

EVS25
Shenzhen, China, Nov 5-9, 2010
**The Development of Remote Self-Learning Platform for
 Hybrid Electric Vehicle**

Zhuang JiHui¹, Xie Hui, Yan Ying, Zhu ZhongWen, Yan FangChao

¹*Zhuang JiHui State Key Laboratory of Engine, Tianjin University, Tianjin 300072, China*
E-mail: zhuangjihui@tju.edu.cn

Abstract

The analysis of statistic data from real-time driving cycle of hybrid electric vehicle shows relationships that help to optimize control strategy. This paper presents a remote self-learning platform based on general packer radio service (GPRS) for control strategy optimization to hybrid electric vehicle. The platform adopts an in-vehicle device to acquire real-time driving data through CAN bus and communicate wirelessly with central server by GPRS network and INTERNET. A fast clustering method is introduced to classify real-time driving data as different driving cycle. According to driving cycle, online statistical analysis is implemented in central server to obtain energy consumption result, and the optimized control strategy is updated by in-vehicle device. During the process of update to control strategy, the wireless communication quality is a vital factor for completeness of data. A Model-based control algorithm to solve wireless network congestion problem is realized depending on the characteristics of the communication quality. The test result shows that the communication process can be improved greatly and the communication quality is increased 30% at least by this algorithm. The transmission load would be reduced automatically in order to make the communication be normal as soon as possible when the network is under congestion.

The study shows that the remote self-learning platform is effective to define and characterize driving cycle of hybrid electric vehicle. In the sample application, remote self-learning platform plays an importance role in optimizing the control and energy management strategy of hybrid electric vehicle.

Keywords—*control strategy, driving cycle, hybrid electric vehicle, model-based control*

1 Introduction

The fossil resource and environment preservation issues lead to a rapid development of hybrid electric vehicle. HEVs pose a challenging energy management problem. How to effectively split the required torque between the EM and the ICE will greatly impact the gas mileage and state of charge of the battery source of energy [1]. In recent year, hybrid electric vehicle energy management has been studied from optimization perspectives.

Several management and control strategies including intelligent, optimal, and fuzzy approaches have been proposed. A driving cycle can be represented as a sequence of driving events. Driving events could be repeated every time a driver uses the same route at the same time [2]. The performance of HEV is very sensitive to driving cycle and driver behaviors. For this reason, it is necessary to adapt appropriate driving control strategy to current driving cycle. A remote data collection system is developed to acquire real-time driving cycle data of hybrid

electric vehicle. In order to realize driving condition and state of hybrid electric vehicle, the collected data is not only including driving cycle parameters such as speed, acceleration, deceleration but also including vehicle statement parameters such as SOC ,battery current, pedal, and motor torque. Using real time collection data of HEV, driving cycle is constructed by remote self-learning platform with SOM network. The other advantage of remote driving cycle self-learning system is the control parameter auto optimization based on the statistic of driving cycle data.

Design of self-learning platform is described in the first part of the paper, and then method of construction with driving cycle is introduced. The typical driving cycle for hybrid electric vehicle in demonstrating area in Tianjin is given by SOM ANN. At last, a model based control algorithm and implementation are discussed in this work.

2 Design of remote self-learning platform

The remote self-learning platform is designed to collect real time HEV driving data based on GPRS network, after that driving cycles are constructed according real time data. Figure 1 shows the structure of platform. It is composed of two parts, in-vehicle device and data server. The working principal of this platform is as follows: the in-vehicle device is fixed in automobile cabin to gather operational and GPS data by CAN bus, then all collection data was transmitted to GPRS network, and then send to central sever which connected to INTERNET by GGSN[3] (Gateway GPRS Support Node). One aspect of in-vehicle is to transmit driving cycle data to database server, and the other aspect is to receive the latest optimized control parameter which calculated by database server then update optimum data to ECU of hybrid electric vehicle. By this way, hybrid electric vehicle is able to self-learning the driving cycle and optimize energy management to improve performance.

