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► **To cite this version:**

Yang Zhou, Alexandre Ravey, Marie-Cecile Pera. Review and analysis of algorithms for the driving condition prediction and its applications. Symposium de Génie Electrique, Université de Lorraine [UL], Jul 2018, Nancy, France. hal-02981911

**HAL Id: hal-02981911**

**<https://hal.science/hal-02981911>**

Submitted on 28 Oct 2020

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# Review and analysis of algorithms for the driving condition prediction and its applications

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**ABSTRACT** -As the fundamental of predictive energy management strategies (PEMSs) for Hybrid Electric Vehicles (HEV), the route prediction accuracy has significant effects on the performance of the corresponding PEMSs, i.e. fuel economy. This paper presents a comprehensive review on the existing prediction algorithms for future driving conditions (FDCs). In the first part, a novel classification of existing energy management strategies (EMS) for HEVs is proposed. And then, the review on existing of FDCs prediction method is carried out. Finally, these prediction methods are classified and their advantages and disadvantages are compared and summarized. Generally speaking, this paper not only conducts a comprehensive analysis and review on existing prediction algorithms but also summarizes their own characteristics, which will help prospective researchers to choose appropriate approaches to seek further performance gaining of PEMSs.

**Key words**— *FDCs prediction methods, Predictive Energy Management, Hybrid electric vehicles.*

## 1. INTRODUCTION

Environmental catastrophes like global warming, air pollution and energy crisis caused by the large amount of carbon-based fossil fuels usage have raised peoples' attention in recent years. As one of the major sources of greenhouse gases (GHG), the conventional internal combustion engine (ICE) powered vehicles need to be updated or replaced to reduce the emission of exhaust gases [1]. To solve this problem, electrical power-providing devices like electrical machines, batteries and super-capacitors are embedded into the traditional ICE-based powertrain system. Vehicles with such hybrid propulsion powertrain system are called Hybrid Electric Vehicles (HEVs) [2], where the electrical power is regarded as the secondary energy sources. With the help of such assisting energy sources, ICEs can always run in the high efficiency area and the drivability during startup process is enhanced compared with conventional one. Therefore, benefiting from such powertrain configurations, dependence on fossil fuels is decreased and thus less exhausted gases will be emitted, which will turn out to be the best mid-term solutions against the pure electric vehicles due to their limited driving range. However, how to build one effective energy management strategies (EMSs) for HEVs to both provide enough energy according to rapid-changing external power demands and reach the best fuel economy is still a not-well-resolved and heated-discussed issue [3].

Benefiting from the predicted distribution of vehicle power demand in the finite horizon, PEMSs can actively make some adjustments and energy allocation planning in advance rather than passive adjustments made by conventional EMSs according to series of predefined rules, engine efficiency maps or instantaneous power demand, which leads to sub-optimal or non-optimal solutions. Therefore, the superiority and potential fuel economy enhancements compared with conventional EMSs made PEMSs the popular topic among researchers in recent years.

In this paper, different from existing classification methods, a novel classification method of for EMSs is proposed based on whether or not the strategies are proposed according to the prediction results of FDCs. The block diagram of this new classification method is shown in Fig. 1.

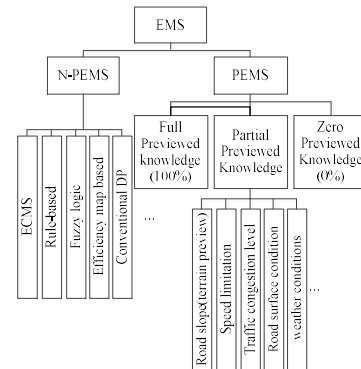


Fig 1 block diagram of novel classification of EMSs

PEMSs can be further classified into three parts according to the levels of future driving information used during prediction process. It should be noted that strategies from these categories are not mutually exclusive and can be either used alone or in combination. For example, in the framework of Model Predictive Control (MPC) based PEMSs, conventional dynamic programming (DP) can be used as a real-time optimal solver to give the satisfied results on the given horizon [4]–[7].

Full previewed knowledge based PEMSs described the situation that the prediction is made based on the fully-previewed knowledge for a given horizon and the performance of such PEMS is considered as the upper limit to assess other PEMSs. In the conventional Markov driving cycle prediction

model, future state sequences are generated iteratively only based on the knowledge of current states and transition probability matrices (TPM), which are estimated from historical database or standard driving cycles. And corresponding EMSs are called “zero previewed knowledge” based PEMSs, where the prediction is made without any future driving information [4], whose results are considered as the lower limit of other PEMSs. Moreover, the main difference between zero previewed knowledge based PEMSs and conventional EMSs is that the latter is proposed only based on non-predictive knowledge like deterministic rules, human intuitions, expert experience etc. Consequently, it is also called non-predictive EMS (N-PEMS).

