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Fuzzy Logic Controller for Energy Management of Power Split Hybrid Electrical Vehicle Transmission

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***Abstract*—This paper investigates energy management strategies for a power split hybrid electric transmissions using a fuzzy design method. *Hybrid Electric Vehicles* (HEV) is one of the most promising research topics for developing efficient and environmentally-friendly transportation solutions. A power split hybrid combines the advantages of both series and parallel hybrid configurations by providing a higher degree of freedom to fulfill the demand of the driver while improving overall fuel efficiency at the cost of higher complexity and non-linearity in the control system design. There are two issues that should be addressed for energy management: torque distribution and battery charge sustenance. The fuzzy controller controls the torque request for the internal combustion engine by taking into consideration the vehicle speed, battery state-of-charge, and the normalized torque request from either the driver or an automated driving controller. The controller has several rules to control the *internal combustion engine* (ICE) torque request. We show that our rule base provides greater control over the ICE operation over a wide range of conditions for optimum fuel consumption. The controller was tested by integrating with a vehicle model and simulated by running it for multiple United States Environmental Protection Agency drive-cycles and then compared to a controller based on a commercially available HEV system.**

I. INTRODUCTION

To meet fuel consumption and emission standards set by government organizations, there has lately been heavy emphasis on HEV transmission development. Unlike traditional vehicles, which have only *internal combustion engine* (ICE) based drivetrains, HEVs utilize ICEs along with electric motors/generators to propel the wheels of the vehicles. The addition of electric motors/generators provides flexibility to the mode of fulfillment of the requested torque to drive the vehicle.

Some research has been done on the use of computational intelligence for adaptively controlling HEV vehicles [1], [2], including systems that focus on plug-in hybrids [3], [4], fuel cell HEVS [5], [6], and parallel HEVs [7], [8], [9]. The main contribution of this paper is the application of fuzzy control to power-split HEV drivetrains, showing that fuzzy control can improve efficiency and performance.

Power split transmissions stand out when compared to standalone series or parallel transmissions. Power split transmissions provide a higher flexibility to operate the electric motor and the ICE to fulfill the request torque for vehicle propulsion. This flexibility provides opportunity to operate the ICE at points of high efficiency. Power split HEVs like the Toyota Prius have been successful in the commercial market due to the advantages that it offers over only series or parallel hybrids.

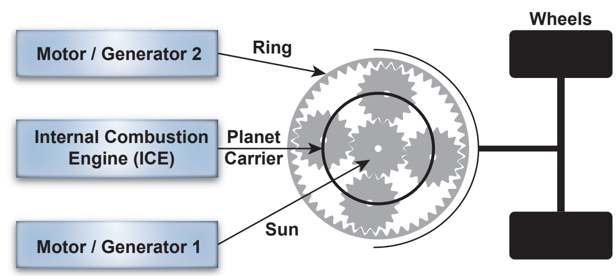


Fig. 1. HEV power split transmission block diagram

II. POWER SPLIT HEV VEHICLE STRUCTURE AND CONTROL METHOD

A. Power split HEV structure

The power split structure designed here is similar to the Hybrid Synergy Drive in the Toyota Prius. It consists of two motor/ generators and one ICE, as shown in Fig. 1. The motor/ generator 1 (MG1) is connected to the ring gear. ICE is connected to the planet carrier and MG1 is connected to the sun gear. MG1 is the primary drive for the wheels and is mechanically coupled to the wheels through the differential (by drving the whole gear constellation). There is no physical coupling between ICE and the wheels; thus, ICE does not directly drive the wheels. ICE is used merely to provide electrical charge via MG2 by driving the ring gear. Figure 1 shows a block diagram of the power split hybrid powertrain. The absence of mechanical coupling between ICE and the wheels provides high flexibility to operate ICE without direct correlation to the speed of the vehicle.

The transmission provides the requested torque by several methods. The requested torque can either be fulfilled by MG1 powered by the battery alone. Or MG1 can be powered by only ICE which is provides electrical energy to MG1 by using MG2 as an inverter. When ICE is running, MG2 acts as a generator, electrically generating the torque supplied by ICE. The requested mechanical torque is thus supplied by MG1 with support from the batteries and/or ICE. ICE provides torque through MG2, which, through the inverter directs to MG1 to fulfill the torque request. Thus, this configuration provides high flexibility to operate ICE at its high efficiency region whenever it is operated. The mathematical model that we use in this paper is based on the Prius and is described by the following equations [7].

