A Review of Intelligent Road Preview Methods for Energy Management of Hybrid Vehicles

Wen Gu, Dezong Zhao, and Byron Mason

Loughborough University, Loughborough, LE11 3TU, UK

Abstract: Due to the shortage of fuel resources and concerns of environmental pressure, vehicle electrification is a promising trend. Hybrid vehicles are suitable alternatives to traditional vehicles. Travelling information is essential for hybrid vehicles to design the optimal control strategy for fuel consumption minimization and emissions reduction. In general, there are two ways to provide the information for the energy management strategy (EMS) design. First is extracting terrain information by utilizing global positioning system (GPS) and intelligent transportation system (ITS). However, this method is difficult to be implemented currently due to the computational complexity of extracting information. This leads to the second method which is predicting future vehicle speed and torque demand in a certain time horizon based on current and previous vehicle states. To support optimal EMS development, this paper presents a comprehensive review of prediction methods based on different levels of trip information for the EMS of hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV).

Keywords: Energy management strategy, prediction algorithm, future trip information

1. INTRODUCTION

In the past several decades, due to the decline of global oil reserves and environmental crisis, HEV has been considered as the ideal transitional phase between the traditional pure fossil fuel vehicles and the all-electric vehicles in the future Liu (2017). HEV has significant advantages over pure fossil vehicles in improving fuel economy and exhaust emissions while meeting drivability requirements. It is a complex system with combination of an internal combustion engine (ICE) and electric motors. To extend the advantage of HEV in aspect of fuel consumption reduction, the EMS plays a critical role.

In general, the most important task of the EMS is to find the best power output proportion between ICE and electric motor to meet the vehicle power demand. To achieve this, several control strategies are proposed and they can be classified into 4 categories: rule based; fuzzy logic; global optimal control; and instantaneous optimal control. Future trip information is essential to all control strategies for real-time implementation. With rapid advances in the development of intelligent vehicles, the available information of driving condition is much easier to access with GPS and ITS. By utilizing knowledge of future trip information, more advanced EMSs are proposed using prediction algorithms Zhang et al. (2009). This study is to investigate the prediction methods using future trip information.

The main contribution of this review study is to classify future driving information into three levels: (1) no GPS information is provided and trip destination cannot be determined; (2) travelling route is predefined and partial information is available through GPS; (3) future route information and driving condition are provided through GPS and ITS. According to different levels of driving information, 3 prediction methods are introduced respectively. The prediction strategies can be categorized in Fig. 1 accordingly.

![Fig. 1. Prediction methods based on different levels of information](image_url)
based approach and artificial intelligence based prediction algorithm. In Section 4, GPS/ITS based predictive EMSs are reviewed, focusing on integrating terrain information and traffic information into driving profile. In Section 5, conclusion is summarized.

2. DRIVING PATTERN RECOGNITION

The GPS/ITS signal is not always available in driving. Trip destination cannot always be predetermined before the travel either. To make utilization of vehicle driving data collected by on-board sensors for better fuel economy, driving pattern recognition method is a popular approach. The main idea of this method is using multiple standard driving cycles to represent all driving conditions. During traveling, controller compares the on-board vehicle data to the database and finds the most similar driving cycle to the current state. Also, it is assumed that future driving condition will not change significantly in a certain period.

Since neural network is an efficient tool to establish nonlinear relationship between inputs and outputs, it is first proposed in Jeon et al. (2002) to recognize driving pattern. In Jeon et al. (2002), 24 parameters are extracted from the driving cycle with different weights and 6 driving cycles are selected to represent the driving conditions. The Hamming network is used to determine which driving pattern is the closest one to the current driving state. Learning vector quantization neural network is proposed to identify the driving cycles in J. Wu, C. H. Zhang (2012) and He et al. (2012). In J. Wu, C. H. Zhang (2012), 10 characteristic parameters are chosen for the 6 representative driving cycles and the length of data is 180 s. The structure of the driving pattern recognition based on neural network is shown in Fig. 2. In He et al. (2012), 7 representative features are selected. The main contribution of He et al. (2012) is decreasing the length of sampling period from normally 250 s to 300 s to 120 s. Moreover, the accuracy is maintained.

Since the neural network is hard to be implemented online because of the high computational burden, some real-time driving pattern recognition methods are reported in Lin et al. (2004a); Zhang and Xiong (2015); Feng et al. (2012). A novel method is introduced in Lin et al. (2004a). Only 4 characteristic parameters are extracted for pattern recognition: the average positive power demand, the standard deviation of positive power demand during driving, the average negative power demand, and the ratio of stop time against total driving time. The representative driving patterns are constructed from mathematical calculation by using average positive power demand and standard deviation of positive power demand. Then the current driving pattern can be determined by using simple optimization algorithm with calculated parameters.

