Fuzzy Logic Based Driving Pattern Recognition for Driving Cycle Analysis

Bor Yann Liaw

School of Ocean and Earth Science and Technology, University of Hawaii, bliaw@hawaii.edu

Abstract

Conducting driving cycle analysis (DCA) using trip data collected from vehicles operated in the field is very difficult. In fact, no comprehensive approach has been conceived to date, except those using standard driving cycles. A successful DCA could significantly enhance our understanding of vehicle performance and readily relate it to real-life driving. In the past few years, we have been developing tools for vehicle performance analysis (VPA). In particular, we were able to collect data from a fleet of 15 Hyundai Santa Fe electric sports utility vehicles (e-SUVs) operated on Oahu, Hawaii, from July 2001 to June 2003. A fuzzy logic-based driving pattern recognition (FL-DPR) technique was used to perform DCA. This technique was successfully applied to create a compositional driving histogram, called "trip driving pattern composition (TDPC)," for each vehicle, which enables us to analyze vehicle performance in great details.

Keywords

BEV, driving cycle analysis, driving pattern recognition, fuzzy logic, vehicle performance analysis

1. INTRODUCTION

Driving cycle analysis (DCA) based on trip data collected from vehicles dispatched in the field and randomly generated in real-life operation is a daunting challenge [Ericsson, 2000 and 2001]. Although many attempts have been tried [Feng and Ross, 1993; Feng et al., 1997; Tong et al., 1999; Rahman et al., 1999; Young et al., 2000; Barth et al., 2002; Dembski et al., 2002], the difficulty lies on the fact that there is no commonly-accepted systematic approach to allow characterization of those randomly generated driving cycles for detailed analysis and comparison. Thus, all past efforts had to rely on standard driving cycles or well-documented routes to emulate real-world driving conditions in order to conduct engineering analysis. However, these conventional practices do not represent or cover all real-world driving conditions, including extremes. Thus, their assessments have only specific and limited value.

Standard driving schedules and dynamometer tests only provide data collected in certain fashions, which do not support analyses on real-world fleet operation in terms of costs and other operational or usage information. Thus, conventional statistical analysis has to be used to address these aspects. However, it is still difficult to collect data to accomplish these studies. Therefore, a disengagement exists between assessments from controlled tests and experiences in real-world driving, not to mention that we have only very limited capability to study the impacts of less- or non-controllable parameters, such as road conditions, traffic patterns, driving habits, or weather conditions, that all influence vehicle performance. A consistent DCA technique is therefore very desirable to allow us correlate between vehicle performance and usage in real-world situations.

The lack of effective DCA might have undermined the development of battery-powered electric vehicles (BEVs), when they were highly promoted in the 1990s. Significant technology barriers, such as limited driving range and lack of battery charging infrastructure, prevented widespread use of BEVs. We, the stakeholders, on the other hand, found ourselves lacking adequate tools to rapidly develop a formidable technology portfolio and to assess its effectiveness in practical use, therefore assisting its market penetration. In other words, the inability to effectively collect and analyze vehicle operation data and to properly evaluate technology deficiency has inhibited us to promote BEV use. This barrier persists to date. Although on-going success in commercializing hybrid electric vehicles (HEVs) by Toyota and Honda claims hopes for transforming our habit toward mobility, utilities that can provide a better assessment will only accelerate this transformation.

The approach that we used in this work is a comprehensive, direct, and effective way to perform DCA using a fuzzy-logic driving pattern recognition (FL-DPR) technique. In this paper, we explain how the FL-DPR works and the DCA is achieved using trip data collected from a fleet of 15 Hyundai Santa Fe e-SUVs dispatched to various users on Oahu, Hawaii, from July 2001 to June 2003. The trip data were recorded second-by-second during daily operation. The data are comprised of more than 10,000 trips over 350,000 km in real-world driving conditions.