$$\begin{aligned}
&(1+\rho)\cdot n_e = \rho\cdot n_g + n_r;\\
&\eta\cdot = (1+1/\rho)\cdot = (1+\rho)\cdot T_r;\\
&n_m = n_r;\\
&T_w = T_m + T_r = T_m + \eta\cdot\ T_e/(1+\rho);\\
&n_w = n_r/K = ((1+\rho)\cdot n_e - \rho\cdot)/K;
\end{aligned}$$

where ρ is the ratio of the sun and ring gears; η is the efficiency of ICE; $(n_e, n_g, n_r, n_m, n_w)$ and $(T_e, T_g, T_r, T_m, T_w)$ are the rotational speeds and torques of ICE, MG2, ring gear, MG1, and drive axle, respectively; K is the final drivetrain ratio. The system power is computed as

$$P = \frac{(T_w - T_m)(1+\rho)w_e}{\eta_3 n} - k_1(T_w - T_m)w_e\eta_1 + \frac{k_2 T_m n_m}{\eta_2},$$

where (η_1, η_2, η_3) are the efficiency of MG2, MG1 and ICE, respectively, and (k_1, k_2) are constants (which are based on specific configurations of the transmission).

B. Control of power split HEV using fuzzy logic

The goal of a good HEV control strategy is to minimize total fuel consumption and emissions without making an impact on performance, reliability, and safety [2]. As it needs to be carefully monitored, the *state of charge* (SOC) of the battery is one of the most important parameters to be controlled. The limits of operation of the battery and the number of charge/discharge cycles affect the longevity of the battery; hence, optimal control of the battery pack is of prime importance. In addition, the power split control must satisfy the power demand of the driver/robotic controller. It must also take into consideration the depth of discharging and charging for the battery since this also plays an important role in the longevity of the battery pack. So, in summary the overall performance of the controller is not just based on fuel mileage, it is also based on battery usage and driver performance. We will examine all these aspects in our analysis.

III. Energy Management Fuzzy Controller Design

The fuzzy controller takes as input the current vehicle speed, the battery SOC, and the torque request from the driver /controller. The output is the ICE torque request. The controller is non-causal and takes into account only the present states of the system to determine the required torque for the ICE. The basic postulation is that greater efficiency can be achieved from ICE when it is operated consistently at its efficient region and by avoiding transients that normally occur in traditional ICE vehicles from sudden acceleration and frequent start-stop operations [8].

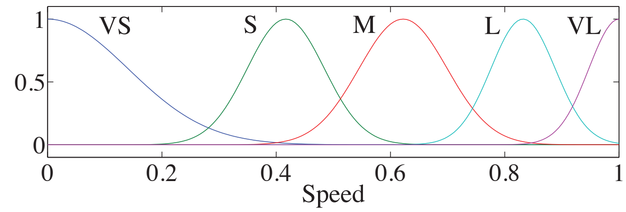


Fig. 2. MFs for normalized vehicle speed

A. Fuzzification of inputs

1) Vehicle speed: The first input to the fuzzy controller is vehicle speed. It is normalized to provide greater flexibility to the controller. The vehicle speed has five membership functions as shown in Fig. 2: VS (very small), S (small), M (medium), L (large), and VL (very large). The membership functions are gaussian with the mean and variances set to provide good controlling action. For lower speeds, wherein MG1 can provide power to the wheels (provided the other input conditions are satisfied) VL is more fuzzy (more uncertain) as to incorporate the effect of MG1 powering the propulsion without much help from ICE. As the vehicle speed increases, the membership functions are more certain and closely spaced to have more control over the different ranges of vehicle speed. It has been observed that high speed operation of vehicles result in comparatively higher consumption of fuel by the ICE and effort has been made to keep this in account. The membership functions were also formulated by taking into the probability of the vehicle moving at the given speeds.

2) Battery state of charge: The second input to the fuzzy controller is the normalized battery SOC as shown in Fig. 3. This is the most important input to the controller and its value makes tremendous impact on the controller output and the overall vehicle fuel consumption. The SOC, being of prime importance needs to be controlled and kept at optimum levels. The SOC has five membership function similar to the vehicle speed but with different mean and variances to provide better controllability of the controller. In general, extremely low and high levels of battery SOC are avoided so as to ensure longevity of the battery pack. Rapid transfer of energy from the battery system produces heat, reducing longevity [1]. Plus, keeping a battery pack on a low SOC can reduce the life of the battery and maximum charge level tremendously. On the other hand, a very high level of battery SOC, close to 0.90-1 is not safe and has been known to cause fires. Thus, the battery SOC range at which we would like to run the battery in normal conditions is from 0.45–0.85. Membership function VS depicts the lower end of the SOC. This lies from 0 to around 0.5. The higher end of the SOC is depicted by VL which ranges from around 0.8 to 1. The SOC range in between is depicted by the S, M and L membership functions. The controller tries to maintain the SOC between 0.45–0.85 while still trying to improve the efficiency of the system.

