Research Article

Cloud Model-Based Energy Management Strategy for Parallel Hybrid Vehicles

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Using the uncertain conversion capacity between the expressions of quantitative and qualitative concept in the cloud model, an energy management strategy based on cloud model is developed for parallel hybrid vehicles (PHVs). By the driver input and the state of charge (SOC) of the energy storage, a set of rules are developed to effectively determine the torque split between the internal combustion engine (ICE) and the electric motor. An analysis of the simulation results is conducted using ADVISOR in order to verify the effectiveness of the proposed control strategy. It is confirmed that the control scheme can be used to improve fuel economy and emission of the hybrid vehicles.

1. Introduction

Growing concerns on environmental issues and energy crises have forced more and more researches to focus on new generation vehicles such as electric vehicle (EV), hybrid electrical vehicle (HEV), and fuel cell electric vehicle (FCEV). Since EV has the shortcoming of short range due to the handicap of battery technology and FCEV is in its early development stages, the HEV seems to be the viable alternative to the ICE automobile at present because of its potential to reduce fuel consumption and environmental pollution.

To fully realize the potential of HEVs, the design of energy management strategy (EMS) is very crucial. The EMS determines the energy flow between all components in order to fulfill the power balance between the load power and the power source. Many research efforts into the EMSs of parallel hybrid vehicle (PHV) have been conducted in recent years. They can be roughly classified into three categories. The first type is rule-based methods [1]. The second type employs intelligent control technology (fuzzy logic, neural networks, agent, etc.) for power distribution of PHVs [2–5]. The third approach is based on optimization methods such as genetic algorithm and dynamic programming [6, 7]. The fourth approach is based on modern control theory such as

optimal control, decoupling control, and robust control [8–10].

Cloud theory, first formulated by De-yi et al. based on the membership function of fuzzy set theory [11], is a model of the uncertainty transformation between quantitative representation and qualitative concept using language value. It is successfully used in many fields, such as intelligence control [12, 13], data mining [14, 15], target recognition [16], pervasive computing [17], and intelligent algorithm improvement [18, 19].

In this paper, a novel EMS based on cloud model is proposed for hybrid electric vehicle. This paper is organized as follows. Section 2 describes the configuration of PHV. Section 3 presents cloud theory. The proposed EMS is given in Section 4. Simulation results and analysis are shown in Section 5. Section 6 is the conclusions.

2. Parallel Hybrid Vehicle Configuration

Figure 1 presents the configuration of a PHV with an electric motor (EM), an internal combustion engine (ICE), and transmission. In this case, both EM and ICE may deliver power to the vehicle wheels. The EM may also be used as

FIGURE 1: Parallel HEV configuration.

a generator to charge the battery by either the regenerative braking or absorbing the excess power from the engine when its output is greater than that required to drive the wheels. The main advantage of PHV is improved dynamic performance due to the direct coupling between the ICE, EM, and the wheels.

The following parameters of main components are used for this study:

- (i) body mass 592 kg;
- (ii) rolling resistance coefficient 0.009;
- (iii) body aerodynamic drag coefficient 0.335;
- (iv) vehicle front area 2 m²;
- (v) wheel radius 0.282 m;
- (vi) five speed manual gearboxes 2.84, 3.77, 5.01, 7.57, and 13.45;
- (vii) SI engine 36 kW;
- (viii) AC motor 17 kW peak;
- (ix) Hawker Genesis VRLA battery 16 12V26Ah10EP.

The size of the engine, electric motor, and the number of battery modules are determined based on a previous study through an optimization approach [20].

3. Cloud Theory

Cloud is a model that expresses the uncertainty transition between qualitative concept and quantitative representation by using natural language. A piece of cloud is made up of many cloud drops that represent a realization of a qualitative concept. The realization has uncertain factors, that is, fuzziness and randomness [12].

3.1. Digital Characteristics of the Membership Clouds. Let U be the set, $U = \{u\}$, as the universe of discourse, and T a linguistic term associated with U . The mapping $C_T(x) : u \rightarrow [0, 1]$, for all $x \in C_T(x)$, namely, the random distribution of $C_T(x)$ in U , is called membership cloud, briefly called cloud. When $C_T(x)$ obeys the normal distribution, cloud is called normal cloud model. It is expressed with three digital characteristics, expected value E_x , entropy E_n , and hyperentropy H_e [11].

