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Journal of Power Sources 174 (2007) 76–88

JOURNAL OF POWER SOURCES

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From driving cycle analysis to understanding battery performance in real-life electric hybrid vehicle operation

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Received 23 February 2007; received in revised form 25 May 2007; accepted 1 June 2007
Available online 16 June 2007

Abstract

This paper proposes a methodology and approach to understand battery performance and life through driving cycle and duty cycle analyses from electric and hybrid vehicle (EHV) operation in real-world situations. Conducting driving cycle analysis with trip data collected from EHV operation in real life is very difficult and challenging. In fact, no comprehensive approach has been accepted to date, except those using standard driving cycles on a dynamometer or a track. Similarly, analyzing duty cycle performance of a battery under real-life operation faces the same challenge. A successful driving cycle analysis, however, can significantly enhance our understanding of EHV performance in real-life driving. Likewise, we also expect similar results through duty cycle analysis for batteries. Since 1995, we have been developing tools to analyze EHV and power source performance. 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 to allow driving and duty cycle analyses in order to understand battery pack performance from a variety of EHV operating conditions. We thus developed a comprehensive approach that comprises fuzzy logic pattern recognition (FL-PR) techniques to perform driving and duty cycle analyses. This approach has been successfully applied to EHV performance analysis via the creation of a compositional driving profile called "driving cycle profile" (DrCP) for each trip. The same approach was used to analyze battery performance via the construction of "duty cycle profile" (DuCP) to express battery usage under various operating conditions. The combination of the two analyses enables us to understand both the usage profile of EHV and battery performance in synergetic details and in a systematic manner using a pattern recognition technique.

Keywords: BEV; Driving cycle analysis; Pattern recognition; Fuzzy logic; Vehicle performance analysis; Battery stress factors

1. Introduction

Conducting driving cycle analysis using trip data collected from vehicles dispatched in real-life operation is very challenging; e.g., [1–18]. Although numerous attempts have been made in the past, no consistent approach has been accepted to allow a systematic, detailed characterization of driving cycles for engineering analysis and comparison, except those standard driving schedules conducted on dynamometers or well-documented tracks, mimicking real-life situations, to permit vehicle performance analyses or other urban and emission studies [3–5,7–9,14–20]. Besides standard driving schedules, sometimes regional driving cycles have to be developed [8,14–18] to emulate real-world conditions in certain regions to enable adequate analyses. Even so, these traditional approaches are still unable to handle extremes that are beyond test capabilities. Therefore, these conventional assessments offer limited success.

For traction power sources such as batteries in electric and hybrid vehicle (EHV) applications, assessments on their performance are, most of the time, conducted in laboratories. Similar to standard driving schedule tests and analyses, these laboratory tests and duty cycle analyses have constraints in their validity to real-life operation. A main issue exists in both cases due to the problem with real-life operation where, even under specific driving cycles or duty cycles, energy consumption strongly depends on ambient operating conditions that are typically uncontrolled. Thus, a systematic, comprehensive analysis of both driving cycles (for vehicle) and duty cycles (for power sources) in real-life operation is highly desirable.

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0378-7753/$ – see front matter
doi:10.1016/j.jpowsour.2007.06.010

In the literature, depending on the context of discussions by different authors, driving cycle, duty cycle, and driving pattern may present different meanings. It is therefore essential to define the terminology used by this paper to ensure clarity. A "driving cycle" in this paper refers to a history of driving, typically represented by a speed versus time curve. A "duty cycle" refers to a history of power usage of a device, typically depicted by a power versus time curve. A "driving pattern" is used to describe a driving condition, taking into account both road condition (e.g., road type) and driving behavior.

The lack of comprehensive driving and duty cycle analytical tools to allow benchmarking both vehicle and battery performance might have undermined the development and commercialization of battery-powered electric vehicles (BEVs) in the 1990s. Significant technology barriers, such as limited driving range and the lack of battery charging infrastructure, prevented widespread use of BEVs during that period. On the other hand, the lack of adequate tools to afford a rapid integration of powertrain components and a quantitative benchmark of technology advancements could have hampered BEV's market penetration. These barriers persist to date. Although the on-going success in commercializing hybrid electric vehicles (HEVs) and the introduction of plug-in hybrids by Toyota and a handful other automakers raise some hope to transform our future automobile and transportation industry to a more efficient and environmentally-friendly operation, a better assessment can only accelerate this process.

Consistent driving and duty cycle analyses are very desirable to allow us correlate between battery performance and EHV usage in real-world situations. The approach that we used in this work relies on a suite of fuzzy logic pattern recognition (FL-PR) techniques that tend to be comprehensive and quantitative to allow (vehicle) driving and (powertrain/battery) duty cycle analyses. In this paper, we explain how the FL-PR technique works to allow driving and duty cycle analyses using trip data collected from a fleet of 15 Hyundai Santa Fe battery-powered electric sports utility vehicles (e-SUVs) in real-world driving conditions. This approach should be quite useful, for instance, for future plug-in hybrids in assessing vehicle and battery performance.

2. Data collection

The fleet of 15 Santa Fe e-SUVs was delivered by Hyundai Motor Company (HMC) of South Korea to Hawaii in July 2001. Fig. 1 shows pictures of one of the Santa Fe e-SUVs and on-board data acquisition device. The vehicles are designed to be purely battery-powered for roadworthy tests. Each vehicle comes with a 60 kW AC inductive motor and power controller with a Panasonic 95 Ah nickel metal hydride EV battery pack (315 V nominal). These vehicles can accept AC charging directly from electrical wall outlets or fast DC charging with a 60 kW PosiCharge^{TM} made by AeroVironment (Monrovia, CA). Trip and charging data are recorded by automated on-board data acquisition system in a flash memory card during vehicle operations or charging periods. All trip and charging data were time-stamped. The data includes information from motor controller, auxiliary power unit (APU), and battery management system on a second-by-second basis, including pack voltage, current, power, motor RPM and many other critical parameters that can afford driving and duty cycle analyses. The database comprised data from more than 255,000 km in 25,000 trips. The data were transferred periodically to a separate collecting medium, filtered, validated, and then recorded into a database for analysis.

The vehicles were dispatched to four primary organizations on Oahu, Hawaii, for a variety of use from July 2001 to June 2003. The vehicles dispatched to Hickam Air Force Base (HAFB) were typically used for security patrol and errands. Hawaiian Electric Company (HECO) and City and County of Honolulu (C&C) used the vehicles for commutes and performing service duties. The vehicles retained at the Hawaii Electric Vehicle Demonstration Project (HEVDP) office, now Hawaii Center for Advanced Transportation Technologies (HCATT), were used for commutes and errands. It is worth noting that drivers at HAFB have to observe strict speed limits (mostly at 25 mph or 40 km h^{-1}), therefore the driving cycles from these vehicles are often different from those of the other locations.

3. Technical approach: analyses, results, and discussion

3.1. Driving cycle analysis

Fuzzy logic pattern recognition is a relatively well-accepted technique for many technology applications, e.g., [21–26]; due to its merit often associated with the need for linguistic, qualitative expression and knowledge in handling non-fuzzy numerical data. This ability is of particular interest to us in dealing with driving cycle analysis, arising from the qualitative nature and need for linguistic expression of driving cycles in such an analysis. Interestingly, few have reported using fuzzy logic or

Fig. 1. Hyundai's Santa Fe e-SUV and on-board data acquisition system.

