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Simple Energy Model for Hydrogen Fuel Cell Vehicles: Model Development and Testing

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Abstract: Hydrogen fuel cell vehicles (HFCVs) are a promising technology for reducing vehicle emissions and improving energy efficiency. Due to the ongoing evolution of this technology, there is limited comprehensive research and documentation regarding the energy modeling of HFCVs. To address this gap, the paper develops a simple HFCV energy consumption model using new fuel cell efficiency estimation methods. Our HFCV energy model leverages real-time vehicle speed, acceleration, and roadway grade data to determine instantaneous power exertion for the computation of hydrogen fuel consumption, battery energy usage, and overall energy consumption. The results suggest that the model's forecasts align well with real-world data, demonstrating average error rates of 0.0% and −0.1% for fuel cell energy and total energy consumption across all four cycles. However, it is observed that the error rate for the UDDS drive cycle can be as high as 13.1%. Moreover, the study confirms the reliability of the proposed model through validation with independent data. The findings indicate that the model precisely predicts energy consumption, with an error rate of 6.7% for fuel cell estimation and 0.2% for total energy estimation compared to empirical data. Furthermore, the model is compared to FASTSim, which was developed by the National Renewable Energy Laboratory (NREL), and the difference between the two models is found to be around 2.5%. Additionally, instantaneous battery state of charge (SOC) predictions from the model closely match observed instantaneous SOC measurements, highlighting the model's effectiveness in estimating real-time changes in the battery SOC. The study investigates the energy impact of various intersection controls to assess the applicability of the proposed energy model. The proposed HFCV energy model offers a practical, versatile alternative, leveraging simplicity without compromising accuracy. Its simplified structure reduces computational requirements, making it ideal for real-time applications, smartphone apps, in-vehicle systems, and transportation simulation tools, while maintaining accuracy and addressing limitations of more complex models.

Keywords: hydrogen; fuel cell vehicle; energy modeling; HFCV energy

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1. Introduction

Hydrogen fuel cell vehicles (HFCVs) are electric vehicles that generate electricity for their motors by harnessing the power of hydrogen gas through a chemical process called fuel cell electrochemistry. These vehicles store compressed hydrogen in high-pressure tanks, and this hydrogen is then fed into the fuel cell stack, where it undergoes a reaction with atmospheric oxygen, producing electrical energy to power the vehicle's electric motors. The sole byproduct of this process is water vapor, making HFCVs a particularly clean and environmentally friendly transportation option. Along with battery electric vehicles (BEVs), HFCVs are considered among the most promising solutions for mitigating greenhouse gas emissions and other harmful pollutants associated with traditional internal combustion engine vehicles (ICEVs).

Due to the ongoing evolution of this technology, there is limited comprehensive research and documentation regarding the performance of fuel cell vehicles. However, based on the existing body of research, it is anticipated that fuel cell vehicles will deliver an exceptionally energy-efficient and emission-free driving experience. In particular, in comparison to traditional vehicles, fuel cell vehicles are expected to provide several advantages, including enhanced fuel efficiency, improved engine efficiency, reduced emissions, and a decrease in greenhouse gas (GHG) emissions. Furthermore, fuel cells can achieve efficiency levels ranging from 40% to 70%, representing a significant improvement over the most efficient ICEVs, which typically operate at around 30% efficiency [1].

The efficiency of an HFCV refers to the amount of energy that is converted from hydrogen to electricity, taking into account the energy losses that occur during the conversion process. The overall efficiency of an HFCV includes the efficiency of several subsystems. (1) Hydrogen storage and delivery: Hydrogen must be stored on board the vehicle and delivered to the fuel cell stack. This process incurs energy losses due to compression and cooling. (2) Fuel cell stack: This stack transforms hydrogen and oxygen into electricity, typically achieving an efficiency rate of approximately 50–60%. (3) Power electronics: The power electronics convert the electricity from the fuel cell stack to a form that can be used to power the vehicle's electric motor. This process also incurs energy losses.

HFCVs can have a range of up to 300 miles and can be refueled in minutes, similar to gasoline or diesel vehicles. However, the availability of hydrogen refueling infrastructure is currently limited in many regions. This is a major challenge for HFCV adoption. HFCVs are considered an alternative to BEVs. They offer the advantages of long range and rapid refueling, but they are not as widely available as BEVs. The future of HFCVs depends on the development of a more robust hydrogen refueling infrastructure. If this can be achieved, HFCVs could become a more viable option for transportation. HFCVs are considered to be zero-emission vehicles, as the only byproduct of the fuel cell reaction is water vapor. HFCVs are more expensive than BEVs, but the cost of hydrogen fuel is expected to come down in the future. HFCVs are still under development, but they have the potential to be a major player in the transportation sector in the near future.

The aim of this study is to establish an energy consumption model for HFCVs that is suitable for real-time applications that can estimate fuel cell and battery energy consumption rates. A novel energy consumption model for HFCVs utilizes operational inputs like current speed and road gradient to calculate energy usage, leveraging data easily accessible from mobile applications and other sources. This model addresses a gap in the current State-of-the-Art by providing a simple model that can be employed in vehicle applications, smartphone apps, and traffic simulation programs. Recently, authors have formulated an energy consumption model tailored for HFCVs [2]. The model evaluates both the immediate fuel cell and the overall energy consumption by utilizing the operational data of the vehicle. This research contributes to the advancement of prior studies by integrating a technique to gauge the efficiency of the fuel cell driveline and providing estimates for the SOC of the battery system.

This paper is structured as follows: The subsequent section provides an overview of current efforts in modeling energy consumption for HFCVs. Following that, this paper details the fuel consumption data specific to HFCVs used in this research. Subsequent sections delve into the development of the proposed model and present the validation results. Then, this paper demonstrates the case study of various intersection controls to assess the applicability of the proposed model. The concluding part of the paper summarizes the key findings.

2. Literature Review

HFCVs are frequently highlighted as critical components in the drive towards decarbonizing transportation systems. Despite their extensive history, these vehicles are currently regarded primarily as a long-term solution compared to other transportation options. A recent study [3] investigated the principal obstacles hindering the widespread adoption of HFCVs. This study identified three major challenges for these vehicles: (i) economic factors, (ii) infrastructure limitations, and (iii) deficiencies in the policy framework. The affordability of HFCVs stands out as a significant impediment to their broader acceptance and swifter integration. The cost of mobility provided by fuel cell vehicles and hydrogen remains comparatively high, rendering them less competitive against conventional cars and other alternatives, such as hybrid or battery electric vehicles. To advance the widespread deployment of fuel cell vehicles, a crucial focus should be on diminishing investment costs. An additional significant hurdle in the acceptance of fuel cell vehicles is the demand for novel and costly infrastructure. Presently, there are limited hydrogen refueling stations globally. The study underscores the necessity of establishing stable, long-term policy conditions and recommends harmonizing efforts across regions to achieve full benefits of HFCVs in the transport sector.

Research by Liu et al. [4] revealed that integrating fuel cell vehicles into China's road transport could cut GHG emissions by 13.9% and lower heavy-duty truck emissions by almost 20% under an optimistic scenario. The intensity of GHG emissions during hydrogen production becomes a pivotal factor in calculating the fuel cycle GHG emissions of fuel cell vehicles. Consequently, the study demonstrated that the pathways used for hydrogen production would be of utmost importance in shaping the future landscape of GHG emissions.

Aminudin et al. [5] examined the advantages and disadvantages of HFCV technology. Furthermore, the authors examined recent challenges associated with the existing fuel cell technology within the automotive sector. The study concluded that HFCVs face notable limitations and hurdles. Collaborative efforts among various stakeholders are essential to surmount these obstacles for the future advancement of HFCVs. The utilization of hydrogen fuel cells is anticipated to exert a significant influence on the transportation sector, leading to cost-effective mass production and commercial availability of fuel cells in the near future.

Acar and Dincer [6] conducted a study to assess hydrogen's role as an environmentally friendly transportation fuel, targeting lower emissions in transportation. They conducted a comparison of diverse vehicle types, encompassing ICEVs, BEVs, hybrid electric vehicles (HEVs), HFCV, and biofuel vehicles. The analysis encompassed CO_2 and SO_2 emissions, carbon's societal costs, energy and exergy efficiencies, fuel usage, pricing, and range limitations. The results revealed that, on average, HFCVs stood out as the most sustainable transportation option. The authors underscored the necessity for environmentally friendly hydrogen production, emphasizing the importance of minimal or zero emissions and high efficiency to genuinely qualify hydrogen as a clean and sustainable fuel.

Kurtz et al. [7] conducted a review of hydrogen transportation infrastructure considering operational difficulties, technical issues, and expenditures. The research pinpointed substantial obstacles to the widespread commercialization of hydrogen systems, including elevated maintenance costs and the restricted accessibility of hydrogen fueling stations. The research proposed immediate infrastructure challenges by establishing cost-effective, dependable hydrogen fueling stations for the extensive adoption of hydrogen-powered transportation.

