Journal of Power Sources 196 (2011) 3271–3279

Contents lists available at ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

An experimental and analytical comparison study of power management methodologies of fuel cell–battery hybrid vehicles

Ahmad Fadel, Biao Zhou*

Department of Mechanical, Automotive & Materials Engineering, University of Windsor, 401 Sunset Ave., Windsor,,ON, Canada N9B 3P4

ARTICLE INFO

Article history:
Received 3 October 2010
Received in revised form 9 November 2010
Accepted 22 November 2010
Available online 26 November 2010

Keywords:
PEMFC
Hybrid fuel cell–battery vehicle
Power management
Battery life
Electric powertrain
Control design

ABSTRACT

The implementation of fuel cell vehicles requires a supervisory control strategy that manages the power distribution between the fuel cell and the energy storage device. Some of the current problems with power management strategies are: fuel efficiency optimization methods require prior knowledge of the driving cycle before they can be implemented, the impact on the fuel cell and battery life cycle are not considered and finally, there are no standardized measures to evaluate the performance of different control methods. In addition to that, the performances of different control methods for power management have not been directly compared using the same mathematical models. The proposed work will present a different optimization approach that uses fuel mass flow rate instead of fuel mass consumption as the cost function and thus, it can be done instantaneously and does not require knowledge of the driving cycle ahead of time. Also this study presents an experimental approach to validate the mathematical simulation results.

1. Introduction

While the addition of an energy storage device to fuel cell vehicles (i.e. fuel cell–battery hybrid vehicles) helps significantly improve the efficiency and transient response, it also adds another dimension to the design process. A power management strategy is needed to optimize the performance of the two energy sources. This paper is focused on studying power management in fuel cell–battery hybrid vehicles. In particular this paper is concerned with configurations where hydrogen fuel is the only source of energy (i.e. not a plug-in configuration). A literature survey shows that various forms of control methods have already been considered and implemented for power management between the fuel cell engine and the battery. In general, these control methods follow either a rule based approach or an optimization approach. Fuzzy logic controllers have been the common method used in the case of the rule based approach. This can be seen in the work of Jeong et al. [1] and Kisacikoglu et al. [2], where a fuzzy logic controller dictates the load sharing based on the state of charge (SOC) of the battery and the vehicle load demand. The optimization approach on the other hand is mainly concerned with the fuel consumption of the vehicle as shown in the work presented by Gao et al. [3] and several others [4–6]. This approach finds the optimal load sharing ratio between the fuel cell and the battery by minimizing a fuel consumption cost function over the range of the driving cycle.

Both of the mentioned approaches have their own drawbacks. The main difficulty with fuzzy logic controllers is that they require training data in order to correctly form the membership functions and set of “if-then” rules that dictate the output of the controller. While the difficulty with the optimization approach is that it requires prior knowledge of the intended driving cycle, which is a challenge in on its own. An alternative approach that combines fuzzy logic and optimization was presented in [7], where Li and Liu used optimization to obtain training data to design the fuzzy logic controller parameters. While this is an improvement on fuzzy logic controllers, it still does not guarantee optimal operation since it is very difficult to predict the real world driving pattern. Recently, another interesting study published by Xu et al. [8] at Tsinghua University presented a different optimization approach that uses fuel mass flow rate instead of fuel mass consumption in the cost function and thus, it can be done instantaneously and does not require knowledge of the driving cycle ahead of time. However, the effectiveness of this approach has not been compared directly with other conventional controllers such as the fuzzy logic controller. This comparison is important because minimizing fuel consumption is only part of the controller objective, the controller must also maintain the battery SOC at acceptable operating conditions. Thus, the main difference between control methods is how they go about sustaining the battery charge level. Some control methods will make the battery discharge/charge more often than others. While maintaining the SOC is important to the battery life, charging the battery

* Corresponding author. Tel.: +1 519 253 3000x2630; fax: +1 519 973 7007.
E-mail address: bzhou@uwindsor.ca (B. Zhou).

0378-7753/$ – see front matter
doi:10.1016/j.jpowsour.2010.11.114

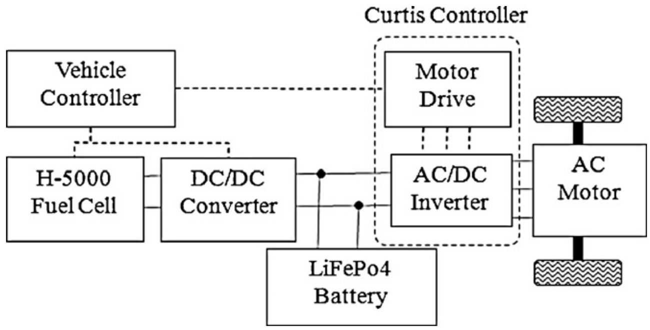

Fig. 1. Vehicle configuration.

more than needed will result in lowering the overall fuel efficiency and also reducing the battery life. Thus, there is a tradeoff between the extended battery life and fuel efficiency when designing power management strategies for fuel cell–battery hybrid vehicles.

The work presented in this paper will carry on the work presented in [8] to design an instantaneous optimization power management controller. However, in order to validate the optimal controller design, this paper establishes a set of performance measures to compare the effectiveness of the designed optimal controller with a fuzzy logic and a PID controller designed for the same vehicle application. These performance measures take into consideration: battery life, total fuel consumption and instantaneous efficiency. Most importantly this paper will present a hardware-in-the-loop experimental setup used to validate the results obtained from the mathematical models.

2. Vehicle configuration

The vehicle chosen as the application case for this study is the SAE Baja vehicle designed and built by undergraduate students at the University of Windsor [9]. The main advantages of using the SAE Baja vehicle is its availability for experimental testing, simplicity of powertrain components and also relative ease of mathematical modeling. Despite the fact that the SAE Baja vehicle does not fall under an actual road vehicle weight class, the conclusions obtained from this study can still be generalized and considered when designing control algorithms for fuel cell vehicles. The vehicle considered in this study has a mass of 308.45 kg, frontal area of 0.9 m^2 and a wheel radius of 0.1397 m.

The rated power of the SAE Baja vehicle is 7 kW, therefore, a 5 kW fuel cell engine, a 10 Ah lithium-ion battery stack and a 13 kW AC induction motor were selected to propel the SAE Baja vehicle. A 10 Ah battery stack was selected because it is sufficient to satisfy the vehicle loads over the length of the driving cycle before reaching 0% state of charge. The fuel cell selected for this application is the H-5000 manufactured by Horizon Fuel Cell Technologies, while the battery stack is assumed to be constructed of the Sony 18650 (1.8 Ah) lithium-ion cells. The selected AC motor has rated torque and speed of 100 Nm and 6000 rpm, which is enough to propel the SAE Baja vehicle at a speed of 30 km h^{-1} and maximum road slope of 15°. The motor speed is controlled through a Curtis Instruments speed controller (model: 1236), where this controller also includes a DC/AC inverter for interfacing the electric motor drive to the DC bus. The powertrain configuration is shown in Fig. 1.