2. TECHNICAL APPROACH

The FL-DPR technique [Liaw et al., 2002; Liaw and Bethune, 2003] is unique, in contrast to conventional statistical characterization of driving cycles. The technique uses MATLABR fuzzy logic toolbox to "recognize" driving patterns in a trip in a histogram-compositional manner, which is more intuitive than the conventional analysis that treats a trip in its entirety with numerical differentiation of subtle differences in a statistical sense. The application of fuzzy rules to recognize driving patterns in a trip enjoys benefits of simplicity and flexibility (or adaptability) native to the fuzzy logic approach. The FL-DPR technique is based on a unique "driving pulse (DP)" concept, which utilizes a methodology that divides a trip into a series of sequential DPs. Each DP represents an active driving period between two contiguous stops. The FL-DPR technique was actually applied to the DPs to associate a driving pattern to a DP. By summarizing the driving patterns associated with the DPs, we were able to compose a progressive histogram of "trip driving pattern composition (TDPC)" for each trip. This TDPC makes DCA become systematic and applicable to any trip as a function of time or distance traveled. Through this process, we can construct a summary histogram showing the composite nature of a trip with a comprehensive description of driving patterns.

2.1 Driving pulses and driving pattern recognition

In the FL-DPR approach, a trip, or a driving cycle (i.e., a speed versus time profile), is made of a series of sequential "DPs," as Figure 1 illustrates. We can characterize each DP with an average speed and distance traveled. Figure 2 shows how we develop the assignment of driving patterns from an average speed versus distance (as-d) plot for FL-DPR. First, the as-d plot is constructed from all DPs derived from all recorded trips in the database (in this particular illustration, the trips shown represent only during September 2001 to March 2002). An arbitrary but intuitive decision is made to assign boundaries of as-d relationship for a specific driving pattern. Five specific driving patterns are used in categorization: which are stop-n-go (SG), urban (U), suburban (SU), rural (R), and highway (H). In general, a high speed and long distance travel is associated with "H" driving, and a low speed and short distance (associated with frequent stops) travel is often considered an "SG" city driving. The other three categories are falling in between. This arbitrary but intuitive assignment is used to create a set of fuzzy rules. The fuzzy rules also allow certain degree of association for a category with adjacent cat-

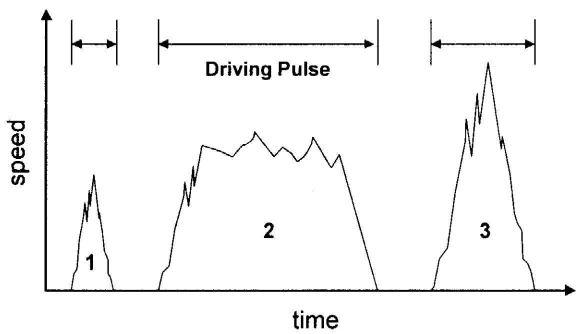

Fig. 1 A driving cycle depicted by a speed versus time curve. The cycle is broken down into a series of sequential isolated "driving pulses," each represents an active driving period bounded by two adjacent stops. The pulse is characterized by an average speed and distance traveled.

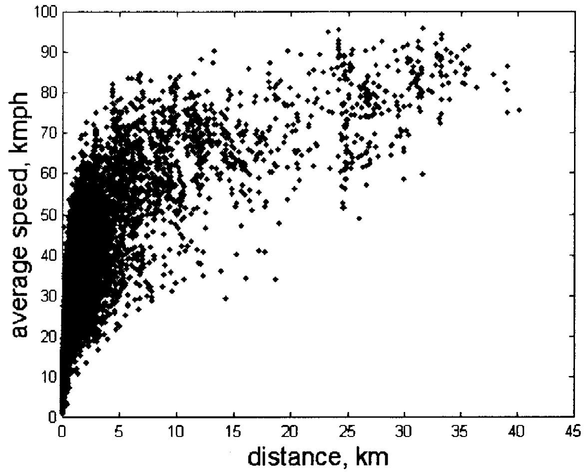

Fig. 2 An average speed versus distance (as-d) plot showing the distribution of driving pulses derived from more than 6,000 trips collected from September 2001 to March 2002. This plot is used to derive driving pattern assignments in fuzzy rules.

