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Optimal power management of fuel cell hybrid vehicles

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Abstract

This paper presents a control strategy developed for optimizing the power flow in a Fuel Cell Hybrid Vehicle structure. This method implements an on-line power management based on the optimal fuzzy controller between dual power sources that consist of a battery bank and a Fuel Cell (FC). The power management strategy in the hybrid control structure is crucial for balancing between efficiency and performance of hybrid systems. For optimization of fuzzy control strategy, the Particle Swarm Optimization (PSO) algorithm has been considered to determine the battery's state of charge and fuel cell power in maximum efficiency operating point. The fuel cell hybrid vehicle includes battery and fuel cell and its power train system include an Electric Motor (EM) and power electronic converters. Simulation results of hybrid system illustrate improvement in the operation efficiency of the fuel cell hybrid vehicle and the battery's state of charge (SOC) and fuel cell utilization factor have been maintained at a reasonable level.

Keywords: Fuel cell; Battery; Hybrid vehicle; Fuzzy control; PSO; optimization.

1. Introduction

The search for improved fuel economy and reduced emissions, without sacrificing performance, safety, reliability, and affordability has made the hybrid vehicles a challenge for the automotive industry. Compared to conventional internal combustion engine vehicles, fuel cell hybrid electric vehicles represent an effective way to substantially reduce fuel consumption. This capability basically is due to: 1) the possibility of downsizing the fuel cell, 2) the ability of the rechargeable storage system to recover energy during braking phases (regenerative braking), and 3) the fact that an additional degree of freedom is available to satisfy the power demands from the driver, since power can be split between thermal and electrical paths. This third point also means that the performance of a HEV system is strongly dependent on the control of this power split. There are many challenges to design a proper control strategy for hybrid vehicle powertrain. For one thing, the vehicle consists of many large subsystems. Drivetrains of hybrid-electric vehicles exhibit highly nonlinear dynamics due to the nonlinearities of diesel engines, fuel cell, electric machines (generators and traction motors) and batteries, gear and suspension, as well as nonlinear

characteristics of power converters. Since these drivetrains are operated as complex systems, modern methods for designing controllers for nonlinear systems must be applied to utilize the full capabilities of hybridelectric vehicles [1–3].

Power management strategies for HEV's can be roughly classified into three categories. The first type employs heuristic control techniques such as rule-based strategy [4] and intelligent strategy [5-6]. These strategies can offer a significant improvement in energy efficiency and are suitable for real-time control strategy that can be used to control a vehicle. The second approach is based on static optimization methods. Commonly, electric power is translated into an equivalent amount of (steady-state) fuel rate in order to calculate the overall fuel cost [7–9]. The optimization scheme then figures out the proper split between the two energy sources using steady-state efficiency maps. Because of the simple point wise optimization nature, it is possible to extend such optimization schemes to solve the simultaneous fuel economy and emission optimization problem. Static approaches are based mainly on the Equivalent fuel Consumption Minimization Strategy (ECMS), which can be adapted to also consider battery SOC and emissions constraints.

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One of the drawbacks of the static approach is that some important dynamic effects, such as those related to drivability and battery SOC variations, cannot be explicitly treated.

The basic idea of the third type of HEV control algorithms considers the dynamic nature of the system when performing the optimization. Furthermore, the optimization is with respect to a time horizon, rather than for an instant in time. In general, power split algorithms resulting from dynamic optimization approaches are more accurate under transient conditions, but are computationally more intensive. The dynamic optimization policy is not implementing able in real driving conditions because it requires knowledge of future speed and load profile [10–12].

This paper is arranged as follows. The configuration of the prototype hybrid electric vehicle system is introduced first, followed by the description of the control system architecture implemented in the vehicle. Next, optimal fuzzy logic control strategy based on PSO algorithm is proposed to develop the power management strategy in the supervisory powertrain controller.

2. Structure of Fuel Cell Hybrid Electric Vehicle

The modeling of a Fuel Cell Hybrid Electric Vehicle (FCHEV) is an important issue that needs to be carefully addressed. Many articles deal with static models that are built up from maps and static relationships between parameters in the model. These models allow for fast simulation, but they cannot show the oscillations and other dynamic phenomena when switching occurs between different modes of operation. However, a good model should consider both accuracy and simulation time. The electric components of a hybrid power system used in this paper comprise a battery bank, DC/DC and DC/AC converters, while the electrochemical component is a Fuel Cell system (FC). The mathematical models describing the dynamic behavior of each of these components are given [13–14].



