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Modelling and control strategy development for fuel cell electric vehicles

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Abstract

This paper describes a modelling and dynamic control design process applicable to the development of fuel cell electric vehicles (FCEVs) and hybrid electric vehicles (HEVs). After an introduction to advanced propulsion technologies the development of FCEV at DaimlerChrysler is described, followed by a discussion on hydrogen as a fuel for FCEV and the challenges related to hydrogen storage. It is essential for advanced vehicles to obtain a range comparable to that of mass production vehicles sold today. Thus, there is a strong need to operate such vehicles with high efficiency and maximize the energy stored onboard a vehicle. A stochastic dynamic programming algorithm was developed and applied to the energy management of this FCEV, which allow fuel economy optimisation while keeping a good driveability.

Keywords: Fuel cell electric vehicle; Hybrid vehicles; Modelling

1. Introduction

Advanced propulsion technologies such as hybrid electric vehicles and fuel cell electric vehicles have the potential to significantly influence future mobility. Over the past few years, interest in alternative automotive powertrain concepts has been steadily increasing. The decisive factors in this development have been an increase in ecological awareness, rising petroleum prices and a number of legal regulations relating to fleet consumption and exhaust emissions—with differing emphasis in the USA and Europe.

In the early seventies, the development of powertrain systems was primarily focused on reducing fuel consumption—a consequence of the oil price shock; but in 1980s and 1990s, interest then turned towards exhaust emissions—an initiative that arose in California. Exhaust emissions is the sector where the greatest progress has been made over the past few decades: in terms of exhaust pollutants, modern combustion engines emit only a tiny fraction of that of their predecessors from the seventies.

Along with increasingly stringent exhaust regulations, fuel consumption has been the subject of increasing attention from the legislating bodies. One example is the corporate average fuel economy (CAFE) fleet consumption legislation in the USA, which requires the average consumption of all vehicles for every automobile manufacturer to adhere to certain limits. A reduction in fuel consumption and the associated drop in CO_2 emissions is thus of crucial importance to all automotive manufacturers. These are the reasons for setting out in search of alternative concepts to improve fuel economy and reduce exhaust emissions.

Electric powertrain development has been ongoing for the past fifteen years. Commercially, battery electric vehicles have not been able to gain widespread acceptance as a low-noise, emission-free alternative because of their limited operating ranges, long recharge time and poor efficiency. Recently, hybrid electric vehicles were introduced to the mass market.

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1.1. Hybrid electric vehicles (HEVs)

Hybrid propulsion – a combination of a prime mover (usually an internal combustion engine) and an auxiliary power source (e.g., electric motor, flywheel, hydraulic pump) – has aroused the interest of almost all automotive manufacturers over the past few years. The most common combination involves an ICE plus an electric motor, which is referred to as a hybrid electric vehicle (HEV).

HEVs in general are classified into series, split and parallel hybrids. They can propel the front and/or the rear axle. In addition, by running the traction motor reversely as a generator, mechanical energy from the engine and/or the vehicle deceleration can be captured and stored in the energy buffer for later use. This allows numerous possibilities to combine one or more electric motors with an internal combustion engine, operating in several different modes to allow more efficient or more desirable operations. Examples of ‘‘desirable characteristics’’ enabled by multiple power sources include the elimination of torque hole of automated transmissions, active damping for driveline vibration during low-gear torque clutch engagement, or ‘‘electric torque converter’’. The HEV market is growing quickly with the increasing number of models offered commercially.

1.2. Fuel cell electric vehicles (FCEVs)

Fuel cell systems are able to deliver electrical power with high efficiency, with low operation noise and little or no emissions from hydrogen or hydrogen-rich reformer gases and air (Mok & Martin, 1999). By-products are exhaust gases, water and waste heat. The generated electrical power can be used in vehicles for propulsion as well as for the operation of electrically powered accessories. Proton exchange membrane (PEM) fuel cells utilize a solid polymer electrolyte membrane, operate at lower temperature and are considered by many to be the most suitable for automotive applications.

Proton exchange membrane (PEM) fuel cell systems require onboard stored hydrogen or hydrogen-rich gases generated onboard from liquid fuels such as methanol or the conventional hydrocarbons gasoline and diesel.

Since most advanced vehicles like HEVs and FCEVs have one energy storage (buffer) device as part of the propulsion system. It is possible (and necessary) to apply advanced control technologies to significantly optimize the vehicle’s fuel economy, emissions and/or drivability.

2. DaimlerChrysler fuel cell vehicles

DaimlerChrysler Corporation has been evaluating fuel cell vehicles since the early 1990s. The first DaimlerChrysler FCV was the NeCar I operating on compressed hydrogen. This commercial van has enough passenger space for the driver and one passenger. The cargo space is used by the large compressed hydrogen tanks and the fuel cell engine. The NeCar II showed dramatic reductions in volume and weight in the fuel cell engine technology. However, the compressed hydrogen tanks still occupied a disproportionate amount of space in this minivan size vehicle. The NeCar III presented the first onboard reforming fuel delivery system incorporated with a fuel cell engine. This onboard methanol reforming system was able to provide enough hydrogen gas to operate the fuel cell engine in a drive cycle. This A-class vehicle sparked the development of onboard fuel reforming as an alternative to storing pure hydrogen onboard.

The Jeep® Commander I was the Chrysler Group’s first FCEV. This concept vehicle focused on onboard reforming of gasoline to utilize the existing fuelling infrastructure. The Jeep® Commander II was the Chrysler Group’s second FCEV. This concept vehicle utilized an onboard methanol reforming system similar to the NeCar III (Tran & Cummins, 2001).