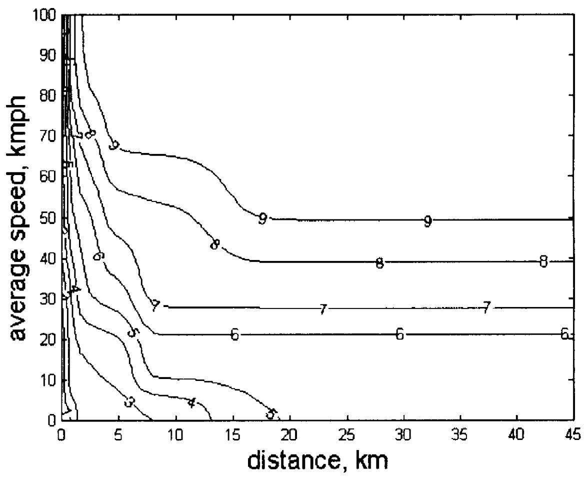

Fig. 3 A mature membership function defines driving pattern assignments according to a set of trained fuzzy rules. The contours show the map of the boundaries of fuzzy output number (FON) in a scale of 0 to 10, which is used to infer driving patterns from stop-n-go to highway driving.

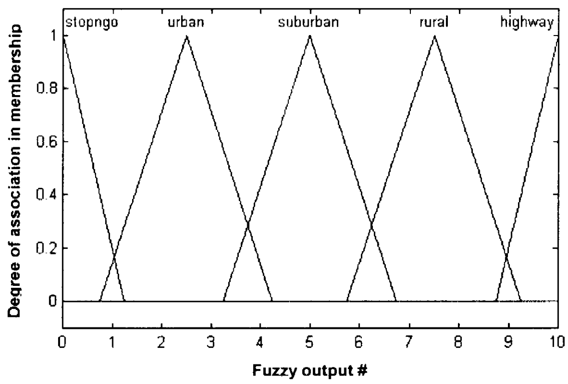

Fig. 4 Classification of driving patterns in five categories

egories, so assignment of driving pattern is not strictly "discrete," but with a "fuzzy" boundary and a "degree of association," as represented by a fuzzy output number (FON). We then carry out a training process by using the initial set of fuzzy rules to analyze an increasing set of randomly selected trips and examining the resulting driving pattern assignments. If the parameters used in the fuzzy rules could not give satisfactory driving pattern recognition for all the trips, they were modified until they can. Through repetitive refinements in the training, a final set of rules is generated. The mature fuzzy rules now map input and output membership functions, which give each driving pulse a FON to be used to infer its driving pattern. Figure 3 shows a map of the contours and boundaries of all FONs on the as-d plot. The inference of FON to driving pattern is shown in Figure 4 as an example, which establishes the driving pattern assignment. By carefully applying fuzzy rules, based on the as-d relationship in a DP, we can assign an intuitive driving pattern to a DP.

2.2 Trip driving pattern composition (TDPC)

With the establishment of FL-DPR, we can examine trip data by summarizing sequential driving patterns for DPs in a TDPC and conduct DCA. Figure 5 illustrates a unique example using a randomly selected trip (ID# 31831524). This trip has a driving cycle with very mixed driving patterns, from SG to H, therefore difficult to analyze with traditional approaches that usually attempt to assign an "overall" driving pattern to a trip in its entirety. The FL-DPR technique, on the contrary, using breakdown of DPs, is capable of assigning a specific driving pattern to a DP, thus allowing composing a sequential summary of driving patterns with time and distance as TDPC. This TDPC can be normalized to percentage of time or distance in the trip, therefore allowing different trips to be compared in a normalized fashion, disregarding differences in time or distance traveled originally. The ability of comparing DCA side-by-side among trips offers a tremendous utility for vehicle performance analysis (VPA) in real-life operation.

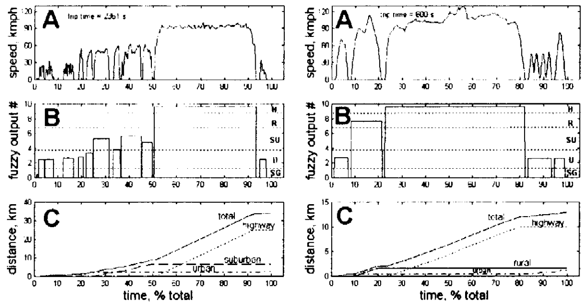

Fig. 5 (left) A randomly selected trip (ID# 31831524) with complicated mixed driving characteristics. (right) Analysis of US06 Supplemental FTP Driving Schedule [EPA, 2004] using FL-DPR, in comparison with the driving pattern shown on left. When both trips are normalized with respect to trip duration, they can be compared side-by-side.

