Review of Driving Conditions Prediction and Driving Style Recognition Based Control Algorithms for Hybrid Electric Vehicles

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***Abstract*-The performance of a vehicle control strategy, in terms of fuel economy improvement and emission reduction, is strongly influenced by driving conditions and drivers' driving styles. The term of 'driving conditions' here means the traffic conditions and road type, which is usually indicated by standard driving cycles, say FTP 75 and NEDC; the term of 'driving styles' here relates to the drivers' behavior, especially how drivers apply pressure on acceleration and brake pedal. To realize optimal fuel economy, it is ideal to obtain the information of future driving conditions and drivers' driving styles. This paper summarizes the methods and parameters that have been utilized to attain this end as well as the results. Based on this study, methods and parameters can be better selected for further improvement of driving conditions prediction and driving style recognition based hybrid electric vehicle control strategy.**

Keywords—*driving condition prediction, driving style recognition, hybrid electric vehicle, control strategy*

I. Introduction

Hybrid electric vehicle (HEV) has become an effective solution to meet the tightening emission regulations and the need of more fuel-efficient vehicles. The performance of an HEV is determined, to a great extent, by the control strategy. Many types of control strategies for HEVs have been proposed in recent years. In [1] authors have reviewed and categorized the control strategies that have been successfully applied to HEV control. However, both rule-based control strategy, including deterministic rule based methods and fuzzy rule based methods, and optimization-based strategies such as dynamic programming (DP) optimization based control algorithms require the knowledge of the entire driving cycle to obtain optimal performance. It is demonstrated in [2] that HEVs are sensitive to drive-cycle variations, and in [3] that with the information of future driving conditions there is significant potential for fuel savings over specific drive cycles.

In particular, for plug-in hybrid electric vehicles (PHEVs), the prediction of driving conditions, especially trip range, becomes even more interesting. To maximize the fuel economy, the control strategy should favor the use of the on-board electric energy before resorting to using the internal combustion engine (ICE). Also, we expect the ICE to work in high-efficiency points whenever it starts and to operate for an extended period of time. In this case, when the SOC drops to lower limit and the ICE works, the SOC may go up. Thus, it is ideal to predict the trip range to avoid the case that the ICE charges the battery to a high SOC by the end of the trip.

In addition to the considerations on driving conditions, drivers' driving styles also have significant influence on fuel economy and emissions [4-6]. Though the terminology varies, driving styles are generally divided into three categories [4, 6, 8, 22]: mild drivers (calm driving or economical driving style), normal drivers (medium driving style), and aggressive drivers (sporting driving style). An aggressive driver will lead to substantially poor fuel economy, while the calm driving style will improve fuel economy. The potential for improving fuel efficiency by improving driver style is estimated to be in the range of 20% to 40% ([7]), or even 60% ([4]).

In this paper, predictive control algorithms and mathematical implementation techniques are investigated according to their objectives. This paper is organized as follows. In Section II, methods of driving conditions estimation are classified. Based on this study, with the help of GPS and intelligent transportation system (ITS), driving cycle information is attainable; without GPS or ITS information, Markov chain can be utilized to estimate future driving conditions, while statistic and cluster analysis based methods can also be implemented easily. In Section III, parameters and methods used to classify drivers' driving styles are studied as well as the methods to mitigate the poor driving styles. Finally, Section IV concludes and summarizes these discussions.

II. Driving Cycle Prediction Based Control Strategy

There are several methods to recognize current and predict future driving conditions. The three main techniques to be discussed below are: GPS (or ITS) based technique, statistic and clustering analysis based methods, and Markov chain based stochastic process prediction technique.

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A. GPS and ITS based Prediction

Taking advantage of GPS, present driving information such as time, speed, trip distance, slope, acceleration, and deceleration can be obtained. In addition, ITS can be used to provide road conditions, speed limits and traffic lights distribution with high accuracy. Combining GPS, ITS and historical data, we can predict the travel/driving profile with a much less uncertainty. With thus obtained driving cycle, fuzzy logic control [9], adaptive equivalent consumption minimization strategy [10] or, more prevalently, DP technique [11-16] could be implemented.

In [9], a fuzzy logic controller was designed with two inputs which are vehicle speed difference and elevation difference between the predicted future and the present condition. The inputs mainly reflect the power demand variation trend in the near future. The output is recharge/discharge control signal of the battery. The control strategy is shown in Table I.