The DaimlerChrysler Town and Country ‘‘Natrium’’, FCEV displayed in Fig. 1, focused on the alternative hydrogen storage technologies. As shown in Fig. 2, all packaging was completed underneath the vehicle. One of the key engineering challenges was to prevent cabin protrusion by the fuel storage system while maintaining a competitive driving range.

The Natrium’s powertrain consists of an 82 kW peak traction system, a 40 kW Li-ion battery pack and a 54 kW fuel cell engine. With 166 l of 20% concentration sodium borohydride fuel, the Natrium can travel 500 km. Vehicle performance was acceptable at 16 s from zero to 100 kph and a top speed of 133 kph. This was the first vehicle to use sodium borohydride ($NaBH_4$) as a hydrogen storage technology to provide hydrogen to the fuel cell engine.

3. Hydrogen storage technologies

Regardless of whether the hydrogen is produced off-board centrally or off-board locally, the method of onboard

Fig. 1. The DaimlerChrysler Town and Country ‘‘Natrium’’.

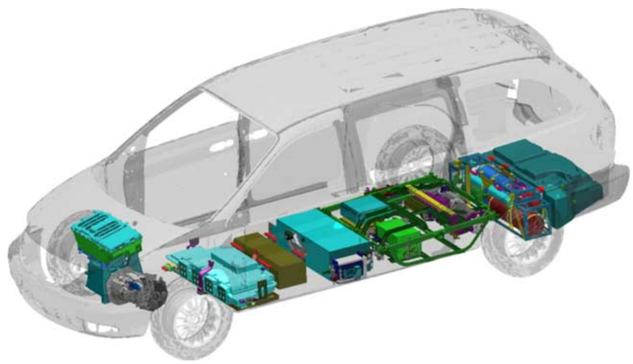

Fig. 2. The Natrium's packaging.

storage is a critical issue (James, Baum, Lomax, Thomas, & Kuhn, 1996). Any vehicle directly fuelled with hydrogen needs a system that can safely and effectively store enough hydrogen onboard to allow for comparable travelling distances to today's vehicles without eliminating passenger or cargo space or adding additional weight. This is a difficult challenge because of hydrogen's low storage density.

Onboard hydrogen storage is one of the key enabling technologies required for mass production of fuel cell vehicles. The best fuel solution for fuelling FCEVs is to use hydrogen directly as the fuel. This choice would remove the need for an onboard fuel reformer. It would also avoid producing carbon dioxide and greenhouse gases in the onboard reforming process. The challenges to using hydrogen as a fuel include finding a hydrogen storage system that is reasonably small and light-weight, along with finding a way to release the stored fuel quickly at the required consumption rate. Although hydrogen packs more energy by weight than any other fuel (about three times more than gasoline), it is hard to store much of it in a fuel tank. Hydrogen being the lightest and smallest of molecules, it is relatively difficult to contain, which poses potential safety problems.

Using a compressed gas storage system is probably the most straightforward option at this time for the simplest, least expensive method for onboard hydrogen. Compressed hydrogen gas storage uses technology similar to that used for compressed natural gas, with stainless steel, aluminium or composite cylinders. The refilling time of compressed hydrogen tanks is similar to that of gasoline tanks. Hydrogen is normally compressed in cylindrical tanks for better pressure distribution along the cylinder walls. One way to increase the amount of fuel stored in the container is to increase pressure, but this requires more expensive storage containers, increasing compression costs and entails investigation into safety issues. Compressed hydrogen storage at high pressure, 700 bar, produces a heavier pressure vessel which is not very attractive as opposed to other potential methods. Lower pressures, while lessening these concerns, would mean taking up more vehicle space. Pressurized hydrogen will need to overcome these issues to provide a similar driving range of 300 miles or better like the current production vehicles.

Liquid hydrogen (LH2) is actually the most common method currently used for off-board hydrogen storage because of the high energy density of liquid hydrogen. A drawback to this method of hydrogen storage is that the process to liquefy hydrogen is energy intensive. Hydrogen's low boiling point requires excellent insulation of storage containers; otherwise, left for a period of time, the storage tanks could become depleted. Maintaining the extreme cold temperatures of LH2 during refuelling and onboard storage currently poses a significant technical challenge to prevent LH2 boil off (up to 25% during refuelling) and 1% lost per day for onboard storage.

There are other advanced methods of onboard hydrogen storage being researched, but most are in very early research stages. Solid state hydrogen storage, carbon nanotubes and chemical hydrides hold the potential of higher energy storage by volume and weight compared to liquid and compressed hydrogen.

Solid state hydrides store and release hydrogen by absorption and desorption. One major obstacle to this method is that the metal compounds used to attract the hydrogen tend to be very heavy resulting in only 1.0–1.5% hydrogen by weight. In addition, some of the metals used for hydrides are very expensive. There are less expensive options but they are impractical for use in fuel cell vehicles as these cheaper metals require extremely high temperatures to release the hydrogen.

Carbon nanostructures – graphite fibers with intricate, high-surface-area configurations – offer another storage alternative. Certain carbon nanostructure materials have been shown to absorb more than one-fifth their weight in hydrogen in initial laboratory reports. However, the technology remains immature at this point in time.