Fuzzy logical controller and k-nearest neighbor algorithm are proposed to classify driving pattern respectively in Zhang and Xiong (2015) and Feng et al. (2012). The main contribution in Zhang and Xiong (2015) is determining fuzzy sets of driving block pattern and then converting the fuzzy set into a known driving pattern. Therefore, the similar driving blocks between different representative driving cycles can be reduced. Also, only average speed and maximum speed are considered as classification parameters. The structure of this method is shown in Fig. 3. There are 15 characteristic parameters with different weighting factors are defined to describe the driving cycle in Feng et al. (2012). A feature vector of an original driving cycle can be calculated based on data of a short period, which is more appropriate for real-time application. Then K-nearest neighbor method is applied to match the current feature vector to the closest representative feature vector.

3. MODEL BASED PREDICTION

3.1 Stochastic based predictive EMS

The Markov chain is used to model and work out dynamic decision-making problems during stochastic situation in Yu et al. (2008). The Markov chain is a promising method under stochastic circumstances. This method can be used to predict the next state of the vehicle based on current state. Many efforts have been carried out on utilizing existing data to model driving condition over a previous period to predict future vehicle velocity or power demand.

The main principle of using Markov chain to describe the driving cycle is introduced in Moura et al. (2010). The driving cycle trajectory is modeled by the first order Markov chain through the following equation:

$$P_{ym} = \text{Prob}(P_{dem}(k+1) = i; P_{dem}(k) = j, v(k) = m)$$  

(1)

Where power demand $P_{dem}$ and vehicle speed $v$ are the Markov state variable, $k$ is the time step, and $P_{ym}$ is the probability of power demand in the next time step.
based on $P_{dem}(k)$ and $v(k)$. The matrix consists of all probabilities of upcoming state variable(s) according to current state and is called transition matrix. An example of transition matrix distribution is shown in Fig. 4.

In the Markov Chain approach, the Monte-Carlo method can be used to generate a future velocity sequence for a shot period in Xie et al. (2017). Monte Carlo approach is adopted in the sample space to achieve the possible state in the next moment of the random process. It supports the posterior distribution which means that the future velocity sequence can be predicted by sampling in the stationary distribution. Moreover, an approach called multi-scale-single-step is adopted in Xie et al. (2017) in the velocity prediction phase. Therefore, a group of state transfer matrices will be generated for the 1st horizon so that the accumulation of errors from the first state can be avoided. In Li et al. (2017), a multi-step Markov prediction method is proposed to predict future vehicle velocity, where multi-step means the length of the prediction horizon. This method indicates that with the increment of the length of prediction horizon, the transition probability distributes more dispersedly.

Other driving conditions are also considered to be predicted by the stochastic model. For parallel HEV, its battery charging and discharging are affected by road grade significantly. Therefore, in Zeng et al. (2015) road grade information in hilly regions and driving profile are described by the finite state Markov chains. The sequence of future road grades can be achieved by dividing the predefined road into finite segments and by discretizing the road grade. The transition matrix can be obtained by observing the road grade sequence at a high frequency. Also, a Markov chain aggregation method is introduced for the road grade model in Filev and Kolmanovsky (2010). This method enables a Markov chain with considerable number of states to a Markov chain with small number of states by using Kullback-Leibler (K-L) divergence rate. For a given long distance route, a finite state Markov chain model may be defined by large amount of states and small size periods. It is not acceptable for real-time application. Using K-L divergence rate, the number of small size horizon will decrease to an acceptable level by considering longer period.

Besides future vehicle velocity sequence prediction, Markov Chain can also be used to calculate future power demand. Many efforts have been done to expand this area. In Lin et al. (2004b) and Liu and Peng (2008), a stochastic model of driver power demand is implemented. In Lin et al. (2004b), an optimal control command of a parallel HEV is generated by a two-dimensional Markov chain based driver model. It enables future power demand to be calculated based on multiple driving cycles. Nearest-neighbor quantization method is used to map the sequence of observed power demand and wheel speed of the given cycles into a sequence of quantized states. Then the transition probability distribution can be estimated. In Liu and Peng (2008), the stochastic driver model in Lin et al. (2004b) is modified and implemented to a power-split HEV by adding two more deterministic states which are battery SoC and vehicle speed. Both the homogeneous Markov chain model and the position dependent Markov chain model are introduced to predict the future power demand based on given routes in Johannesson et al. (2007). The first model is a three-dimension Markov chain model constructed of the relationship between velocity, acceleration and power demand. The transition probability of future power demand is determined from simulated data. This model is used to describe the stationary distribution of velocity and power requirement along a given road which excludes the influence of the specific position. Position dependent Markov chain model considers the position along the route when describes the velocity and power demand distribution. For example, if a road segment in driving profile is uphill, then the higher probability for high future torque demand is preferred. To achieve this, the route is divided into many discrete finite segments. In Ripaccioli et al. (2010), it indicates that the power demand along the route is a discrete time stochastic process and solved by Markov chain model. The Markov chain is defined by a transition probability matrix which is estimated by means of frequency analysis based on multiple driving cycles. There are 3 driving cycles generated to present urban, suburban and highway driving.