FIGURE 2: Three digital characteristics of normal cloud.

Suppose $R_1(E_x, E_n)$ express the random function obeying normal distribution; then

$$\begin{aligned} x_i &= R_1(E_x, E_n), \\ P_i &= R_1(E_n, H_e), \\ \mu_i &= e^{-(1/2)((x_i - E_x)/P_i)^2}. \end{aligned} \quad (1)$$

Cloud model composed of drop (x_i, μ_i) ($i = 1, 2, \dots$) is called one-dimension cloud model, denoted by (E_x, E_n, H_e) [21]. The typical example of one-dimension normal cloud model and its digital characteristics ($E_x = 0$, $E_n = 0.4$, and $H_e = 0.04$) are shown in Figure 2. The expected value E_x is the position at U corresponding to the center of gravity of the cloud. The entropy E_n is a measure of the coverage of the concept within the universe of discourse. The hyperentropy H_e is the entropy of E_n , which is a measure of dispersion of the cloud drops.

Suppose R_2 express two-dimension random function obeying normal distribution; then

$$\begin{aligned} (x_i, y_i) &= R_2(E_x, E_y, E_{n_x}, E_{n_y}), \\ (P_{x_i}, P_{y_i}) &= R_2(E_{n_x}, E_{n_y}, H_{e_x}, H_{e_y}), \\ \mu_i &= e^{-(1/2)[(x_i - E_x)^2/P_{x_i}^2 + (y_i - E_y)^2/P_{y_i}^2]}. \end{aligned} \quad (2)$$

Cloud model composed of drop (x_i, y_i, μ_i) ($i = 1, 2, \dots$) is called two-dimension cloud model, where E_x and E_{n_x} are expected value, E_{n_y} and E_y are entropy, and (E_x, E_{n_x}, H_{e_x}) and (E_y, E_{n_y}, H_{e_y}) are two relatively independent one-dimensional cloud.

3.2. Cloud Generator. Cloud generator includes positive and backward cloud generator, which is used for realizing the transform between quantitative value and qualitative concept. As shown in Figures 3 and 4, given three characteristics E_x , E_n , and H_e , the positive cloud generator can produce the required cloud drops; accordingly, the backward cloud

FIGURE 3: The positive cloud generator.

FIGURE 4: The backward cloud generator.

generator can get digital characteristics from the given cloud drops. The positive cloud generator also contains two kinds of generator, X -condition generator when given the numerical value x in the universe of discourse and Y -condition generator if the membership degree μ is given [14].

The above-mentioned cloud generator is for one-dimension case. As for two-dimension case, its positive cloud is produced by two group characteristics (E_x, E_n, H_e) and (E_y, E_n, H_e) ; the backward cloud generator produces two group data. X -condition cloud needs to be given x and y value; Y -condition cloud gets drops by being given one or two membership degree values.

3.3. Rule Constructor of Cloud Model. The rule constructor of cloud model is composed of X -condition and Y -condition cloud generator. It can be divided into one-dimension, two-dimension, and multidimension according to the different combination. For example, one-dimension single rule is implemented by connecting a one-dimension X -condition cloud generator and a one-dimension Y -condition cloud generator, when a two-dimension X -condition cloud generator combining a one-dimension Y -condition cloud generator is called two-dimension single rule constructor. The multirule constructor of cloud model is constituted by two or more single rule constructors, which can reflect multicomplexed rules as follows:

$$\begin{aligned} &\text{IF } A_1 \text{ and } B_1 \text{ THEN } C_1, \\ &\text{IF } A_2 \text{ and } B_2 \text{ THEN } C_2, \\ &\vdots \end{aligned} \quad (3)$$

where A_i and B_i are linguistic concepts represented by cloud models. Figure 5 shows a two-dimension multirule constructor. Using these multirule constructors, intelligence control based on cloud model can be implemented [22].

4. Cloud Model-Based Energy Management Strategy

This section describes the EMS based on cloud theory for a parallel hybrid vehicle. The energy in the system should be managed in such a way that the power demand from the driver is satisfied consistently, the battery SOC is maintained

within desired operating range, and the overall system efficiency is optimal.