In chemical hydride storage technologies, stable and relatively benign compounds such as boron, sodium, and calcium hydride are processed with water in a catalytic fuel reactor to generate pure hydrogen. In addition, the reaction by-products can be recycled for reuse. Chemical hydrides such as sodium borohydride ($NaBH_4$) have the capacity to hold up to 10.3% hydrogen by weight on the materials level. The basic chemical reaction in Fig. 3 shows the advantages of a pure hydrogen product and a waste product that can be recycled (Amendola et al., 2000).

Sodium borohydride has many advantages over compressed hydrogen. The fuel solution is not flammable and has little environmental impact if spilled. The waste fuel

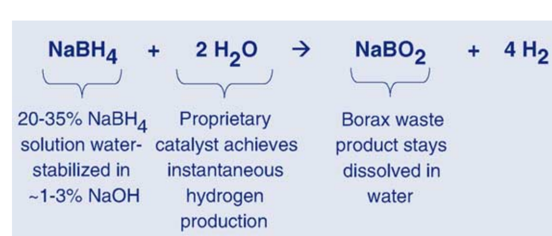

Fig. 3. Chemical equation for stoichiometric reaction of sodium borohydride and water.

belongs to the Borax family which can be recycled back to sodium borohydride for reuse. The higher volumetric storage efficiency of this chemical hydride allows the packaging of the whole alternative electric powertrain with no protrusion into the passenger or cargo space. An equivalent hydrogen storage system using compressed hydrogen at 350 bar, would occupy the last row of seat and the trunk space of the vehicle.

The beauty of hydrogen production is that it is not dependent on one particular feedstock or processing route. However, the efficiency of generation and consumption of hydrogen is critical when comparing to conventional fuels on a wells-to-wheels cycle. Thus, advanced controls methodology can contribute to increase the vehicle fuel consumption efficiency.

4. Advanced controls for fuel cell electric vehicles

Control algorithms for modern vehicles play a role similar to that of computer operating systems—they coordinate the complex operation of many sub-modules and fully characterize the behaviour of the overall system. They play a very critical role in the development of all future vehicles. In the case of fuel cell vehicles, important vehicle performance attributes to be carefully managed by the control algorithms include drivability, component reliability, and fuel economy (Pukrushpan, Peng, & Stefanopoulou, 2002a; Pukrushpan, Stefanopoulou, & Peng, 2002b; Yang, Bates, Fletcher, & Pow, 1998).

To improve the fuel economy of a fuel cell vehicle, it is important to ensure the sub-systems are functioning in a coordinated manner. During the early stage of fuel cell vehicle development, it is tempting to rely on heuristic rules and trial-and-error experimenting for control development, due to the fact it is relatively easy to create an acceptable design within short period of time. To enhance the long-term viability of fuel cell vehicles, however, it is necessary to introduce a model based design approach so that the design process is re-useable and rigorous, and the final design achieves a guaranteed level of optimality. In addition, a model-based engineering approach enables combined optimal design (configuration and component selection) and optimal control (fully explores the potential of the components), which is of ultimate importance during the evaluation of alternative controls technologies for FCEV.

When DaimlerChrysler initiated the Town and Country Natrium concept fuel cell vehicle, engineers began by specifying the components to meet the design criteria. Once all the components were selected, simulations were then conducted to create the best operation scenario. The goal was to design for the most reliable states of operation and performance. Although this technique led to a drivable car the fuel efficiency was less than desirable. To improve fuel economy, DaimlerChrysler and the University of Michigan created a co-operative research project to investigate a solution. A design procedure for identifying an optimal fuel economy control strategy was identified. The collaboration led to the creation of a dynamic simulation model for the target vehicle (Natrium) in the MATLAB/SIMULINK environment.

A simplified model that captures the efficiency characteristics of the vehicle is then obtained, by ignoring all dynamics of the original complex model, and preserving the battery state of charge (SOC) and vehicle speed as the only two dynamic states. A stochastic dynamic programming (SDP) design approach is then introduced. This SDP approach optimizes the operation of the FCEV, under the traction/braking power probability distribution obtained through four distinct driving cycles—representing urban, city and highway driving. The performance of the SDP optimal control is compared against a benchmark algorithm, which was developed based on the traditional rule-based approach. The block diagram of the DaimlerChrysler Natrium prototype vehicle is shown in Fig. 4. The objective of the model is determination of the power management strategy necessary for the propulsion of the vehicle.

4.1. Power management control model of the DaimlerChrysler Town and Country Natrium FC vehicle

The fuel cell vehicle model consists of several subsystems. In order to create an accurate power management model, each subsystem had to be identified and modelled, with special attention given to the relevant component efficiency information. Each subsystem required a proper method of model development, as described in the following.

It is assumed that the fuel cell system always has sufficient hydrogen supply and the dynamics associated with the fuel processing system does not influence the vehicle performance significantly. The fuel processing system was not modelled because it always maintains the hydrogen supply quite well.

The fuel cell block in Fig. 4 uses polarization curves to represent the current and voltage relationship of the fuel cell

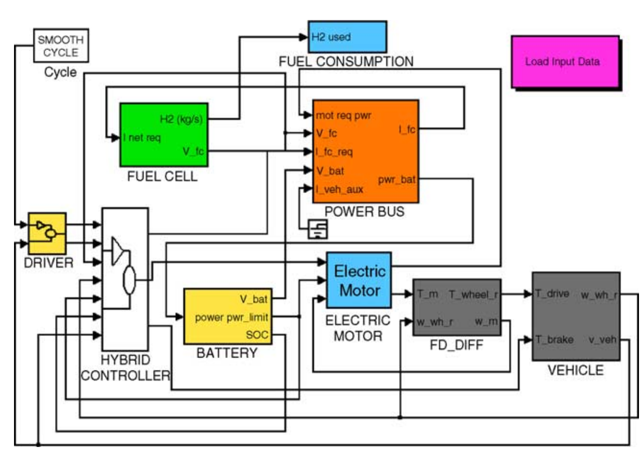

Fig. 4. FCEV simulation model.