3. Vehicle model

The mathematical models for each one of the vehicle components are implemented in MATLAB/Simulink. The vehicle is modeled using the simple longitudinal vehicle dynamics equations, where the total power required to drive the vehicle is calculated

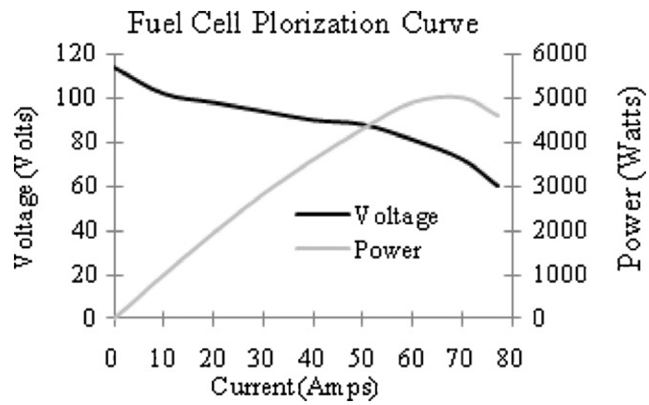

Fig. 2. Fuel cell polarization curve.

based on the aerodynamic drag, rolling resistance, acceleration and road grade power requirements:

$$P = \left[\tfrac{1}{2}\rho C d V^2 + mg\,\mathrm{Cr}\cos\theta + mg\sin\theta + ma\right](r_{\text{wheel}})\omega \quad (1)$$

where V, a, and ω are the vehicle velocity (m s^{-1}), acceleration (m s^{-2}) and wheel angular velocity (rad s^{-1}) respectively. The electric motor drive is modeled based on experimental data provided by the manufacturer; the data is used to construct a lookup table that determines the motor torque, power and also the amount of rms-current being drawn given a known motor speed.

4. Fuel cell model

For the purpose of this study, the fuel cell model is kept as simple as possible, where the fuel cell is modeled as a voltage source with a variable voltage loss across its terminals. The voltage loss was determined based on the polarization curve provided by Horizon Fuel Cell Technologies [10]. Also, a three second time constant is simulated on the fuel cell response by adding a first order transfer function to its output voltage signal. The hydrogen fuel mass flow rate is calculated as follows:

$$\dot{m}_{H_2} = \frac{N(i_{fc})(M_{\text{hydrogen}})}{n_e F} \quad (2)$$

where N is the number of cells, M is the molar mass of hydrogen gas, n_e is the number of electrons transferred and F is Faraday's constant. The polarization curve is shown in Fig. 2.

The fuel cell efficiency is obtained by dividing the fuel cell polarization curve voltage by the higher heating value theoretical voltage (1.48 V) as shown in Fig. 3. Note that for the sake of simplicity, and since this model is focused on the control algorithm, the efficiency losses due to parasitic loads are not considered.

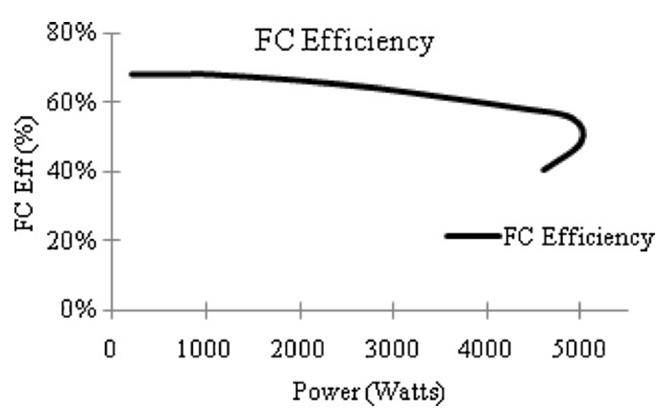

Fig. 3. Fuel cell efficiency.

In order to accommodate for the fuel cell voltage drop, a DC/DC converter is used to maintain a constant voltage output while varying the output current. The converter used is a current controlled boost converter. The change in efficiency of the DC/DC converter as the power transferred is increased is assumed to be minimal, thus, an average value for the efficiency can be used. In this paper, the DC/DC converter efficiency is assumed to have an average value of 90%.

5. Battery model

The battery stack is modeled based on experimental test data available in literature. In a study to develop a mathematical model for lithium-ion batteries, Khateeb et al. [11] performed discharge tests on the Sony 18650 Li-ion battery cell in order to develop a relationship between the battery state of charge, the open circuit voltage and the internal resistance. The experimental results were curve fitted and the voltage drop across the battery terminals is represented using the following equations:

$$R(\mathrm{SOC}) = 0.20139 + 0.58863(1-\mathrm{SOC}) - 0.81697(1-\mathrm{SOC})^2 + 0.79035(1-\mathrm{SOC})^3 \quad (3)$$

$$V_o(\mathrm{SOC}) = 3.95587 - 1.42918(1-\mathrm{SOC}) + 2.83095(1-\mathrm{SOC})^2 - 3.7497(1-\mathrm{SOC})^3 \quad (4)$$

$$\mathrm{SOC}(t) = 1 - \frac{\int i dt}{Q(\mathrm{Ah})} \quad (5)$$

Therefore, the total voltage drop across the battery terminals is calculated by subtracting the internal resistance voltage loss from the open circuit voltage:

$$V_{\mathrm{batt}} = n_s(V_o(\mathrm{SOC}) - IR(\mathrm{SOC})) \quad (6)$$

where n_s is the number of battery cells in series. The battery efficiency in discharge mode is determined based on the open circuit voltage as shown below:

$$\mathrm{Eff}_{\mathrm{batt}} = \frac{V_{\mathrm{batt}}}{V_o(\mathrm{SOC})} \quad (7)$$

6. Performance measures

While, system efficiency and fuel consumption are the two main performance measures that are always considered for hybrid vehicles, the life time of the battery in the hybrid powertrain is often not considered. Even though estimating the life of battery requires extensive testing, the battery life is mainly related to the number of charge/discharge cycles. In hybrid vehicles however, the battery does not go through full charge/discharge cycles, instead it is forced to go through partial SOC cycling. Although, lithium batteries do not suffer from "memory effect", it has been shown in a study by Kato et al. [12] that partial SOC cycling can still have an impact on the battery life. Thus, the two power management methods examined in this work will be compared based on the number of partial SOC charge/discharge cycles the battery has to go through during the simulation.