Li et al. [8] introduced the KBCO algorithm, a Kriging-based bi-objective optimization technique, to optimize energy efficiency in hydrogen fuel cell vehicles. HFCVs have complex control systems with various parameters, and the KBCO algorithm optimizes these parameters to enhance HFCV performance. The research used ADVISOR, created by the National Renewable Energy Laboratory (NREL), to analyze HFCV performance. The proposed algorithm was found to be effective in solving complex energy control strategies of hydrogen fuel cells and batteries, while reducing hydrogen consumption within velocity, acceleration, and battery state constraints.

Xu et al. [9] proposed a dynamic HFCV model incorporating fuel economy and system durability. Their research optimized powertrain parameters for a specified driving cycle, focusing on fuel efficiency and durability through a Pareto-optimal two-loop framework using dynamic programming. For each powertrain parameter combination, a global optimum energy management strategy was utilized. Optimization of coefficients for the dynamic programming algorithm was performed to reduce calculation time while maintaining accuracy. Then, the study compared the results across all parameter sets and selected the Pareto-optimal solution, balancing fuel economy and system durability.

Kaya and Hames [10] examined control strategies for fuel cell vehicles to save fuel consumption. They compared two distinct control strategies developed for HFCVs with the conventional control approaches. The research investigated system efficiency, technology lifespan, fuel consumption, and vehicle operations for various HFCV control methods. Due to their simplicity and flexible parameters, the proposed control strategies can be seamlessly applied to different HFCV models.

Shusheng et al. [11] conducted a comparative study on hybrid and pure fuel cell drive models for onboard hydrogen-producing fuel cell EVs using ADVISOR. The results demonstrated efficient fuel cell and lithium battery operation, with hybrid fuel cells showing reduced power fluctuations, leading to enhanced energy efficiency and extended lifespan.

Caux et al. [12] introduced a novel combinatorial approach for the optimal management of HEV energy distribution. This system comprises two energy sources: a fuel cell as the primary source and a supercapacitor for energy storage. A new mathematical model was developed to accurately represent the operation of the HEV energy chain, and the method was employed to derive an optimal solution aligned with hydrogen consumption. Simulations were conducted on diverse realistic mission profiles, revealing a substantial improvement in solution quality and computation time compared to alternative approaches found in the literature.

FASTSim (Future Automotive Systems Technology Simulator) [13,14] is a vehicle simulation platform created by NREL (National Renewable Energy Laboratory). It is designed to quantify the energy consumption, performance, and cost of various vehicle types, including ICEVs, HEVs, BEVs, and HFCVs. FASTSim allows users to simulate real-world driving conditions and assess how different vehicle configurations and technologies impact fuel efficiency, emissions, and overall energy consumption. FASTSim is widely used to model vehicle technologies and their potential benefits in terms of energy savings and emission reductions. FASTSim estimates the energy consumption of HFCVs by simulating their operation over specific driving cycles, such as city or highway driving, to reflect real-world conditions. It models the vehicle's powertrain, including the fuel cell stack, electric motor, and battery, and calculates the energy flow within the system by tracking how much hydrogen is consumed to generate power. Based on the total energy demand from the driving cycle, FASTSim estimates hydrogen consumption by converting electrical energy needs into hydrogen usage, considering the fuel cell's efficiency.

Autonomie [15–17], a comprehensive vehicle system simulation tool developed by Argonne National Laboratory, can estimate the energy consumption of HFCVs. Autonomie enables researchers and engineers to simulate and analyze diverse advanced vehicle technologies, assessing energy usage, performance, and costs across various powertrain setups. Autonomie simulates the entire vehicle system, incorporating detailed models of the fuel cell stack, electric motor, hydrogen storage, and other key components. By using control algorithms and real-world driving conditions, Autonomie can accurately predict the energy usage of HFCVs across different driving cycles and operational scenarios. This makes it a valuable tool for assessing the efficiency and viability of hydrogen fuel cell technology in transportation applications.

Both FASTSim and Autonomie are capable of estimating hydrogen fuel cell vehicle (HFCV) energy consumption. FASTSim is particularly well-suited for users who need quick estimates over standard driving cycles with minimal setup, making it ideal for rapid fleet-level comparisons or assessing the impact of technological improvements on vehicle efficiency. In contrast, Autonomie is designed for more advanced users who require detailed simulations of HFCV systems. It offers extensive customization at the component level and delivers high-fidelity results, making it highly effective for optimizing control strategies or designing new vehicle architectures with a focus on precision and flexibility.

Previous studies highlighted the development of a hydrogen fuel cell system and the control strategies for HFCVs. Currently, there are few HFCV energy models, and few HEV energy consumption models that are eligible for real-time connected and automated vehicle (CAV) applications. A previous study [18] proposed four essential prerequisites for measuring fuel/energy consumption: real-time computation, precision, simplicity in model structure, and ease of calibration. The energy model should provide accurate results with minimal input variables and be applicable to general vehicle operations. To satisfy real-time applications in CAV transportation applications, an optimal fuel/energy consumption model must fulfill various criteria. This paper aims to create an HFCV energy model that adheres to these specified criteria. Authors [2] recently developed a simple energy consumption model for hydrogen fuel cell vehicles. This model assesses the instantaneous fuel cell and overall energy consumption based on the operational data of the vehicle. This research effort enhances the previous study by incorporating a method to estimate the efficiency of the fuel cell driveline and estimating the SOC of the battery system.

The primary contribution of this study lies in the creation of a detailed energy consumption model tailored specifically for HFCVs. This model quantifies the energy impact of HFCVs in real-time CAV transportation operations embedded within various applications. Diverging from previous research, the HFCV energy consumption model utilizes readily accessible data, such as instantaneous speed, acceleration, and roadway grades. Key parameters can be easily accessible from GPS loggers or smartphone apps, enabling seamless integration into traffic simulation models, smartphones, and in-vehicle systems for accurate HFCV energy consumption analysis. Also, we developed a fuel cell driveline efficiency method using a function based on the vehicle's power at the wheels relative to the maximum vehicle power. Our research indicates that this technique is the most efficient and practical approach to estimate fuel cell driveline efficiency.

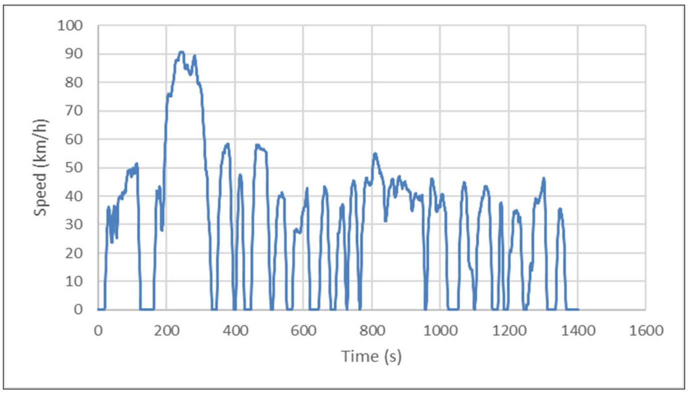
3. Hydrogen Energy Consumption Data

To develop an HFCV energy model that can quantify the impact of automated vehicle (AV) and/or CAV operations, we utilized a disaggregate energy consumption dataset that includes instantaneous energy consumption data and vehicle operational data. In particular, we used a 2017 Toyota Mirai energy consumption dataset that was collected by the Fuel Cell Technologies Office at the Argonne National Laboratory with Transport Canada's Innovation Centre. This dataset includes 10 Hz energy consumption data with various vehicle operational information, including time, dynamometer speed, tractive force, distance, temperature, etc. The data are currently available at the Downloadable Dynamometer Database. The test vehicle was operated with a hydrogen fuel cell stack (114 kW) and a nickel–metal hydride battery (1.6 kWh). The test vehicle can store compressed hydrogen gas at 10,000 psi in a 5 kg H_2 fuel tank. The data include multiple test results, including various temperature testing results. This study utilized standard temperature test results, for which the data were collected at a specific temperature of 22.2 °C (72 °F). Further, we did not include any tests that included cold or warm starts.

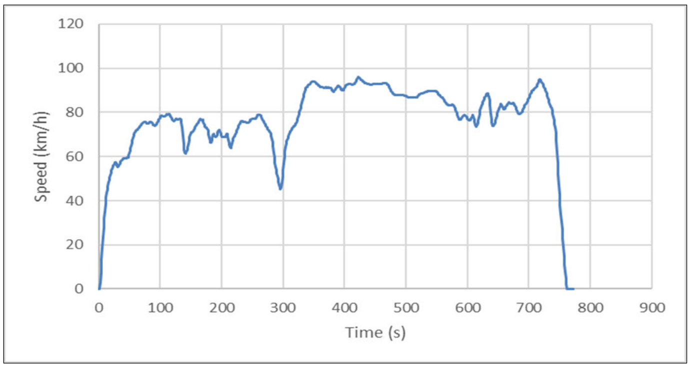
This study utilized the four driving cycles. The four driving cycles were the Urban Dynamometer Driving Schedule (UDDS), the Highway Fuel Economy Test (HWFET), the New European Driving Cycle (NEDC), and the speed cycle. The table below shows the driving characteristics of the four driving cycles. The driving cycles cover a wide range of real-world driving conditions, involving idling, low speed, high speed, and aggressive acceleration conditions. The UDDS cycle typically represents low-speed city driving conditions with multiple stop and go behaviors. The average speed of the trip is 38.9 km/h, and the maximum speed is 91.3 km/h. The freeway cycle, HWFET, was used to determine the highway fuel economy rating and represent a typical highway driving scenario. The average speed of the HWFET is 77.2 km/h, and the maximum speed is 96.0 km/h.