Fig. 1. Structure of Fuel Cell Hybrid Electric Vehicle

3. Power Management Problem in Fuel Cell Hybrid Electric Vehicles

The hybrid vehicle is equipped with an electrical traction system, composed of a set of batteries and an electric motor/generator, coupled with fuel cell. Depending on the energy management, two different configurations can be selected: series hybrid vehicles and parallel hybrid vehicles [3]. In the series architecture, the ICE supplies the energy for recharging the battery and its size depends on the mean required power; therefore, the thermal engine works at constant load with reduced pollutant emissions, high reliability and long working life. Fig.1. presents a block diagram of a PHEV with an electrical machine (EM) and fuel cell that EM and ICE power are combined together to propel the vehicle. There are five different ways to operate the system, depending on the flow of energy: 1) provide power to the wheels with only the ICE; 2) only the EM; or 3) both the ICE and the EM simultaneously; 4) charge the battery, using part of the ICE power to drive the EM as a generator; 5) by letting wheels drive the EM as a generator that provides power to the battery that causes to improving fuel efficiency.

During braking or deceleration, the electric motor acts as a generator to charge the battery via the power converter. Also, since both the engine and electric motor are coupled to the same drive shaft, the battery can be charged by the engine via the electric motor when the vehicle is at light load. Recently, the Honda Insight HEV has adopted a similar power flow control.

A common method to control of the complex dynamic systems with many uncertainties is designing some different of local controllers each for a specific operating area or determined objects and then designing of a switching strategy through the subsystems to achieve the global objectives of the system. The control of hybrid electric vehicle systems involves some complex control processes, such as; generating Throttle (or brake) command according to external environment changes and the driver's expectation, splitting the power between the two power-sources to sustain the efficiency of the engine and/or charging/discharging efficiency of the battery at a relatively high level and driving the mechanical and electrical components to meet the requirement from above level. These processes usually involve logic switching, jump, sample-data control signals, and certainly, the continuous signals; hence hybrid electric vehicle system is a hybrid dynamical system.

Hybrid and switched systems have numerous applications in control of mechanical systems, automotive industry, flight and air traffic control, switching power converters, process control, robotics, etc. Hybrid systems consist of a continuous-time and/or discrete-time process interacting with a logical or decision-making process. The continuous/discrete-time subsystem is represented as a set of differential/difference equations whereas the logical/decision making subsystem (supervisor) is represented as a finite state machine or a more general discrete event system, e.g. a Petri net. In the hybrid system context, the continuous/discrete time subsystem affects the discrete transitions of the supervisor and the supervisor affects the dynamic evolution of the continuous/discrete-time subsystem.



Fig. 2. Proposed layout for power management in FCHEV

3.1. Driver's Intention Predictor (DIP)

The DIP is introduced in this fuzzy logic controller to enhance the drivability of this vehicle. The output of DIP can be considered as the demanded torque reference satisfying the driver's acceleration/deceleration reflected in acceleration pedal stroke and its rate. Since the driver's intention is reflected on the acceleration pedal stroke, Acc and its rate, ΔAcc , using these values as inputs of the DIP, the demanded power reference proper to the driver's accelerating/decelerating intention can be produced. The three-dimensional surface of fuzzy system is shown in Fig.3, where Acc is normalized from 0 to 1 and $\triangle Acc$ is from -1 to 1. The driver's intention is normalized from -50 to 50.



Fig. 3. Input and Output membership functions of DIP

3.2. Driver's Power Computation (DPC)

The second block in power management strategy converts driver's intention to road load. For this purpose the maximum available power is computed by adding the maximum available electric motor power. The maximum available electric motor power depends on the instantaneous speed of electric motor and is computed by using the efficiency map of each component. Then, driver's intention multiplies by the maximum available power. The positive part of power is road load and negative part is braking power which implies to braking controller.

3.3. Fuel Cell Power Controller (FCPC)

In FCHEV one of the primary goals is to set the fuel cell operation in its peak efficiency region. This improves the overall efficiency of the powertrain. The FC operation is set according to the road load and the battery state of charge (SOC). This strategy is used to run the FC about its peak efficiency region. In this strategy, the operating points of the FC are set near the torque region, where efficiency is the maximum for that particular engine speed. Since an electric motor (EM) is available to load-level, the HEV can use its electric machine to force the engine to operate in a region that consumes less fuel, while maintaining the state of charge (SOC) of the battery pack over the majority of the drive cycle. This is achieved by using the electric motor to compensate for the dearth in torque required to meet the road load. The power management strategy in the hybrid control structure is crucial for balancing between efficiency and performance of hybrid systems. The term "power management" refers to the design of the higher-level control algorithm that determines the proper power level to be generated, and its split between the fuel cell stack and battery while satisfying the power demand from the load and maintaining adequate energy in the energy storage device.