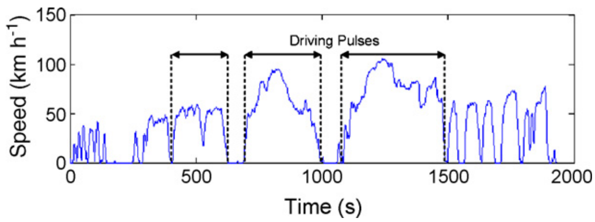

Fig. 2. Schematic of a driving cycle (speed vs. time curve) broken down into a series of sequential isolated "driving pulses" (DP).

other pattern recognition techniques for driving cycle analysis, state-of-charge estimation or power control systems [27–32]. Recently, we began to consider using such a FL-PR technique and the MATLAB® fuzzy logic toolbox for driving and duty cycle analyses [33–35].

Our FL-PR approach is built upon a "driving pulse" (DP) concept (Fig. 2). A "DP" is defined as an active driving period between two contiguous stops in a trip. We used two conjugate variables, "average speed" and "distance" traveled, to describe each DP. Each trip can then be expressed by a series of DPs. By associating to each DP a specific driving event, a "driving cycle profile" (DrCP) representative of the driving condition evolution throughout the trip can be constructed.

A critical step in constructing the DrCP is to classify a driving event for each DP. This is achieved by interpreting the distribution of DPs on an "average speed versus distance" (*V–d*) plot with all trip data collected in the fleet operation. Fig. 3 presents the distribution of DPs derived from the database. This (*V–d*) plot is used as the basis to develop fuzzy logic membership

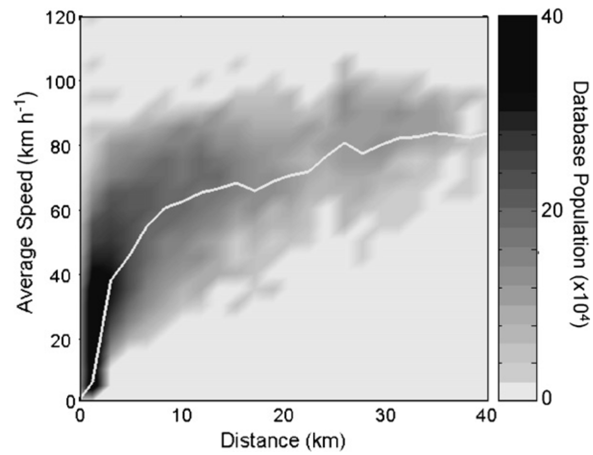

Fig. 3. An average speed vs. distance (*V–d*) distribution plot (resolution: 25 × 25 in full scale).

functions and fuzzy rules to establish a driving event classification scheme using the conjugate variables, i.e., average speed and distance. Fig. 4 depicts this process and the classification of the driving events to construct DrCP. Five specific driving event categories are used in the classification: stop-n-go (SnG), urban (U), suburban (SU), rural (R), and highway (H) driving. This classification scheme is quite comprehensive and intuitive in nature. For instance, when a DP has a low average speed and short travel distance, it implies that driving occurs most likely in a busy street, which we call a "SnG" driving event. Vice versa, if a DP exhibits a high average speed and travels a long distance, we most likely will consider that the driving is taking place on

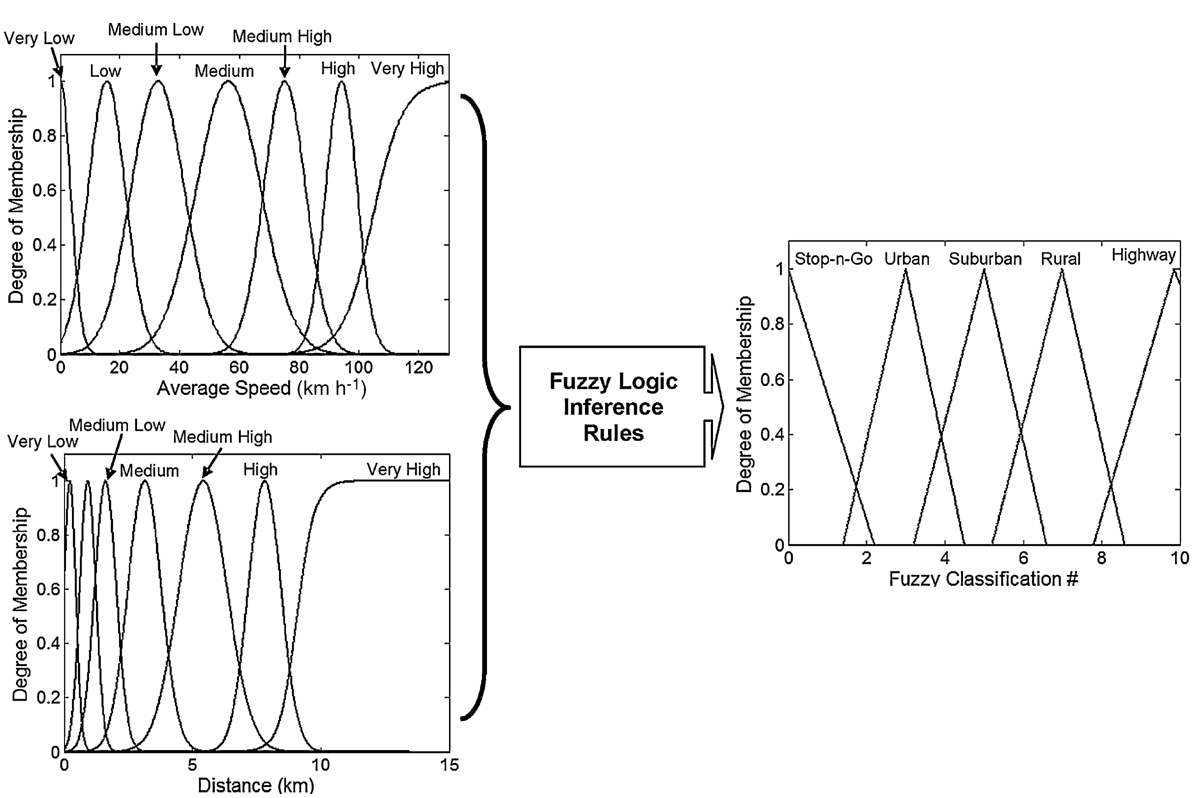

Fig. 4. Fuzzy logic inference system used to classify driving events for DPs.

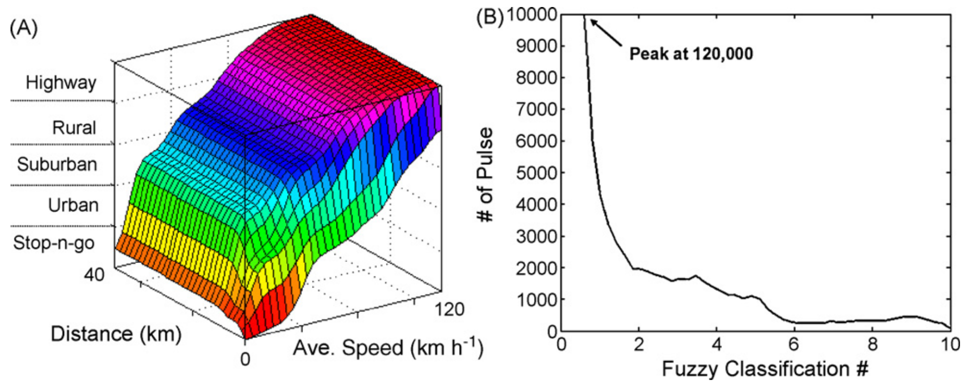

Fig. 5. (A) Driving events classification scheme (B) distribution of DPs as a function of fuzzy classification.

a highway, thus we call this type of driving a "highway" driving event. Using this FL-PR technique, we were able to construct DrCP for each trip in a systematic manner. The fuzzy sets and rules permit certain degree of association for a driving event membership overlapped with the adjacent ones. This capability is different from the traditional numerical analyses in which the classification is more strict and discrete. The fuzzy algorithm allows the expression be handled in a numerical, quantitative manner by a fuzzy classification number (FCN), which is a scale (arbitrarily chosen to be 0–10) to reflect the outcome of the fuzzy sets calculated from the membership functions.