Figure 2 presents a plot of average consumption of electric energy per hundred kilo meters for both of the study vehicles. Figure 3 shows a plot of average consumption of fuel per hundred kilo meters for both of the study vehicles. It can be seen that average fuel consumption is 53.4L per hundred KM, the minimum fuel consumption is 46.3L per hundred KM by number 0004 vehicle and the maximum fuel consumption is 56.8L per hundred KM by number 0003 vehicle. As to

optimize control strategy, power split between EM and ICE can be analyzed according those data. As seen in Figure 4 and Figure 5, both of the vehicles show similar relationships, but there is a clear difference of number 0001 vehicle in May, no doubt due to May Day Holiday traffic condition.

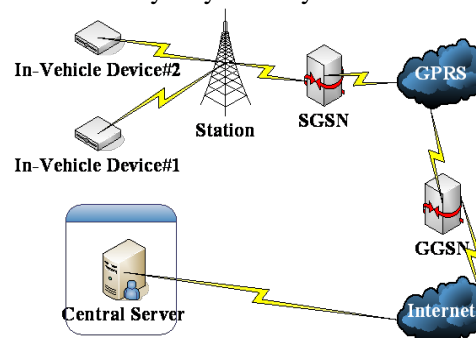


Figure1: Working principal of platform based on GPRS and INTERNET

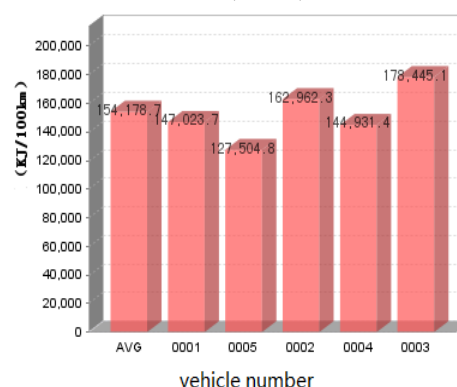


Figure2: Average consumption of electric energy per hundred kilo meters

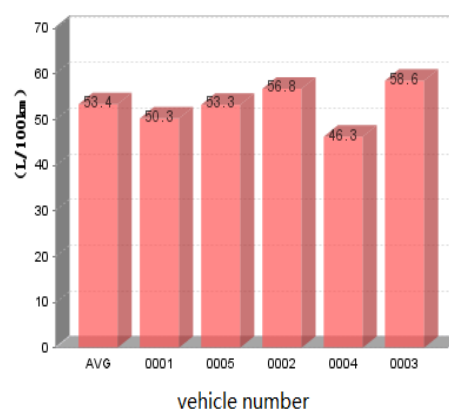


Figure3: Average fuel consumption per hundred kilo meters

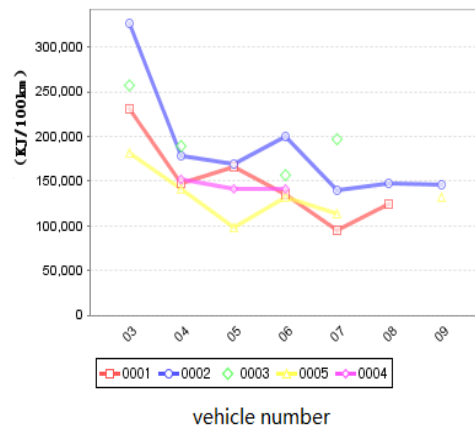


Figure4: Consumption of electric energy per hundred kilo meters, time in months

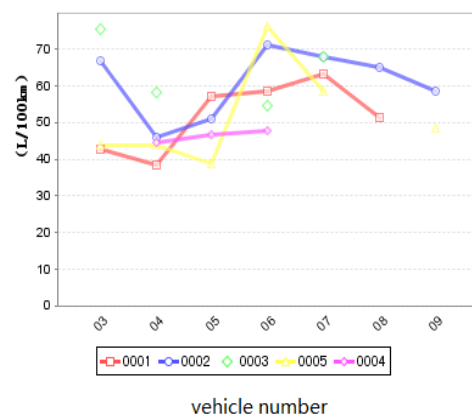


Figure5: Consumption of fuel per hundred kilo meters, time in months

The conceptual design of self-learning driving cycle is shown in Figure 6. Real-time vehicle driving parameters of speed, as well as travel distance are collected by in-vehicle device which is connected to CAN bus of hybrid electric vehicle. These driving parameters are transmitted to a data server by in-vehicle device using GPRS network. Driving cycle is generally defined in terms of the speed profile of the vehicle in a particular environment [4]. The task of self-learning is to extract the key statistical features, or characteristics parameters, of the driving cycle. Generally, it is not possible to extract the complete set of 62 parameters suggested by Ericsson [5] from typical drive cycle information. In this paper, driving parameters are analyzed statistically and calculated T1-T28 which characterizes a driving cycle. The definition of T1-T28 parameters are listed in table I. T1-T28 parameters are used as input of SOM[6] neural network which can classify the current driving cycle as one of three representative driving cycle. An important feature