Another performance measure is the overall system efficiency. The system efficiency of a hybrid powertrain depends on the mode of operation: hybrid drive, regenerative braking or just charging the battery. Therefore, an efficiency expression can be derived using the following "if-else" statements:

If power demand > 0, then:

$$\mathrm{Eff}_{\mathrm{hybrid}} = \frac{P_{\mathrm{drive}}}{(\dot{m}_{\mathrm{H_2}})(\mathrm{HHV}_{\mathrm{H_2}}) + (I_{\mathrm{batt}})(V_{\mathrm{batt\_OC}}(\mathrm{SOC})/(\mathrm{Eff}_{\mathrm{fc}}\mathrm{Eff}_{\mathrm{DC}}))} \quad (8)$$

Note that the battery's open circuit voltage is divided by the fuel cell and DC/DC converter efficiencies since the vehicle is assumed to have no plug-in capabilities.

Else, if power demand < 0, then:

$$\mathrm{Eff}_{\mathrm{regen}} = \frac{\left|(I_{\mathrm{batt}})(V_{\mathrm{batt\_OC}}(\mathrm{SOC}))\right|}{(\dot{m}_{\mathrm{H_2}})(\mathrm{HHV}_{\mathrm{H_2}}) + \left|P_{\mathrm{drive}}\right|} \quad (9)$$

Else, if battery power < 0, then:

$$\mathrm{Eff}_{\mathrm{charge}} = \frac{P_{\mathrm{drive}} + \left|(I_{\mathrm{batt}})(V_{\mathrm{batt\_OC}}(\mathrm{SOC}))\right|}{(\dot{m}_{\mathrm{H_2}})(\mathrm{HHV}_{\mathrm{H_2}})} \quad (10)$$

where $\dot{m}_{\mathrm{H_2}}$ is the hydrogen fuel mass flow rate (kg s^{-1}), $\mathrm{HHV}_{\mathrm{H_2}}$ is the higher heating value of hydrogen fuel (141.9 MJ kg^{-1}), V_{batt} is the measured battery voltage at its terminals, $V_{\mathrm{batt\_OC}}$ (SOC) is the open circuit voltage as a function of the state of charge of the battery and $\mathrm{Eff}_{\mathrm{DC}}$ is the efficiency of the DC/DC converter. Note that the if/else statement allows the battery to either be a sources or a sink, and thus the sign of the current does not impact the calculation and that is why the absolute value function is used.

In addition to the overall system efficiency, the miles per gallon of gasoline equivalent (MPGGE) is also an important measure that gives an insight as to how the fuel cell vehicle compares to internal combustion engine vehicles in terms of its fuel consumption. The conversion to the equivalent miles per gallon of gasoline is done on the basis of the hydrogen fuel energy content compared to the gasoline energy content. The energy content of liquid gasoline fuel is taken to be 115,000 BTU per gallon, while the energy content of gaseous hydrogen fuel is 113,738 BTU per kilogram, thus, the energy in one gallon of gasoline is equivalent to that in 1.012 kg of hydrogen fuel. Therefore, the MPGGE is calculated as follows:

$$\mathrm{MPGGE} = \left(\frac{\text{miles}}{\text{kg of H}_2}\right)\left(1.012\frac{\text{kg of H}_2}{\text{gallon of gasoline}}\right) \quad (11)$$

The total fuel mass consumed during a driving cycle can be calculated by integrating the fuel mass flow rate over the driving cycle time period. However, in order to accurately measure the amount of fuel consumed for the entire driving cycle, the initial and final state of charge (SOC) of the battery must also be taken into consideration. In other words, if the battery is assumed to have a 60% initial SOC, then the amount of fuel required to recharge the battery back to its initial SOC must be considered when calculating the total fuel mass as shown in the following:

$$m_{\mathrm{fuel}}(t) = \int_0^t \dot{m}_{\mathrm{driving}}(t)\mathrm{d}t + m_{\mathrm{cha}}(t) \quad (12)$$

The second term (m_{cha}) in the equation above, represents the fuel mass required to recharge the battery back to its initial state of charge. This term is determined by first calculating the amount of energy required to recharge the battery from its final SOC to its initial SOC:

$$\Delta E(t) = [Q(\mathrm{SOC}(t) - \mathrm{SOC_i})]V_{\mathrm{nom}} \quad (13)$$

where ΔE is the energy in Watt-hour, Q is the rated battery capacity in Ampere-hour, V_{nom} is the nominal battery voltage, SOC(t) is the final state of charge, and $\mathrm{SOC_i}$ is the initial state of charge. Then, the total hydrogen mass consumed in recharging the battery can be calculated using the hydrogen fuel higher heating value (141.9 MJ kg^{-1}):

$$m_{\mathrm{cha}}(t) = \Delta E(t)\left(\frac{3600\,\mathrm{s}}{\mathrm{hour}}\right)\left(\frac{\mathrm{kg}}{141.9\times10^6\,\mathrm{J}}\right)\left(\frac{1}{\mathrm{Eff_{sys}}}\right) \quad (14)$$

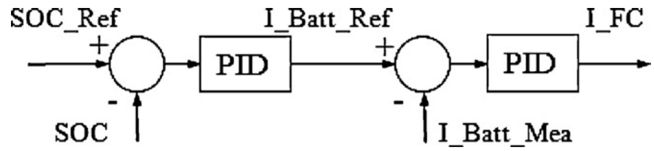

Fig. 4. PID controller.

Note that Eff_{sys} is a nominal value of the fuel cell and battery efficiencies.

7. PID control approach

The ultimate goal in this control method is to monitor and maintain the state of charge of the battery at its nominal value of 60%. In the case where the SOC of the battery drops significantly below the reference value, a current request is sent to the fuel cell in order to charge the battery. The magnitude of fuel cell current request is also controlled by the power needed to drive the vehicle. Thus, in order to satisfy both the battery SOC and the vehicle power demand, two control loops are required; a battery current control loop and a fuel cell current control loop. A PID controller is used to compare the calculated SOC with a reference value to generate a battery current demand signal. This generated signal is then used as a reference value for the battery current. Another PID controller is then used to generate a fuel cell current demand based on the difference between the battery current and its reference value. The controller is explained by the diagram in Fig. 4.