To validate if the fuzzy sets and rules offer proper classification of driving events, we carried out validation by using an initial set of fuzzy rules to analyze a limited set of trip files. The validation was determined by human intercession DP-by-DP and trip-by-trip. If a DP classification was not interpreted properly by the fuzzy rules, the membership functions were modified, and the same intercession repeated again until all interpretations were satisfactory to the intercessor's opinion. Although this interpretation and validation are subjective, yet systematic, we believe that the error margin introduced by the human interpretation will not substantially change the outcome of the discussion. When the rules can interpret driving cycles properly, we then increase the number of trips to examine the accuracy of the rules in making proper driving event classification. Refinement of the rules continues until a proper interpretation of driving cycles among all trips in the database is achieved. Through this iteration and refinement process, a final set of fuzzy rules was created. The interpretation of driving cycles with this mature set of fuzzy rules is shown in Fig. 5(A) where a surface map displays the projection of driving events based on the interpretation of average speed and distance membership functions illustrated in Fig. 4. The surface map shows the interpretation of the five driving events by the FL-PR technique in terms of average speed and distance. Fig. 5(B) shows the distribution of DPs in terms of FCN. This plot is useful to study the constitution of DPs as interpreted by the FL-PR technique, primarily to look into any potential bias that could be introduced by the fuzzy sets. It is reasonable to expect that the distribution of DPs will follow a relatively inverse relationship with FCN, since most of the DPs usually come from a higher frequency of occurrence in the SnG driving in Honolulu, whereas rural and highway driving is less encountered. This is a regional driving cycle characteristic for Honolulu.

From this FL-PR technique and associated DrCP, a driving cycle analysis can be conducted. Fig. 6 illustrates an example using a selected trip, which has a driving cycle with very mixed driving conditions, from SnG to H. It is difficult to analyze this trip with any of the traditional approaches, which usually attempts to classify a trip with an "overall" driving cycle in its entirety. The FL-PR technique, in contrast, using DPs, each with a specific driving event in a compositional DrCP, provides a much more comprehensive expression to allow driving cycle analysis.

It is important to point out that the DrCP can be normalized in percentage of time and distance traveled in a trip. This normalization avoids the incompatibility issue arisen from different durations and distances depicted in various trips, therefore it provides a common basis to allow different trips to be compared on a normalized fashion. The ability to compare different driving cycles side-by-side indeed offers a tremendous merit and utility for vehicle performance analysis (VPA) in real-life operation. Fig. 7 is a good example to illustrate this aspect. Fig. 7(b) represents a driving cycle adopted by the US Environmental Protection Agency (EPA) in the Federal Test Procedure (FTP) [36] as US06 Supplemental FTP Driving Schedule (SFTPDS), which is an aggressive driving schedule with high acceleration. In A plots of both trips, upon normalization with respect to trip duration and distance, the two driving cycles exhibit a high degree of similarity in driving event composition, although their dura-

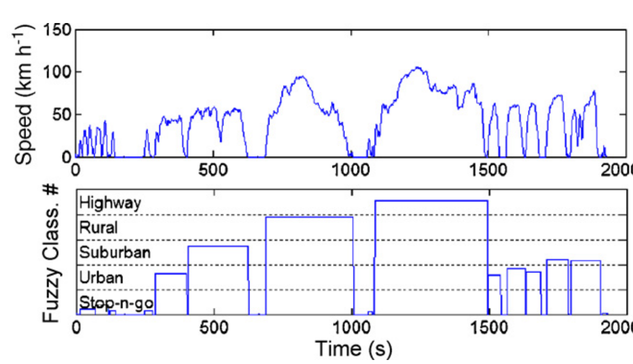

Fig. 6. An example of driving cycle profile (DrCP) using the FL-PR technique.

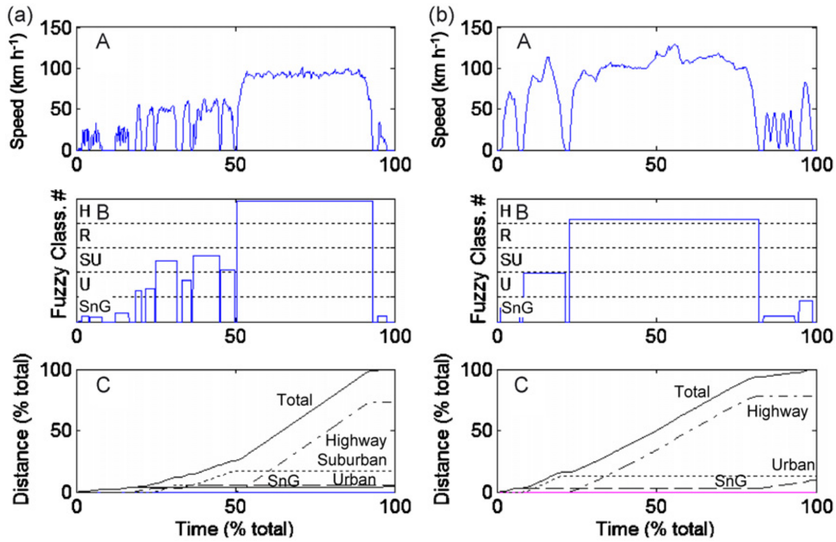

Fig. 7. (a) Trip ID# 31831524 analyzed by the FL-PR technique and (b) US06 Supplemental FTP Driving Schedule [36] using the same technique.

tion and distance are quite different (2361 s versus 600 s, and 34 km versus 13 km, respectively). In B plots, we show the driving cycle analysis using the FL-PR technique. The chronicle sequence of the driving events as shown in the DrCP is different. However, the summary diagrams as shown in C plots, which exhibit the progression of driving events in time and distance, are very similar. The representations shown in A–C plots in the driving cycle analysis using this FL-PR technique are therefore very useful in depicting the similarities and differences among trips, even though they could be different in duration and/or distance that were traditionally difficult to be analyzed and compared. It therefore suffices to say that our analysis provides the following bifurcate aspects:

- Similar to conventional analyses, descriptive statistical information can be derived via the analysis; thus, trip (ID# 31831524) was about four times longer than US06 SFTPDS and was 34 km with an average speed of 62.0 km per hour (km h^{-1}), in contrast to 12.9 km and 83.4 km h^{-1} in US06 SFTPDS;
- We can further yield quantitative summaries detailing the trip as a 73.4% H and 26.5% combined U/SU cycle, in contrast to the US06 SFTPDS with 77.8% H and 22.2% U/SnG driving.