3) Normalized accelerator pedal position: The last input to the fuzzy controller is the normalized *accelerator pedal*

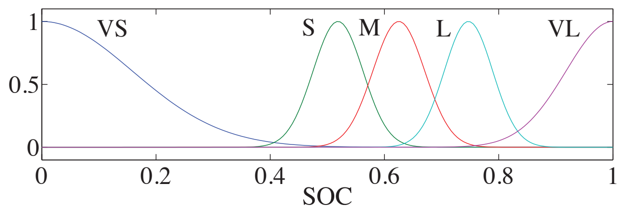


Fig. 3. MFs for normalized SOC

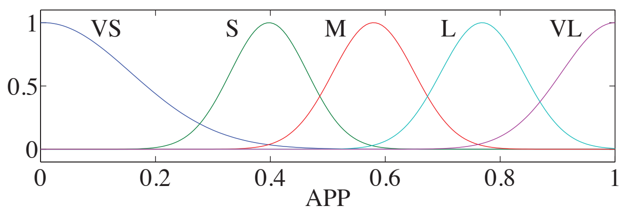


Fig. 4. MFs for normalized APP

position (APP), for which we developed the MFs shown in Fig. 4. Accelerator pedal information is used to gauge the driver torque request. For high torque request, MG1 may not be able to fulfill the request. In such a scenario, the torque request is fulfilled with the help of both MG1 and ICE. For low SOC condition, the requested torque is completed by the ICE since the battery does not have enough energy to propel the vehicle using MG1. APP has 5 membership functions. Low torque requests can be handled well by the MG1, hence VS is more uncertain than other membership functions. Fulfillment of the torque request is the primary aim for any driver controller, and this controller determines when the ICE operates and helps in the fulfillment of the torque request.

B. *Fuzzy inference system*

The *Fuzzy Inference System* (FIS), illustrated in Fig. 5, forms the core of the control for the ICE torque request signal. It takes into consideration the three inputs (vehicle speed, SOC, and APP). The output is the normalized ICE torque request. The Mamdani method for fuzzy inference is applied for the fuzzification and defuzzification. The rule base is formed and tuned through expert experience and understanding of HEVs, focusing on the power split transmission design.

C. *Defuzzification of output*

1) Normalized ICE torque request: The only output from the fuzzy controller is ICE torque request, for which the output rules are shown in Fig. 6. The rule table, detailed in Table I, specifies the conditions and the values for the operation of the ICE request. These rules were designed from expert intuition regarding the operation of the power split transmission with the aims of fuel efficiency, optimal battery state, and driver performance. We now describe the ideas behind our fuzzy rule base.

