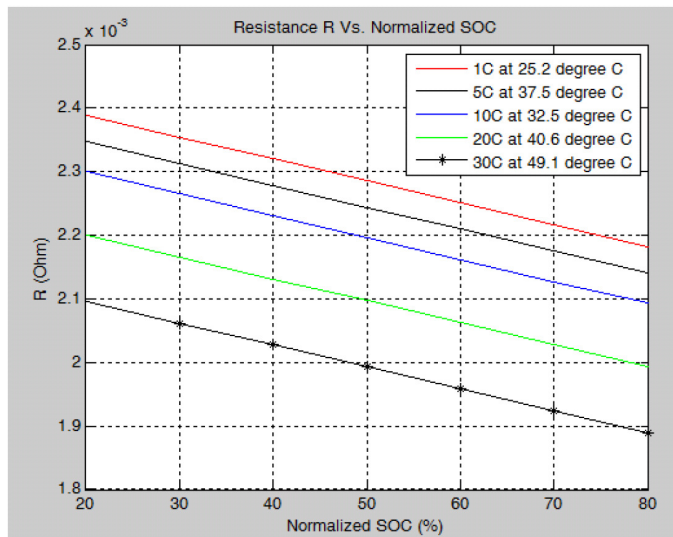


Figure 3. Discharging curves: validate the results.

Figure 4. E_0 vs. normalized SOC (discharging).Figure 5. R vs. normalized SOC (discharging).

For the charging curves, the procedure is similar but the challenges were in two folds: first, some of curves are overlapping, which are considered as one curve. Second, there is no temperature dependant data and if the fitting consider fixed temperature the results will be close to singular, which makes the results not very accurate. For that, the charging curves are fitted using [equation \(3\)](#)

$$V = E + IR$$

$$V = \alpha_0 + \alpha_1 \times SOC - I(\beta_0 + \beta_1 \times SOC)$$

(3)

Where $\alpha_i, \beta_i, i=0, 1$ are parameters to be found by curve fitting. [Figure 6](#) shows the charging fitting results, and [Figures 7](#) and [8](#) show the E_0 and R respectively, versus SOC.

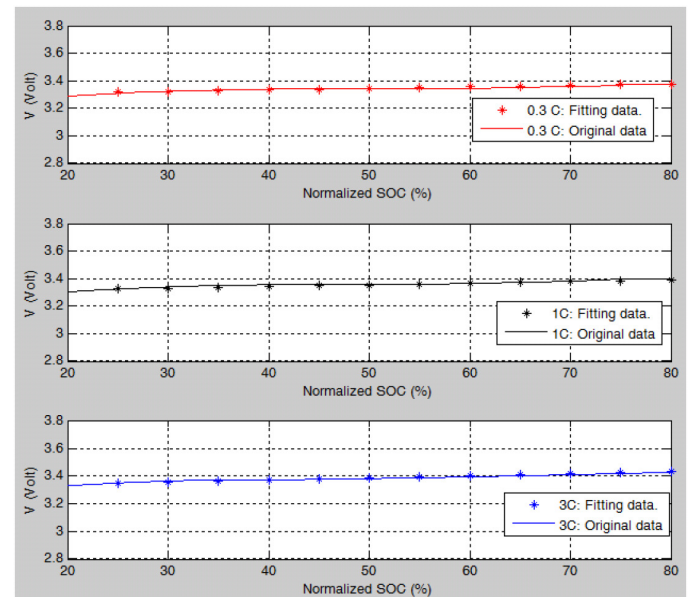
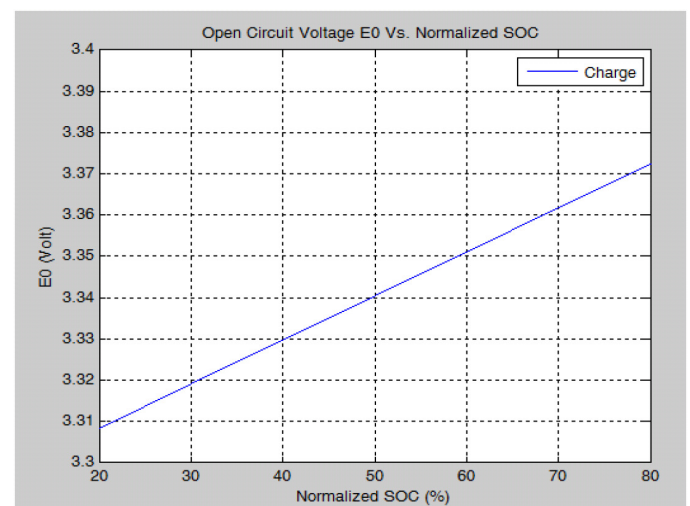
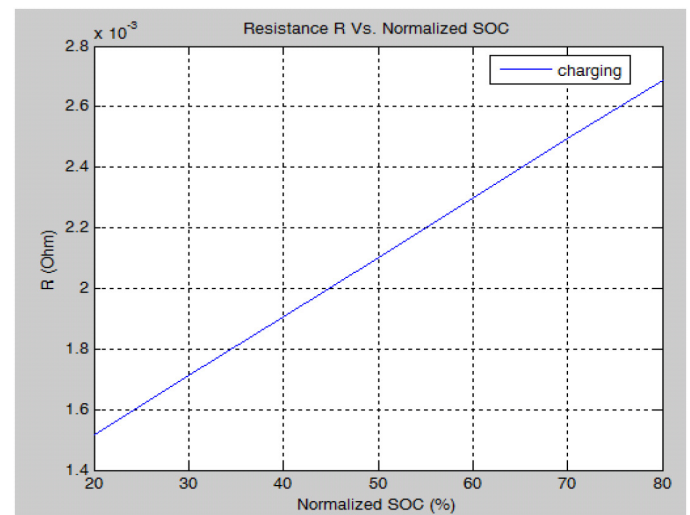


Figure 6. Charging curves: validation results.

Figure 7. E_0 vs. normalized SOC (charging).Figure 8. R vs. normalized SOC (charging).