TABLE I
FUZZY RULE BASED PREDICTIVE CONTROL STRATEGY

Future State	Increasing elevation	Constant elevation	Decreasing elevation
Decreasing vehicle speed	No charging/ discharging	Normal discharging	Deep discharging
Constant traffic flow	Normal charging	No charging/ discharging	Normal discharging
Increasing vehicle speed	High charging	Normal charging	No charging/ discharging

In [11], the impact of future road terrain information is studied, and the focus is on realizing fuel economy gains with road grade preview. Future terrain information is difficult to predict with historical and real-time data, so statistic and cluster analysis based recognition methods are not as effective. If the origin and destination of a trip are already defined, however, GPS becomes an effective approach to supply terrain information. [11] applies the terrain information to DP and charge up the battery before the vehicle is going uphill, which is explained in Fig. 1. On the other hand, DP charges rather than discharges the battery in short uphill intervals and, due to higher torque demands, the engine is more efficient.

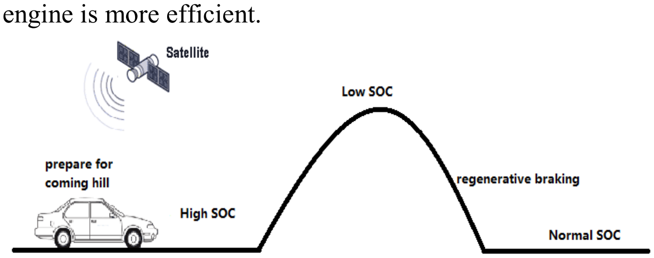

Fig. 1. Energy management based on terrain prediction

For a PHEV, we expect the SOC to reach the lower limit at the end of the trip, so that the battery can be recharged by the power grid rather than by ICE. Also, for a trip longer than the pure-electric-drive range, it is more economical to operate the ICE and motor together throughout the trip (i.e. using global optimization) than to operate the vehicle as battery electric vehicle and then operate it as series HEV [16], as explained in Fig. 2. In [16] researchers utilize the GPS information to predict the driving distance together with future terrain information and approximate velocity; up to 13% reduction of fuel consumption and 8% cost reduction is achieved with rule-based strategy. If the future velocity is exactly known, additional 1% improvement is achieved.

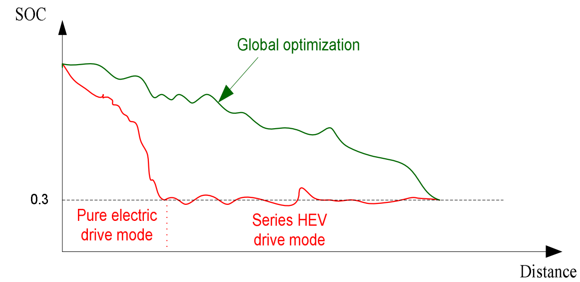

Fig. 2. Energy management based on terrain prediction

B. Statistic and Cluster Analysis based Recognition

As ITS signals are available only on some of freeways and GPS is not used for daily commute or familiar destinations, external information could not be widely used for local trips. To take full advantage of the data available on board, statistic and clustering methods are preferable. The basic idea is to collect the historical and current driving cycle parameters to analyze the previous driving pattern, and assume the driving conditions in the future, typically 1~2 minutes, will keep relatively consistent.

1. Data Collected to Recognize Driving Conditions

To correctly recognize the driving condition, the parameters to be collected should be decided. If there are too many parameters, the computing burden is too heavy for real-time control; on the other hand, too few parameters may not represent a certain driving cycle.

The study on characteristic parameters for driving cycles has started since as early as 1978 when researchers introduced 10 driving pattern parameters [17]: average speed, average speed excluding stop, average acceleration, average deceleration, mean length of a driving period, average number of acceleration-deceleration changes within one driving period, proportion of standstill time, proportion of acceleration time, proportion of deceleration time, and proportion of time at constant speed. In [18] researchers uses two parameters, average trip speed and distance per stop, to cluster driving cycles into three categories – highway, suburban, and urban. However, there are several misclassifications shown in the estimation result in [18] with the two parameters mentioned above, and hence other parameters, such as average moving speed, acceleration, regenerative braking energy, and velocity fluctuation, are shown to be related to energy consumption.