3. DATA COLLECTION

The trip data were collected from BEVs operated in real-life driving conditions. The fleet of 15 Santa Fe e-SUVs was prototyped by Hyundai Motor Company (HMC) of South Korea and delivered to Hawaii in July 2001. Figure 6 shows the picture of a Santa Fe e-SUV and the on-board data acquisition device. Trip and charging data are stored with automated on-board acquisition protocols in a flash memory card. The time-stamped trip data include those from the motor controller, APU, and the

Fig. 6 Hyundai's Santa Fe e-SUV and on-board data acquisition system

battery management system on a second-by-second basis. The data were transferred periodically onto a separate collecting medium, filtered, validated, and then translated into a correct format in the database for analysis.

4. RESULTS, ANALYSES, AND DISCUSSION

The unique utility of using the FL-DPR technique and the normalized TDPC affords us to compare DCA side-by-side to show similarities or differences among trips. Figure 5 shows DCA results for a trip (ID# 31831524) and a comparable US06 Supplemental Federal Test Procedure Driving Schedule (US06 SFTPDS) [EPA, 2004], an aggressive driving schedule with high acceleration, for comparison. This trip (ID# 31831524) is about four times longer than the US06 SFTPDS. The trip is 73.4% H and 26.5% combined U/SU cycle. In contrast, the US06 SFTPDS has 77.8% H and 9.4% U driving. The trip was 34 km with an average speed of 62.0 km per hour (kmph). In contrast, the US06 SFTPDS posts 12.9 km and 83.4 kmph, respectively. The TDPCs for both cycles are shown in the B and C plots in the figure.

Another unique utility of the FL-DPR technique and the TDPC is that we can afford to examine a trip from a fraction to the entire trip; and, with summarization from subsequent trips, we can yield a summary histogram of a specific duration, thus daily, weekly, monthly, quarterly, or even lifetime report of the vehicle operation can be generated from the trip data in the database, with a consistent categorization, in a systematic manner, as shown in Figure 7. This approach could be a powerful tool for additional analyses, such as those for market study, traffic assessment, or fleet management, etc. For example, the ability to compare trips side-by-side allows us to look into variations in vehicle operation and performance at different locations. As shown in Figure 8, DPs for two particular vehicles are highlighted in dark