Another useful derivative of the FL-PR technique and the DrCP presentation is that we can afford to examine a vehicle of its performance from a fraction of a trip to the entire service lifetime, on a consistent, normalized basis. This is accomplished by summarizing trip records to compose a summary for a vehicle and to generate daily, weekly, monthly, quarterly, or even lifetime report regarding the vehicle operation with a consistent classification of driving cycles in a systematic manner, as shown in Fig. 8. This summary could be a powerful tool for additional analyses. For example, it can be used for fleet management to assess vehicle usage and operation efficiency of the fleet. It can assess traffic conditions if trips on the same route but at different times can be collected and analyzed. It can be used even for market study if a large fleet and users are involved, so one can study driving habits, vehicle usage, and other aspects statistically. An overall summary of the breakdown of contributions from the driving events at different locations is shown in Fig. 9. The unique driving event distribution in the driving cycle at the HAFB operation is quite visible, especially the much less contribution from highway driving. On the other hand, both C&C and HECO operations have much more commutes that reflect

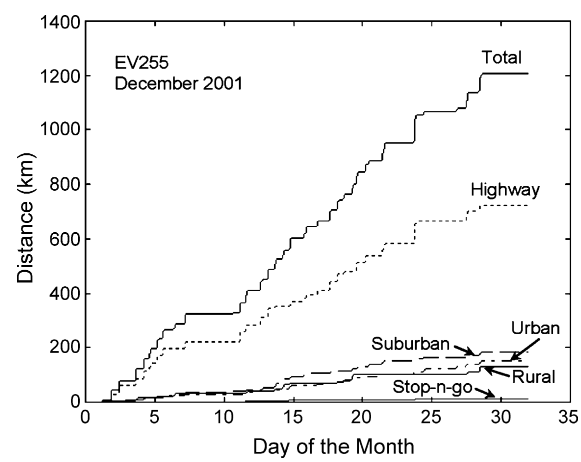

Fig. 8. A monthly DrCP summary report on operation and usage of a BEV.

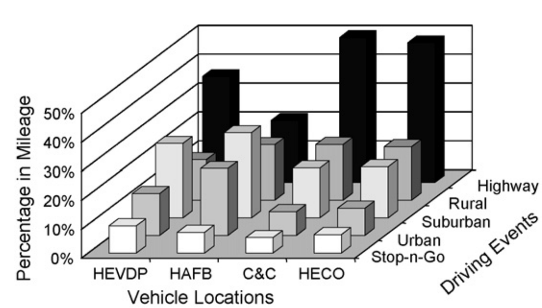

Fig. 9. A breakdown of driving event distribution as a function of location and driving event.

Table 1
Comparison of the usage of vehicle 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 (SnG/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

more highway contributions in their respective driving event distribution.

The driving cycle analysis with the FL-PR technique provides us additional capabilities to study impacts on vehicle and battery performance directly from driving events and vehicle operation at different locations. As an example, in Table 1, we summarize the usage of three vehicles at three different locations for 3 months for comparison. For simplicity, the analysis includes contributions from driving events in two major categories: local (i.e., combined SnG/U/SU) and R/H. Among the three locations, we began to inspect the unique HAFB operation first. In general, the fluctuations in the number of trips vary noticeably among the three locations, and there is no consistent pattern associated with these fluctuations. HAFB operation however consistently has lower mileage, compared with those of the other two. It suggests that the trips made by HAFB are generally much shorter in distance than those by the other two. This observation is consistent with the driving event distribution shown in the next two rows in the table, where HAFB trips are mostly composed of local driving approximately 70–80% versus 12–28% in the C&C and HECO trips.

3.2. Vehicle performance analysis (VPA)

One of the major objectives in conducting driving cycle analysis is to assess vehicle performance. A useful exercise in vehicle performance analysis (VPA) can be achieved by studying “effective force” (EF) for propulsion as a probe to evaluate the effectiveness in energy utilization in vehicle operation. EF is expressed in kWh km^{-1}. We can use EF for VPA through the following process.

Fig. 10 shows the distribution of EF versus driving events (as represented by FCN) of all the DPs in the database. The dispersion of EF in the plot indicates that, as the driving events get closer to local driving (i.e., lower FCN); the distribution of EF becomes more spread out. This is conceivable, as the driving conditions such as traffic or road conditions begin to show increasing impacts on the effectiveness of energy use as expressed by EF at lower FCN. From this plot, a mean EF (MEF) can be calculated by averaging all EF values within an interval of 0.25 in FCN. The resulting MEF curve is shown by the solid line. The MEF is assumed neutral (non-biased) to any driving conditions, including traffic, weather, aerodynamics, driving habit, road conditions (such as grading), if a sufficiently large set of data was used in the calculation. However, Fig. 10 shows that from highway (H, 8 < FCN < 10) to rural (R, 6 < FCN < 8), the MEF remains constant, although the EF distribution becomes more scattered when FCN becomes smaller. From suburban (SU, 4 < FCN < 6) to urban (U, 2 < FCN < 4) then to the majority of stop-n-go (SnG, 0.5 < FCN), the MEF exhibits a steady increase in value as FCN decreases. This behavior reflects the increasing influence of the driving conditions (from traffic, grading, etc.) as posed by the steadily increasing spread of the EF distribution. When the driving comes close to frequent SnG (FCN < 0.5), this influence becomes so profound that the MEF begins to rise in an chaotic manner. It should be cautioned that

- The bell-shape spread in the EF distribution was capped at the low bound limit to zero, therefore the representation may have discounted the contribution from negative values in EF; for example, those originated from DPs in down hill driving.
- The contribution of auxiliary power unit (APU) energy consumptions from instruments and controls, which is continuous and does not result in any driving distance, may have created a biased attribute to the increasing EF value in the low FCN region. It is because these driving events have shorter distance and duration, they may disproportionally take up increasing APU contribution in EF as FCN decreases.

The trend line of MEF observed in Fig. 10 offers some encouraging evidence to support the validity of the FL-PR technique for classification of driving events since the trend of the MEF curve is comprehensible. Even one could question if the membership functions used in the FL-PR technique were subjective, the application of MEF in VPA is still viable. We shall use the following analysis to continue to present some interesting examples.

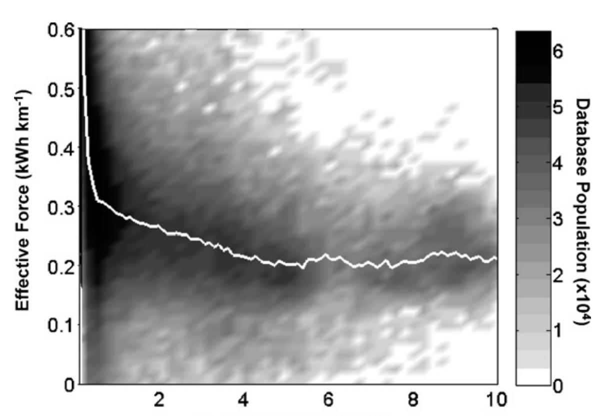

Fig. 10. Effective force (EF) for driving vs. FCN plot, showing how EF varies with driving events (resolution: 50 × 50 in full scale).