The NEDC serves as a driving cycle designed to evaluate emission levels and fuel efficiency in passenger cars (excluding light trucks and commercial vehicles). Also known as the Motor Vehicle Emissions Group cycle, the NEDC attempts to represent typical

European car usage. The cycle comprises four repeated ECE-15 urban driving cycles and one extra-urban driving cycle. The NEDC test procedure is employed for measuring CO_2 and fuel consumption, as well as electric energy consumption and range in hybrid and fully electric vehicles. The speed drive cycle is employed to assess the effects of different constant speeds, encompassing 15 km/h, 30 km/h, 45 km/h, 60 km/h, and 75 km/h. The study utilized data from two repeated driving cycles of the HWFET cycle and the NEDC cycle. We only used data gathered under hot, stabilized conditions, without utilizing air-conditioning test data. Neither cold-start data nor hot or cold weather-condition data were included in the study. Figure 1 shows the speed profiles of the four driving cycles.



(**a**)



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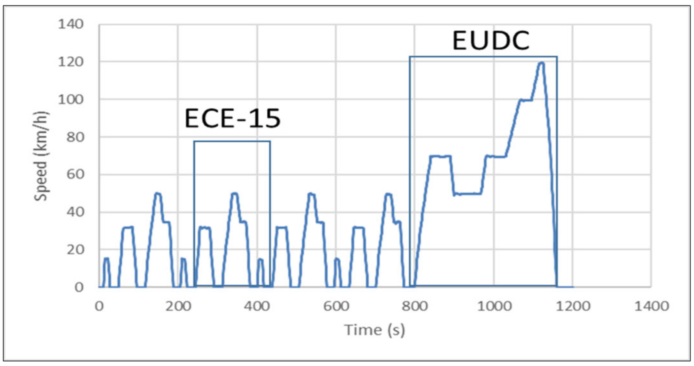
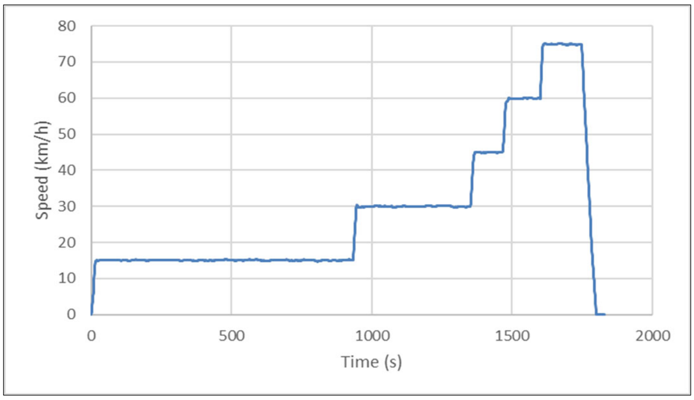


(**c**)

Figure 1. *Cont.*



(**d**)

Figure 1. Driving cycles: (**a**) UDDS, (**b**) HWFET, (**c**) NEDC, and (**d**) speed.

4. HFCV Energy Consumption Modeling

Determining the fuel efficiency of HFCVs is complex due to their sophisticated fuel cell and battery systems. An HFCV's powertrain includes a fuel cell stack, a power electronics controller, a battery pack, a DC/DC converter, and an electric traction motor. The fuel cell stack is composed of individual fuel cells that generate electricity from hydrogen and oxygen. The battery pack stores energy recovered through regenerative braking and provides additional power to the electric traction motor. The power electronics controller manages the flow of electrical energy from the fuel cell and the traction battery, regulating the speed and torque output of the electric traction motor. The electric traction motor drives the vehicle using power from both the fuel cell and the battery pack. Additionally, the DC/DC converter converts high-voltage DC power from the traction battery pack to the low-voltage DC power needed for vehicle accessories and auxiliary battery charging.

The rates at which vehicles consume fuel or energy are usually determined by analyzing the relationship between instantaneous fuel consumption or energy consumption rates and instantaneous measurements from various factors like vehicle power, force (or tractive effort), acceleration, speed, and road conditions. Figure 2 illustrates the relationship between HFCV energy consumption and the power at the wheels from the Toyota Mirai data. The figure illustrates a strong correlation between the power generated at the vehicle's wheels and the energy consumption of the HFCV. Figure 2c shows the total energy consumption, which combines the battery-generated energy (shown in Figure 2a) and the fuel cell-generated energy (shown in Figure 2b). The figure shows that the total energy consumption is positively correlated with the required vehicle power, and the fuel energy consumption in Figure 2b is significantly higher than the battery-generated energy in Figure 2a.

After analyzing the HFCV energy consumption data, we found four operational modes, namely idling mode, regenerative braking mode, fuel cell mode, and battery mode. The idle mode is when the vehicle is in idle mode and only minimal auxiliary or idling power is required. We found that the test vehicle normally consumed 0.45 kWh/s during the idling mode. The regenerative braking mode is typically observed during deceleration events. The energy recovery system allows vehicles to convert kinetic energy from braking into electrical power to charge the vehicle's battery. The regenerative braking system is the most popular feature of BEVs and hybrid electric vehicles. During the regenerative braking mode, the test vehicle recharges the battery and slightly increases the SOC. The fuel cell mode comprises a fuel cell main mode, in which most of the energy is generated from the fuel cell module, and a fuel only mode, in which all energy is generated by the fuel cell module. Similarly, the battery model contains a battery main mode, in which most of the energy is generated by the battery unit, and a battery-only mode, in which all energy is generated by the battery unit.

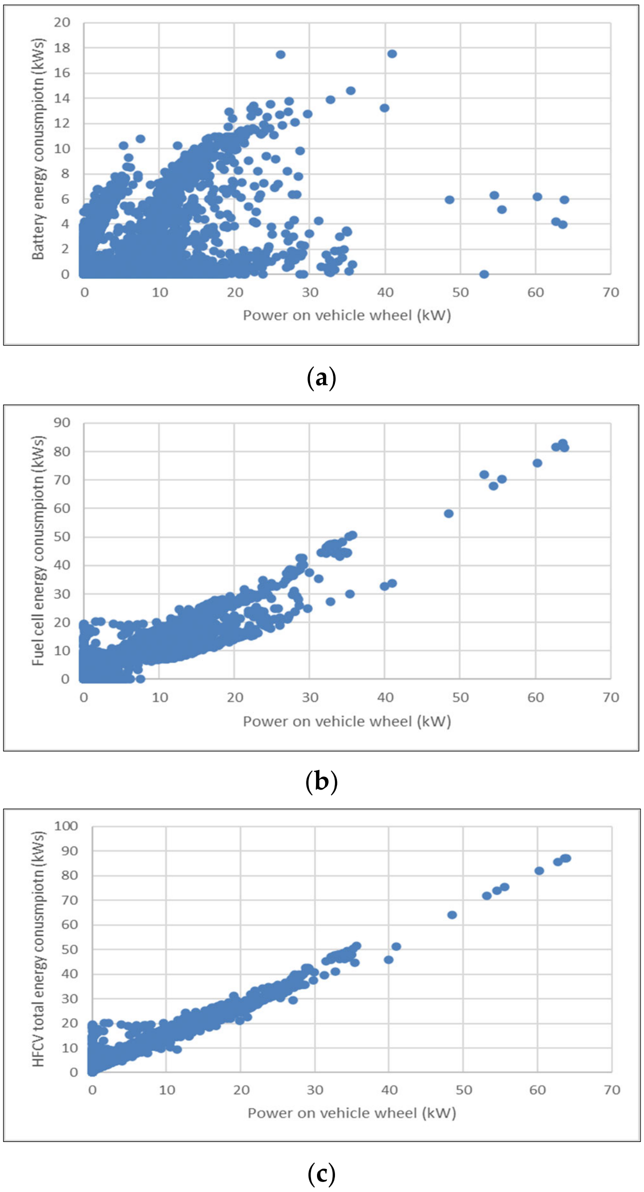


Figure 2. HFCV energy consumption and required vehicle power: (**a**) battery energy, (**b**) fuel cell, and (**c**) fuel cell and battery energy.