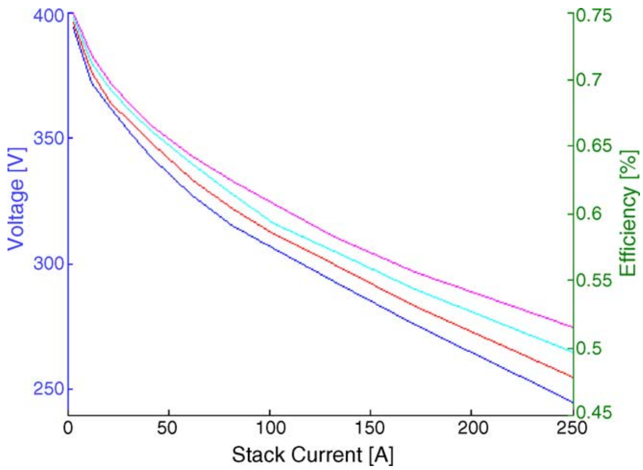

Fig. 5. Fuel cell stack efficiency at different cathode pressure.

stack used in the Natrium. Operating at a near constant temperature, the stack voltage is a function of stack current and cathode pressure, $V_{st} = f(I_{st}, p_{ca})$. Using road test data, the stack was found to operate at efficiencies between 55% and 65% (see Fig. 5). The reacted hydrogen, $W_{H_2,rct}$, can be calculated from:

$$W_{H_2,rct} = M_{H_2} \frac{n_{st} I_{st}}{2F}, \tag{1}$$

where M_{H_2} is the molar mass of hydrogen, n_{st} the number of cells, and F is the Faraday number. The flow rate of dry air flowing into the cathode is expressed by

$$W_{a,ca} = \frac{\lambda_{O_2} M_{O_2} n_{st} I_{st}}{4 y_{O_2,ca} F}, \tag{2}$$

where M_{O_2} is the molar mass of oxygen and λ_{O_2} is the oxygen excess ratio which is the ratio of oxygen supplied to oxygen reacted. The oxygen excess ratio is assumed to be maintained closed to the desired level ($\lambda_{O_2} = 2$). An algebraic air compressor model is used to compute the power necessary to run the compressor, which accounts for the majority of the fuel cell parasitic load:

$$P_{cp} = \frac{C_p T_{amb}}{\eta_{cp}} \left[\left(\frac{p_{sm}}{p_{amb}} \right)^{(\gamma-1)/\gamma} - 1 \right] W_{cp}, \tag{3}$$

where γ is the air specific heat ratio, C_p the air specific heat, η_{cp} the compressor efficiency, p_{amb} and T_{amb} the atmospheric pressure and temperature, respectively, W_{cp} the compressor mass flow rate which can be approximated by $W_{a,ca}$ in Eq. (2), and p_{sm} is the supply manifold pressure which can be obtained from the compressor map, $p_{sm}/p_{amb} = f_{cp,p}(W_{cp})$. Based on a linearized nozzle flow equation (Pukrushpan et al., 2002a,b), the cathode pressure, p_{ca}, is given by

$$p_{ca} = p_{sm} - \frac{W_{cp}}{k_{nozzle}}, \tag{4}$$

where k_{nozzle} is a constant.

A quad-directional dc/dc converter is used to connect the fuel cell system to the battery. The power can only flow from the fuel cell side to the battery side. The current drawn from the fuel cell system is controlled by a current control unit in the dc/dc converter. Extensive testing was conducted to obtain the dc/dc converter efficiency and to identify a second order transfer function from its input (reference fuel cell current) to output (actual fuel cell current). The battery used in this prototype vehicle is a 40 kW Li-ion pack. A resistance circuit model is used to represent its operation. The battery current is calculated by the equation:

$$I_{bat} = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4(R_{int} + R_t) P_b}}{2(R_{int} + R_t)}, \tag{5}$$

where P_b is the output power of the battery, R_{int} the internal resistance, V_{oc} the open circuit voltage, and R_t is the terminal ohmic resistance. The terminal voltage of the battery is then given by $V_{bat} = V_{oc} - I_{bat}(R_{int} + R_t)$. The SOC is the only state variable of the battery system:

$$\frac{\mathrm{d\,SOC}}{\mathrm{d}t} = -\frac{I_{bat}}{q_m}, \tag{6}$$

where q_m is the maximum battery charge.

The ac induction motor used in the Natrium vehicle has a rated peak power of 82 kW. The motor/inverter is modelled as a first-order system to simulate its closed-loop dynamic behaviour:

$$\frac{\mathrm{d}\tau_m}{\mathrm{d}t} = \frac{1}{T_m} (-\tau_m + \min(\tau_{m,req}, \tau_{m\_max}(\omega_m))), \tag{7}$$

where $\tau_{m,req}$ is the requested motor torque, τ_{m_max} the maximum torque the motor can generate under current motor speed, τ_m the calculated motor torque, and T_m characterizes the time constant of the electrical dynamics. The motor efficiency is represented by a look-up table depending on the motor output torque and the motor speed: $\eta_m(\tau_m, \omega_m)$.