8. Fuzzy logic approach

The two input variables to the fuzzy logic controller are the pedal position and the SOC of the battery. The fuzzy logic controller aims at maintaining the SOC at nominal level, for this reason the first control input to the fuzzy logic controller is the SOC of the battery. The second input variable is selected to be the driver pedal position. This variable represents the driver's response to two factors: the resistance force and the desired speed, in other words, the driver will either press or release the pedal depending on how fast he/she wants to drive and also how much resistance force (air drag, rolling drag and gravity) the vehicle is facing. The pedal position is determined using the classic cruise control example, where a PID controller is used to adjust the driver "pedal position" from −1 to 1 depending on how well the vehicle is matching the command speed. Physically, a pedal position from 0 to 1 represents the driver using the accelerator, while a pedal position from 0 to −1 represents the driver using the brake.

The first output variable of the fuzzy controller is chosen to be the degree of hybridization, calculated as follows:

$$DOH = \frac{\text{power supplied by fuel cell to motor}}{\text{power demand}} \quad (15)$$

While, normally DOH is used when sizing the vehicle components, it is used in this controller as the main control variable. The value of DOH ranges from 0 to 1, with 0 representing a full battery vehicle (powered by battery only) and 1 representing a full fuel cell vehicle (powered by fuel cell only). Once the DOH is determined from the controller, it is multiplied by the required vehicle power to obtain the required fuel cell power. A lookup table is then used to convert the power requirement into current requirement. The controller block diagram is shown in Fig. 5.

The second output variable of the fuzzy logic controller is the current needed to maintain the battery SOC near the optimal value. Since a 10 Ah battery is used, it is estimated that the maximum current required to charge the battery if it were at 0% SOC is 5 A. Thus, the value for the "FC charge current" output will range from 0 to 5 A

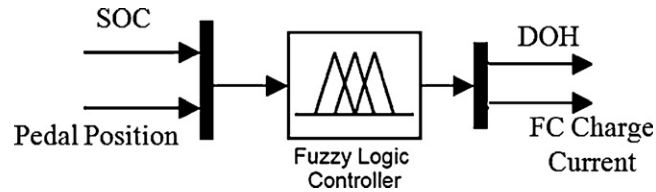

Fig. 5. Fuzzy logic controller.

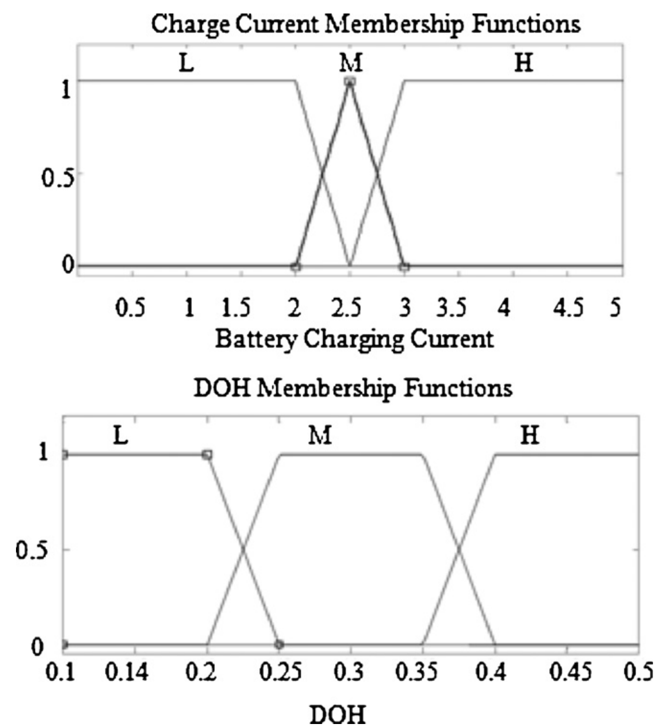

Fig. 6. Output membership functions.

depending on the SOC of the battery. The membership functions for DOH and charge current are shown in Fig. 6, where it is classified into three modes of operation: low, medium and high. The medium mode of operation was chosen to cover the largest span of possible DOHs, and thus reducing the fuel cell's transient response.

The membership functions for the SOC and pedal position input variables are shown in Fig. 7. The SOC of the battery is classified into three main categories low, medium and high to correspond to a nominal SOC of 60%. The pedal position on the other hand is

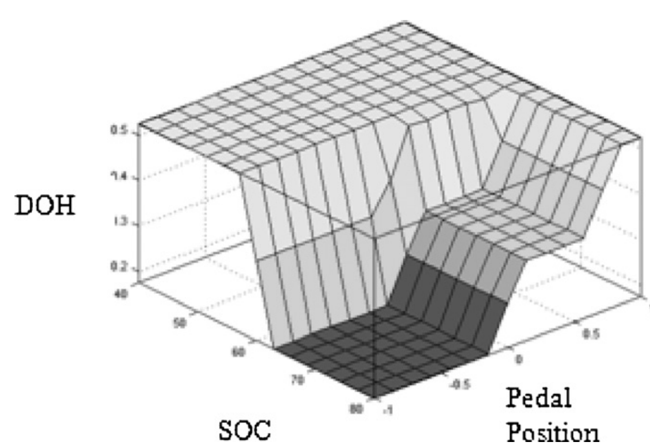

Fig. 7. Input membership functions.

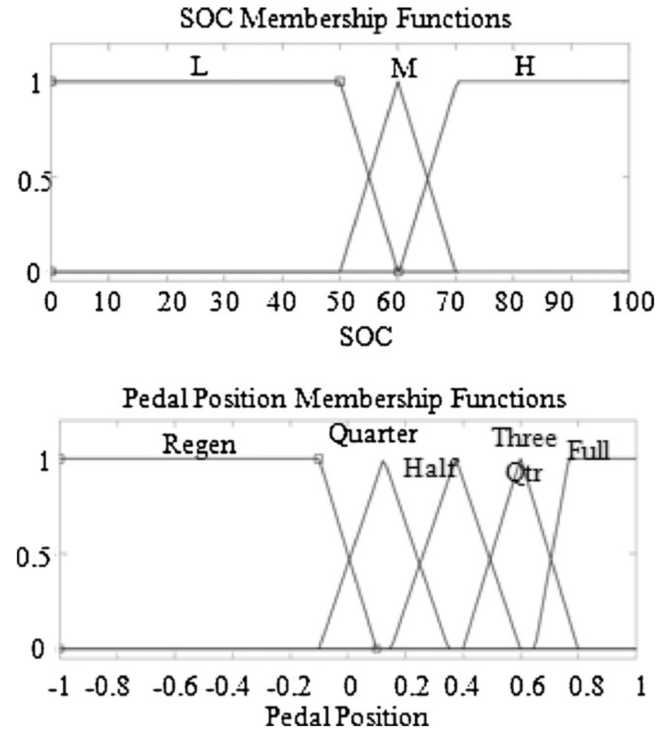

Fig. 8. Fuzzy logic mathematical relationship.

varied from −1 to 1, where all negative values are categorized as "regen" mode and the positive values are divided into four sections: quarter, half, three quarters and full pedal displacement.