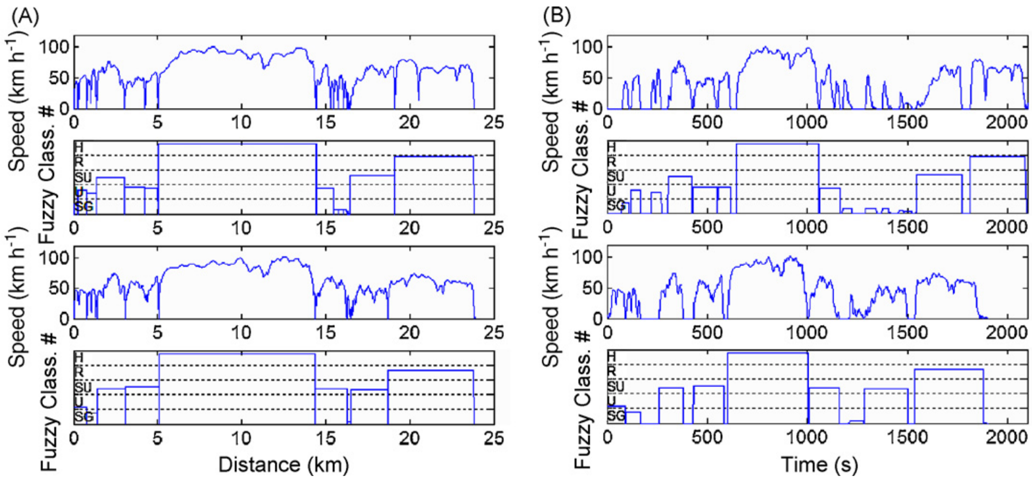

Fig. 11. Two trips of the same route show different traffic patterns and the resulting DrCP. (A) Plots are illustrated in distance. (B) Plots are illustrated in time.

Fig. 11 shows two separate trips of the same route and the respective driving cycle analysis that reflect different traffic patterns. The trip of the upper figures spanned for 2139 s and consumed 6.93 kWh. The trip below took 1907 s and consumed 6.47 kWh. If we can collect a sufficient number of trips of the same route, the traffic patterns for this particular route might be available for analysis and comparison to understand causes that created such patterns, which might depend on time of the day, traffic signal location, grading, etc. In this figure, two different presentations are exhibited. These in column (A) are displayed by distance to provide spatial correspondence. Those in column (B) are illustrated in time to show temporal correspondence. As we can easily observe that because the two trips have different durations, likely due to traffic influence, the plots in column (B) that reflect temporal sequence are not helpful in correlating the two trips. Those in column (A), in contrast, do show better correspondence. We thus prefer to show the trips in distance, instead of duration. Using this spatial presentation, the traffic-induced duration variation was minimized therefore a comprehensive comparison can be made in accord with spatial correspondence. Comparing the two trip profiles in column (A), we make the following observations:

- Certain points of the route can be marked with distinct speed, accelerations/decelerations or stops, which imply that distinct landmarks (traffic lights, intersections, or stop signs) or road conditions (highways exit to city streets) may exist, which dominate the make-up of DP and traffic pattern.
- For the same section of the route, different traffic patterns may induce different DP make-up and driving event classification.

With these essential elements in shaping the traffic in mind, we should point out that a driving event describes a driving condition for the DP. A driving event does not have to match with road type, thus one could drive on a highway; but, with jammed bumper-to-bumper traffic, the driving event might be classified as stop-n-go, similar to driving on a busy downtown street during traffic hours.

Another interesting example is presented in Fig. 12, where round trips for the same route are presented. In this case, the return trip is presented with a reversed spatial coordinate to give proper spatial correspondence. Analogous to Fig. 11, we made the same observations. Thus, disparity in traffic pattern can lead to different DrCP (Fig. 12) and EF values (Fig. 13). As expected, for some sections of the route, where the traffic patterns are substantially different, the corresponding DrCP and EF differ accordingly, as shown in Fig. 13, respectively. For instance, between 3.5 and 8 km in the upper trip (as highlighted by the dashed frame), the driving cycle is very different from that of the reverse trip in the same section. Therefore, the make-up of DPs, the associated DrCP, and EF values show significant disparities. A similar scenario is also observed for the last section of the upper trip (between 18.5 km and the end of the trip), in comparison with the same section of the reverse trip.

The actual EF can also be compared to the MEF for this particular DrCP, as shown in Fig. 13. For example, we examined the section from the beginning of the upper trip to 3.5 km. Within

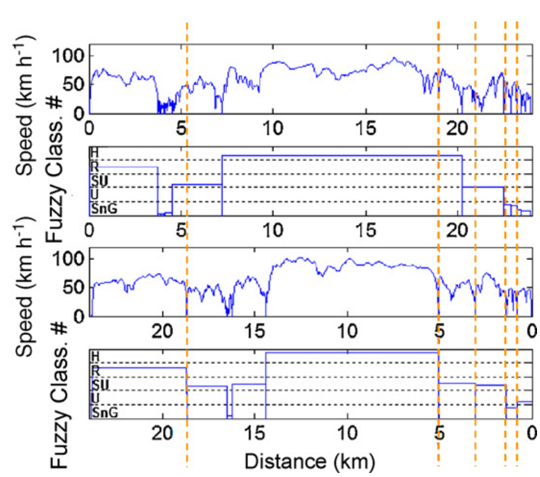

Fig. 12. Driving cycle analysis for a round trip on a commute route. Dashed lines are shown to relate spatial correspondence at certain points in the route.

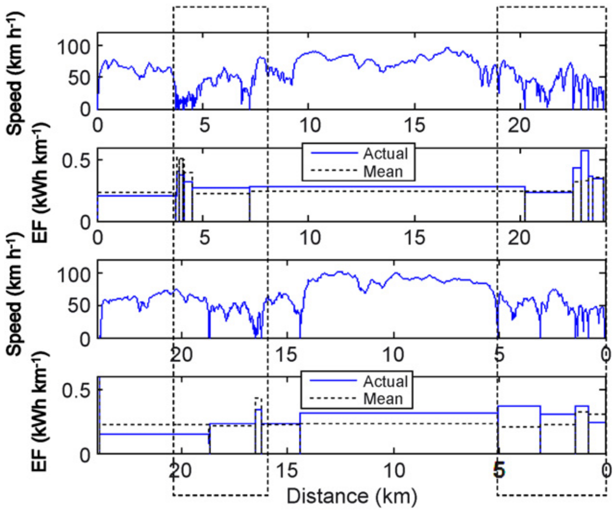

Fig. 13. Vehicle performance analysis of the effective forces (EF) for driving in the round trip showing the actual EF vs. the MEF representing each specific driving cycle. The two dashed frames refer to the two particular sections mentioned in Section 3.2.

this section, both trips exhibit similar DrCP; therefore, we shall expect similar EF in both trips. The actual EFs are not only different, but also different from the MEF associated with this profile. Since in this section both trips have a similar DrCP, we would not expect any disparity due to traffic. The difference observed might come from grading and/or aerodynamic factors, which require further inspection of other relevant information of this particular route. This type of VPA is valuable as evident from our unique driving cycle analysis using the FL-PR technique to make-up DrCP and EF.

3.3. Duty cycle analysis

The aforementioned driving cycle analysis provided us a useful and comprehensive approach to analyze vehicle usage and performance. It is conceivable to use a similar approach to analyze battery usage and performance in real-life operation. Before we describe the methodology of how to analyze duty cycles, it is useful to discuss some semantics regarding duty cycles. Fig. 14 is a representation of a driving cycle and the associated duty cycle in the powertrain operation. In the figure, the motor speed in RPM is shown for this particular driving cycle to illustrate the transient nature and dynamics involved in the powertrain system. Also illustrated is battery pack information, including excursions of capacity, state-of-charge (SOC), and energy profiles side-by-side with corresponding battery pack current, voltage, and power excursion profiles. This representation shows the aggregate behavior of the vehicle and powertrain system in column (A) and in column (B) the transient, dynamic behavior of the powertrain components (motor/controller and battery pack). In a broad sense, we can collectively call the graphs in column (A) driving cycles and column (B) duty cycles for vehicle and powertrain components, respectively.