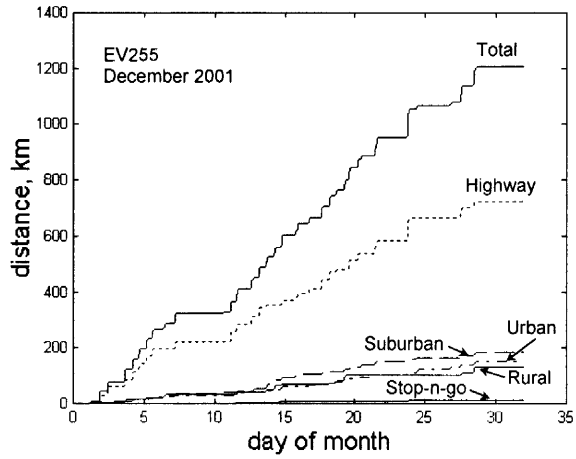

Fig. 7 A monthly summary report of a BEV operation and usage derived from TDPC

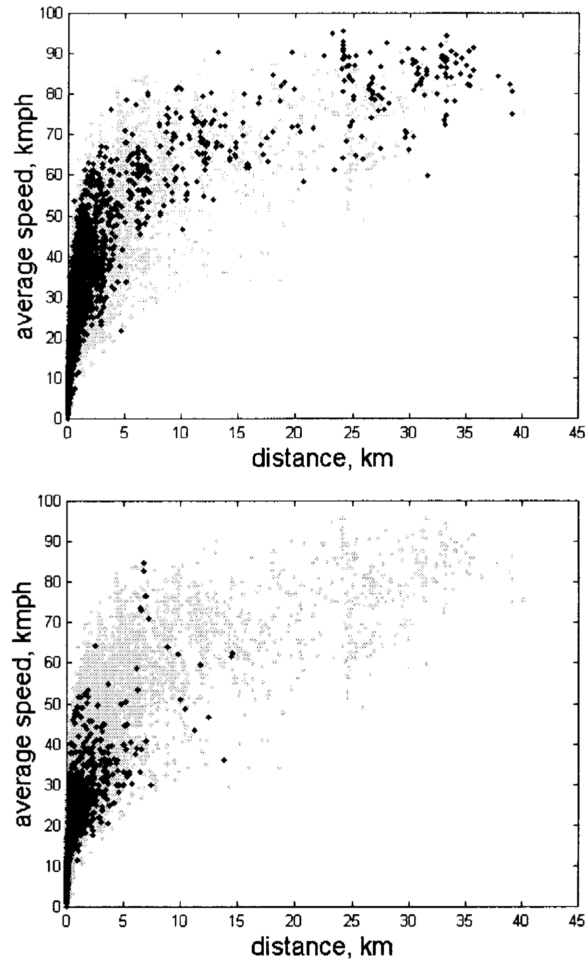

Fig. 8 Comparison of two vehicles at different locations, operated by the City and County Office of Honolulu (C&C) (top) and the Hickam Air Force Base (HAFB) (bottom), showing the difference in demographic distribution of driving pulses and patterns of use.

symbols, respectively, to show their usage patterns, in contrast to those of the entire fleet, which are shown in gray symbols. The one on the left represents a vehicle operated by the City and County (C&C) of Honolulu, and the other on the right by Hickam Air Force Base (HAFB). Divergence in the vehicle usage patterns at the two locations is clearly shown. The C&C vehicle was operated often with highway commute and city/urban driving made during working hours, therefore its operation consists of an assembly of diverse driving patterns. The HAFB vehicle was used primarily by security guards on the base, thus its operation was constantly constrained by low speed limits. This comparison illustrates the capability of analyzing divergence in vehicle driving pattern and usage directly from live vehicle trip information, which is unique, and also superior to the conventional statistical approaches that log data separately, and thus are difficult in performing such detailed correlation.

The FL-DPR technique provides us additional capability to study influences on vehicle and battery performance directly from driving patterns and vehicle operation at different locations. As an example, in Table 1, we summarize the usage pattern and energy use in three vehicles at three different locations for three months to compare their energy use efficiency over each month. For simplicity, the analysis includes contributions from driving patterns in two major groups: local (combined SG/U/SU) and R/H. The efficiency rating (ER) is based on energy use efficiency (i.e., energy consumption per distance traveled, or in kWh/km) derived from each individual driving pulse and converted to a scale of 0-10 with a simple conversion factor.

Table 1 Comparison of the usage and performance characteristics of three vehicles at different locations

Organization	HAFB			HECO			C&C		
Month	1	2	3	1	2	3	1	2	3
No. of trips > 0.03 km	65	96	89	112	107	73	154	93	153
Distance driven, km	196	243	318	1701	1238	935	1372	905	1445
% Local (SG/U/SU)	69.5	80.6	74.8	18.8	24.8	12.5	26.5	28.1	25.2
% R/H	27.0	14.9	21.4	78.8	71.9	85.6	71.4	69.4	72.7
Trip avg. ER*	2.67	3.05	2.96	2.56	2.60	2.46	2.81	3.09	3.29
(Standard Deviation)	(0.79)	(0.73)	(0.68)	(0.69)	(0.70)	(1.06)	(1.74)	(1.74)	(1.72)
Local avg. ER	2.91	3.47	3.03	2.91	2.88	2.75	2.52	2.77	3.06
(Standard Deviation)	(1.02)	(1.27)	(0.88)	(1.31)	(1.28)	(1.09)	(1.39)	(1.33)	(1.52)
R/H avg. ER	2.96	3.68	3.47	3.16	3.01	3.27	3.18	3.24	3.46
(Standard Deviation)	(0.57)	(0.75)	(0.86)	(0.74)	(0.83)	(0.36)	(0.82)	(0.82)	(1.09)

* ER: Efficiency rating

4.1 Vehicle performance analysis (VPA)

The ER is then used in an intuitive VPA, as Figure 9 shows, via a correlation of ER versus driving pattern (as presented by FON). A mean efficiency rating (MER) is the mean of all ER values in an interval of 0.25 in FON, as shown by the solid line.