This research determined the subsequent energy consumption patterns in HFCVs for four operational modes. We found that when the HFCV is in idling mode, a fixed energy consumption rate is utilized from the battery; and that during the regenerative braking mode, the HFCV does not consume any energy from either the fuel cell or battery, and it charges the battery based on a regenerative energy efficiency relationship [19]. In this study, we utilized vehicle speed and vehicle power to determine the fuel cell mode and the battery mode. We found that the battery mode is in operation when the vehicle power and vehicle speed is relatively low. In particular, when the speed is lower than a specific speed (v_a) at a vehicle power at the vehicle wheels (P_{wheels}), the HFCV utilizes the battery mode. Figure 3 illustrates the boundary conditions for the battery mode using a linear relationship of a specific speed ($v_a = 1.86 \times P_{wheels} + 18.8$) and a vehicle power at the vehicle wheels (P_{wheels}). Finally, the HFCV utilizes the fuel cell mode when the speed is greater than a specific speed (v_b) and the power at the wheels is greater than P_a. During the fuel cell mode, the fuel cell provides the main power, and the vehicles utilize supplemental power generated by the battery. The proposed HFCV energy consumption model is formulated in Equations (1) through (7). The power at the wheels (P_{wheels}) is computed using Equation (1):

$$P_{wheels}(t) = max\left\{0, \frac{\left(ma(t) + mg\ \frac{C_r}{1000}(c_1v(t) + c_2) + \frac{1}{2\times3.6^2}\rho_{Air}A_fC_Dv^2(t) + mg\ \theta\right)v(t)}{3.6}\right\}, \quad (1)$$

$$P_{battery}(t) = P_{idle} \text{ for } P_{Wheels}(t) = 0\ and\ v(t) = 0\ (idling\ mode), \quad (2)$$

$$P_{battery}(t) = P_{wheels}(t)\eta_{rb}(t) + P_{idle} \text{ for } P_{wheels}(t) < 0\ (regenerative\ braking\ mode), \quad (3)$$

$$P_{battery}(t) = \begin{cases} (P_{wheels}(t) + P_{idle})\eta_{batt} & \text{for } P_{wheels}(t) > 0,\ (t) \le v_a\ (battery\ mode) \\ (P_{wheels}(t) + P_{idle})\eta_{supple}\eta_{batt} & \text{for } P_{wheels}(t) > 0,\ v(t) > v_a\ (supplemental\ power)' \end{cases} \quad (4)$$

$$P_{FuelCell}(t) = P_{wheels}(t) * \eta_{fuelcell} \text{ for } P_{wheels} > P_a \text{ and } v(t) > v_b\ (fuel\ cell\ mode), \quad (5)$$

$$P_{battery\_Crate}(t) = C_{rate} * Max\ Battery\ Capacity * \Delta t\ /\ 3600 \quad (6)$$

$$P_{battery}(t) = \begin{cases} P_{battery\_Crate}(t) \text{ for } P_{battery\_crate} \le P_{battery} \\ P_{battery}(t) \text{ for } P_{battery\_crate} > P_{battery} \end{cases}, \quad (7)$$

$$P_{HFCV}(t) = P_{battery}(t) + P_{FuelCell}(t), \quad (8)$$

$$EC(t) = P_{HFCV}(t) \times \Delta t \quad (9)$$

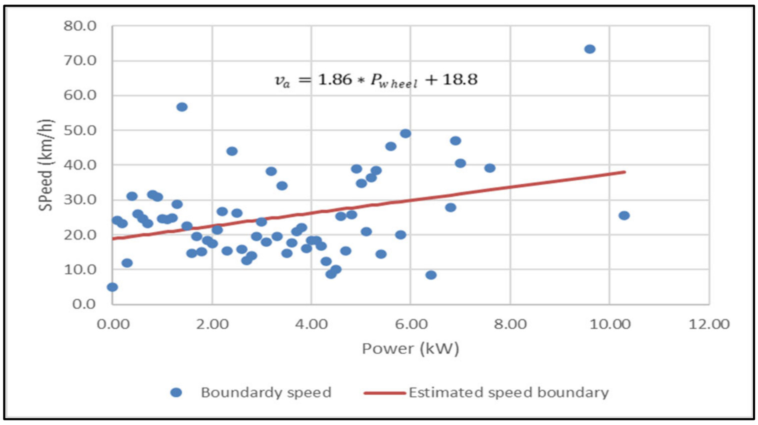


Figure 3. Boundary condition for battery mode.

The suggested model is universal and was employed for illustrative purposes using the 2017 Toyota Mirai as an example. Here, m is the vehicle mass ($m = 1928$ kg for the curb weight of the test Toyota Mirai); $a(t) = dv(t)/dt$ is the acceleration of the vehicle in m/s^2 after ensuring that the vehicle speed is converted to m/s ($a(t)$ takes negative values when the vehicle decelerates); $g = 9.8066\ \text{m/s}^2$ is the gravitational acceleration; θ is the road grade; and $C_r = 1.75$, $c_1 = 0.0328$, and $c_2 = 4.575$ are the rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type. The typical values of vehicle coefficients are reported in [19]. $\rho_{Air} = 1.2256\ \text{kg/m}^3$ is the air mass energy density of hydrogen, which is equal to 33.6 kWh of usable energy per kg; $A_f = 2.3316\ \text{m}^2$ is the frontal area of the vehicle; C_D is the aerodynamic drag coefficient of the vehicle (taken to be 0.28); and $v(t)$ is the vehicle speed in km/h [20].

$P_{Battery}$ and $P_{FuelCell}$ represent the power produced by the battery and the fuel cell, respectively. $P_{Battery}$ is estimated based on operational mode, as described in Equations (2)–(4). P_{idle} is a fixed idling power consumption rate, 0.45 kW, which is computed as the average idling power consumption of the dataset. η_{rb} is a regenerative braking energy efficiency, which is a function of vehicle deceleration. The detailed description is found in [19]. η_{batt} represents battery efficiency, and we adopted an efficiency value of 93% based on a recent reference [21]. η_{supple} is a supplemental power efficiency of battery. $\eta_{supple} = 0.216\%$ was estimated empirically using data comparing fuel cell power consumption data and the battery supplemental power consumption data.

The power consumed by the fuel cell is computed using Equation (5). Various efficiency factors are considered to estimate the power consumption of the fuel cell unit. We tested numerous methods for assessing fuel cell driveline efficiency and found that using a function based on the vehicle's power at the wheels relative to the maximum vehicle power is the most accurate and straightforward method for estimating fuel cell driveline efficiency. This study utilizes fuel cell driveline efficiency, $\eta_{fuelcell}$, which is computed as a function of the vehicle power at the wheels relative to the maximum vehicle power, as illustrated in Figure 4. Also, statistical analysis found that v_b is 23 km/h and P_a is 0.2 kW for the specific test vehicle. In Figure 4, it is observed that there are fewer data points in the 0.3–0.5 range of the current power/maximum power ratio in our fuel cell efficiency curve. This scarcity of data points in this range is not considered problematic for our analysis. In our approach, we treated these sparse data points as potential outliers, based on the typical efficiency characteristics of HFCVs. Generally, HFCVs exhibit efficiency values less than 0.7 under normal operating conditions. By focusing on the more densely populated regions of the efficiency curve, we aimed to create a model that accurately represents the efficiency characteristics of HFCVs in their most frequent operating scenarios. This approach allows us to provide a robust and reliable efficiency estimation for the majority of HFCV operating conditions.

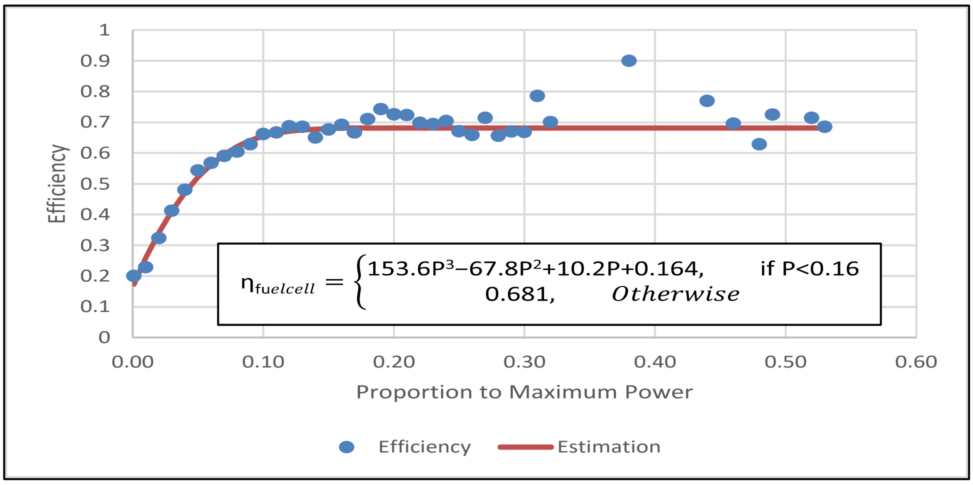


Figure 4. Fuel cell driveline efficiency estimation.

The C-rate of an electric vehicle battery refers to the rate at which a battery is charged or discharged relative to its capacity. The C-rate is typically expressed as a multiple of the battery's capacity. For example, if a battery has a capacity of 1 kWh, and it is charged or discharged at a rate of 1C, this means that the battery can be charged or discharged in one hour. The C-rate is important because it helps to quantify how quickly energy can be delivered to or drawn from the battery. Higher C-rates generally mean faster charging or discharging, but they can also impact the overall lifespan and efficiency of the battery. The C-rate is variable based on the battery characteristics and the SOC. This research found charging and discharging C-rates of 19.7 and 11.0, respectively, as indicated by the collected data. Equation (6) outlines the estimation of $P_{Battery\_Crate}$ using the C-rate. In cases where $P_{Battery}$ is greater than $P_{Battery\_Crate}$, Equation (7) is employed to substitute the value of $P_{Battery}$ with $P_{Battery\_Crate}$.