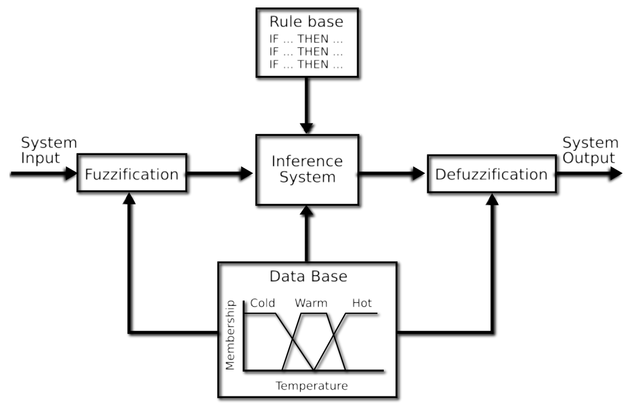


Fig. 5. Fuzzy inference system

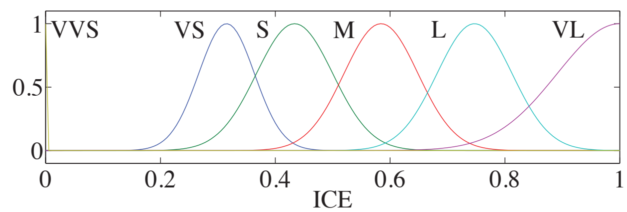


Fig. 6. MFs for Normalized ICE Torque Req

TABLE I
FUZZY RULES OUTPUT FOR ICE REVOLUTIONS PER MINUTE

		ICE RPM				
SOC	**APP**	**VS**	**S**	**M**	**L**	**VL**
VS	**VS**	M	M	L	L	L
VS	**S**	M	M	L	L	L
VS	**M**	M	M	L	L	VL
VS	**L**	L	M	L	VL	VL
VS	**VL**	VL	L	VL	VL	VL
S	**VS**	S	S	M	L	L
S	**S**	S	S	M	L	L
S	**M**	M	S	M	L	VL
S	**L**	M	S	M	L	VL
S	**VL**	L	M	L	VL	VL
M	**VS**	VVS	VVS	VVS	VVS	VVS
M	**S**	VVS	VS	S	M	M
M	**M**	VVS	VS	S	M	M
M	**L**	VVS	S	S	L	M
M	**VL**	VVS	S	M	L	L
L	**VS**	VVS	VVS	VVS	VVS	M
L	**S**	VVS	VVS	VVS	VS	L
L	**M**	VVS	VVS	VVS	VVS	VVS
L	**L**	VVS	VVS	VVS	VVS	VL
L	**VL**	VVS	VVS	VVS	VVS	VL
VL	**VS**	VVS	VVS	VVS	VVS	VVS
VL	**S**	VVS	VVS	VVS	VVS	VVS
VL	**M**	VVS	VVS	VVS	VVS	VVS
VL	**L**	VVS	VVS	VVS	VVS	VVS
VL	**VL**	VVS	VVS	VVS	VVS	VVS

D. Controller operation for different driving scenarios

At lower speeds and low torque requests, electric-only mode provides good fuel efficiency as the MG1 can provide the required torque by drawing power from the battery only. This operation is constrained by the battery SOC because MG1 cannot operate solely on battery energy when the battery is low on charge. In this case, the ICE is also operated, serving to charge the battery. A similar situation also arises when the torque request is small or medium. Contrastively, for high torque request situations the ICE is operated to aid MG1. Irrespective of the torque request, when the battery SOC is low, the ICE is operated to charge the battery, perhaps also aiding the propulsion (albeit indirectly).

At medium speeds and low torque request, the vehicle is powered by only MG1 if the SOC is within the required range. If the SOC is low then the ICE is operated to charge the battery without supplying the power directly to MG1. If the torque request in this case is medium then the ICE operates to also supply power to MG1 through the inverter. When the SOC is high, the ICE is not operated and MG1 provides the requested torque.

At higher speeds and low torque request, the vehicle needs power not only from MG1 but also from the ICE. The ICE power is transferred to MG1 through the inverter, considering the constraint that the SOC is within the required range. If the SOC is below the permissible limit then the ICE is operated at a higher torque request so as to redirect its torque to MG1 through the inverter.

IV. Simulation Results

The proposed fuzzy controller was incorporated in a simulated vehicle model and made to run through simultaneous multiple UDDS cycles and the resulting performance was analyzed. The total duration of the cycle was around 5,500 seconds (1.5 hours) worth of UDDS cycles. This was done to analyze the functionality and performance of the controller for long drive cycles wherein the battery SOC could discharge and recharge multiple times, which can be seen in the resulting figures.

A. Simulation results for fuzzy controller

Figure 7 shows the results for the fuzzy controller when the vehicle is driven through multiple simultaneous US EPA *Urban Dynamometer Driving Schedule* (UDDS) drive cycles. The figure displays the system states during the drive cycles. View (a) shows the normalized vehicle speed; (b) shows the normalized SOC; view (c) is of the normalized pedal position; and (d) shows the output of the system, the normalized ICE torque request. The important system state to be analyzed is the SOC. Using our controller, the SOC does not undergo deep charging/discharging over the benchmark driving cycles. This provides better quality and life of the battery along with providing a satisfying fuel economy.

B. Simulation results for standard rule-based controller

To compare with the fuzzy controller, a standard rule-based controller was designed which mimics, to the best of our knowledge, a current commercial HEV power split controller. The results of the controller are included in Fig. 8. The SOC, in view (b), can be seen to undergo deep charging/discharging cycles, which illustrates the standard procedure of energy management. Although this may result in more utilization of the available energy, it results in shorter battery life which may lead to replacing the battery, a serious environmental impact.