Referring the study of [19-21], [22] uses up to 62 parameters to describe a certain driving cycle, and classifies them into 16 independent groups, 9 of which are proposed to affect fuel economy and emission significantly. In [23] authors use 40 of the 62 parameters and add 7 more parameters to describe a driving cycle. However, too many parameters cause higher hardware cost and longer computational time, which could not be implemented to onboard vehicles. Recent studies try to reduce the characteristic parameters implemented to real-time driving cycle recognition. [24] uses 24 parameters to represent a certain driving cycle, [25] and [26] further reduce the number of characteristic parameters to 14 and 17, respectively. [27] studies the influence of 11 parameters on driving cycle recognition, and proposes that by using 4 of them the prediction result is good enough. [28] uses 3 parameters, while [29] uses 2 parameters. The simplest approach uses only one parameter, the average speed for each micro-trip (the distance between two successive stops of a vehicle), to classify traffic conditions [30]. The parameters used in [24-30] to recognize driving cycles are shown in Table II.

TABLE II
SUMMARY OF PARAMETERS USED TO RECOGNIZE DRIVING CYCLES

Parameter	[24]	[25]	[26]	[27]	[28]	[29]	[30]
Average velocity	*	*	*	*			
Average running velocity except stop	*						*
Stop time/total time	*			*		(*)	
Positive acceleration kinetic energy change per unit mass per unit distance	*						
Average acceleration	*	*	*				
Average deceleration	*	*	*				
Average positive grade	*						
Average negative grade	*						
Positive grade time/total time	*						
Negative grade time/total time	*						
Number of stops per kilometer	*						
Average micro-trip time(from start to stop)	*						
Acceleration time/total time	*						
Deceleration time/total time	*						
Standard deviation of acceleration	*	*	*	(*)			
Standard deviation of deceleration	*		*				
Maximum velocity	*	*	*	(*)			
Standard deviation of velocity	*		*	(*)			
Average grade	*						
Maximum grade	*						
Minimum grade	*						
Standard deviation of grade	*						
Standard deviation of positive grade	*						
Standard deviation of negative grade	*						
Trip distance		*					
Maximum acceleration		*	*	*			
Minimum deceleration		*	*	*			
% of time in certain speed intervals		*	*				
% of time in certain acceleration intervals			*				
% of time in certain deceleration intervals		*	*				
# of acceleration/deceleration shifts per 100m where the difference of adjacent local max-speed and min-speed was > 2 km/h		*					
Maximum product of velocity and acceleration				(*)			
Minimum product of velocity and acceleration				(*)			
Average product of velocity and acceleration				(*)			
Standard deviation of product of velocity and acceleration				(*)			
Current velocity					*		
Driver power demand					*		
SOC					*		
Average positive power demand						*	
Average negative power demand						(*)	
Standard deviation of positive power demand						*	

Note: * means the parameter is used in corresponding paper, (*) means this parameter is initially considered but later discarded after determining that the results were not sensitive to this parameter (i.e. Not a dominant parameter).

From the table, it is observed that average speed is most frequently used (4 times), followed by average acceleration/deceleration, maximum acceleration, maximum velocity, minimum deceleration, and standard deviation of acceleration which are used for 3 times, respectively. Both [25] and [26] consider the information of velocity and acceleration distribution in subintervals, which offer a new thread of characteristic parameters. [28] and [29] use totally different parameters from the rest. [28] only uses current state to estimate future driving conditions without considering the historical data; this method has much uncertainty in the prediction results. Only two parameters are used in [29] and good prediction accuracy is achieved; however, as power demand could not be measured directly but based on the driver intension recognition and analysis algorithm, so it is crucial to correctly analyze the power demand of the driver.

2. *Length of Time Window for Data Collection and Processing*

The statistic methods based control algorithms typically record pertinent driving cycle information at equally spaced time intervals, say, one second. Based on the data collected, the characteristic parameters such as average speed can be then calculated with a fixed time window, say 150s. This method synchronizes with the operating mode of a controller with a certain crystal frequency. There is also some data calculated with an unfixed time window, such as distance between two successive stops [18] and average running velocity except stops [24] which are calculated whenever the car is stopped. However, most of the parameters shown in Table II can be calculated with a fixed time window.