In this study, we assume the vehicle weight is a constant variable. The proposed model estimates the vehicle's energy consumption (EC) (kWh/s) over a time step, Δt (Equation (9)); the instantaneous power consumed (kW); and hydrogen consumed (kg). The hydrogen storage of the test Toyota Mirai is 5 kg.

5. Model Test and Validation

The model validation results demonstrate that the proposed model estimated fuel cell and battery energy consumption with reasonable accuracy for four representative driving cycles. In particular, the model estimated the fuel cell energy consumption with errors of 13.1%, 1.1%, 2.1%, and −10.0% for the UDDS, HWFET, NEDC, and speed cycles, respectively, as demonstrated in Table 1. We found that the model overestimated the fuel cell energy consumption for the UDDS cycle and underestimated for the speed cycle. It seems the model was not accurately calibrated for slow-speed driving conditions for the UDDS and speed cycles. The results showed that the overall model accuracy combining all urban and freeway driving cycles was −0.0%.

Table 1. Model estimation results.

	Fuel Cell Energy Estimation		
	Raw Data (kWh/km)	**Estimated (kWh/km)**	**Error Rate (%)**
UDDS	0.132	0.149	13.1%
Highway	0.278	0.281	1.1%
NEDC	0.295	0.301	2.1%
Speed	0.223	0.200	−10.0%
Total	0.234	0.234	0.0%
	Battery Energy Estimation		
	Raw Data (kWh/km)	**Estimated (kWh/km)**	**Error Rate (%)**
UDDS	0.062	0.061	−0.5%
Highway	0.028	0.034	18.1%
NEDC	0.079	0.076	−3.7%
Speed	0.030	0.026	−15.3%
Total	0.047	0.046	−0.7%
	Fuel Cell and Battery Estimation		
	Raw Data (kWh/km)	**Estimated (kWh/km)**	**Error Rate (%)**
UDDS	0.193	0.210	8.8%
Highway	0.306	0.314	2.7%
NEDC	0.374	0.377	0.9%
Speed	0.253	0.226	−10.7%
Total	0.280	0.280	−0.1%

The table provides an estimate for battery energy consumption. The outcomes indicate that the battery energy consumption had errors of −0.5% 18.1%, −3.7%, and −15.3% for the UDDS, HWFET, NEDC, and speed cycles, respectively. The results demonstrated that the accuracy of the overall battery model, when encompassing all driving conditions, was −0.7%.

The research also found that the suggested model predicted the combined energy consumption of the fuel cell and battery, with errors of 8.8%, 2.7%, 0.9%, and −10.7% for the UDDS, HWFET, NEDC, and speed cycles, respectively. These findings show that the proposed model provides accurate energy consumption estimates, with only a −0.1% deviation, when compared to experimental data for the total energy consumption across all drive cycles.

Figure 5 depicts a comparison between the NEDC driving cycle's instantaneous fuel cell energy consumption rate and the overall energy consumption rate, which combines both fuel cell and battery energy usage, in relation to the measured instantaneous energy consumption rate of the test vehicle. The graph also illustrates the vehicle energy consumption rate estimates generated by the proposed model, relying on instantaneous power and vehicle speed. As shown in the figure, the projected energy consumption generally mirrored the peaks and valleys observed in the measured vehicle energy consumption. The results clearly highlight a strong alignment between the instantaneous energy consumption predictions and the measurements obtained in the laboratory. However, it is worth noting that the proposed model occasionally slightly overestimated or underestimated certain fuel consumption rates during the NEDC. Notably, the model underestimated fuel consumption rates in the initial and final segments of the driving cycle, at times 26 s and 2369 s. The observed underestimation of energy consumption rates in the initial and final segments of the driving cycle can be attributed to data-collection errors in these specific portions. Despite these minor discrepancies, the overall prediction pattern of our model demonstrates reasonable accuracy and consistency throughout the entire driving cycle. The localized deviations at the beginning and end of the cycle are considered negligible when evaluating the model's performance holistically.

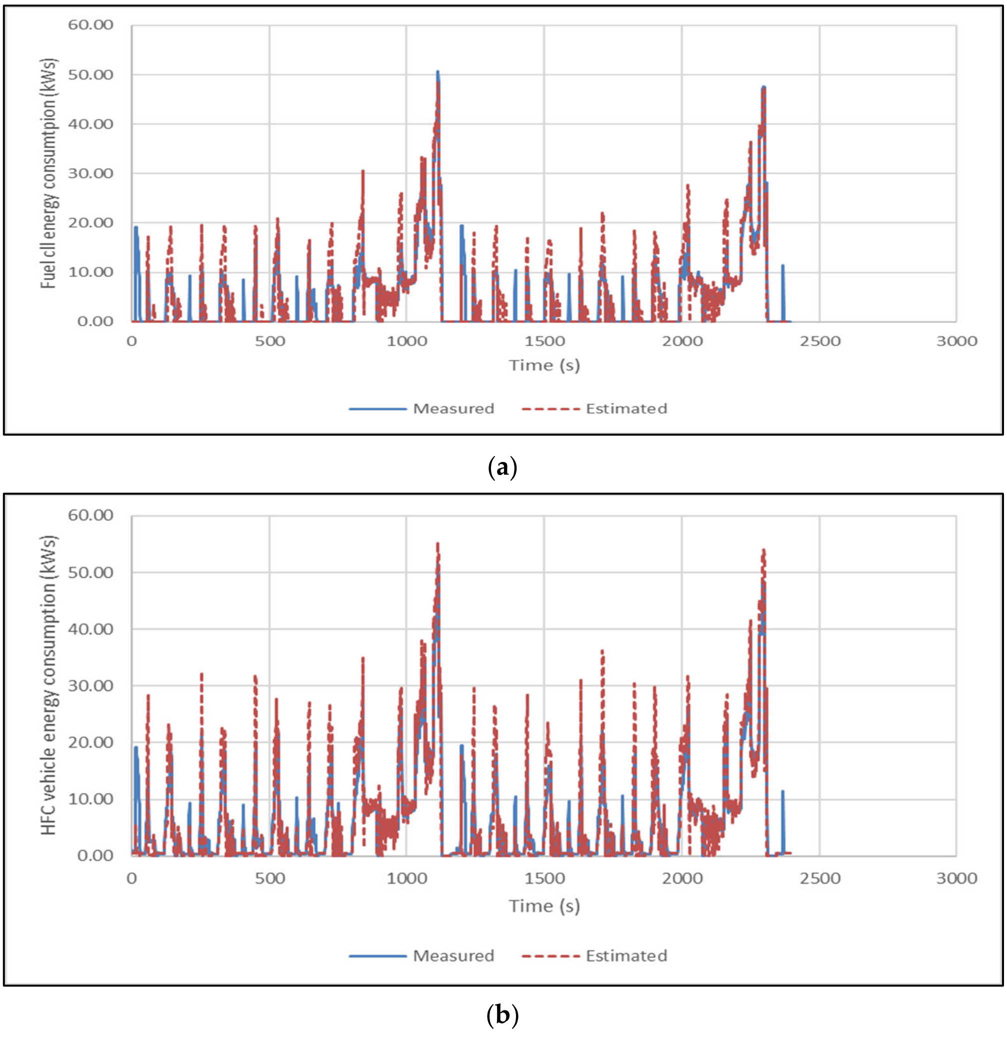


Figure 5. Model prediction of NEDC: (**a**) fuel cell consumption and (**b**) total consumption.

The proposed model was validated using an independent dataset, employing data from the Japanese JC08 cycle (JC08). These data were gathered at the Argonne National Laboratory, utilizing the 2017 Toyota Mirai as the test vehicle. For result validation, we specifically chose the Japanese JC08 cycle (JC08). This selection was made because the JC08 cycle data were not utilized in the development of our model, thus serving as an independent dataset. By using JC08 data for validation, we were able to assess the model's performance on a completely separate and unbiased set of driving conditions. This approach allows us to demonstrate the model's robustness and generalizability beyond the specific cycles used in its development.

The JC08 drive cycle is a set of testing procedures and conditions used in Japan to evaluate the fuel efficiency and emissions of vehicles. It is one of the testing protocols employed by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism (MLIT) for certification purposes. The JC08 drive cycle is designed to simulate typical driving conditions in Japan. It represents a specific driving pattern with defined speed profiles, acceleration, and deceleration characteristics. The cycle takes into account various driving scenarios, such as city driving, suburban roads, and highway conditions. While the JC08 drive cycle was developed and used in Japan, the drive cycle is widely utilized in other regions and countries, such as the EPA cycle in the United States or the NEDC (New European Driving Cycle) in Europe. The JC08 cycle lasts for 1204 s, covering a total distance of 8.17 km. The average speed during the cycle is 24.4 km/h (or 34.8 km/h when excluding idle periods), with a maximum speed reaching 81.6 km/h.