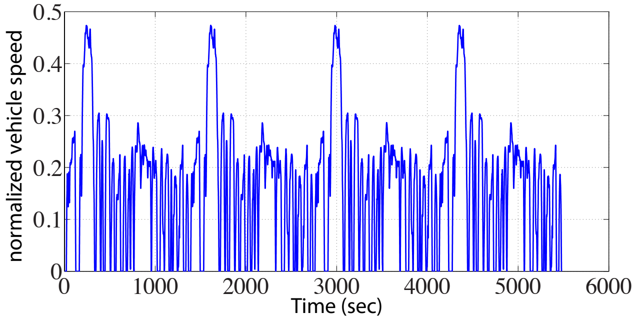
V. Comparison of Fuzzy Controller and Commercial System

The two controllers were compared with the same vehicle parameters and drive cycles. As the SOC results show in Figs. 7 and 8, the fuzzy controller is clearly better at maintaining a healthy battery SOC. Furthermore, the fuzzy controller gave a relatively good improvement in fuel efficiency in comparison to the standard controller; although, admittedly the fuzzy controller employs a more sophisticated and complex rule base for operation. The fuzzy controller gave a fuel mileage of 72 miles per gallon as compared to 64 miles per gallon for the standard system. This is more than 10% increase in fuel economy, which is a very good improvement. Furthermore, this mileage improvement is achieved with having the battery undergo deep charging and discharging cycles. This characteristic would in the long term have a big positive impact on the life span and performance on the battery pack thus reducing the total cost associated with maintaining the battery. The reason that the fuzzy controller is more efficient is that the ICE is strategically switched on and off more frequently, thus saving fuel consumption. Along with that, the controller is designed to operate the ICE at its highest efficiency region, thus aiding fuel economy.

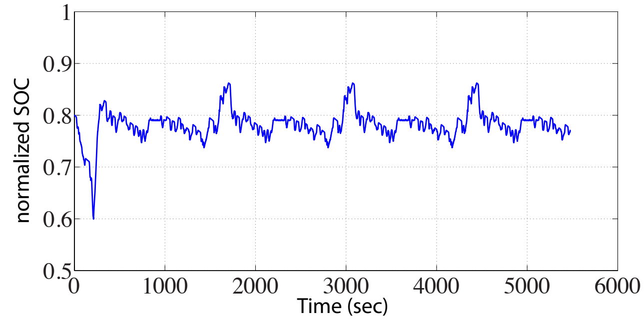
VI. Comparison of Fuzzy Controller Operation with Different Battery Sizes

Battery size forms an important part of the HEV design. There is a trade off between the size of the battery and its cost and weight. A comparison was made between three different battery types with different capacities to gauge the operation of our proposed fuzzy controller with these battery types and sizes.

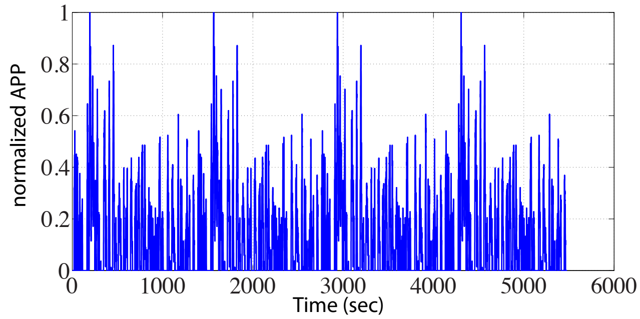
Three battery options were simulated: lead acid, nickel metal hydride (NiMH), and lithium ion (Li-Ion). Each of these batteries have different characteristics, e.g., capacity, energy density (energy per weight), voltage rating, and current rating. The lead acid battery was simulated with a capacity of 5Ah, a voltage rating of 100V, and current rating of 75A; the NiMH battery had a capacity of 5Ah, a voltage rating of 300V, and a current rating of 80A; and the Li-Ion battery had a capacity of 13Ah, a voltage rating of 300V, and current rating of 167A. From Figs. 9–11 it is observed that the controller adapts well to the three types of batteries; although, it does stress the smaller lead-acid and NiMH batteries by deep charging and discharging them (though staying within the required range).