4.1. Description of Power Controller. The power controller in this study is used to determine the proper torque split to cause the ICE to work possibly in the vicinity of its optimal operating points at all times. The optimal operating points are determined based on ICE parameters at the current vehicle speed, so as to minimize instantaneous fuel consumption and emissions [23]. Figure 6 presents a simplified block diagram of the power controller. The inputs to the proposed cloud controller are the battery SOC and the torque conversion factor p , which is the ratio of the difference ΔT between the vehicle torque requirement T_{req} and the ICE optimal torque to the ICE optimal torque $T_{\text{ICE,opt}}$. The output is defined as the normalized ratio of ICE torque command to ICE optimal torque, denoted by K . Once K is determined, the ICE torque command (T_{ICE}) can be made as K multiplied by ICE optimal torque at current condition ($T_{\text{ICE}} = K \times T_{\text{ICE,opt}}$), and the EM torque command (T_{EM}) is to be the desired vehicle torque minus the ICE torque command ($T_{\text{EM}} = T_{\text{req}} - T_{\text{ICE}}$).

4.2. Cloud Controller Implementation. It is actually a kind of mapping that cloud controller realizes the relationship between input and output. The controller is composed of multirule inference part and output data processing section. As shown in Figure 3, the inference part achieves the inference results by X -condition cloud and Y -condition cloud. To obtain precise value, multirule control can use maximum membership method, reverse cloud method, and weighted average method. Taking into account the real-time characteristic of control, this design uses the weighted average method. Suppose there are n rules in the rule base; when inputs x_A and x_B activate different rule antecedent $\text{PCG}_{A_1 B_1} \sim \text{PCG}_{A_n B_n}$, different μ_{ni} are produced to activate the corresponding rule consequently; then a lot of $\text{drop}_i(y_i, \mu_{ni})$ are created. After dealing with these drops by the weighted average method, output z is obtained. Suppose $p \in A = [-1.5, 1.5]$, $\text{SOC} \in B = [0, 1]$, and $K \in C = [0, 1.2]$, where A , B , and C are all real numbers set. At these three sets, five input cloud models and six output cloud models are separately defined. These models are $A_1 \sim A_5$, $B_1 \sim B_5$, and $C_1 \sim C_5$, which are expressed as (E_x, E_n, H_e) by the digital characteristics of normal cloud model. Learning from the idea of fuzzy theory, cloud models are constructed as follows:

$$\begin{aligned} A_1 &= \text{"too low"} = (-1.5, 0.35, 0.01); \\ A_2 &= \text{"low"} = (-0.5, 0.17, 0.01); \\ A_3 &= \text{"normal"} = (0, 0.17, 0.01); \\ A_4 &= \text{"high"} = (0.5, 0.17, 0.01); \\ A_5 &= \text{"too high"} = (1.5, 0.17, 0.01); \\ B_1 &= \text{"too low"} = (0, 0.1, 0.01); \\ B_2 &= \text{"low"} = (0.3, 0.07, 0.01); \\ B_3 &= \text{"normal"} = (0.6, 0.07, 0.01); \\ B_4 &= \text{"high"} = (0.75, 0.05, 0.01); \\ B_5 &= \text{"low"} = (1, 0.07, 0.01); \end{aligned}$$

FIGURE 5: The multirule constructor.

FIGURE 6: Simplified block diagram of the power controller.

C_1 = "too low" = (0, 0.13, 0.01);

C_2 = "medium low" = (0.4, 0.07, 0.01);

C_3 = "low" = (0.6, 0.07, 0.01);

C_4 = "normal" = (0.8, 0.07, 0.01);

C_5 = "high" = (1.2, 0.13, 0.01).

Similar to the fuzzy controller, the basic idea of a cloud controller is to formulate human knowledge and reasoning, which can be represented as a collection of if-then rules, in a way tractable for computers. The designed cloud controller

has 25 inference rules, which are expressed by matrix as follows:

$$R = \{r_{ij}\} = \begin{bmatrix} 4 & 5 & 5 & 5 & 5 \\ 4 & 4 & 4 & 4 & 5 \\ 3 & 3 & 3 & 4 & 5 \\ 2 & 2 & 2 & 3 & 4 \\ 1 & 1 & 2 & 2 & 3 \end{bmatrix}, \quad (4)$$

where r_{ij} denotes the inference rule "if A_i and B_j , then C_k , $i = j = 1, 2, \dots, 5$, $k = 1, 2, \dots, 6$." For example, r_{23} express the rule "if A_2 and B_3 , then C_4 ."