of this platform is its ability to use drive cycle analysis to determine the optimum control strategy.

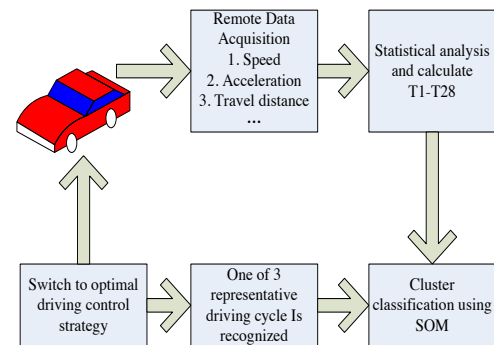


Figure6: Diagram of remote self-learning driving cycle

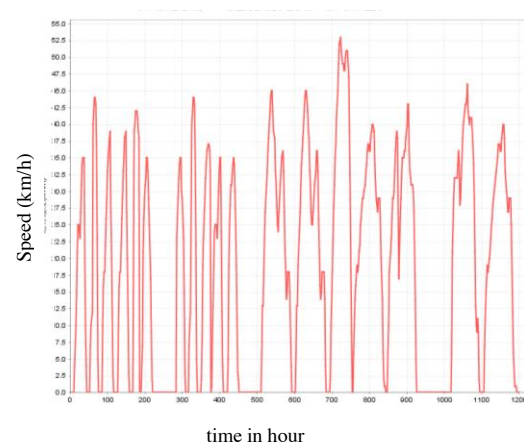


Figure7: Generated driving cycle of Tianjin

Table1: Characteristic parameters of driving cycle

	Definition	Symbol	Unit
1	Travel time	T	s
2	Acceleration time	Ta	s
3	Deceleration time	Td	s
4	Uniform time	Tc	s
5	Idle time	Ti	s
6	Travel distance	S	km
7	Max speed	Vmax	km/h
8	Average speed	Vm	km/h
9	Running speed(except idle speed)	Vmr	km/h
10	Standard deviation of speed	Vsd	km/h
11	Max acceleration	a max	m/s ²
12	Max deceleration	a min	m/s ²
13	Average acceleration	aa	m/s ²
14	Average deceleration	ad	m/s ²
15	Standard deviation of acceleration	asd	m/s ²
16	Ratio of speed between 0 to 10 km/h	P0_10	%
17	Ratio of speed between 10 to 20 km/h	P10_20	%

18	Ratio of speed between 20 to 30 km/h	P20_30	%
19	Ratio of speed between 30 to 40 km/h	P30_40	%
20	Ratio of speed between 40 to 50 km/h	P40_50	%
21	Ratio of speed between 50 to 60 km/h	P50_60	%
22	Ratio of speed between 60 to 70 km/h	P60_70	%
23	Ratio of speed between 70 to 80 km/h	P70_80	%
24	Ratio of speed >80km/h	P80	%
25	Ratio of acceleration	Pa	%
26	Ratio of deceleration	Pd	%
27	Ratio of uniform	Pc	%
28	Ratio of idle	Pi	%

Three representative driving cycle including congested, mixture, and freeway are given based on real-time driving data. According to T1-T28, a cluster method of SOM neural network is applied to classify different driving cycle. To classify driving cycle, SOM network decides which representative driving cycle is closest to a current driving cycle by comparing T1-T28 parameters between each typically driving cycle and a current driving cycle. Micro-trip data which eigenvalue error can be limited within 10% is selected randomly to make up a typical driving cycle in 900~1200s[7] as shown in Figure 7. With the increasing sample data, it is obvious that generated typical driving cycle will be more and more consisted to real driving cycle.