Figure 6 illustrates a comparison between the projected energy consumption rates of the hydrogen fuel cell vehicle (HFCV) and the data obtained from laboratory testing using the JC08 cycle. According to the proposed model, the fuel cell estimation yielded a predicted consumption of 4.22 kWh, while the actual test vehicle consumed 3.95 kWh in the laboratory, resulting in a 6.7% error. In terms of total energy consumption, the model forecasted 5.70 kWh, and the test vehicle consumed 5.69 kWh, with a 0.2% error. Figure 6b provides a comprehensive second-by-second analysis of both fuel cell estimation and total energy consumption, demonstrating the proposed model's accurate prediction of fuel cell energy consumption and overall energy consumption during the JC08 trip, in comparison to the measured energy consumption rate of the test vehicle. These results highlight the effectiveness of the proposed model in accurately estimating HFCV energy consumption for various driving scenarios, such as city driving, suburban roads, and highway conditions.

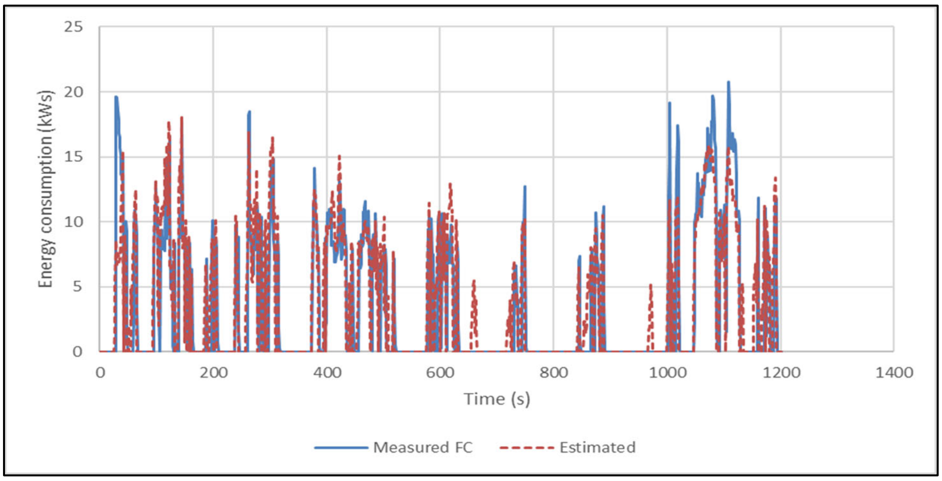
While the proposed model simplifies the conditional battery mode, the battery mode also depends on the battery's SOC. SOC_f, a final SOC, is estimated based on the total SOC changes during the trip using Equations (8) and (9). The capacity of the test vehicle's battery, $Battery_{Capacity}$, is 1.6 kWh. $P_{Battery}$ in Equation (7) is utilized to estimate the SOC changes over a time step, Δt.

$$SOC_f(t) = SOC_0 - \sum_{i=0}^{n} \Delta SOC_i(t), \tag{10}$$

$$\Delta SOC_i(t) = SOC_{(i-1)}(t) - \frac{P_{battery}(t)}{3600 * Battery_{Capacity}} \tag{11}$$

The SOC model findings revealed that the proposed model reasonably approximates the final SOC values for three typical driving cycles. Specifically, the model predicted SOC values with errors of 8.5%, −11.9%, and 3.0% for the UDDS, HWFET, and NEDC cycles, respectively. The speed cycle results are not presented in the table due to the unavailability of SOC data for this particular cycle. The SOC model presented in Equations (10) and (11) serves as an independent validation tool rather than an integral component of the proposed HFCV energy consumption model. The SOC model does not directly influence or integrate with the energy calculations. Its primary function is to provide a comparative analysis between estimated and actual SOC values, offering insights into the model's temporal performance.

In Figure 7, the model's SOC predictions are illustrated, and they closely align with the observed instantaneous SOC measurements, demonstrating the model's effectiveness in estimating real-time changes in SOC. The figure also displays real-time vehicle acceleration measurements. Notably, the model effectively captured a consistent SOC reduction between 887 s and 1126 s, followed by a sudden SOC increase from 1127 s to 1153 s. In summary, the model accurately predicted energy consumption and SOC for hydrogen fuel cell vehicles with errors within a reasonable range compared to actual data. This feature empowers the model to evaluate the effects of transportation initiatives, such as eco-friendly driving practices and real-time applications and CAVs.



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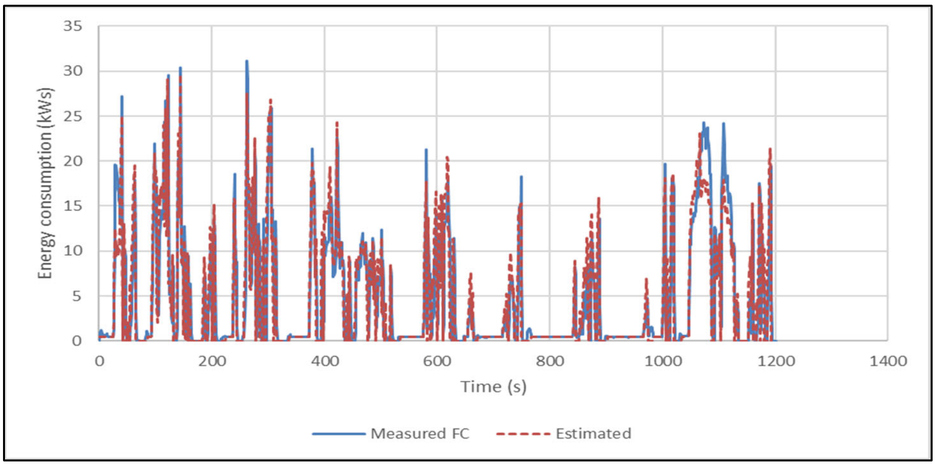


(**b**)

Figure 6. Model validation of JC08: (**a**) fuel cell consumption and (**b**) total consumption.

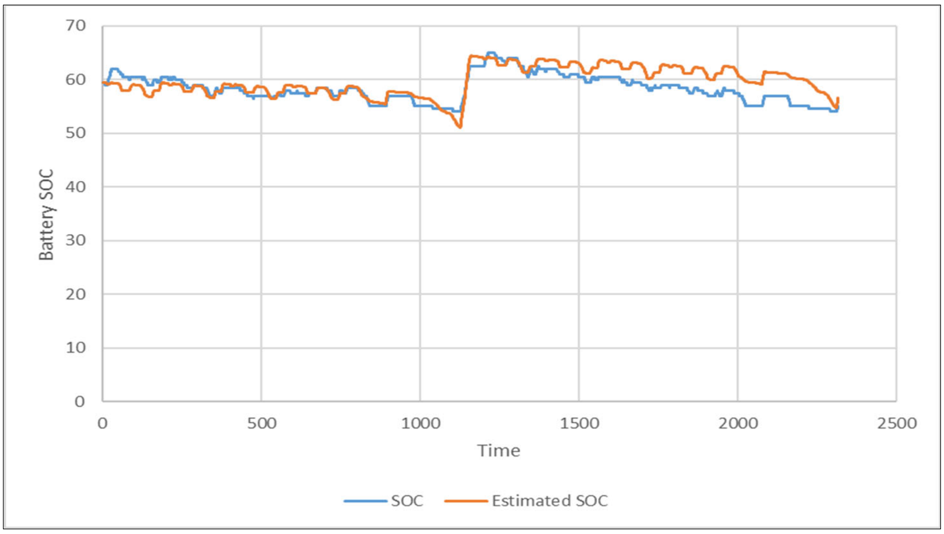
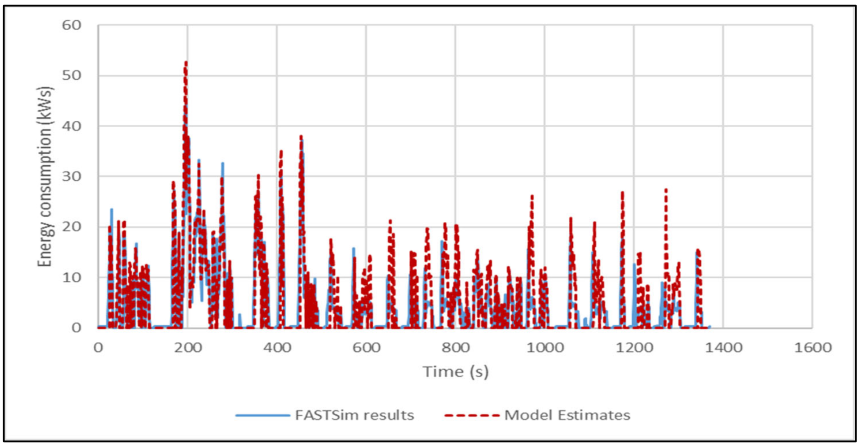


Figure 7. NEDC SOC estimation.