The above-mentioned cloud model of inputs, outputs, and rules was determined by simulation to increase the system efficiency and to maintain the battery SOC. Using these models and rules, reasoning process from known conditions

FIGURE 7: Output result of cloud controller.

FIGURE 8: Missed speed and SOC history over UDDS driving cycle.

to quantitative output is implemented. Figure 7 shows the result of cloud controller.

5. Simulation Results

The advanced vehicle simulator, ADVISOR [24], was used for simulation studies in this work. ADVISOR employs a combined forward/backward facing approach for the vehicle performance simulation. The strategy is tested on four standard driving cycles: the new European driving cycle (NEDC), the urban dynamometer driving schedule (UDDS), the federal test procedure (FTP), and the highway fuel economy test (HWFET). These speed profiles, representing

urban and highway scenarios, are widely used in the literature to evaluate the performance of the proposed EMS [25].

As mentioned before, the bottom line for the control strategy is that the vehicle must follow the driver's request and the battery SOC is kept in a certain range. These constraints are adequately satisfied by the proposed EMS; the difference between required and achieved speed (missed speed) as well as the history of SOC over UDDS cycle is shown in Figure 8. It is clear that there is an excellent agreement between the achieved speed and target speed and the charge sustaining requirement is satisfied.

To investigate the effectiveness of the proposed strategy and study the impact of the driving cycle on the cloud control

TABLE 1: Comparison of fuel consumption and emissions for four cycles.

	UDDS		FTP		HWFET		NEDC	
	FLC	Cloud	FLC	Cloud	FLC	Cloud	FLC	Cloud
FC (l/100 km)	6.0	5.5	5.8	5.3	4.3	3.7	5.7	5.1
HC (g/km)	0.368	0.34	0.283	0.262	0.263	0.23	0.379	0.359
CO (g/km)	1.044	1.096	0.79	0.828	0.829	0.87	1.049	1.106
NO _x (g/km)	0.319	0.278	0.259	0.226	0.252	0.206	0.315	0.263

TABLE 2: Comparison of component losses for two controllers for four driving cycles.

	ICE losses (kWh)	Electric motor (kWh)	Transmission losses (kWh)	Battery losses (kWh)
UDDS				
FLC	4.68	0.034	0.089	0.087
Cloud	4.37	0.050	0.089	0.087
FTP				
FLC	6.56	0.053	0.13	0.13
Cloud	6.14	0.076	0.13	0.13
HWFET				
FLC	4.40	0.039	0.13	0.054
Cloud	3.93	0.065	0.13	0.054
NEDC				
FLC	4.06	0.031	0.097	0.073
Cloud	3.79	0.05	0.096	0.067

strategy, the simulation is also performed over FTP, HWFET, and NEDC driving cycles. In addition, for comparing the results, the same simulations have been done with the default FLC based on efficiency mode in ADVISOR, which is similar to the proposed EMS with optimizing ICE operation. Table 1 shows the fuel consumption and emissions of both controllers for four driving cycles. To compare with the FLC, the fuel consumption of powertrain with cloud controller is fewer for all four cycles. To the HC and NO_x emissions, the proposed controller is better than the FLC. However, the CO emission is worse for all four cycles.

Table 2 presents the component losses for four cycles. The losses of transmission and battery are almost the same for four cycles with two mentioned controllers. The EM loss for four cycles with cloud controller is higher than the cycles with FLC. However, the overall efficiency of the cloud controller is better than of the FLC since the ICE loss for the cycles with cloud controller is far less than with the FLC.

6. Conclusions

A cloud model-based energy management strategy for parallel hybrid vehicles (PHVs) is presented. The objective of the proposed EMS is to minimize the fuel consumption and maintain the battery SOC within its operational range while satisfying the driver requirements. The EMS is evaluated in a simulation environment using four standard driving cycles. The results show that the proposed strategy provides an improvement in fuel economy and has stronger robustness.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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