The power flow control strategy is designed to determine the proper power level between the FC stack and battery energy storage, while satisfying the power demand from the load and maintaining adequate energy in the energy storage device. Frequent power demand variations and unpredictable load profile are unavoidable uncertainties. Also, nonlinear and often time-varying subsystems add to the complexity of the structure of a hybrid system. Moreover, the control strategy must act online to distribute the power between power sources based on the system conditions. Hence an online control strategy based on fuzzy logic has been proposed for instantaneous nower management in [5].

The core of the rule set of the fuzzy controller is illustrated in Table 1.

But the parameters of the proposed fuzzy controller during the power management have been considered constantly and it has not the adaptive property. As shown in Fig.4, the maximum efficiency of FC is around the power of 30 kW; according to Fig.5, the maximum efficiency of battery energy storage during the charge and discharge cycles is around the state of charge of 75%. Table 1. Fuzzy rule base of proposed control strategy

Inputs		Output	
\mathbf{P}_{req}	SOC	P _{batt}	P _{fc} (k)
low	low	Low	medium
medium	low	Medium	high
medium	high	Low	medium
medium	high	Medium	low
high	high	Medium	high
high	high	Low	medium
high	high	High	medium
high	low	Low	medium
high	low	medium	high
low	high		Zero



Fig. 4. Efficiency map of the fuel cell stack



Fig. 5. Charge and discharge diagram of battery

In order to design the optimal fuzzy controller, the PSO algorithms are applied to search globally optimal parameters of the fuzzy logic. This process has been explained in next section.

$$E(k) = \sum_{k=1}^{N-1} w_1 (P_{fc}(k) - P_{fc_opt})^2 + w_2 (SOC(k) - SOC_{opt})^2$$
(5)

where N is the duration of the power demand and w_1 , w_2 and w_3 are the weighting coefficients representing the relative importance of the objectives and they must satisfy the equation (2)

 $w_1 + w_2 = I$

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling [15]. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles and each individual adjusts its flying according to its own flying experience and its companion's flying experience. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This value is called 'pbest'. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called 'gbest'. Much work has been done on the analysis of fuzzy control rules and membership function parameters [16]. The PSO algorithms were used to get the optimal values and parameters of our FLC. The structure of proposed algorithm has been shown in Fig.6. In particular, particle i remember the best position it visited so far, referred to as *pbesti*, and the best position by its neighbors. There are two versions for defining the neighbors' best position, namely *lbest* and gbest. In the local version, each particle keeps track of the best position *lbest* attained by the particles within its topological neighborhood.

For the global version, the best position *gbest* is determined by any particles in the entire swarm. Hence, the *gbest* model is a special case of the *lbest* model. The PSO is an iterative evolutionary algorithm. At each iteration, particle i adjusts its velocity v_{ij} and position p_{ij} through each dimension j by referring to the personal best position (*pbest_{ij}*) and the swarm's best position (*gbest_j*, if the global version is adopted) using Eqs. (7) and (8) as follows:

$$v_{ii} = k(v_{ii} + c_1 r_1 (pbest_{ii} - p_{ii}) + c_2 r_2 (gbest - p_{ii}))$$
(7)

and

$$p_{ii} = p_{ii} + v_{ii} \tag{8}$$

where c_1 and c_2 are the acceleration constants, r1 and r2 are random real numbers drawn from U(0, 1), and *k* is the constriction factor. Clerc and Kennedy [16] has pointed out that the use of a constriction factor is needed to insure convergence of the PSO, and it is determined by

(6)

$$k = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{9}$$

where $\varphi = c_1 + c_2 > 4$. Typically, φ is set to 4.1 and k is thus 0.729. In this paper, these parameters are selected according to the trial and error process during the running of fuel cell vehicle on predefined driving cycle.

As such, the particle flies through candidate solutions toward $pbest_i$ and gbest in a navigated way while still could explore new potential solutions by the random multipliers to escape from local optima. The PSO algorithm is terminated with a maximal number of iterations or the best particle position of the entire swarm cannot be improved further after a sufficiently large number of iterations.