6. Model Comparison with FASTSim

FASTSim [13,14], developed by the National Renewable Energy Laboratory (NREL), is a widely used vehicle simulation tool designed to estimate energy consumption, performance, and cost for various vehicle types under real-world driving conditions. It simulates vehicle powertrains, including fuel cells, electric motors, and batteries, to calculate energy flow and hydrogen consumption in HFCVs. It is a lightweight, physics-based vehicle simulation tool designed to evaluate vehicle energy consumption. FASTSim and the proposed model employ different approaches to estimate vehicle energy consumption, particularly regarding motor efficiency. FASTSim relies on detailed motor efficiency maps or lookup tables that define the relationship between motor speed, torque, and efficiency. In contrast, the proposed model calculates the power required at the wheels and determines how the vehicle delivers that power based on a fuel cell driveline efficiency estimation method. This approach eliminates the need for specific motor efficiency data, which are often difficult to obtain for individual vehicles. By avoiding this requirement, the proposed model offers a more flexible solution for estimating HFCV energy consumption, especially in scenarios where detailed component-level data are unavailable or hard to access.

Figure 8 offers a visual comparison between the FASTSim results and the model estimates for energy consumption over time for three driving cycles (UDDS, HWFET, and NEDC). In this figure, both FASTSim and the proposed model follow similar overall trends in terms of when energy consumption increases or decreases over time. Peaks and lows occur at roughly the same points across all three driving cycles. The proposed model shows slightly more frequent fluctuations compared to FASTSim's smoother results.



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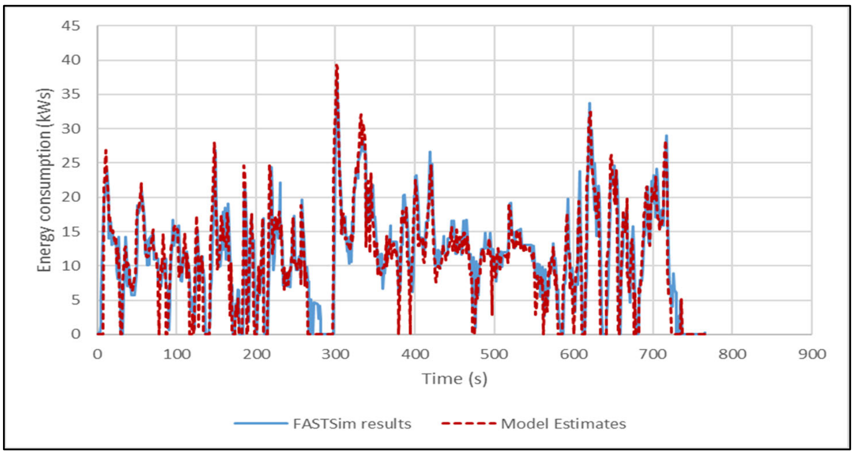

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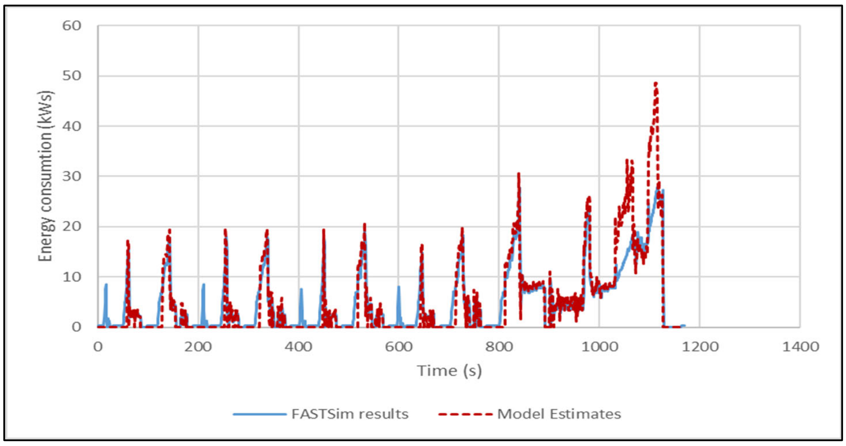
Figure 8. *Cont.*



(**c**)

Figure 8. Model comparison with FASTSim results: (**a**) UDDS, (**b**) HWFET, and (**c**) NEDC.

Table 2 provides a comparison of energy consumption estimates (in kWh) between the collected data, the proposed model, and FASTSim across three driving cycles: UDDS, highway, and NEDC. For UDDS, the proposed model overestimates the energy consumption by 13.50%, whereas FASTSim has a much smaller error rate of 2.10%. For HWFET, the proposed model performs very well in this cycle, with an error rate of only −0.40%, indicating a slight underestimation, while FASTSim overestimates energy consumption with a higher error rate of 3.90%. For NEDC, both models underestimate energy consumption for this driving cycle, but FASTSim has a larger underestimation (−9.50%) compared to the proposed model (−6.30%). When considering all cycles together, both models perform well, with low overall error rates. The proposed model slightly overestimates total energy consumption by 1.70%, while FASTSim slightly underestimates it by 0.80%. The overall difference between the two models is small, at just 2.50%, indicating that both models are reasonably close in their total predictions.

Table 2. Energy consumption comparison of FASTSim and the proposed model.

	Raw Data (kWh)	Proposed Model (kWh)	Proposed Model Error Rate (%)	FASTSim (kWh)	FASTSim Error Rate (%)	Proposed Model vs. FASTSim Difference (%)
UDDS	1.58	1.80	13.5%	1.62	2.1%	11.2%
HWFET	2.31	2.30	−0.4%	2.40	3.9%	−4.1%
NEDC	1.75	1.64	−6.3%	1.59	−9.5%	3.6%
Total	5.65	5.74	1.7%	5.60	−0.8%	2.5%

7. Traffic Simulation Model Test Using HFCV Energy Model

This section evaluates how the developed HFCV model can estimate energy consumption and the effects of energy consumption on various transportation operations.

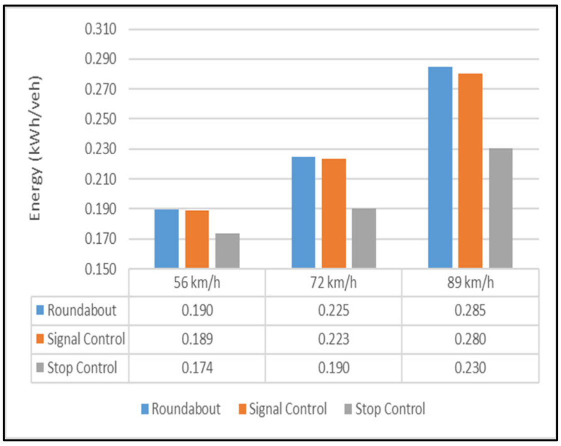
Expanding on prior research [22], the authors assessed the impact of intersection controls on energy consumption across various powertrain types (BEV, ICEV, HFCV, and HEV). INTEGRATION software version 2.40 [23–25], a validated microscopic traffic simulation platform, facilitated realistic modeling of vehicle behavior under diverse intersection controls.

The case study focused on the intersection of Ariane Way and Virginia 606 in Loudoun County, Virginia, serving as a crucial alternative route for travelers accessing Washington Dulles Airport. The speed limits are 88 km/h for eastbound and westbound traffic and 40 km/h for northbound and southbound traffic, with two-way stop signs controlling traffic flow. Notably, traffic volume remains relatively low during non-peak hours but significantly increases during peak hours, resulting in congestion and lengthy queues on Ariane Way, typically ranging from 10 to 15 vehicles.

To simulate traffic flow, we leveraged existing simulation models incorporating field-derived parameters: speed, volume, saturation flow rate, jam density, lanes, and striping data. Base saturation flow rates and jam densities were set at 1800 vehicles/hour/lane and 120 vehicles/km/lane, except for northbound approaches, which accounted for aggressive driving (2000 vehicles/hour/lane). Gap times ranged from 3 to 4 s. The model was calibrated and validated against field data. Signalized intersections featured two-phase movements with 35 s cycles, while roundabouts used 50 km/h entry speeds and 60 m diameters, as recommended in "Roundabouts: An Information Guide" [26].

The energy and fuel consumption for HFCVs, BEVs, HEVs, and ICEVs were estimated using second-by-second vehicle speed profiles generated by the INTEGRATION software. We used this detailed speed and acceleration data to calculate energy consumption rates for each second for HFCVs, ICEVs, BEVs, and HEVs. To estimate the energy and fuel consumption results for BEVs, HEVs, and ICEVs, we employed the VT-CPEM [19], VT-HEV [18], and VT-CPFM [27] models, respectively. The impact of different approach speeds was assessed using three scenarios: 56 km/h (35 mph), 72 km/h (45 mph), and 89 km/h (55 mph).