As a result, the performance of PEMSs is highly related to the prediction accuracy [1] and the strategies to handle mis-predictions [8], [9]. In previous works, various methods are utilized for predicting future driving conditions in different scenarios and relative researches have been carried out to increase the prediction precision. According to these prediction methods, corresponding PEMSs have better performances on the fuel economy and battery lifetimes. However, there is no comprehensive review of the existing prediction methods and their characteristics in previous works.

Thus, this paper firstly presents a novel classification method for PEMSs of HEVs and the significance of FDCs prediction are also discussed. Secondly, review of each FDCs prediction method is conducted, following by a brief comparative study of their benefits and drawbacks. The classification of existing FDCs prediction methods is built at last. This paper's main contribution is that it can help prospective researchers to select the proper prediction methods which will increase the overall performance on PEMSs.

## 2. REVIEWS ON FDCS PREDICTION METHODS

According to existing literatures, several approaches are utilized to predict future vehicle power demand, velocity, and drivers' power request, including Artificial Intelligence (AI) based methods [4], [10]–[25], Markov based approaches [5], [24], [26]–[36], Exponentially Varying Model based approaches [37]–[41], telematics technique based approaches [8], [42]–[55] and other methods [9], [10], [56]–[60]. A comprehensive review and comparative analysis of these methods are carried out in the following parts.

### 2.1. Artificial Intelligence (AI) based methods

AI based methods like Artificial Neural Networks (ANNs), Bayesian algorithms, decision tree algorithm and support vector machine (SVM), have strong ability in describing the compound relationships between inputs and outputs by the “training” process. Due to their characteristics, relative works have been done in recent researches for predicting FDCs based on AI-based approaches [4], [10]–[25].

It can be summarized that, from previous works, the AI-based prediction methods can be divided into two main parts. The first one is called “recognition based” prediction, whose main steps of prediction procedure are:

Firstly, representative parameters are defined and extracted from existing or standard driving cycles and then are used to train a classification model; secondly, same parameters for real driving profile are extracted, compared with standard cycles and then classified into different predefined modes based on the similarity of each representative parameter; thirdly, prediction can thus be made and the corresponding EMSs can

be established and implemented based on the prediction/classification results.

The precision of this approach depends on the driving cycles used to train the prediction/classification model and its block diagram of prediction process is shown in fig 2.

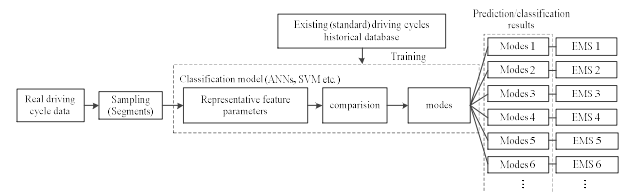


Fig 2 block diagram of recognition based prediction

Regarding the number of representative parameters used for recognition in previous works, 62 [17], 40 [16], 17 [15] and 14 [14] parameters are used to characterize a specific driving cycle. This number is decreased to only 3 [13] or 2 [12]. The more parameters used, the more precise the prediction/recognition will be, while the computational burden of this process will increase accordingly. Consequently, the focus of recognition based prediction is mainly on the tradeoff between the computation efficiency and the recognition accuracy for real-time use.

In [18], statistical data extracted from six standard driving cycles is used to train the classification model based on a learning vector quantization (LVQ) NN. In [19], a data-driven hierarchical clustering classifier is used to extract representative parameters from the real driving cycles and then SVM is used to generate the prediction sequence. In [20], a feed-forward back-propagation NN (BPNN) based route segment identification method is proposed, whose results have been used to choose proper predefined PEMSs.

The second part is called “experience-based” prediction, which means if the current driving conditions are obviously different from the historical patterns, then the accuracy will be influenced. The prediction process of this approach is shown in Fig 3.

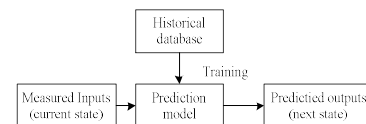


Fig 3 block diagram of experience based prediction

In Fig 3, historical database is used to train the prediction models, which describe the multi-variable, non-linear and constrained relationships/functions between the measured inputs and predicted outputs.

For example, in [23], back-propagation neural network (BPNN) is used to establish the trip condition prediction model to obtain future velocity profile considering both traffic factors and non-traffic factors. In [25], Non-linear Autoregressive Neural Network (NARNN) cooperated with the moving window technique is presented to give the prediction results of future speed-time series, by updating the training database with newly-measured data automatically. Radial Basis Function NN is utilized to predict the future distribution of torque [11], velocity and power demand [24] aiming at improving the overall performance of EMSs.