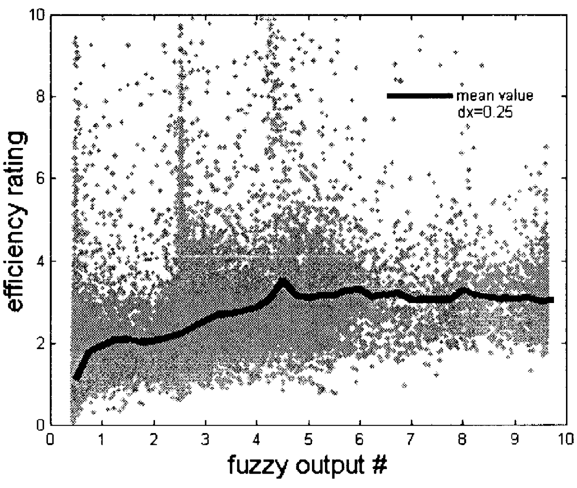

Fig. 9 Efficiency rating versus FON plot, showing how the efficiency varies with the driving patterns

The MER is assumed to be neutral (non-biased) to any driving conditions, such as traffic, weather, aerodynamics, driving habit, road condition, grading, or drivetrain fluctuation, etc. Although the criteria used in FL-DPR might be subjective to our opinions in driving pattern assignment or ER calculation, the application of MER for VPA is still valuable. For example, by comparing a specific ER in a driving pulse versus the MER, as shown in Figure 10, in trip #31831524, we can examine possible attributes to the deviation. Upon further inspection of this particular trip, since we knew the route, we believe that the higher ER between 20 and 50% of time and the lower ER between 50 and 93% of time were most likely due to grading. Collecting all trips corresponding to this particular route, we could further evaluate traffic pattern, and other attributes, in relation to any dynamic variation in ER, within the same framework of live vehicle operation data collection and systematic DCA. Several possible benefits of this practice could be derived, including the possibilities of (1) using real-world vehicle trip data to validate information determined by standard driving cycles, (2) synthesis and model prediction of hypothetical driving cycles, and (3) development of effective strategy for fleet management and scheduling. Those possibilities are being investigated by us and will be reported in our follow-on papers.

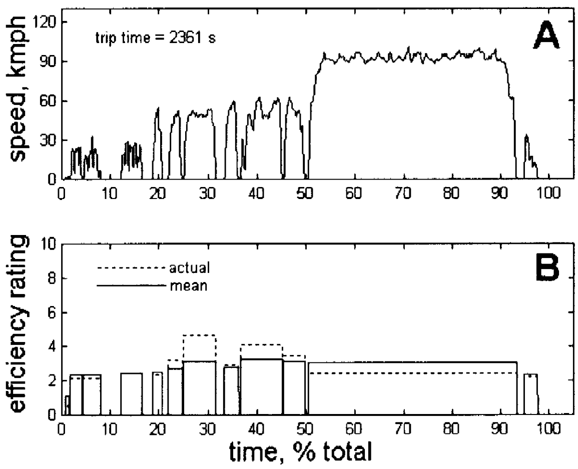

Fig. 10 Vehicle performance analysis of the efficiency rating for trip (ID# 31831524), showing the actual efficiency rating versus the mean value calculated for the specific driving pattern.