An on-line updating method is adopted in Bichi et al. (2010) to optimize Markov chain transition matrix. A linear filtering algorithm is used to predict the transition matrix. It will converge to the correct value if future power demand is calculated by a Markov chain model. In Cairano et al. (2014), an innovative approach is applied to update the transition matrix along the changing of driver behavior. The number of transitions from state i and the total number of transitions from each state observed so far is stored. Then transition matrix can be updated based on previous information. Also, an estimator is applied to overcome the error which is caused by large changes on driver behavior.

In Payri et al. (2014), the driving conditions are provided to estimate probability of future power demand based on a stochastic Markov chain model. A specified parameter is introduced to balance the expected battery energy consumption over an infinite time horizon. Then the expectation of the battery energy requirement can be calculated by a discrete method. After that a deterministic control
method is applied to regulate battery behavior. In Zeng and Wang (2016), the battery SoC and fuel consumption over each road segment of a fixed route are considered as random variables instead of vehicle speed or vehicle acceleration. The battery SoC can be obtained as a function of the initial SoC of the predefined route segment and the strategy parameter. The transition matrix of battery SoC and fuel consumption are estimated based on historical data. The initial battery SoC and the specific parameter are discretized during the calculation. A stochastic discrete model can be achieved which based on fixed route segment. The initial battery SoC at each segment performs as the state.

3.2 Artificial intelligence based predictive EMS

Besides the stochastic based prediction method, artificial intelligence approach has also introduced due to the advantage in learning strong nonlinearity. In Sun et al. (2015a) a study in hierarchical feed forward neural network structure is conducted. There are 3 types of neural network structures studied in Sun et al. (2015a), which are back propagation (BP) neural network, layer recurrent (LR) neural network and radial basis function (RBF) neural network. The main idea of these approaches is assuming that the previous driving condition is related to the future driving cycle. Therefore, historical data or previous driving condition information is used to train the network model and to predict the temporary future driving condition. In Sun et al. (2015a), it shows that a 3-layer back propagation network can estimate any nonlinear relationship using a Sigmoid function as the activation function. However, the learning process takes a long time to converge and predict precision cannot be promised. LR network uses a self-connected hidden layer, which enables temporal dynamic feature to be explored. The Gaussian function is chosen as the active function for RBF network which leads to better convergence speed and lower computational burden. It is used widely for time series prediction. A short-term vehicle velocity prediction method based on RBF neural network is proposed in Xiang et al. (2017). A 3-layer RBF neural network is used to predict future velocity in the next 5 s. Pedal position and the historical velocity data are input patterns and predictive velocity sequence is output pattern. Then the future torque demand can be calculated by a predetermined equation.

4. GPS/ITS BASED PREDICTION

Nowadays, real-time traffic data is more universal and easier accessible for drivers by applying GPS/ITS technology. The popularization of real-time traffic data enables the predictive energy management framework can operate based on instantaneous driving condition data. In Zhang et al. (2009), it indicates that the fuel economy can be improved up to 18% if the route distance is predefined. Also, if full terrain and driving cycle information are available during driving. 5% additional fuel consumption reduction can be achieved.

In general, regarding the approach recently used, the GPS/ITS based prediction EMS can be categorized into three subclasses. The first one utilizes GPS/ITS to generate future driving profile. The second subclass methods are developing adaptive control strategies with instantaneous optimal control methods like equivalent fuel consumption minimization strategy (ECMS). The last one is generating reference SoC trajectory using information provided by GPS/ITS, especially for PHEV.

4.1 Driving profile generation

In Van Keulen et al. (2010) and van Keulen et al. (2010), the authors utilize information provided by a navigation system to predict the vehicle velocity and power demand trajectories of the upcoming road. The information of road grades and velocity limitations are integrated with vehicle road load parameters to estimates future upcoming velocity and torque demand. The predicted future vehicle velocity trajectory for each segment is described by 4 key parameters, which are max acceleration, max deceleration, constant velocity, and coast distance.