Fig. 6. The evolution procedure of PSO Algorithms

4. Driving Cycle

Driving cycles are defined as the test cycles used to standardize the evaluation of the vehicles' fuel economy and emissions. Driving cycles are speed-time

sequences that represent the traffic conditions and driving behavior in a specific area. Driving patterns may vary from city to city and from area to area. Therefore, the use of an available driving cycle obtained for the certain cities or countries are not necessarily applicable for other cities. In this power management study, in order to evaluate the proposed control strategy, the European community (ECE-EUDC cycle) has been considered. This driving cycle is shown in Fig. 7 [17]. A driving cycle consists of a mixture of driving modes including idle, cruise, acceleration and deceleration. The maximum, minimum and average speeds are also considered as the cycle characteristics. Table 2 compares the parameters of these driving cycles. Significant variations may be expected depending on the type of the driving cycle.



Fig. 7. The European community ECE-EUDC cycle

ECE-EUDC	
Time(sec)	1225
Dist.(km)	10.87
V _{max} (km/h)	119.3
V _{avg} (km/h)	31.91
Acc max (m/s ²)	1.05
Dece max (m/s ²)	-1.38
Acc avg (m/s ²)	0.54
Vece max (m/s ²)	-0.78
Idle time (%)	27.67

5. Simulation Results

The topology used in this study for the combined fuel cell and battery system, power conditioning units, and load is shown in Fig. 1. The proposed FC system operates in parallel with a battery bank connected to the dc bus via a dc/dc converter. The battery bank serves as a short duration power source to meet load demand that cannot be met by the FC system, particularly during transient or peak demand periods. In this study, the battery bank is designed to provide the difference between the load and the fuel cell system output power. Simulation results are obtained by developing detailed MATLAB software packages using the mathematical and electrical models of the system described earlier. The fuel cell hybrid vehicle system parameters in this study are given in Table 2.

Table 2. Vehicle Parameters

Fuel cell	41 kW	
	75 kW AC Solectria	
Electrical Motor	ACgtx20/AC300	
	Induction Electric Motor	
D //	26 Ah Lead Acid Battery,	
Battery	25 modules	
Vehicle Mass	1350kg	
Coeff. of drag	0.335	
Frontal area	$2m^2$	

Simulation results are obtained for the time interval between 0 and 1225 sec. Figures 8–13 show the fuel cell power, battery power, battery current, battery voltage and battery state of charge, respectively, as a function of time. Fig.8 shows the fuel cell power. From Fig. 8 and Fig. 9, it is evident that the FC system and battery bank together share this load requirement. During peak load demand, the load power requirement is higher than the power generated by the FC system.



Fig. 8. Fuel cell power (kW)



Fig. 9. Battery power (kW)

Therefore, the FC system supplies the available power and the battery bank supplies the remaining extra power. If the power demand is low, only the battery bank supplies power to load. In these conditions the battery's SOC is decreased, as shown in Fig. 10.



While the power demand is increasing, the fuel cell power is raised smoothly and power and power deviations are provided by battery. Battery response for load changes is faster than fuel cell system. The battery bank supplies power to meet the fast load change and fuel cell power changes slowly for fuel cell stack safety and durability. So it has the variation between negative (charging) and positive (discharging) according to the required load demand. Although the battery bank voltage is affected by the load conditions as seen in Fig. 11.



Fig. 11. Battery voltage (volt)

At this time, the battery bank discharge current is very high and the battery bank terminal voltage drops significantly. If the produced power by the fuel cell is more than the required power of load, the extra power of fuel cell is used to charge the battery and the battery state of charge goes high. Although batteries seem to act like simple electrical energy storage devices, when they deliver and accept energy, they actually undergo thermally-dependent electrochemical processes that make them difficult to model. We use RC battery model [2] in this simulation. According to Fig. 10, battery's state of charge at the first and end of cycle are approximately equal and it is an important characteristic of the new energy management strategy. The electric motor torque is illustrated in Fig. 12. As shown, it varies between positive and negative



Fig. 12. Electric motor torque (N.m)

The vehicle speed is presented in Fig. 13. As illustrated, the control strategy makes that the vehicle tracks the driving cycle well.



Fig. 13. Vehicle speed (mph)

6. Conclusion

This paper presents a new approach for power sharing in a hybrid fuel cell/battery electric vehicle to improve the system efficiency and battery life with acceptable load following capability. This method implemented a real time power management by a hybrid controller between dual sources in this kind of hybrid systems. This structure included two energy sources, battery and the stack of fuel cell. The proposed method involves an advance PSO-fuzzy controller that manages the power between fuel cell and battery power sources. Simulation results are given to show the overall system performance including load-following and power management of the system.

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