Fig. 8 shows the mathematical relationship between the inputs and the outputs of the fuzzy logic controller; essentially the output is a lookup table as a function of the battery state of charge and the driver pedal position.

9. Instantaneous optimization approach

The problem of designing a power management strategy for hybrid vehicles can be formulated into an optimization problem, in which the cost function is the fuel consumption. However, as mentioned in Section 1, global optimizations are not feasible due to the need to know the driving cycle ahead of time. Thus, a local optimization will be used instead. The local cost function is based on the fuel flow rate supplied by the fuel cell. Since in the fuel cell–battery hybrid vehicle all of the energy supplied essentially comes from the hydrogen fuel, the energy withdrawn from both sources must be converted into equivalent hydrogen fuel flow rate. This was accomplished as follows:

$$\dot{m}_{\mathrm{eq}} = \dot{m}_{\mathrm{fc}} + c(\dot{m}_{\mathrm{batt}}) \tag{16}$$

In this case, the fuel cell and battery equivalent fuel mass flow rates are defined using the higher heating value of hydrogen ($141.9 \times 10^6\,\mathrm{J\,kg^{-1}}$):

$$\dot{m}_{\mathrm{batt}} = \frac{i_{\mathrm{batt}} V_{\mathrm{batt\_OC}}}{141.9 \times 10^6\,\mathrm{J}} \frac{1}{\mathrm{Eff_{fc}Eff_{batt}Eff_{DC}}} \tag{17}$$

$$\dot{m}_{\mathrm{fc}} = \frac{i_{\mathrm{fc}} v_{\mathrm{fc}}}{141.9 \times 10^6\,\mathrm{J}} \frac{1}{\mathrm{Eff_{fc}}} \tag{18}$$

where $\mathrm{Eff_{fc}}$, $\mathrm{Eff_{Dc}}$ and $\mathrm{Eff_{batt}}$ are the fuel cell, DC/DC converter and battery efficiencies. The fuel cell efficiency is obtained by a lookup table from the manufacturer, while an average value is used for the battery efficiency.

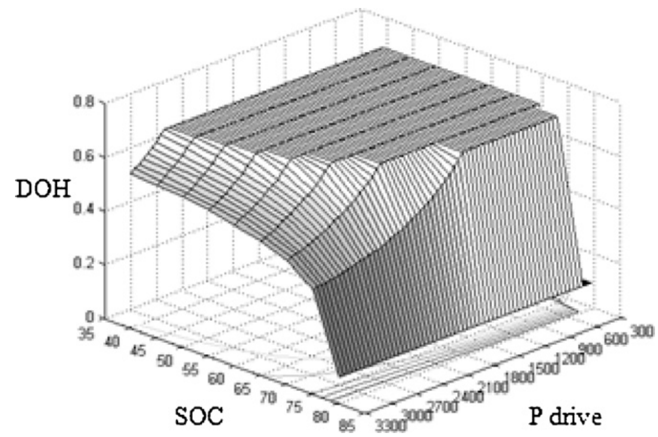

Fig. 9. DOH optimization surface plot.

Another parameter that must be included in the optimization is the SOC of the battery. In order to incorporate the SOC of the battery in the optimization problem, the battery equivalent fuel flow rate is multiplied by a variable factor "*c*". This variable is varied between 0 and 2 depending on the SOC of the battery and can be defined as follows:

$$c = 1 - \frac{\mathrm{SOC} - ((\mathrm{SOC_{max}} + \mathrm{SOC_{min}})/2)}{(\mathrm{SOC_{max}} - \mathrm{SOC_{min}})/2} \tag{19}$$

In this equation, $\mathrm{SOC_{max}}$ and $\mathrm{SOC_{min}}$ are the maximum and minimum allowed SOC of the battery. In order to stay consistent with the fuzzy logic approach presented previously, the SOC range will be between 50% and 70%. This optimization problem is solved without using any complex mathematical algorithm; instead a simple for-loop is used to find the least hydrogen fuel flow rate while varying DOH and the SOC. The result is a relationship between the requested power, the SOC of the battery and the DOH, which can be implemented in the controller as a two-dimensional lookup table.

Fig. 9 shows the optimization results. It is clear to see that most of the time the optimal fuel flow rate is achieved if the DOH is highest, in other words, if the fuel cell is used as the main power source with minimal supply from the battery. This comes as no surprise since the most efficient way to transfer hydrogen power to the electric drive is by going directly from the fuel cell. However, that is not always true since maintaining the SOC of the battery between 50% and 70% is a control objective. Thus, it can be seen that as the battery SOC is increased, the DOH becomes smaller favouring the battery over fuel cell in order to bring down its SOC, on the other hand, as the SOC is decreased below its average, the DOH becomes higher to recharge the battery. In addition to that, the efficiency of the fuel cell varies as the power request is increased, this also plays into finding the most optimal DOH, and can be seen in the variation of DOH as power request is increased.

10. Simulation results

The federal test procedure (FTP-72) drive cycle also known as the urban dynamometer driving schedule (UDDS) was used for testing the powertrain performance. This driving cycle is mainly used to simulate city driving conditions, where the vehicle is forced to accelerate and decelerate very frequently. Thus, it is suitable for this study, since the main goal is to improve the transient behavior of fuel cell powered vehicles. However, in order to accommodate the maximum speed of the SAE Baja vehicle ($60\,\mathrm{km\,h^{-1}}$), the drive cycle was scaled down by a factor of 1.5, resulting in a $20.63\,\mathrm{km\,h^{-1}}$ average speed over a distance of 8 km driving cycle. The total power

Table 1
Hydrogen fuel consumption.