To realize real-time control, the historical data should be acquired online in a certain time window. If the time window is too short, the historical data may not reflect the driving cycle correctly; if the time window is too large, the computational burden may be too heavy for real-time control. In [24], a time window of 300s is used, which means the controller updates the control strategy every 300 seconds according to the data collected in previous 300 seconds. Similarly, [27] uses a time window of 150s. A fixed time window is easy to understand and implement, but this method is based on the assumption that the traffic condition in the future time window, 150s or even 300s, is the same as in the previous time window, which is not necessarily the case.

In [25] and [29], though the same time window of 150s is used, the control strategy is updated every 3 and 5 seconds, respectively. For example, in [25] the control strategy is updated at t=150s based on the historical data of 1~150s, and is then updated at t=153s based on the data of 3~153s. This method can be summarized as

$$\begin{cases} \vec{D}(k) = \vec{f}\left(\vec{P}(t) \middle| tn[(k-\Delta w), k]\right) \\ \vec{C}(t|t\,[k,(k+\Delta t)) = \vec{G}(\vec{D}(k)) \end{cases} \quad (1)$$

where Δw is the time window for data collection, $\vec{P}(t)$ is the data collected, such as velocity, at each time step, $\vec{f}$ is a vector of functions, such as max, min, and average, to process the data, $\vec{D}(k)$ is a vector of parameters to be used in driving cycle recognition, $\vec{G}$ is a set of functions to decide the current vector of control parameters $\vec{C}$, such as ICE throttle angle and motor current, and Δt is the time period for current control strategy to last. In particular, if $\Delta w = \Delta t$, (1) represents the data collection and processing method in [24] and [27].

If $\Delta w \neq \Delta w$ (as in [25] and [29] $\Delta w \gg \Delta t$), the prediction in [25] or [29] is more accurate with same memory cost as in [27]. Specially, [25] studied how the length of Δi and Δt affect prediction accuracy, pointing out that with larger Δa and shorter Δt, the prediction accuracy will increase. It is also observed in [27] that if the time window is further increased from 150 seconds to 200 seconds, the accuracy will only slightly increase with a much higher cost on computation time.

3. *Methods for Data Analyzing*

To predict current driving cycle with the historical parameters, the characteristic parameters should be extracted from the known driving cycles and be used to train the classification tools or methods. [31] provides the characteristic parameters of 11 standard driving cycles. Then the data acquired during driving could be analyzed and classified into one of the groups which represent a certain driving cycle, which represents a certain set of driving conditions. The classification algorithms mainly include Bayesian classifying algorithm, decision tree, rough set theory, fuzzy clustering analysis, neutral network (NN), and support vector machine [32].

For driving cycle recognition, NN ([23-25, 28]) is the most popular. The NN is first trained by the characteristic parameters extracted from known driving cycles, until high prediction accuracy is obtained on the test data set. The inputs p_1, p_2, …, p_n are the characteristic parameters, and the output is the driving cycle number (e.g. 1 for urban cycle, 2 for suburban cycle, 3 for highway cycle, and etc.). Then the network can be used to recognize current driving condition and predict the near future. With the historical data as input, the current driving condition could be found. An example of learning vector quantization (LVQ) NN is shown in Fig. 3 with n inputs, m neutral cells, and k driving cycles from which one will be the final output.

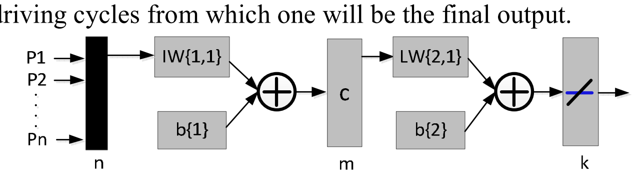

Fig. 3. Example of LVQ NN used for driving condition recognition

Support vector machine is another useful tool for parameters classification, and has been used in [32]. The principle of support vector machine is to find an optimized classification hyperplane which maximizes the region between the hyperplane and the nearest samples [33]. One example of the application of classification hyperplane in a two-dimensional classification problem is shown in Fig. 4.

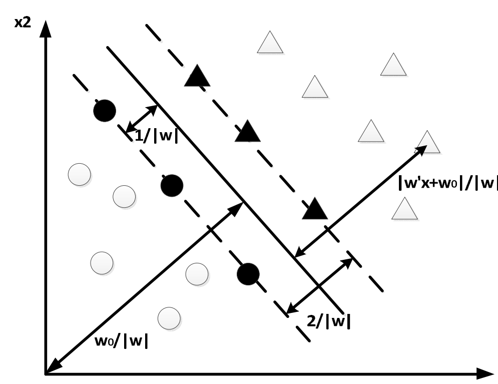

Fig. 4. The application of classification hyperplane in a two-dimensional classification problem.