3 Model-based control algorithm to solve wireless network congestion

GPRS communication is involving with problem about sudden network congestion, rate of data loss and time delay [8]. Many simulation researches have been developed to deal with network congress problem[9]. The key issue of network communication is to ensure stability and reliability during data transmission from in-vehicle device to server. A model based algorithm which can adaptive adjust transmit cycle and package length on the basis of given time T and given quality coefficient Q is realized in this paper. The coefficient of Q is defined to descript GPRS network quality [10], that is

$$Q=1- (\alpha_1 *D+\alpha_2 P) \quad (1)$$

Where D-time delay between start frame to ACK frame P - Proportion of lost package in recent 100 packages .

α_1 -weight of D

α_2 -weight of P

Transmission cycle and package length of data is adjustable by in-vehicle device, and transmission time must be taken into account. Transmission time T, package length L and transmission cycle F show nonlinear time-varying relationship with Q. Elman neural network, which is a typical recursive network, was proposed by Elman in 1990 according to speech processing problems[11]. Due to its advantage in processing dynamic behavior, Elman neural network is applied widely. The reverse model based algorithm is implemented by Elman neural network in this paper. The structure of reverse model controller is shown in Figure 8. With given Q^* and T, reverse model controller calculate F^* and L^* which can achieve better communication quality for data transmission.

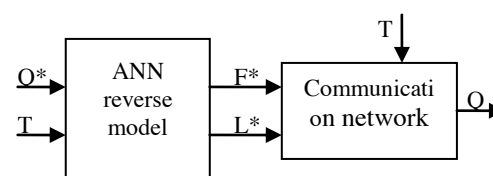


Figure8: Diagram of communication controller
Figure 9 shows control behavior of transmission cycle and package length while Q equals 90%. Figure 10 shows control result of Q by corresponding transmission cycle and package length. It is very clear that Q value alters within the range of 50%~75% and drop rapidly from 14:00 to 18:00 without model based algorithm. After adopting model based controller, communication quality coefficient Q kept in relative high lever above 80% even in the network congestion.

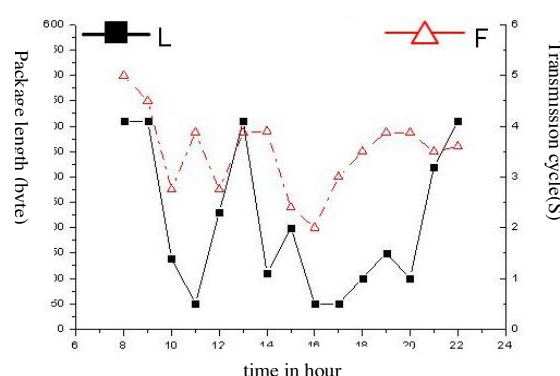


Figure9: Regulating process of the inverse model

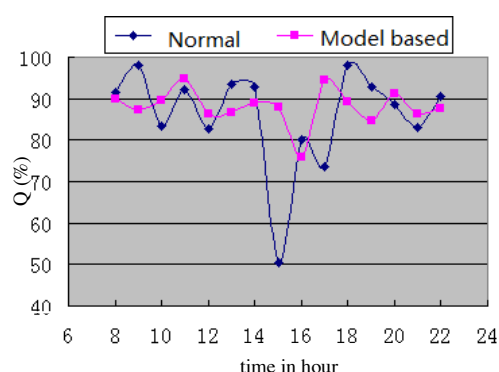


Figure10: Communication quality control

4 Conclusion

Remote self-learning platform was developed to collect real-time driving data and the driving data should be analyzed and stored by central server. A fast clustering algorithm is proposed to classify driving data into Congested, freeway, and mixture driving cycle. Meanwhile, depending on the driving cycle optimized control strategy is selected and transmitted to controller of hybrid electric vehicle. The transmission period and the quality of data are in linear relation, so the load of the GPRS network changes frequently. The communication quality can be highly improved by a model-based control algorithm.