	Distance traveled (km)	Total fuel consumed (kg)	H_2 density @ 35 MPa (kg H_2 L^{-1})	Gas tank volume (l)
PID method	8	0.008920	0.014	0.6372
Fuzzy method	8	0.008875	0.014	0.6339
Optimization method	8	0.008601	0.014	0.6144

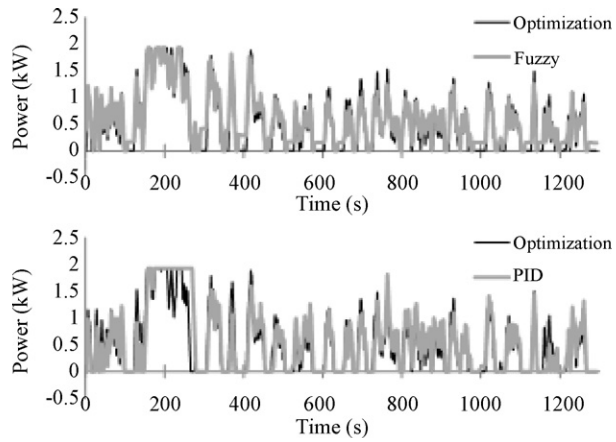

Fig. 10. FTP cycle power demand.

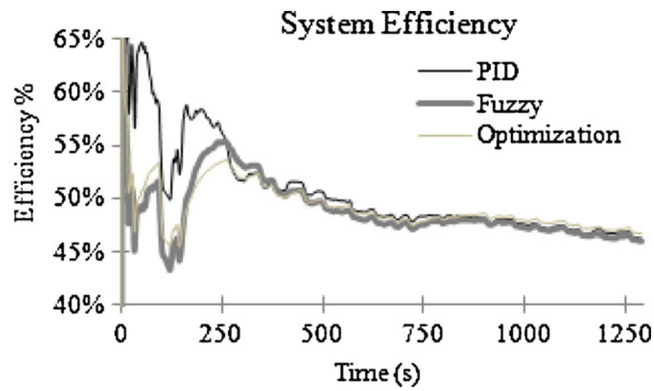

Fig. 12. FTP cycle system efficiency.

demand and the fuel cell power contribution for the fuzzy approach and optimization approach are shown in Fig. 10.

The change in the battery SOC during the simulation is shown in Fig. 11. Due to the fact that the simulation time is less than 30 min, the variation in the SOC is not significant as it is kept within 5%. However, it is clear to see the impact of the control strategy on the SOC, the fuzzy logic control and PID approaches are more charge sustaining than the optimization approach. The change in SOC shows how aggressive each control method is in maintaining the battery SOC. This is in fact the main difference between hybrid vehicle control strategies. Most control strategies operate around keeping the SOC closer to a previously defined value, in this case 60% is that value; however, keeping the SOC around that value will impact the fuel efficiency of the vehicle. Thus, there is a tradeoff in the way the SOC is maintained and the DOH that prolongs the battery life and also optimizes fuel consumption.

The overall system efficiency curve for each control method is shown in Fig. 12. In the case of a non-plug-in hybrid configuration, the system efficiency essentially corresponds to the fuel consumption since all energy comes from the hydrogen fuel. However, since in this study the efficiency definition changes depending on the mode of operation, it is important to see how the overall system efficiency compares between the three control methods. The results reflect the overall slight advantage that the optimization approach offers.

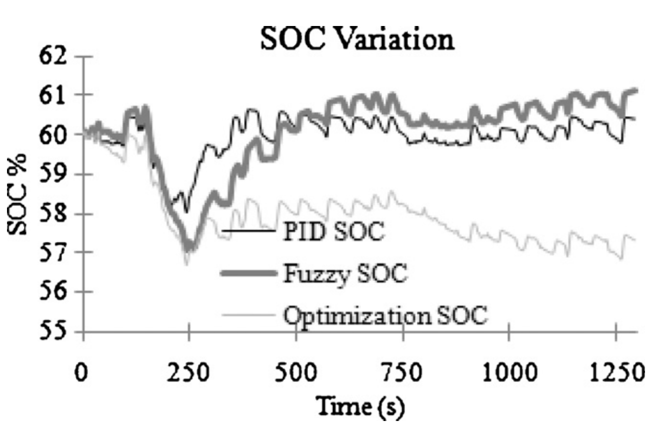

Fig. 11. FTP cycle battery SOC variation.

The next step is to compare the fuel consumption (in kg of H_2 fuel) of the vehicle over the 8 km it travels in the FTP-72 driving cycle. The fuel consumption data are shown in Table 1. Although, the difference is very small, it is clear to see as expected the optimization method requires the least amount of fuel to get through the driving cycle.

If the storage tank volume is taken into consideration (assuming hydrogen is stored at 35 MPA) the optimization method saves approximately 20 mL to drive a distance of 8 km. Thus, if the vehicle is designed to have a driving range of 400 km for example, then the optimization control method would save approximately 1 L of fuel storage room. This number can become even more significant when taking into consideration a midsize sedan or a van as opposed to the SAE Baja vehicle. The MPGGE for each case was also calculated, and it was determined that over the FTP driving cycle, the case with fuzzy logic controller scores an MPGGE of 570.14 and the one with optimization based controller scores an MPGGE of 585.35. In both cases the MPGGE calculation takes into account both fuel needed to drive the vehicle and the fuel needed to recharge the battery to its initial SOC. Note that the obtained MPGGE values are for the 308 kg Baja vehicle and this explains why they seem so high compared to actual road vehicles, for example the Honda FCX Clarity has a marketed MPGGE value of 72.8. Nonetheless, the MPGGE value gives a good comparison of the performance of each control methodology.

Table 2
Battery cycle count.

	PID		Fuzzy		Optimization	
	Discharge	Charge	Discharge	Charge	Discharge	Charge
0.1%	**63**	45	**62**	49	**58**	47
0.5%	**17**	19	**19**	14	**21**	19
1.0%	**2**	3	**5**	5	**7**	2
2.0%	**2**	2	**0**	1	**4**	3
3.0%	0	0	0	0	0	0
5.0%	0	0	0	0	0	0