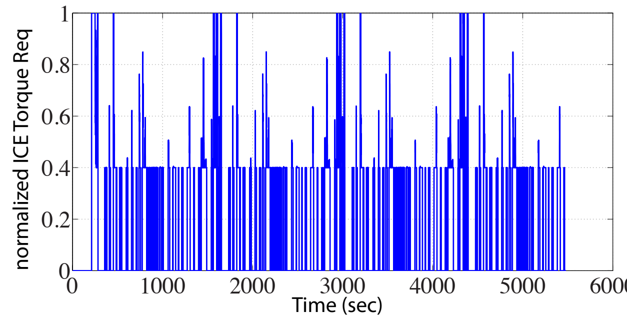
(a) Normalized vehicle speed



(b) Normalized state of charge

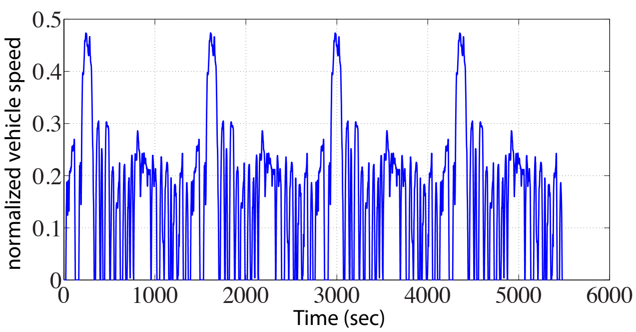


(c) Normalized accelerator pedal position

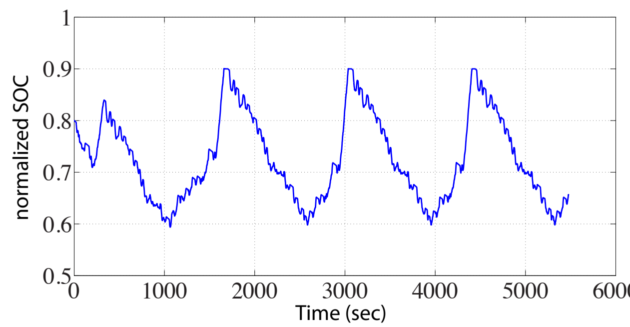


(d) Normalized ICE torque request

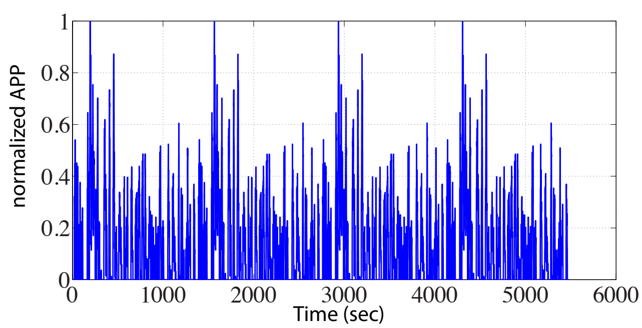
Fig. 7. Results of fuzzy controller for multiple UDDS cycles



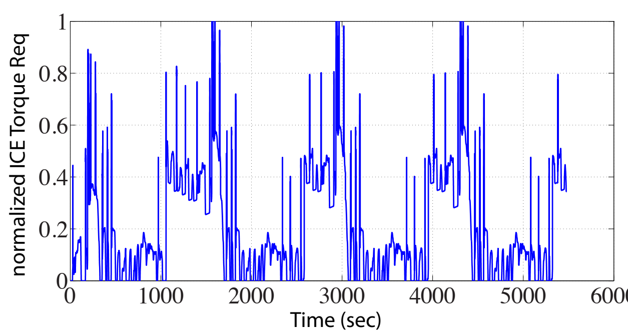
(a) Normalized vehicle speed



(b) Normalized state of charge



(c) Normalized accelerator pedal position



(d) Normalized ICE torque request

Fig. 8. Results of standard rule based controller for multiple UDDS cycles

Smaller batteries, being cheaper and lighter, pose a trade off between deep charging/discharging and their overall cost. A significant difference in fuel economy was not observed for the different battery sizes: the lead-acid achieved 70mpg, the NiMH showed 72mpg, and the Li-Ion achieved 73mpg.

VII. Conclusion

Overall, the fuzzy controller provides a good linguistic approach to the power split hybrid energy management. Compared to a standard rule-based controller based on a current HEV power split system, the fuzzy controller performs significantly better in terms of battery state-of-charge and fuel economy. Furthermore, we showed that the fuzzy controller adapts well to different battery configurations. These configurations allow the system to use a smaller battery as state-of-charge condition is maintained at a stricter level than the standard rule-based controller currently being used. This can give significant advantage as a smaller battery allows a lower weight and cost and improves upon the environmental impact of producing the large batteries necessary for current HEV systems.

In the future, we will expand on this work to produce a power split HEV system controller which adapts to the driver's intended driving conditions, say by using trip information from a GPS or predefined route plan. Also, these ideas could be tied in with intelligent transportation systems, using sensor information to detect traffic conditions and adjusting the rule-base as appropriate. We believe that these ideas will enable big advances in HEV fuel efficiency and performance.