In the duty cycle analysis for EHV applications, we consider the power excursion profile the most essential to analyze. With a more dynamic nature of the profile, we need to approach the analysis with a different perspective. Similar to the driving cycles, we use a "duty pulse" (DuP) concept as the building block to establish a "duty cycle profile" (DuCP) classification scheme for duty cycle analysis. To analyze duty cycles, we selected a matrix of two conjugate variables: the peak power of each DuP and the number of DuP's per minute to characterize DuCP. These two variables are selected due to the consideration of their importance to battery performance and life. In our consideration, the

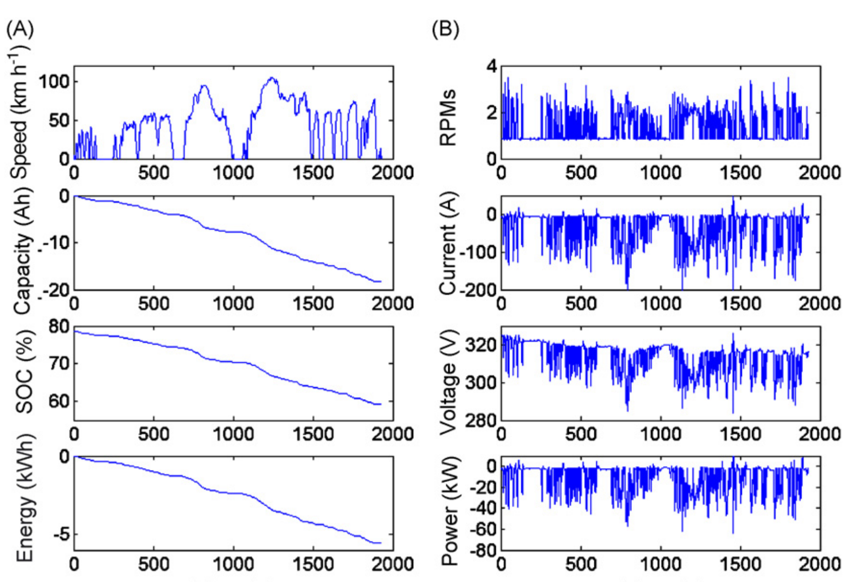

Fig. 14. (A) A driving cycle and the associated battery capacity, state-of-charge and energy consumption profiles, (B) the corresponding duty cycle, RPM, battery pack current, voltage, and power excursion profiles.

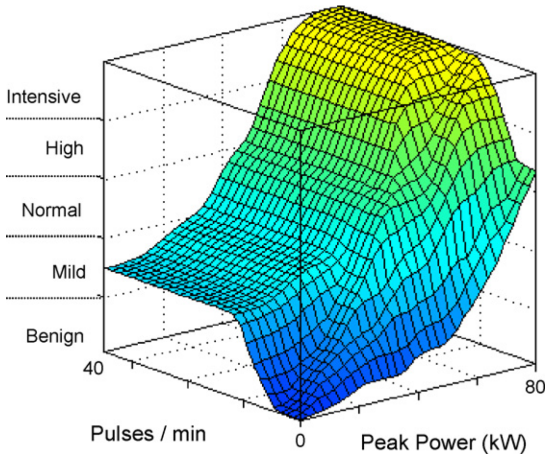

Fig. 15. A duty event classification scheme constructed from a fuzzy logic inference system.

intensity of the peak power and the frequency of DuP occurrence are two primary stress factors affecting battery performance and life. There are other relevant variables; for instance, the average power and energy consumption associated with each DuP that can also be used in duty cycle analysis. It is important to point out the unique relationship between the two "conjugate" variables as we select them. For example, whereas the average speed and distance is a conjugate pair for driving cycle analysis, the distance is an accumulation of speed over the DP duration. Analogously, whereas the average power and energy consumption is a conjugate pair for duty cycle analysis, the energy consumption is a summation of power over the DuP duration. It is conceivable that the average power and energy consumption can also be used as stress factors for assessing battery performance and life. All these conjugate variables can be used in the fuzzy sets via membership associations to classify DuP for DuCP in duty cycle analysis. Using a very similar FL-PR scheme as described in Fig. 4, we developed and constructed an inference system for DuP classification.

The resulting classification for DuP with five levels of description based on peak power and DuP occurrence frequency is shown in Fig. 15. These five DuP descriptions: intensive, high, normal, mild, and benign, are intended for use in defining stress factors for assessing their impacts on battery performance and life. Using this classification scheme, we show an example of duty cycle in a power versus time curve and the resulting DuCP interpretation in Fig. 16. This is the same example that we illustrated for the driving cycle in Figs. 6 and 14.

In light of the driving cycle analysis shown in Fig. 9, an accompanying duty cycle analysis could be quite insightful. It is also useful to make a connection between the two analyses. The following example is an interesting connection between the two. Through the analysis of peak power and DuP occurrence frequency for all DuP, the distribution of DuP with peak power level is summarized in Fig. 17. The figure shows that at low peak power (4–20 kW) HAFB driving exhibits a much higher occurrence percentage in the distribution of DuP in the duty cycle. The HAFB distribution curve also peaks at a lower peak power level (about 9 kW) than the others that peak around 20 kW. It is

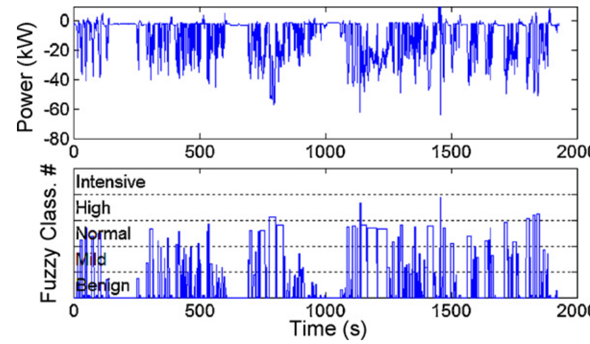

Fig. 16. Power vs. time and duty cycle profile (DuCP) using the FL-PR technique described in Fig. 15.

conceivable that this phenomenon is a reflection of the driving events in conjunction with the speed limit constraints observed at HAFB, as revealed in the driving events distributions shown in Fig. 9 and Table 1. This is a noteworthy case for HAFB, where speed limits on the base resulted in noticeable impacts on the driving events and DuCP.

Another example of making connections between the two sets of analyses is explained next for dependence of energy consumption on driving condition, it is important to recognize the inertial nature of the driving cycle versus the spontaneous and dynamic nature of the duty cycle. It is worth noting that duty cycle may include regenerative braking, which is not a characteristic in driving cycle, but can critically affect battery performance. There are other subtle disparities between duty and driving cycles, which also need attentions in the analysis, a deceleration of the vehicle may corresponds to a period where little power was drawn. This may reflect a situation where the vehicle was slowing down from a relatively high speed, while the energy consumption was nil. If regenerative braking kicked in, the powertrain might actually experience energy gain. Despite these details, a well-behaved correspondence between energy consumption and driving distance can be yielded from the duty cycle analysis. Fig. 18 illustrates this relationship. A linear correspondence between the energy consumption and driving distance is observed, as expected, when all the DPs in the database are compiled to construct this plot. The density plot also reveals the spread of the DP distribution, due to fluctuations in driving condition.