C. *Markov Chain based Predictive Control*

Markov chain is a useful tool for stochastic process prediction, which is suitable for modeling the power demand from the driver. Different from statistic methods mentioned above, for a Markov process, the future condition is dependent only on current state but independent of the past. The optimal control strategy is then established based on Stochastic Dynamic Programming [34-37] or genetic fuzzy logic control [38].

A stochastic Markov process contains finite dimension of states, and at time k, all the states constitute a state vector,

$$X_k = \{\alpha_k, \beta_k, \gamma_k, \cdots\} \tag{2}$$

where

$$\begin{gathered} \alpha_k \in \{\alpha_1, \alpha_2, \cdots, \alpha_m\} \\ \beta_k \in \{\beta_1, \beta_2, \cdots, \beta_n\} \\ \gamma_k \in \{\gamma_1, \gamma_2, \cdots, \gamma_l\} \\ \vdots \end{gathered}$$

can represent demanded power, vehicle velocity, engine torque, and etc. Note that k represents the time step and may be greater than *m*, *n*, or *l*···. At each time step *k* the Markov process stays at the same state or moves to another according to transition probability

$$P\{\alpha_k = \alpha_{k+1}, \beta_k = \beta_{k+1}, \gamma_k = \gamma_{k+1}, \cdots | \alpha_k, \beta_k, \gamma_k, \cdots\} \tag{3}$$

which is defined for all possible combinations of $\alpha, \beta, \gamma, \cdots$.

As it is the exponential relation between the computation time and number of variables, usually no more than 3 variables are used to describe driving conditions. In [34], homogeneous Markov-chain model is built with two state variables, power demand and velocity, and position-dependent Markov-chain model is built with two state variables, velocity and acceleration, of which the power demand is a function. In [35] the state vector contains two variables, power demand and wheel speed, while in [36] the split of power delivered between the ICE and the electric motor is calculated based on state variables of torque demand and the current angular velocity of the power plant. [37] uses only one variable of power request.

The matrix of P is available if the driving cycle is known, however if this algorithm is used for driving condition prediction, the matrix need to be acquired during the driving cycle. In [38] the transition probabilities are estimated by

$$P\{P_{req}(k+1) = z_i | P_{req}(k) = z_i\} = m_{ij} / m_i \tag{4}$$

where m_{ij} is the number of occurrences of the transition from z_i to z_j, and mi is total number of times that z_i has occurred. So in [36] the prediction is started only after the initially empty probability matrix and rewards matrix is updated during the driving.

III. Driving Style Recognition based Control Strategy

As mentioned in Section I, with recognition and compensation of driver's driving styles, there is great potential for improving fuel economy. Recent research has taken into account the driver behavior, and in this paper classification methods are studied as well as the methods to mitigate the effect of aggressive driving on fuel economy. Note that the driving style recognition should be based on certain driving conditions. In congested traffic conditions, calm drivers have to accelerate and decelerate frequently while in highway cycles even aggressive drivers will keep a relatively constant acceleration pedal position.

A. *Driver Style Classification*

In [42] a "Driving Style Questionnaire" (DSQ) which has 8 scales was developed from a questionnaire survey and principal component analysis. Then, through an application to analysis of car following behavior at low speed, validity of the DSQ was examined by correlation analysis with behavioral indices and its usefulness was shown from modeling approach. The 222 drivers who participate in the survey are characterized in to 8 types. Although this research could not be implemented in the real-time control, it offers several useful parameters in the questionnaire to distinguish the driver types.

In [4] three types of driving style, mild, normal, and aggressive, are studied in simulation with different driver models. The simulation results shows that an aggressive driving pattern has a significant contribution to poor fuel economy of the vehicle (as large as 60%) while mild driving pattern will improve fuel economy. However, [4] doesn't explain how to classify driving behaviors.