Figure 9 evaluates energy consumption and fuel efficiency at three distinct intersection types (roundabouts, signalized intersections, and two-way stop signs) for different approach speeds: 56 km/h, 72 km/h, and 89 km/h. The figure reveals that HFCVs and ICEVs exhibit similar energy/fuel consumption patterns, while BEVs and HEVs show different patterns. Specifically, for HFCVs, the roundabout control results in the highest energy consumption, and the two-way stop-sign control results in the lowest energy consumption across all approach speeds. For ICEVs, the signal control consumes the most fuel at an approach speed of 56 km/h, whereas the roundabout consumes the most fuel at speeds of 72 km/h and 89 km/h. For BEVs, the energy/fuel differences among the three traffic controls are minor, with less than 1% variation. At an approach speed of 56 km/h, the signal control consumes the least energy, and the roundabout consumes the most. At 72 km/h, the signal control consumes the least energy, while the stop control consumes the most. At 88 km/h, the stop control consumes the least energy, and the signal control consumes the most. For HEVs, the stop control consumes the least energy at all three speeds, while the roundabout consumes the most energy at 56 km/h and 72 km/h, and the signal control consumes the most energy at 89 km/h.



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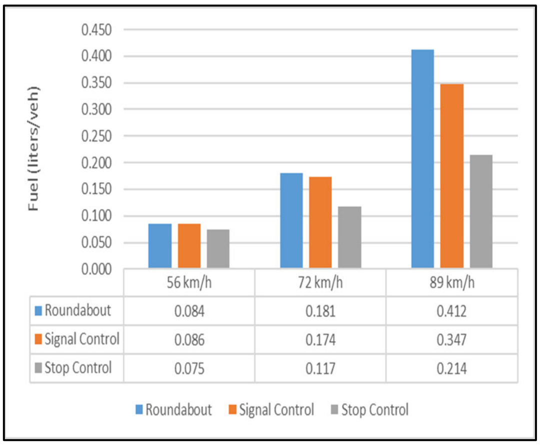

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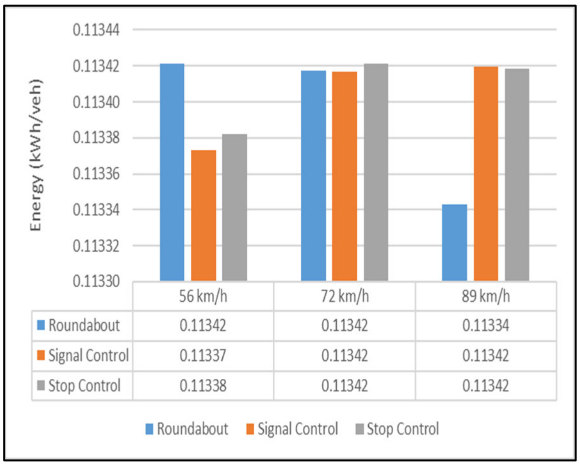
Figure 9. *Cont.*



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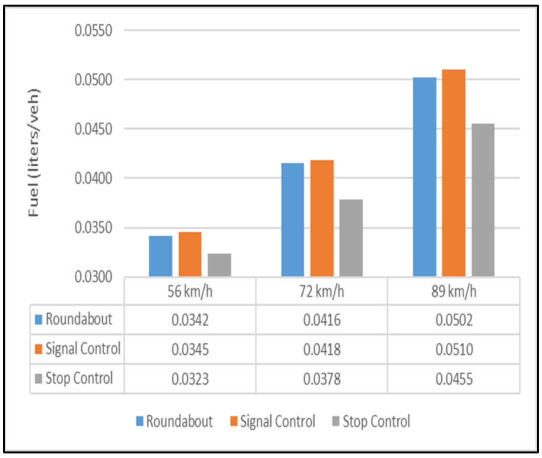

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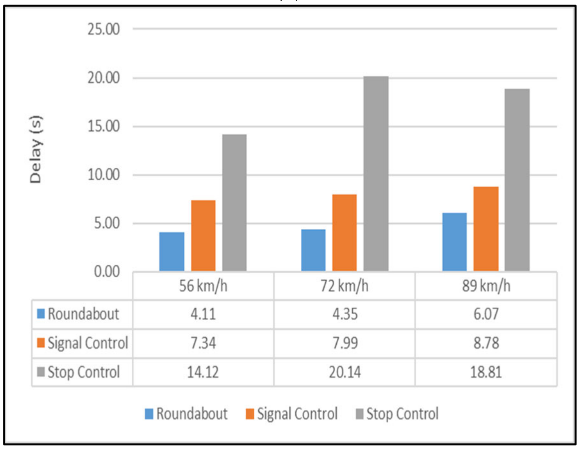

(**e**)

Figure 9. Simulation test results. (**a**) HFCV, (**b**) ICEV, (**c**) BEV, and (**d**) HEV. (**e**) Average delay per vehicle.

The figure also demonstrates that roundabouts and signal controls reduce delays by up to 71% and 60%, respectively, compared to stop-sign controls. This suggests that traffic control designs that minimize delays may lead to increased energy/fuel consumption for vehicles. For this case study, the results indicate that the most energy/fuel-efficient traffic controls vary for HFCVs, BEVs, HEVs, and ICEVs. Considering these findings, traffic planners and engineers should carefully balance improvements in both energy/fuel consumption and traffic delays.

8. Conclusions

In this work, a novel energy model for HFCVs was developed. The findings indicate a strong alignment between the model's predictions and real-world data, with average error rates of 0.0% and −0.1% for fuel cell and total energy consumption across all four cycles. However, it was noted that the error rate for a specific cycle, like the UDDS, could be as high as 13.1%. Additionally, the study affirmed the reliability of the proposed model through validation using independent data. The results revealed that the innovative model accurately forecasted energy consumption, with error rates of 6.7% for fuel cell estimation and 0.2% for total energy estimation compared to empirical data. The study also presented SOC estimation results, demonstrating the model's accuracy in predicting real-time SOC changes by closely aligning with observed measurements. The study also included a comparison with FASTSim results. When looking at all driving cycles combined, both models demonstrate good performance, showing low overall error rates. The proposed model slightly overpredicts total energy consumption by 1.70%, while FASTSim slightly underpredicts it by 0.80%. The overall difference between the two models is minimal, at just 2.50%, indicating that both models are reasonably close in their total predictions. The study investigated the energy impact of various intersection controls, including roundabouts, traffic signals, and stop signs, to assess the applicability of the proposed energy model. The model's design made it simple to calculate energy consumption by utilizing data from traffic simulation software.

The proposed model offers significant advantages over FASTSim or other HFCV energy models, primarily due to its simplified structure. The structure of our model significantly reduces computational requirements through several key features. By utilizing simple input variables instead of complex vehicle input variables or engine map data, our model minimizes data processing and memory allocation needs. The absence of torque-versus-speed models and complex component interactions enables more straightforward mathematical operations, substantially reducing the number of calculations required per simulation step. Furthermore, the model's design, with fewer interdependencies between variables, avoids recursive calculations and iterative processes that typically increase computational load. These streamlined aspects contribute to a more computationally efficient model, making it particularly suitable for applications where processing power or memory might be limited. This approach likely results in reduced computational requirements, making it particularly beneficial for real-time applications or scenarios with limited computational resources. By prioritizing simplicity without compromising accuracy, the proposed model addresses limitations of more complex systems like other models, offering a practical and versatile alternative for HFCV modeling.

While the proposed model currently relies on data from a single vehicle, the use of data from only one vehicle in developing the HFCV energy model is a necessary step given the significant challenges and costs associated with obtaining comprehensive data. This preliminary study serves to validate the model's framework and demonstrate its potential, using high-quality data from a representative vehicle to ensure accurate performance metrics. While the current model is based on limited data, it is designed to be scalable and refined with additional data in future research. The research team plans to incorporate more data as they become available to enhance the model's accuracy and robustness. Further, temperature effects play a crucial role in HFCV energy modeling. In our future research, we will focus on developing methodologies to accurately model the impact of temperature on HFCV energy consumption, including cold and warm starts. This approach will enhance the model's accuracy and applicability across various operating conditions, providing a more comprehensive understanding of HFCV performance in real-world scenarios

In conclusion, this research suggests that HFCVs have the potential to serve as a more efficient and environmentally friendly option compared to traditional vehicles. The outcomes offer a valuable resource for policymakers, transportation and environmental engineers, and auto manufacturers, and a reliable means to quantify the energy consumption impact of HFCVs in transportation projects.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

$a(t)$	Acceleration of the vehicle
A_f	Frontal area of the vehicle
C_D	Aerodynamic drag coefficient of the vehicle
C_r, c_1 and c_2	Rolling resistance parameters
$EC(t)$	Energy consumption
g	Gravitational acceleration
m	Vehicle mass
P_{aux}	Power due to the auxiliary systems
P_a	Specific power
P_b	Specific power
P_{idle}	Idle power
$P_{battery}(t)$	Power from battery
$P_{battery\_Crate}(t)$	Battery C-rate
$P_{FuelCell}(t)$	Power from fuel cell
$P_{HFCV}(t)$	Power from fuel cell and battery
$P_{Wheels}(t)$	Power at the wheels
$v(t)$	Vehicle speed
v_a	Specific vehicle speed
α, β	Vehicle-specific parameters
ρ_{Air}	Air mass density
η_{rb}	Regenerative braking energy efficiency
η_{batt}	Battery efficiency
η_{supple}	Supplemental power efficiency
θ	Road grade

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