The vehicle model contains rotational wheel dynamics and linear vehicle dynamics. The state equation of the wheel speed is written as

$$\frac{\mathrm{d}\omega_{wh}}{\mathrm{d}t} = \frac{1}{J_r} (\tau_{wh} - \tau_b - B_{wh}\omega_{wh} - r_{wh}(F_x + F_r)), \tag{8}$$

where τ_{wh} is the driving torque from the motor, τ_b the frictional brake torque, B_{wh} the viscous damping, r_{wh} the tire radius, F_x the tire longitudinal force, F_r the rolling resistance force, and J_r is the equivalent moment of inertia of rotating components including the motor, axles, and wheels in the vehicle. The rolling resistance force is given by $F_r = C_r F_z$, where C_r is the rolling resistance coefficient and F_z is the tire normal force. The tire longitudinal force is calculated by $F_x = \mu_{wh}(\lambda_{wh}) F_z$, where μ_{wh} is the road friction coefficient and λ_{wh} is the wheel slip. The vehicle speed is calculated from the state equation:

$$\frac{\mathrm{d}v_v}{\mathrm{d}t} = \frac{1}{M_v} \left(F_x - \frac{v_v}{|v_v|} (F_a(v_v)) \right), \tag{9}$$

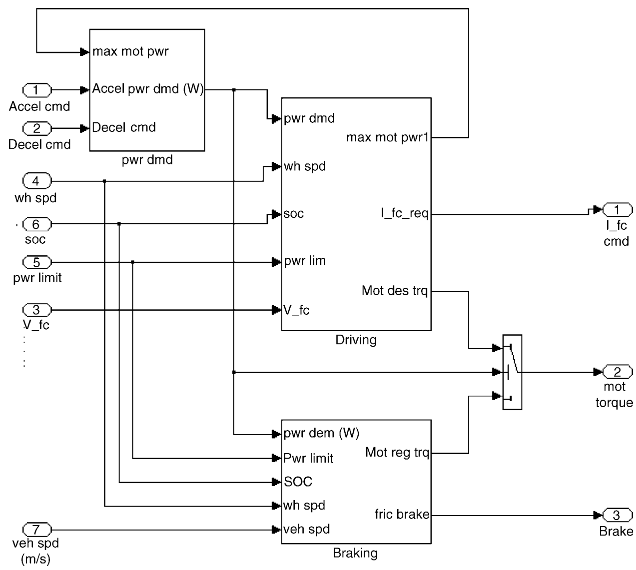

Fig. 6. Block diagram of the hybrid controller.

where v_v is the vehicle speed, F_a the aerodynamic drag force, and M_v is the mass of the vehicle. The aerodynamic drag force is given by $F_a = 0.5 C_d \rho_a A_v v_v^2$, where C_d is the aerodynamic drag coefficient, ρ_a the density of air, and A_v is the frontal area of the vehicle. The ‘‘driver’’ block of Fig. 4 is a PI feedback controller whose function is to affect the vehicle to follow the specified driving cycle. It generates positive (acceleration) or negative (deceleration) commands to the ‘‘hybrid controller’’ block, which is the heart of this control design study.

The block diagram of the hybrid controller is shown in Fig. 6. It is assumed that the control strategy will be divided into two parts: traction and braking. The following high-level signals are used for the control decisions: vehicle speed, wheel speed, battery SOC, fuel cell voltage and battery power limit.

With all of the subsystems modelled, attention is then focused on power management.

4.2. Control problem formulation

The power management problem to be solved in this section is as follows: To identify the optimal control strategy for the operation of the two power sources (fuel cell and battery) so that the hydrogen consumption is minimized. In the meantime, the vehicle drivability and battery SOC balance have to be satisfied. In other words, the ‘‘fuel economy optimization’’ is a constrained dynamic optimization problem, subject to the higher-priority goals of drivability and charge sustaining. The optimal control algorithm to be identified is a supervisory controller that communicates with a set of sub-system controllers through a Control Area Network (CAN-bus) (see Fig. 7).

The supervisory controller is designed to cover global system design objectives. These objectives include optimal fuel economy and drivability issues. Commands from the

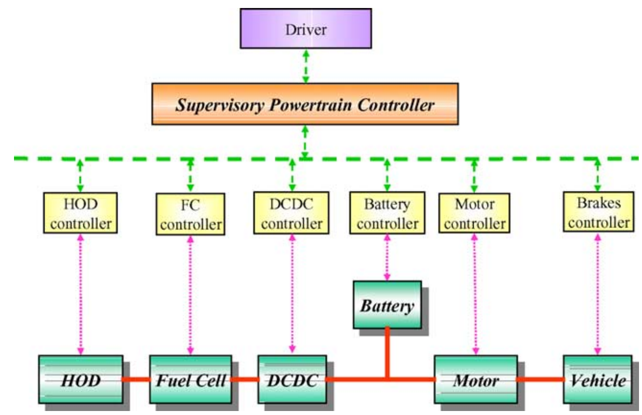

Fig. 7. Control system architecture in the Natrium electric fuel cell vehicle.

supervisory controller are then used as set-points to be followed by the sub-systems, subject to local considerations such as fuel cell reliability, battery life, etc.

However, any deviation from the commands from the supervisory control may render the overall system less than optimal. Therefore, it is highly desirable to model the ‘‘local constraints’’ as accurately as possible, and include them into the decision process of the supervisory controller, so that the obtained decision is truly optimal. That is why we started the control design process by constructing a detailed model, which includes the efficiency behaviour and performance constraints of all sub-systems.