### 2.2. Markov based methods

In this part, the future possibility distributions of vehicles' velocity, acceleration and power demand are considered as



proposed by researchers. For example, a fast dual-loop Nonlinear PEMSs for HEVs was proposed [66], where the inner loop aimed at tracking the reference trajectories based on the knowledge of predicted driving cycle; An autoregressive integrated moving average (ARIMA) based method was built to predict the future road grade with high precision [67]; Prediction of route situation was generated by a cabin model and then be utilized to provide future power demands [68]. In [69], a gain scheduled driver model with a longitudinal vehicle model was used for predicting the future driving profile. In [70], authors illustrated an approaches to recognize commuter routes from previous driving data using hierarchical agglomerative clustering technique. In [60], a prediction method was created aiming at the frequency distribution of vehicles future position. Moreover, several driving pattern recognition and classification approaches were built based on analytical LVQ-NN [58], similarity degree [57], fuzzy logic [59], [9], Probabilistic Support Vector Machine (PSVM) [10] and Kalman filter [56] for establishing PEMSs to decrease the fuel consumption.

3. FURTHER DISCUSSION

In this section, based on the comprehensive review of FDCs prediction methods, the classification of these methods is proposed at first and the block diagram of this classification is shown in Fig 5. And then main benefits and drawbacks of these methods are compared and summarized in table 1 according to the corresponding analysis in former sections. As can be seen in table 1, different types of prediction methods have a different characteristic, which means they are suitable for various application scenarios. For practical applications, prospective designer should carefully asses the possible driving scenarios before selecting prediction methods. It is likely that in the real complicated driving environments, more than one prediction algorithms should be used together to provide with the satisfied results.

The content in this section will help designers to have a clear view of FDCs prediction methods and select proper methods according to their characteristics leading to the better performance in corresponding PEMSs.

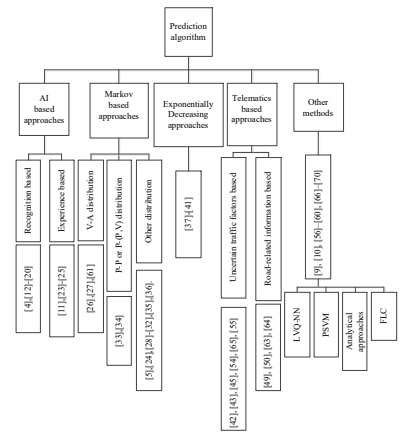


Fig 5 block diagram of classification of FDCs prediction methods

4. CONCLUSIONS

This paper presents a comprehensive study on existing algorithms for predicting future driving conditions. Through detailed analysis and comparisons of these algorithms in this paper, it is clear that each of them has own pros and cons, which makes them suitable for different application scenarios. For real time applications, it is significant to make tradeoffs between prediction accuracy and computation burden, which requires utilizing the combination of different types of prediction methods together to make prediction in both short and long terms for adapting to various changeable external environments. Moreover, reducing uncertainty of future driving conditions by integrating preview knowledge is also necessary. However, prediction with high accuracy cannot be guaranteed all the time, so reliable backup strategies deserve to be explored to reduce the dependency of PEMSs on prediction results. Further precision enhancements highly rely on the advanced traffic modelling technique and overall intelligence of transportation, which will be another research interest. Future works will concentrate on how to develop an online prediction based EMSs for fuel cell hybrid electric vehicle and how to make the reasonable tradeoff between the prediction accuracy and computation burden by combining various prediction methods.

Table 1 Main benefits and drawbacks of FDCs prediction methods

Method	Main Benefits	Main Drawbacks
Markov based	<ol style="list-style-type: none"> <li>1. Less dependency of preview driving knowledge;</li> <li>2. Suitable for modeling stochastic process.</li> <li>3. Reasonable accuracy on similar driving conditions.</li> </ol>	<ol style="list-style-type: none"> <li>1. Lower prediction accuracy when there is obvious discrepancy between real and historical driving conditions;</li> <li>2. Difficulties in integrating with real-time traffic information.</li> </ol>
AI based	<ol style="list-style-type: none"> <li>1. Powerful in finding the non-linear multiple-variables relationship;</li> <li>2. Potential of integrating preview driving knowledge;</li> <li>3. Strong capacity in “learning” from database.</li> </ol>	<ol style="list-style-type: none"> <li>1. The training process is time-consuming;</li> <li>2. Complexity and the “overfitting” problem;</li> <li>3. Difficulties in on-line application.</li> </ol>
Telematics based	<ol style="list-style-type: none"> <li>1. More accurate real-time driving data available;</li> <li>2. Reduce the uncertainty of future conditions;</li> <li>3. Potential of applying EMSs on whole traffic flows.</li> </ol>	<ol style="list-style-type: none"> <li>1. No common method for integrating telematics data into the EMS;</li> <li>2. Large computation burden;</li> <li>3. Early stage of Intelligent transportation system and traffic flow modeling techniques;</li> </ol>
Exponentially decreasing	<ol style="list-style-type: none"> <li>1. Easy and robust to implement;</li> <li>2. No future information required and Computational-friendly;</li> <li>3. Good benchmark.</li> </ol>	<ol style="list-style-type: none"> <li>1. Do not have good adaptation to various external environment;</li> <li>2. Decaying parameters need to be tuned by DP process;</li> <li>3. Not suitable for practical application.</li> </ol>

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