Fig. 19, on the other hand, exhibits the distribution of EF as a function of driving distance. This plot is related to Fig. 10, where EF distribution is plotted against driving events

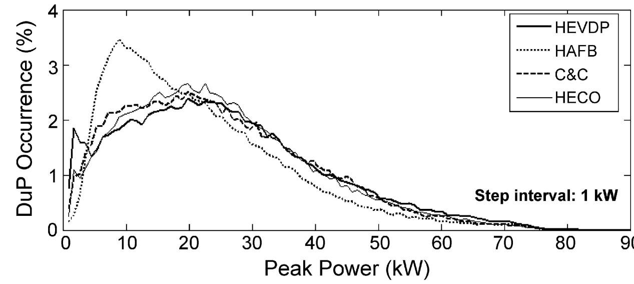

Fig. 17. DuP distribution in terms of peak power level in duty cycle analysis.

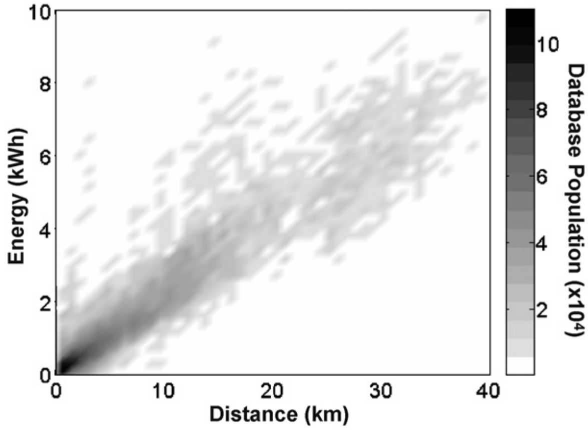

Fig. 18. Energy consumption vs. driving distance plot. The population of DP on this plot is shown by the density scale on the right (resolution: 50 × 50 in full scale).

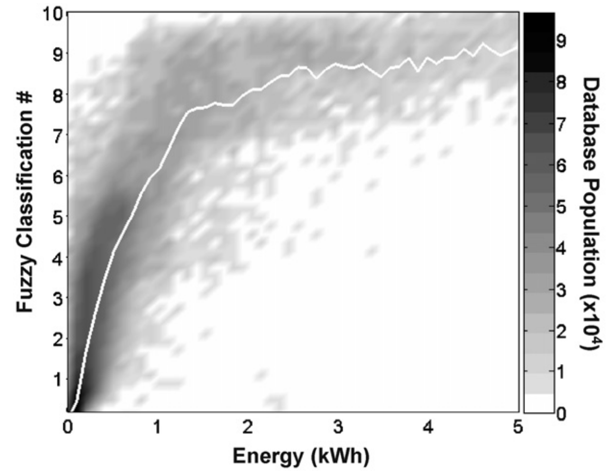

Fig. 20. Energy consumption as a function of driving event distribution (resolution: 50 × 50 in full scale).

(FCN). In Fig. 19, the MEF remains relatively constant (about 0.21 kWh km^{-1}) through the entire range, although the scattering of the EF increases more dramatically as the distance decreases. The same attributes as discussed in Fig. 10 should have contributed to this phenomenon.

Fig. 20 shows a different kind of information as we plot the energy consumption against driving events (FCN). In this plot, as the driving event changes from local (SnG/U/SU) to highway (H) driving, we would anticipate the energy consumption to increase as well. However, the increase is not monotonic. In the local driving, most of the driving events do not engage in long distance driving. Therefore, it is conceivable that the energy consumption will increase with FCN with an accelerated pace. In rural and highway (R/H) driving, the driving distance becomes a critical factor to the amount of energy used. In this case, we shall expect that the energy consumption increases more drastically with distance, a deciding factor in driving event classification for R/H.

Fig. 21 shows the peak power and driving event correspondence. The mean value of the peak power is shown as the solid line. The spread of the power pulses is significant, largely due to driving condition. The correspondence is quite monotonic, as the driving events changes from local to highway driving the peak power also increases, mainly because the demands for acceleration to higher speed occur more frequently.

3.4. Understanding battery performance through vehicle usage profile

The ultimate goal for both driving and duty cycle analyses is to identify key parameters and develop a methodology for probing, assessing, and predicting battery performance and life in real-life situations depending on road condition and driving habit. With our understanding of the bifurcate (inertial versus spontaneous) nature of having driving and duty cycles in our analysis scheme, it seems prudent to take the advantage of this dual characters in the development of the assessment methodology. By considering both short-term fluctuations (in duty cycles) and resulting inertial changes (in the driving cycles) a vehicle usage profile (VUP) can be constructed. A step further, we can construct a complex inference system to characterize and predict the short- and long-term effects of battery performance and life under various operating conditions. An important step in design-

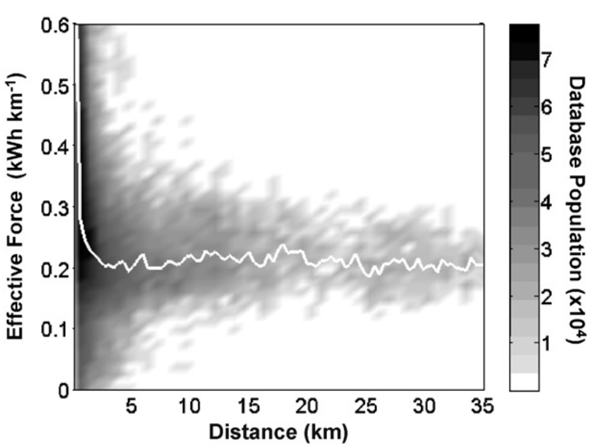

Fig. 19. Distribution of EF as a function of driving distance. The MEF is shown by the white solid line (resolution: 50 × 50 in full scale).

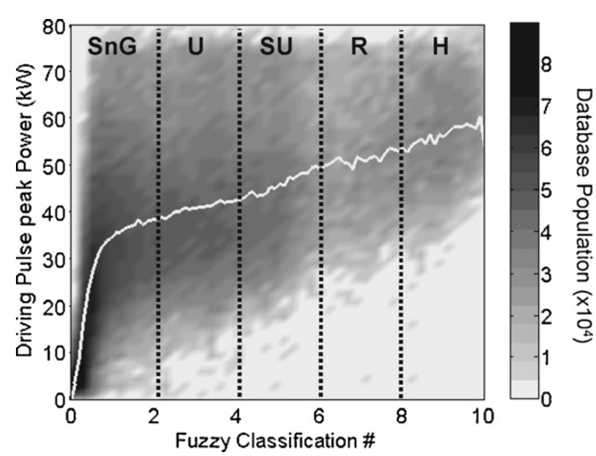

Fig. 21. Distribution of peak power vs. driving events (FCN) (resolution: 50 × 50 in full scale).

ing and developing such an assessment scheme is to identify and define battery stress factors that can allow us properly probe battery behavior and its responses to the usage profile. We can then define this assessment scheme as vehicle usage patterns, so we can directly relate battery performance and life to the operation of the vehicle.