Reference

- [1] D. W. Gao, C. Mi, and A. Emadi, *Modeling and simulation of electric and hybrid vehicles*, in Proc. IEEE, vol. 95, no. 4, pp. 729–745, Apr. 2007.
- [2] Montazeri-Gh, M.; Ahmadi, A.; Asadi, M.; *Driving condition recognition for genetic-fuzzy HEV Control*, Genetic and Evolving Systems, 2008. GEFS 2008. 3rd International Workshop on 4-7 March 2008 Page(s):65 - 70
- [3] Shiao-Li Tsao; *Scalable gateway GPRS support node for GPRS/UMTS networks*, Vehicular Technology Conference, 2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th Volume 4, 24-28 Sept. 2002 Page(s):2239 - 2243 vol.4
- [4] R. Bata, Y. Yacoub, W. Wang, D. Lyons, M. Gambino, and G. Rideout, *Heavy duty testing cycles: survey and comparison*, SAE Paper 942 263, 1994.
- [5] E. Ericsson, *Independent driving pattern factors and their influence on fuel-use and exhaust emission factors*, Transportation Res. Part D, vol. 6, pp. 325–341, 2001.
- [6] Brugger, D.; Bogdan, M.; Rosenstiel, W.; *Automatic Cluster Detection in Kohonen's SOM*, Neural Networks, IEEE Transactions on

Volume 19, Issue 3, March 2008 Page(s):442 - 459

- [7] Li Meng—liang, Li Wei, Fang Mao—dong, et al. *The parse method of actual running cycle of vehicle on road* [J]. Journal of Wuhan University of Technology, 2003, 27(1):69
- [8] J. Rendbn, F. Casadevall, D. Serarols. Snoop; *TCP performance over GPRS*. [J]. Vehicular Technology Conference, 2001. VTC 2001 Spring. IEEE VTS 53rd.
- [9] G. Bianchi, A. Capone, L. Fratta, *Packet data service over GSM networks with dynamic stealing of voice channels* [J]. IEEE, 1995:1152–1156.
- [10] Peter Stuckmann, Niels Ehlers, Bianca Wouters. *GPRS traffic performance measurements* [J]. Vehicular Technology Conference, 2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th
- [11] Jeffrey L. Elman, *Finding structure in time* [J]. Cognitive Science, 1990, 14:179—211

Authors



Jihui Zhuang
Affiliation: State Key Laboratory of Engine
Mailing Address: Tianjin University, Tianjin 300072, China
Tel: 022-27407723
Fax: 022-27407723
Email: Zhuangjihui@tju.edu.cn



Hui Xie
Affiliation: State Key Laboratory of Engine
Mailing Address: Tianjin University, Tianjin 300072, China
Tel: 022-27407723
Fax: 022-27407723
Email: xiehui@tju.edu.cn



Ying Yan
Affiliation: State Key Laboratory of Engine
Mailing Address: Tianjin University, Tianjin 300072, China
Tel: 022-27407723
Fax: 022-27407723
Email: yanying@tju.edu.cn

Zhongwen Zhu



Affiliation: State Key Laboratory of Engine
Mailing Address: Tianjin University, Tianjin 300072, China
Tel: 022-27407723
Fax: 022-27407723
Email: zhuzhongwen@tju.edu.cn



Fangchao Yan
Affiliation: State Key Laboratory of
Engine
Mailing Address: Tianjin University,
Tianjin 300072, China
Tel:022-27407723
Fax:022-27407723
Email:yanfangchao@tju.edu.cn