In Styler and Nourbakhsh (2015), the neural network is used to predict the future vehicle torque demand with an essential assumption. It assumes that if the state measurement is independent of the upcoming load, then the prediction will be useless. The present states provided by GPS like speed, acceleration and power demand are used to match to similar states in the dataset. The observed power demands followed those similar states are used as prediction. A similar method is also introduced in Tianheng et al. (2015), where GPS and ITS provide travel distance, maximum velocity, average velocity and maximum acceleration. The future power demand can be predicted through putting those parameters into the RBF neural network. The advantage of the proposed approach is that it can correlate the upcoming vehicle power demand with the current traffic condition directly.

An optimal control strategy for PHEV considering real-time traffic condition is proposed in Gong et al. (2007) and Gong et al. (2008). The optimal control sequence is obtained by applying backwards dynamic programming method, while the traffic condition is considered by trip modeling. The aim of trip modeling is generating driving cycle for each trip and is achieved by using path-finding algorithm in the geographic information system. When the driving cycle for each segment is obtained, the optimal charge depleting strategy for PHEV can be calculated. In Gong et al. (2008), the influence of instantaneous traffic flow is modeled as stochastic disturbance while Gong et al. (2007) assumes there is no sudden traffic change. Only average speed and acceleration of the segment are utilized in Gong et al. (2008) to estimate segment-wise power demand and SoC change. Previous work has been continued in Bin et al. (2009). More parameters are considered into the EMS and trip model, especially road grade and load change. The multi-information-based trip model is achieved which facilitates spatial domain dynamic programming by diving the detailed trip model into different constant speed segment lengths. Moreover, the length of segment can be adjusted depending on the type of driving cycle detected.

Predictive EMS which utilizes the previewed traffic pattern and terrain information are developed in He et al. (2005). Mixed integer linear programming methodology, with no assumptions on the control structure, is used to find the predictive EMS. In Gong et al. (2011) and
Gong et al. (2010), a method which enables the Markov chain model based on real-time driving data fleet is introduced. The nearest neighbor quantization method is used to map the sequence of observed driving cycle data and acceleration data into a sequence of quantized states. For each state, the distribution probabilities are determined by counting the number of occurrence of each transition and the corresponding state based on the real-world driving data. A less stochastic method is selected in Kohut et al. (2009) to predict the future speed around the vehicle. Two data sources are used: California Freeway Performance Measurement System data base are selected to generate long distance traffic velocity and on-board GPS provides short distance vehicle speed. Then controller combines the information so the future velocity can be predicted based on the vehicle travel distance instead of time series. The control sequences are solved by model predictive control.

4.2 Adaptive energy management strategy

A future state prediction method based on fuzzy logic control approach is proposed in Rajagopalan and Washington (2002). Based on the information provided by GPS regarding current vehicle state over a predefined route, simple future driving condition can be determined, for example slower or faster traffic ahead, going downhill or uphill. Then rule based control strategy is applied to calculate the control sequence. In Hajimir and Salmasi (2006), a novel method is proposed by integrating predicted future vehicle state into fuzzy logic control algorithm to improve fuel consumption and battery life. The core idea is similar as the method introduced in Rajagopalan and Washington (2002) which adopts fuzzy control method to decide how the vehicle should react to the future driving condition provided by GPS. In Musardo et al. (2005), a real-time adaptive control framework is proposed utilizing driving information provided by GPS, as shown in Fig. 5. The main contribution of this instantaneous optimal control method is that the equivalence factor of the ECMS can be adjusted according to past and current vehicle speed and GPS data.

4.3 Reference SoC trajectory optimization

On a trip planning level, GPS and ITS are useful for reference SoC generating for adaptive controller of PHEV. A novel control framework with a higher supervisory level controller for long horizon battery SoC planning is proposed in Sun et al. (2015b) and Heppeler et al. (2017), using the real-time traffic data. Based on the route information and predicted future velocity, future power demand can be calculated by a backward simplified powertrain model. Using discrete dynamic programming method, the reference SoC trajectory is calculated as shown in Fig. 6.

5. CONCLUSION

In this paper, future driving condition forecasting methods are divided into three subclasses: driving pattern recognition, model based method and GPS/ITS based method.
When GPS data is not available or travel destination cannot be determined during the trip, pattern recognition is the most robustness method. Using neural network, fuzzy logic control method, control solution of representative driving cycle can be chosen from the database. Two important model based methods are introduced in model based prediction approach: stochastic model prediction and artificial intelligence prediction. Markov chain is the common approach for stochastic process prediction. It can be used to generate future vehicle velocity sequence or future power demand based on current states. Neural network is also introduced to predict upcoming driving condition, combining with on-line training method. The GPS/ITS based predictive EMS is classified into three categories. Firstly, driving cycle of a giving route can be generate, with terrain information and traffic condition. Secondly adaptive instantaneous optimal control strategy can be obtained. And finally, reference SoC trajectory of PHEV can be planed based on information provided by GPS/ITS.

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