Similar classification is given in [6] and [8] with different analyzing and classifying methods. [8] uses a driving simulator as experimental platform, and based on the distribution of driving parameters, such as velocity, on figures, three driving styles (economical, medium and sporting driving styles) were differentiated. [6] presents jerk analysis method, in which the second derivative of speed is measured and, mathematically, jerk feature is calculated as

$$\gamma = \frac{SD_J}{\bar{J}} \tag{5}$$

where SD_J is standard deviation of the jerk over a specified window, $\bar{J}$ is the jerk of the normal driving style on current road-type. $\bar{J}$ for 11 standard driving cycles are calculated, and two thresholds, $norm_{threshold} = 0.5$ and $agg_{threshold} = 1.0$, are used in [6].

Since there is a large variation in how drivers apply pressure to accelerator and brake pedals, [39] uses Gaussian mixture models (GMM) and utilizes the force on accelerator pedal and brake pedal to identify the driving pattern. The identification is according to the equation

$$\arg\max_k p(X|\lambda_k) \tag{6}$$

where X is a sequence of feature vectors, λ_k is GMM of driver k and k is Driver ID1,2, ..., 30.

[23] uses average acceleration together with standard deviation (SD) of acceleration over a specific driving range to identify the driving style. Fuzzy driving style identifier (DSI) is designed referring to the conclusion in [39] that typical average acceleration ranges in city cycles for different driving styles are: (1) calm driving, 1.48–2.13 ft/s^2; (2) normal driving, 2.13–2.62 ft/s^2; and (3) aggressive driving, 2.79–3.61 ft/s^2. For highway traffic, average accelerations ranges from 0.26–0.66 ft/s^2. The fuzzy rules are shown in Table III, where $\bar{a}$ (ft/s^2) is average acceleration and $\frac{SD}{\bar{a}}$ (ft/s^2) is the ratio of standard deviation to average acceleration.

TABLE III
FUZZY RULES TO IDENTIFY DRIVING STYLES

$\bar{a}$ \ $\frac{SD}{\bar{a}}$	Small	Middle	Large
Small	Calm	Calm	Normal
Middle	Normal	Normal	Aggressive
Large	Aggressive	Aggressive	Aggressive

Fuzzy logic based adaptive algorithm was also used in [41] to estimate driver's long term and short term preferences, and a Real time Advisory Controller was designed to provide visual and haptic feedbacks to the driver to change his or her driving style or behavior.

B. Driving Style Recognition based Control Strategy

Though many researchers have looked at how to identify and classify driver styles, little progress has been made on how to utilize this information and how to modify driver behavior. As HEVs have two or more power resources, it is possible to compensate the torque demand fluctuation of aggressive driving style by adjusting motor torque while keeping the engine working with a relative constant torque. As the motor is more efficient than the engine, the fuel economy can be improved.

In [43] for aggressive drivers, less of torque demand, 10% for instance, is allocated to engine to avoid fuel consumption due to the transient operation of the engine. On the other hand, maximum 10% of the increment of engine torque is considered for calm driving and 0% for normal driving. In this case, the overall output torque will follow the driver's driving intention.

IV. CONCLUSIONS

The information of future driving conditions and drivers' driving styles is essential for optimal HEV control. This paper summarizes the methods and parameters that have been utilized to attain this end. In this study two important influence factors, driving conditions and driving style, of fuel economy of HEVs are discussed, respectively.

The algorithms to obtain future driving conditions include GPS (ITS) based algorithm, statistic method, and Markov chain based algorithm. With the help of GPS, future driving information, such as terrain information and trip distance which is crucial to HEV or PHEV power management, can be obtained easily. Statistic method is also very effective especially in some cases that there is not an access to GPS information. The parameters that are utilized to predict future driving condition are summarized and analyzed. Markov chain is quite suitable for prediction of driving condition which is a stochastic process, but the number of input parameters is limited by the computational burden.

The drivers' driving styles can commonly be classified into three categories, calm, normal, and aggressive, among which aggressive driving has great contribution to poor fuel economy while calm driving is helpful to improve fuel economy. Several methods can be used to recognize drivers' driving styles, including statistic method, jerk analysis, Gaussian mixture models, and fuzzy classification method. Then the drivers' driving styles can be compensated, and hence the fuel economy is improved by reallocating the output torque between ICE and motor without changing the total output torque of the powertrain, which means the driving intention is strictly followed.

Referring to this study, researchers can better select methods and parameters for predicting driving conditions and drivers' driving styles. Also, the methods to utilize the information can be referred for further improvement of hybrid electric vehicle control strategy.

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