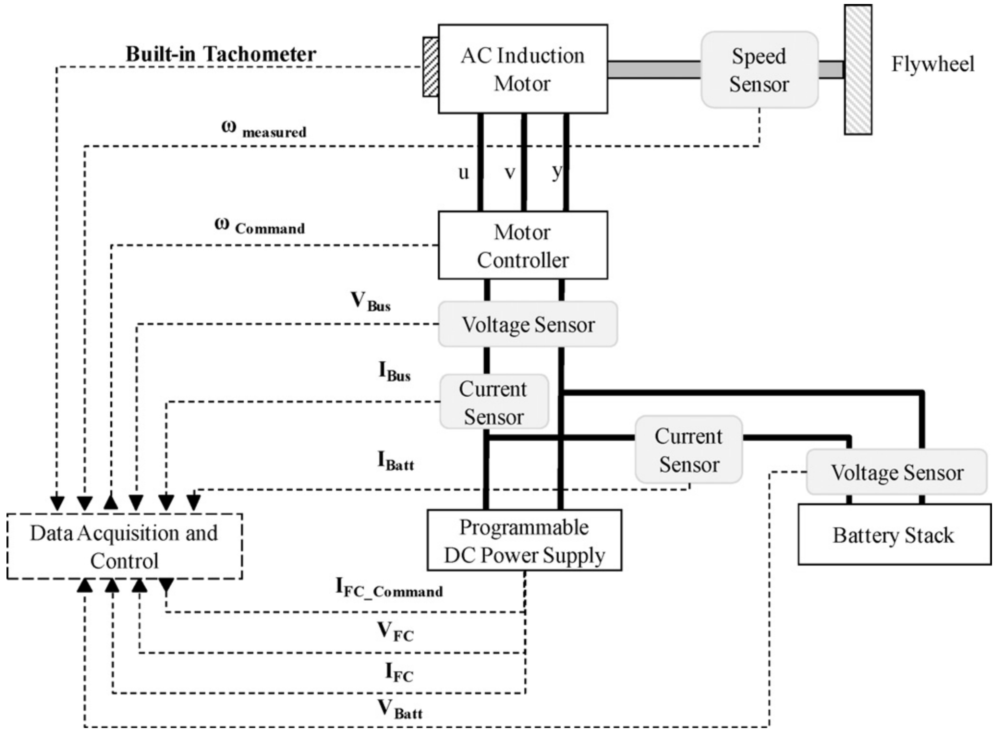

Fig. 13. Experimental setup.

Table 2 clearly shows that the number of cycles at small magnitudes is very much the same as all three controllers if the discharge magnitude is less than 0.1% change in SOC. However, as the magnitude of the change in SOC increases, the optimization approach seems to have the largest number of discharge cycles. This can be seen at 0.5%, 1%, and 2% change in SOC magnitudes, where the optimization approach has a total number of cycles of 32 compared with 21 for PID and 24 for fuzzy logic. In the case of charging cycles, the PID control method has the largest number of charging cycles at most magnitudes, with a small of decrease at lower SOC change magnitudes. This can be justified by the fact that the PID controller is more focused on charging the battery to a desired SOC, where the SOC is constantly monitored and maintained at 60%. The optimization approach on the other hand, has the least number of charge cycles when compared with the other two control methods, which is expected given how it optimizes the fuel consumption by limiting the fuel cell contribution. Overall, the optimization approach seems to have the most impact on the battery life by forcing it to go through more discharge cycles. However, determining how much that increase in the number of cycling has on the battery life is a different research area in on its own, and there is no clear way of telling whether a slight increase in the cycle count is as significant as the fuel consumption savings to the designer.

11. Experimental setup

While MATLAB/Simulink provides an excellent platform to design such a vehicle, the robustness of the design must be validated on the real electric powertrain components. Thus, an experimental test bench is needed to validate the designed power management control methods. The test bench implemented in this research is explained by the schematic in Fig. 13.

Due to its simplicity and ease of instrumentation and control, an inertia dynamometer is selected to be the load for the test bench. This idea was mainly inspired by an existing work done at the University of Waterloo, where a flywheel dynamometer was used to simulate hybrid regenerative braking [13]. Due to its higher efficiency and relatively lower cost an AC induction motor was selected to drive the SAE Baja vehicle. In order to control the AC motor and interface it to the fuel cell and battery DC bus, a vector drive controller/inverter combination that are normally used for electric fork lift utility vehicles are selected.

12. Experimental results

In order to quantify how the experimental setup matches the desired simulation, the mathematical model in MATLAB/Simulink was modified by adjusting the driving cycle to the accelerated cycle. Also, the longitudinal vehicle dynamics model was modified to only take into consideration the inertial forces acting on the vehicle. A direct comparison of the electrical power demanded by the load in the experimental setup and the mathematical simulation model is shown in Fig. 14, where both the simulation and experimental power demands are calculated based on the electrical measurements of the system (i.e. power = total current × bus voltage).

A second comparison was done between the measured output speed at the motor shaft and the output speed in the simulation model. The comparison is shown in Fig. 15.

The main objective of the experimental setup is to be able to validate if the comparison results between the three control meth-

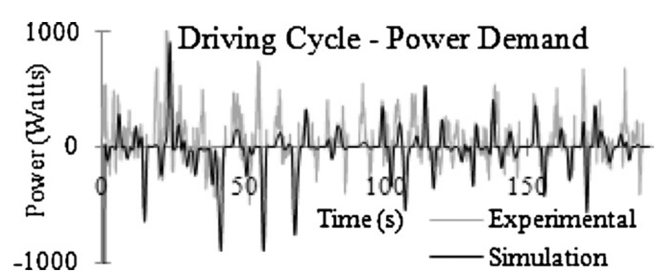

Fig. 14. Total power demand comparison.

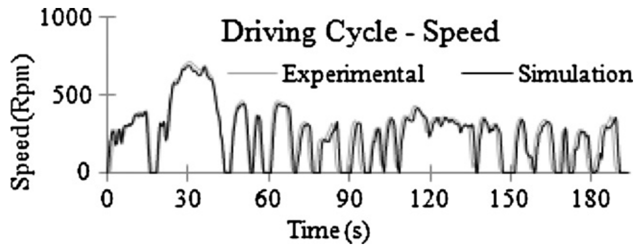

Fig. 15. Speed profile comparison.

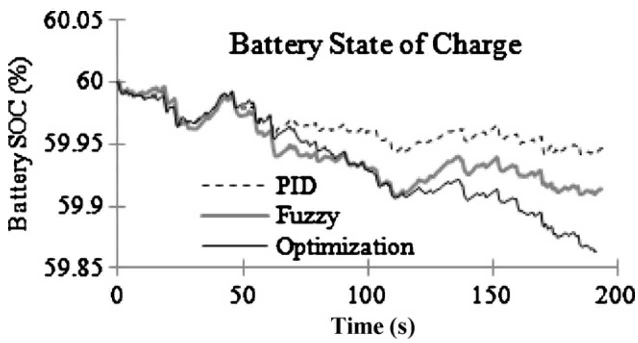

Fig. 16. Experimental SOC variation.

ods obtained in the mathematical model do in fact remain true for the real system. As shown earlier the power demand obtained using the experimental setup does not exactly match the mathematically simulated power demand, thus, a direct quantitative comparison is not very indicative of whether or not the experimental results match the simulation results. Instead, the results are compared by considering the patterns of how the outputs of controllers behave with respect to each other. In the case of the battery SOC variation during the accelerated driving cycle, the results are shown in Fig. 16. Although, the battery SOC does not vary significantly (less than 1% change), the pattern in the SOC variation using each control method is indicative of whether or not the controller is operating as expected from the simulation model.