The basic role of the supervisory controller design is to consider the characteristics of all the sub-systems, and coordinate their operations in an optimal fashion. We commonly refer this problem as a ‘‘power management problem’’ because the final decision boils down to this: ‘‘How much power (electric current) should be drawn from the fuel cell?’’ Once this question is answered, the operations of all other sub-systems are fully determined due to the drivability requirement and power balance of the overall system (see Fig. 8).

A simple rule based control strategy is first designed, which is later used as the benchmark for our optimal controller. The rules used are popular ideas for series hybrid vehicles. The basic rule is as follows: the fuel cell is turned on to charge the battery to a pre-determined high level of

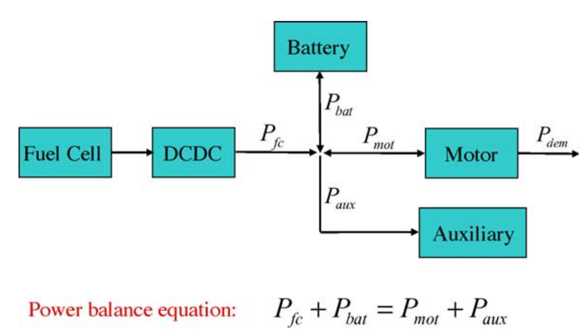

Fig. 8. Power management problem for the fuel cell electric vehicle.

SOC, and will be shut down and remain off until the battery SOC drops to a pre-determined low SOC level. However, a minimum fuel cell power is selected; thus, the fuel cell might be turned on regardless of the battery SOC, if the power demand is high. In addition, to avoid frequent on/off switching of the fuel cell system, a rule is added so that the decision on the fuel cell operation depends on past on/off status of the fuel cell system. The power request for the fuel cell essentially follows the driver traction command, but will be modified to charge the battery. This power modification is a function of the battery SOC. The deceleration control is simple: absorb regenerative energy as much as possible, subject to the motor and battery constraints. We assume no regenerative-braking constraint to simplify the modelling. In the next section, the power management problem of the Natrium vehicle is solved from an approach we developed for a parallel hybrid electric vehicle (Lin, Peng, & Grizzle, 2004).

4.3. Stochastic dynamic programming approach

As mentioned before, the power management control algorithm will be solved as a stochastic problem. The driver power demand is modelled as a discrete-time stochastic process by using a Markov chain model. The dynamics of the power demand can be characterized by a one-step transition probability, which maps the current power demand and vehicle speed into a future power demand:

$$p_{il,j} = Pr\{w = P^{j}_{\mathrm{dem}} \,|\, P_{\mathrm{dem}} = P^{i}_{\mathrm{dem}}, \omega_{\mathrm{wh}} = \omega^{l}_{\mathrm{wh}}\}, \quad i, j = 1, 2, \ldots, N_p, \quad l = 1, 2, \ldots, N_\omega, \tag{10}$$

where the power demand, P_{dem}, and the wheel speed, ω_{wh}, are quantized into N_p points and N_ω points, respectively. To construct the transition probability function, four different driving cycles including city, suburban, and highway driving scenarios are selected. From the speed profile of these cycles, the corresponding P_{dem} and ω_{wh} at each time step (e.g., 1 s) could be calculated based on the vehicle model. Using nearest-neighbor quantization, the sequence of observations (P_{dem}, ω_{wh}) was mapped to a sequence of quantized states $(P^{i}_{\mathrm{dem}}, \omega^{l}_{\mathrm{wh}})$. The transition probability could then be estimated by

$$\hat{p}_{il,j} = \frac{m_{il,j}}{m_{il}} \quad \text{if } m_{il} \neq 0, \tag{11}$$

where $m_{il,j}$ is the number of times that the transition from P^{i}_{dem} to P^{j}_{dem} has occurred given that the wheel speed state was ω^{l}_{wh}, and $m_{il} = \sum_{j=1}^{n} m_{il,j}$ is the total number of times that P^{i}_{dem} has occurred at wheel speed ω^{l}_{wh}. This random power generation process becomes part of the "driver" dynamics, as shown in Fig. 9. Two of the key benefits of the stochastic dynamic programming approach, compared with its deterministic counterpart (Lin, Peng, Grizzle, & Kang, 2003), are (i) the obtained control law can be directly implemented; (ii) the control law is not cycle-specific. Instead, it is optimized for the given propulsion power probability distribution, which could be obtained as a weighted representation of diverse driving conditions.

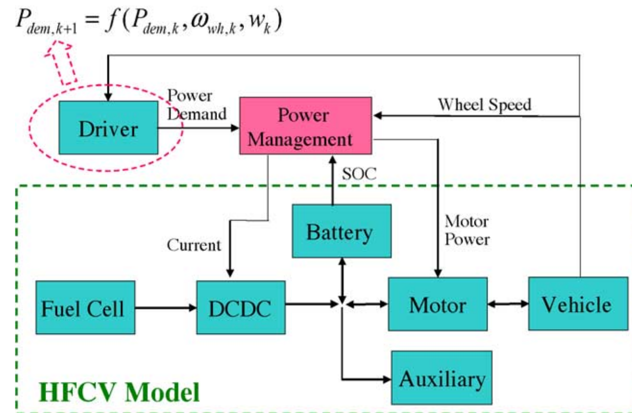

Fig. 9. Block diagram of the stochastic fuel cell power management problem.