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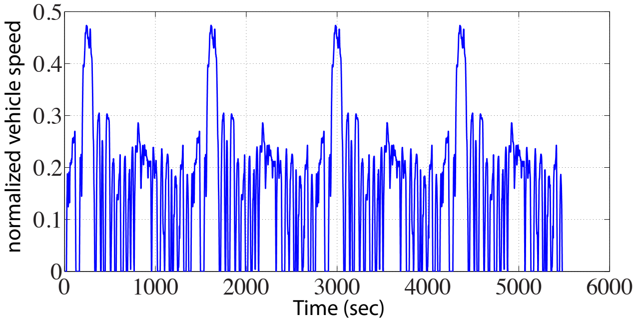
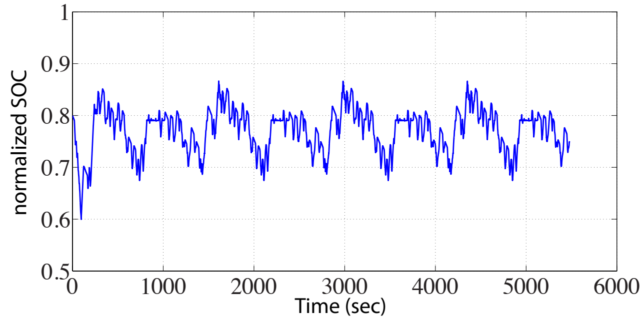
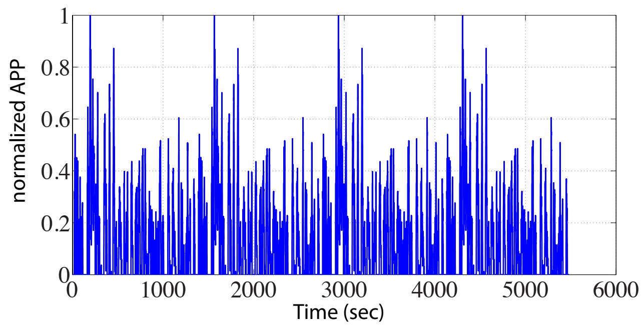


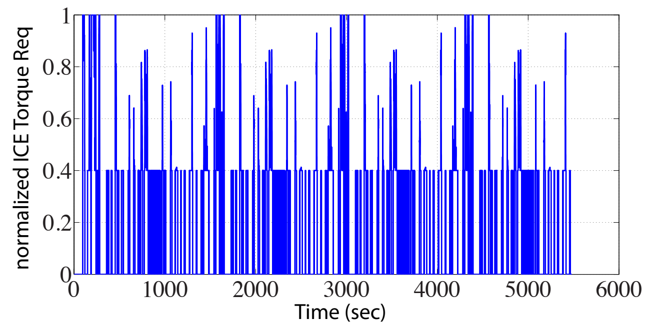
(a) Normalized vehicle speed



(b) Normalized state of charge

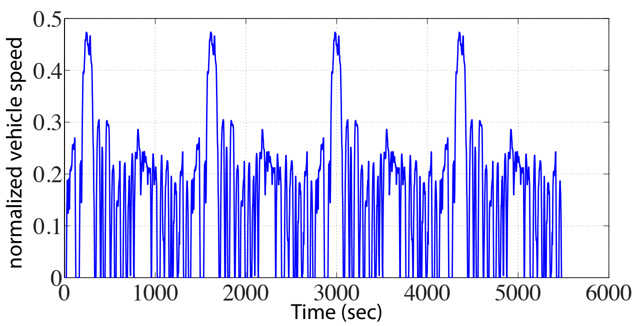


(c) Normalized accelerator pedal position

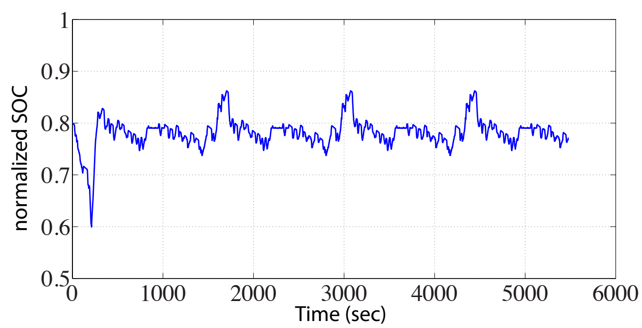


(d) Normalized ICE torque request

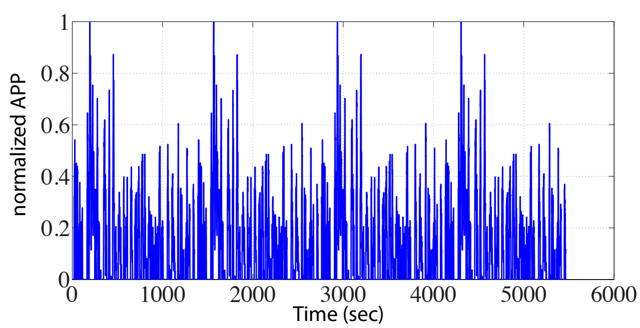
Fig. 9. Fuzzy controller for multiple UDDS cycles using lead acid battery