5. CONCLUSION

Traditionally it is difficult and challenging to conduct DCA using field test data. On the other hand, a successful DCA of this nature can greatly benefit a technology development, as we explained above. A unique contribution from this fuzzy-logic driving pattern recognition (FL-DPR) technique is the ability to construct a trip driving pattern composition (TDPC) in terms of percentage of time or distance traveled. The TDPC can then be used to compare trip characteristics side-by-side among trips, correlate vehicle's driving and usage patterns with performance characteristics, such as energy use efficiency (or battery life, which is feasible but was not presented here). This approach could be extended to systematically analyze impacts from traffic, aerodynamics, road condition, driving habit on vehicle performance, or derive useful vehicle usage information to assist market study or fleet management. Potential benefits include (1) practical and useful vehicle performance analysis using live trip data, (2) direct vehicle design using field test data and virtual prototyping, and (3) simulation and modeling for hypothetical driving cycles, including environmental impacts analyses.

Acknowledgements

The author would like to express his gratitude to the U.S. Department of Transportation and the Hawaii Center of Advanced Transportation Technologies (HCATT), previously known as the Hawaii Electric Vehicle Demonstration Project (HEVDP), administrated by the High Technology Development Corp. (HTDC) of the State of Hawaii, for funding support, and to, particularly, Mr. Thomas L. Quinn, who has been very supportive to this work. Significant engineering and technical support from the Hyundai Motor Company of South Korea on data acquisition system is highly appreciated. Special thanks should go to Mr. Jin Hun Cho, Ki Ho Yoo, Chae Mo Yang, and Jun Hyuck Seo, who have been very instrumental in assisting data collection, and the HMC management, particularly Dr. Chul-Soo Kim, for substantial commitment and support. The author would also like to send his gratitude to Enova Systems, Inc., especially to Dr. Don Kang and Todd Martin, for providing significant contributions to vehicle maintenance and test facility operation. He would also like to express his gratitude to many in the Hickam Air Force Base, Hawaiian Electric Company, and the City and County of Honolulu, who assisted in the vehicle operations and data collection. In addition, he would like to thank Mr. Carl Perazzola and his staff in the U.S. Air Force Advanced Alternative Power Transportation Technology Office (AAPTTO) for providing follow-on funding support. Finally, he thanks all his students and staff, including Keith P. Bethune, Benoit Dailliez, and Alea Teeters, for their hard work and contributions to the success of the data collection and analysis.

References

Barth, M., Mobile Source Emissions New Generation Model: Using a Hybrid Database Prediction Technique, *A final report to U.S. Environmental Protection Agency*, 2002.

Dembski, N., Analysis and Experimental Refinement of Real-World Driving Cycles, *SAE paper 2002-01-0069*, Society of Automotive Engineers, 2002.

Ericsson, E., Independent Driving Pattern Factors and Their Influence on Fuel-use and Exhaust Emission Factors, *Transportation Research Record*, Part D 6, 325-374, 2001.

Ericsson, E., Variability in Urban Driving Patterns, *Transportation Research Record*, Part D 5, 337-354, 2000.

Feng, A., and M. Ross, A Model of Fuel Economy and Driving Patterns, *SAE paper 1993-01-0328*, Society of Automotive Engineers, 1993.

Feng, A., Impacts of Diverse Driving Cycles in Electric and Hybrid Vehicle Performance, *SAE paper 1997-01-2646*, Society of Automotive Engineers, 1997.

Liaw, B. Y., and K. P. Bethune, A Systematic Driving Pattern Recognition. I. Fuzzy Logic Approach, *Submitted to J. Transportation Research C*, 2003.

Liaw, B. Y., Time-Series Field Trip Data Analysis Using Adaptive Recognition Approach. Analysis on Driving Patterns and Vehicle Usage for Electric Vehicles, *Proceedings EVS-19*, 2002.

Rahman, Z., A Study of Design Issues on Electrically Peaking Hybrid Electric Vehicle for Diverse Urban Driving Patterns, *SAE paper 1999-01-1151*, Society of Automotive Engineers, 1999.

Tong, H. Y., Development of a Driving Cycle for Honk Kong, *Atmospheric Environment*, Vol. 33, 2323-2335, 1999.

U.S. Environmental Protection Agency (EPA), http://www.epa.gov/otaq/emisslab/methods, 2004.

Young, C., Analysis of Weekday/Weekend Driving Differences in an In-Use Vehicle Fleet, *Proceedings the 10th CRC On-Road Vehicle Emissions Workshop*, 2000.

(Received May 4, 2004; accepted June 11, 2004)