The fact that the stochastic dynamic programming guarantees global optimal solution even for nonlinear systems comes at a price: it suffers the so-called "curse of dimensionality" and only works with dynamic systems with low number of state variables (Bertsekas, 1995). The SIMULINK model presented in Section 4.1, thus, needs to be simplified before it can be used in the SDP design approach. The reduced-order model used for SDP only contains three state variables: battery state of charge, wheel speed, and power demand. The first two states are described by deterministic dynamic equations (Eqs. (6) and (8)), which are essentially the slowest modes of the original SIMULINK model. The last state is described by a stochastic dynamic equation, governed by the transition probability function in Eq. (10). To fit into the SDP framework, dynamic equations are rewritten in a discrete-time format, and the time step is chosen to be 1 s. In addition to these three state variables, the algebraic equations and look-up tables presented in Section 4.1 are used to calculate other (faster) variables, including battery current, battery voltage, motor torque, fuel cell auxiliary power, hydrogen and air flow rates, and fuel cell voltage.

Our objective is to find an optimal control policy, $u = \pi(x)$, that maps observed states (i.e., SOC, wheel speed, and power demand) to control decision (i.e., fuel cell current request) so as to minimize the expected cost of hydrogen consumption and battery energy usage over infinite horizon:

$$J = \lim_{N \to \infty} \underset{w_k}{E} \left\{ \sum_{k=0}^{N-1} \gamma^{k} (W_{\mathrm{H_2,rct}} + \alpha M_{\mathrm{SOC}}) \right\}, \tag{12}$$

where $0 < \gamma < 1$ is the discount factor, α the weighting factor, $W_{\mathrm{H_2,rct}}$ is the reacted hydrogen, and M_{SOC} penalizes the SOC deviation, which is measured by a quadratic distance between the current SOC value and the SOC reference point, $M_{\mathrm{SOC}} = (\mathrm{SOC} - \mathrm{SOC_{ref}})^2$. Based on Bellman's optimality equation, the SDP problem is solved by a policy iteration algorithm. The policy iteration conducts a policy evaluation step and a policy improvement step in an iterative manner until the optimal cost function converges (Puterman, 1994). The approximate value function for a given policy, $J_\pi(x)$, is first calculated by iteratively updating the Bellman equation in the policy evaluation step:

$$J_\pi^{s+1}(x^i) = g(x^i, \pi(x^i)) + \underset{w}{E}\{\gamma J_\pi^s(x')\} \tag{13}$$

for all state grid i, where s is the iteration number, and x' is the new states evolving from x^i based on dynamic equations. Subsequently, an improved control policy can be obtained from the updated approximate value function in the policy improvement step:

$$\pi'(x^i) = \underset{u \in U(x^i)}{\operatorname{argmin}}[g(x^i, u) + \underset{w}{E}\{\gamma J_\pi(x')\}] \tag{14}$$

for all i, where J_π is the approximate cost function obtained from the policy evaluation step. After the new policy is obtained, we go back to the policy evaluation step to update the cost function using the new policy. This iterative process is repeated until J_π converges within a selected tolerance level. The obtained full-state feedback control law can then be evaluated using the original, complex SIMULINK model. The SDP design procedure is shown in Fig. 10.

4.4. Simulation results

The SDP control algorithm obtained in the previous subsection has the form of $I_{\mathrm{fc,req}} = \pi^*(\mathrm{SOC}, \omega_{\mathrm{wh}}, P_{\mathrm{dem}})$. In other words, an optimal fuel cell current is determined, as a full-state feedback law of battery SOC, wheel speed (assumed to be algebraically related to the vehicle speed) and driver power demand. This optimal fuel cell current becomes the current request command for the fuel cell side of the dc/dc converter. The power surplus or deficit (from the driver demand power) determines the appropriate battery power level.

This control law was simulated extensively and the results showed that the controller achieved the two required performance attributes under all cases, the drivability (driver power demand is always satisfied) and battery charge sustaining. The overall vehicle fuel economy was then examined.

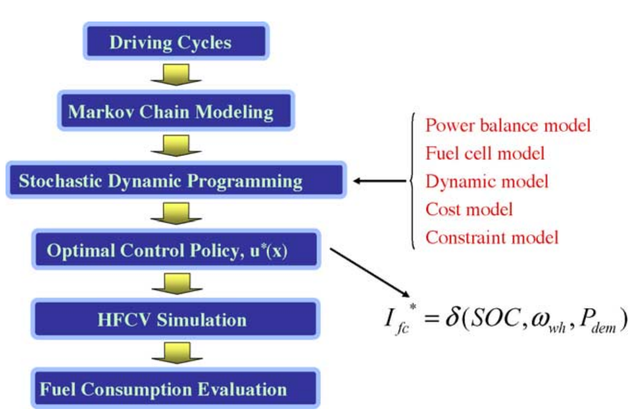

Fig. 10. Stochastic dynamic programming approach.