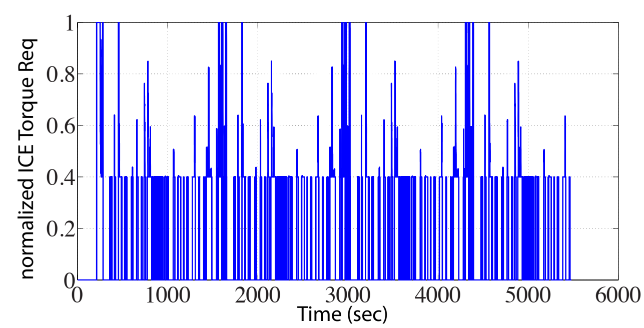
(a) Normalized vehicle speed



(b) Normalized state of charge

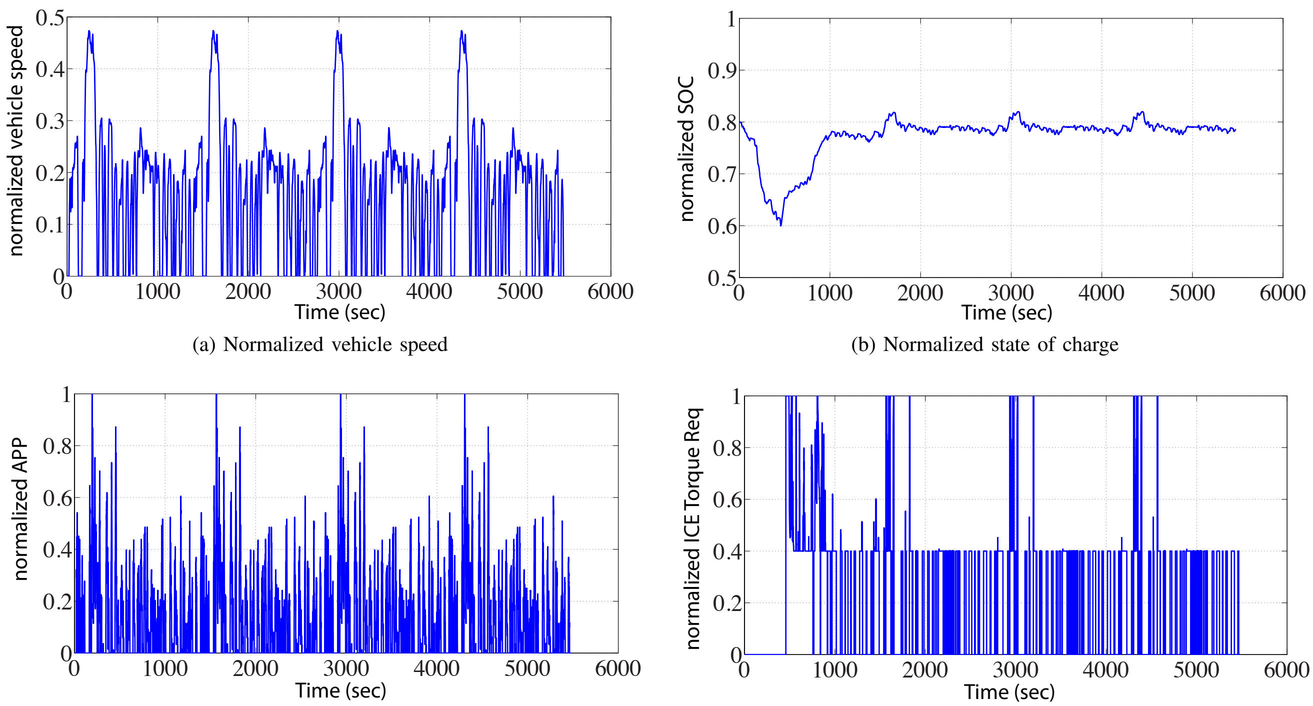


(c) Normalized accelerator pedal position



(d) Normalized ICE torque request

Fig. 10. Fuzzy controller for multiple UDDS cycles using NiMH battery



(a) Normalized vehicle speed

(b) Normalized state of charge

(c) Normalized accelerator pedal position

(d) Normalized ICE torque request

Fig. 11. Fuzzy controller for multiple UDDS cycles using Li-Ion battery