The total fuel consumption using each control method is considered next. The results show that the optimization approach has the least fuel consumption over the driving cycle, which coincides with the mathematical simulations. However, the amount of fuel saved is on the order of 0.0000111 kg, which corresponds to a hydrogen fuel tank of 0.02417 L. Thus, the difference between using the fuzzy logic or the optimization approach would be a hydrogen fuel tank volume savings of 0.00079 L, which is very insignificant even when considering a longer traveling distance. Table 3 shows a summary of the results.

The last comparison criteria between the control methods is their impact on the battery health, which is indicated by the number of charge/discharge cycles the battery has to go through during the driving cycle. Fig. 17 shows the total number of charge/discharge cycles from the experimental results. Since the total change in the SOC is very small, only the total number of cycles is considered, meaning that each change in the sign of the SOC is counted as a

Table 3
Experimental fuel consumption.

	Distance traveled (km)	Total fuel consumed (kg)	H_2 density @ 35 MPa (kg H_2 L^{-1})	Gas tank volume (l)
PID method	8	0.0003656	0.014	0.02611
Fuzzy method	8	0.0003495	0.014	0.02496
Optimization method	8	0.0003384	0.014	0.02417

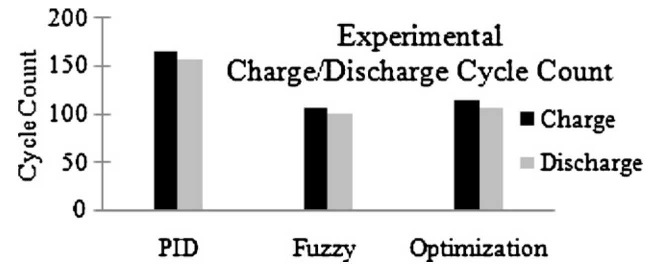

Fig. 17. Experimental cycle count.

Table 4
Summary of comparison.

	PID	Fuzzy logic	Optimization
Strategy	Load leveling	Rule based	Load following
Fuel efficiency	Lowest	In the middle	Highest
Battery cycling	Small cycles	Small cycles	Big cycles

beginning of a charge or discharge cycle, regardless of the magnitude. The PID control method results in the largest number of cycles in the battery, which can be explained by the goal of this method which is to keep the SOC near 60% at all times. The fuzzy and the optimization approaches result in a very close number of charge/discharge cycles. Therefore, even if the magnitude is small, the results obtained from the experiment are very similar to the simulation results.

13. Conclusion

Considering the direct comparison results presented, it is difficult to make a conclusion on which control methodology is the most appropriate for this application, since that really depends on the priorities of the designer. The results have clearly shown that the instantaneous optimization results in the least fuel consumption and thus most efficient hybrid configuration. However, the results also show that savings in the fuel consumption are small when compared to fuel consumption numbers of similar cars that are currently on the road. The other main factor that was considered in the comparison is the battery cycling using each control method. In general it was shown using both the simulation and experimentally, that the optimization approach results in the least number of cycles if the cycle magnitude is very small (on the order of 0.1% SOC) however, when looking at cycles with larger magnitudes, the optimization approach forces the battery through the most charge/discharge cycles. Thus, there seems to be a tradeoff between improving the fuel consumption of the vehicle or improving the degradation time of its powertrain components. Deciding which factor is more important will depend on the application. Also it should be mentioned that although it is true that partial SOC cycling can result in battery capacity degradation, there is still no clear indication of how many partial SOC cycles the battery can withstand before it starts to degrade. Overall, the comparison between the three control methods is shown in Table 4.

To summarize, the main accomplishment of this work is in presenting an alternative local optimization approach that does not require prior knowledge of the driving cycle and a set of performance measures to evaluate the effectiveness of the proposed approach. In order to validate the effectiveness of the optimization approach, standard performance measures that consider battery life, fuel consumption and system efficiency were developed. In addition to that, the experimental setup used to validate the simulation results presents a platform for further work that can be done in the area of power management and electric vehicle powertrain design.

Acknowledgments

The authors are grateful to the Auto21TM Networks of Centers of Excellence (Grant D303-DFC), the Natural Sciences and Engineering Research Council of Canada (NSERC), the Canada Foundation for Innovation (CFI), the Ontario Innovation Trust (OIT), and the University of Windsor for the support of this work.

References

[1] K.-S. Jeong, W.-Y. Lee, C.-S. Kim, Journal of Power Sources 145 (2) (2005) 319–326.
[2] M.C Kisacikoglua, M. Uzunoglua, M.S. Alama, International Journal of Hydrogen Energy 34 (3) (2009) 1497–1507.
[3] W. Gao, M. Chris, International Journal of Electric and Hybrid Vehicles 1 (1) (2007) 57–70.
[4] H.-J. Yoon, S.-J. Lee, SAE 112 (7) (2003) 579–586.
[5] S. Wang, K. Huang, Z. Jin, Y. Peng, IEEE Conference on Industrial Electronics and Applications (2007) 2010–2012.
[6] Pisu, Pierluigi, R. Giorgio, IEEE (2005) 65–72.
[7] C.-Y. Li, G.-P. Liu, Journal of Power Sources 192 (1) (2009) 525–533.
[8] L. Xu, J. Li, J. Hua, X. Li, Ouyang, Minggao, International Journal of Hydrogen Energy 34 (2009) 7323–7333.
[9] M. Barnett, W. Bombardier, M. Bowie, M. Burford, D. Chesnik, X. Ding, C. Drummond, A. Fadel, I. Funkenhauser, H. hiebert, B. Huang, C. Jankowski, J.C. Juba, J. Kelly, K. Krzemien, Kubacki, D. Langlois, S. Masse, W. O'Moore, D. Pedro, M. Smith, University of Windsor SAE Baja Design, University of Windsor, 2007.
[10] Horizon Fuel Cell Technologies, http://www.horizonfuelcell.com/store/h5000 (accessed January 2009).
[11] S.A. Khateeb, M. Farid, J. Robert, S. Al-Hallaj, Journal of Power Sources 158 (1) (2006) 673–678.
[12] K. Kato, A. Negishi, K. Nozaki, I. Tsuda, K. Takano, Journal of Power Sources 117 (12) (2003) 118–123.
[13] Micheal Kiers, Automotive regenerative braking utilizing electrochemical capacitor energy storage. Master's Thesis, University of Waterloo, 2004.