Table 1
Simulation results

Policy	H_2 consumption (g)
UDDSHDV (urban dynamometer driving schedule for heavy-duty vehicles)	
Baseline rule-based	103.01
SDP	100.16
WVUINTER (west Virginia interstate driving schedule)	
Baseline rule-based	277.30
SDP	272.11
UDDS (EPA urban dynamometer driving schedule)	
Baseline rule-based	129.41
SDP	125.45
HWFET (EPA highway fuel economy test)	
Baseline rule-based	183.58
SDP	180.47

Fuel (hydrogen) consumption of the SDP controller and the baseline rule-based controller over four driving cycles are shown in Table 1. It can be seen that the SDP controller consistently achieves a better fuel economy, and consumes 2.5–3% less hydrogen than the baseline rule-based controller. This improvement sounds somewhat small but is quite significant because of two reasons. First, as can be seen from Fig. 5, the fuel cell stack has a relatively "flat" efficiency map, which is quite different from those typical of gasoline engines. For the driving cycles we used, the fuel cell stack frequently operates at the efficiency between 55% and 65%, so a 3% improvement is actually quite significant. Secondly, the design procedure represents a systematic, reuseable process with guaranteed level of optimality. No matter how much improvement is achieved, it is comforting to know that the obtained control law is optimal and has already taken full advantage of the potential of all subsystems.

4.5. Implementation of stochastic fuel cell power management strategy

The stochastic fuel cell power management algorithm described above will need to be tested in hardware. Since the model was first designed as a simulation, integration into the real vehicle controls needs to be done. Part of the evolution of vehicle controls development is DaimlerChrysler's procedure of rapid prototyping of control algorithms. The control code in the Natrium is also a SIMULINK-based model, so implementing the controls comes down to tying the right variable together and accounting for some parameters not considered during simulation.

Implementation of the stochastic fuel cell power management strategy is planned for the month of April 2004. By that time, tests will have been conducted on a vehicle test bench and should reveal actual results and drivability issues. A few questions eventually arise and can force components to be redesigned. A proper example of this, is how a power management controls algorithm effects the battery cooling system. Also, is the algorithm more prone to wear on a particular component? Simulations can answer a good portion of these questions, but results are not fully understood, until a method is implemented into a vehicle and tested.

When the code is implemented into the Natrium, tests will be conducted on a dynamometer for benchmarking and gas analysis. This allows us to make comparisons to other techniques and keep all system changes quantifiable.

Later, the vehicle will be test driven at a DaimlerChrysler Proving Grounds. These real road results can then be compared to previous tested results for more comprehensive understanding of the value of the proposed design procedure.

5. Conclusions

As advanced propulsion technologies transition into mass production vehicles, advanced control algorithms will have to be incorporated into the vehicle development process and become an integrated part of their execution. These vehicles will have the potential to provide sustainable personal mobility that are cleaner and more efficient than ever before. For over a decade, DaimlerChrysler has been the leader of the automotive industry in fuel cell vehicle technology, and strives to keep that edge by investigating not only alternative hydrogen storage techniques, but also advancing the control architecture of vehicles that use them.

One of the most important aspects of bringing these simulations together was the fundamental testing of each component in a controlled environment. Examination of responses to standard inputs produced a solid foundation for proper modelling that is suitable for control design and development.

The fuel consumption analysis of the DaimlerChrysler Town and Country Natrium provided the motivation for DaimlerChrysler and the University of Michigan for this cooperative research project. This work exemplifies DaimlerChrysler's commitment to utilize new technologies from academic recourses into practical applications.

Some of the benefits of implementing stochastic dynamic programming design approach is a possible 2–3% (an increase of about 15 km in range) increase in fuel economy and ease of implementation of the controls. The model-based approach makes it possible to quickly implement innovative control algorithms, evaluate the impact of alternative techniques and test the performance of new concept vehicles in a short period of time.

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Andreas Schell was appointed senior manager, Fuel Cell Systems, Advance Vehicle Engineering in July of 2002. Mr. Schell is responsible for North-American DaimlerChrysler fuel cell vehicle activity, coupled with research and development of fuel cells and hydrogen. Mr. Schell joined the company in 1996 as a development engineer for advanced propulsion systems and has since held a variety of positions of responsibility in corporate research and product development. Recent accomplishments include coordinating a major fuel cell demonstration program in cooperation with international energy partners and the Department of Energy.Significant elements of his professional and academic background include:• Program manager, Fuel Cells, Liberty Group Technical Affairs and Fuel Cell Vehicle Development, 2002;• Manager, Advanced Vehicle Controls, Research and Development, 2000;• Engineer, Hybrid and Fuel Cell Electric Vehicles, Research and Development, 1996;• MSME, Technical University Clausthal-Zellerfeld, Germany, 1995;• Currently Mr. Schell is studying for his MBA at the Michigan State University.Schell was born on 29 July 1969 in Herborn, Germany.

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Doanh Tran was appointed manager, Fuel Cell Systems Advance Vehicle Engineering, Chrysler Group in July 2001. The new title coincided with the merger of the company to become DaimlerChrysler. The combining of the two teams (Chrysler and Mercedes-Benz) created an advantageous vehicle development process via the sharing of technology. Tran's contribution helped positioned the company to become a leader in fuel cell technology. Tran joined Chrysler Corporation in May 1998 as an engineer in the Liberty Technical Affairs Group assigned to fuel cell vehicle development. His accomplishments and academic background includes:• Electric vehicles engineer, Tour De Sol Race for NESEA, 1991–1993;• Jeep® Commander I, concept on board gasoline reformer, 1998;• Jeep® Commander II, fully functional onboard methanol reformer, 2000;• Town and Country Natrium, fully functional onboard chemical hydride reformer, 2001;• Michigan site manager for DOE Controlled Fleet Demonstration Project, 2004;• BSME, Texas A&M University, 1993;• MSME, Texas A&M University, 1995;• MBA, Michigan State University, 2004.Tran was born in Nha Trang, VietNam on 28 May 1970.

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