How to define a set of stress factors in assessing battery performance and life is still out in debate. Some earlier work can be found in the literature [37–42]. A recent work by Wenzl et al. [42] attempted to address this issue for storage applications. In our approach, we attempt to take the merits of integrating driving cycle and duty cycle analyses into a consistent classification of battery stress factors and VUP. Through the characterization of DrCP and DuCP, we make a connection between driving-duty cycles and battery stress factors, which will allow us to perform battery modeling and simulation for prediction of performance and life under various operating conditions in real life.

More importantly, we can use both laboratory and field test data to validate predictions from the model simulation, therefore we can bridge the gap of understanding between laboratory and real-life situations. It should be noted that field-testing provides a much broader range and more complex condition and allows us to assess battery performance in a more complicated setting than the laboratory tests. The ultimate goal will be to validate seamlessly real life and laboratory conditions in the simulation, so performance and life prediction will be consistent disregarding the operating setting is real life or not.

The above postulation prompts us to analyze the relationship between DuCP and DrCP more in depth. A simplified scheme can be constructed, for instance, from both of them, to define a battery stress factor and VUP. Fig. 22 exhibits such a classification scheme. This simple scheme can be used to classify combined battery/vehicle usage profiles, based on a similar FL-PR set to construct Fig. 22. Fig. 23 demonstrates how a driving cycle can be transformed into a VUP, from low to aggressive. These five classifications are designed to express their potential impacts on battery behavior. At the present stage, we are still in the process of characterizing how these impacts can be correlated with battery performance degradation.

Fig. 24 presents an overview of the processes involved to assess the VUP. The first process involves the determination of the DrCP for the driving cycle using our unique FL-PR technique to classify driving events, as driving condition changes. Analogously, a similar FL-PR technique was used to characterize the duty cycle into DuCP to assess the power usage in the driving through a succession of duty events. Finally, both driving and duty events have to be combined to express the VUP. We envision combining these three profiles to give the characteristics of the driving pattern of this specific trip.

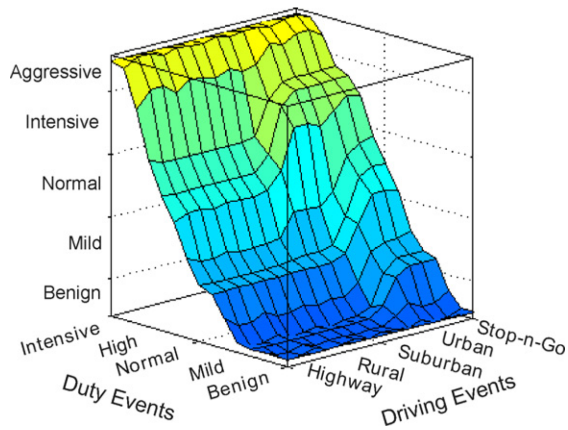

Fig. 22. A battery stress factor and vehicle usage classification scheme based on driving and duty cycle profiles.

4. Future directions

We have illustrated an interesting approach to demonstrate that through simple FL-PR techniques, we created a unique opportunity to analyze driving patterns, including driving and duty cycles and vehicle usage, from data collected from real-life EHV operation. By carefully characterizing driving and duty events, we can compose useful profiles to describe driving and duty cycles via the FL-PR classification schemes. We have used various presentations to show that these analyses indeed provide comprehensive information on the vehicle and battery performance. On the other hand, a series of more careful validation needs to be engaged to reach a consistent interpretation of the results. We continue to progress in this direction to complete the entire analysis with a well-behaved representation within a consistent framework.

We continue to find new relationships to explore and to use the new results to validate what has been discovered so far. The duty cycle analyses and the correlation to quantifiable battery performance degradation are the major focus of our current efforts. We are in the process of understanding and quantifying critical

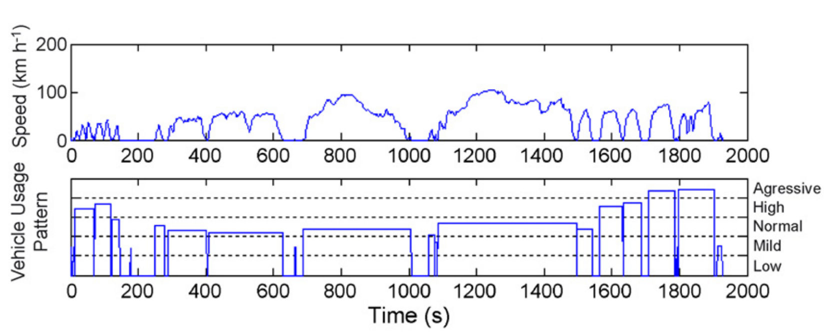

Fig. 23. Classification of vehicle usage profile for a driving cycle.

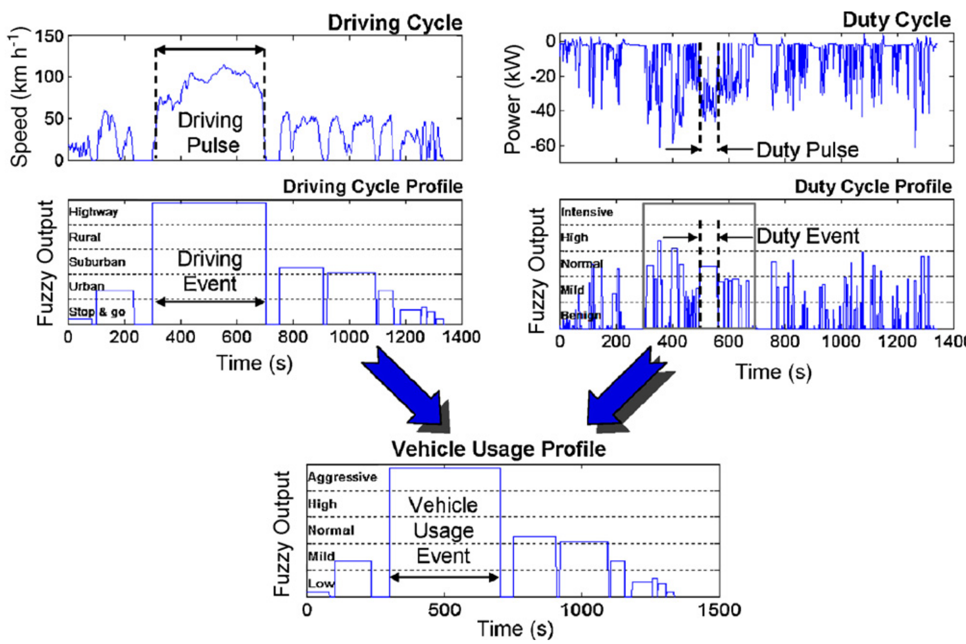

Fig. 24. Illustration of DrCP, DuCP, and resulting vehicle usage profile.

parameters that can be used to define battery stress factors. We are also in the process of establishing quantifiable and reliable techniques to characterize battery performance and degradation, so the matrix of degradation can be correlated with the stress factors. A good example is our recent work using incremental capacity analysis [43–45] to identify and quantify capacity loss for commercial cells in the laboratory tests. We are assessing the validity of using this approach for battery evaluations in the field, with anticipation that real-life data can be collected and used for validation.

Another aspect that we did not elaborate is computer modeling and simulation that can be used to predict battery performance and life. Much progress has been made in this aspect that numerical models for batteries can now be easily integrated with test protocols and laboratory evaluations to yield high fidelity predictions. The models not only can be used to predict battery behavior but also can be deployed to facilitate powertrain control and battery pack management. Most of our recent work [46–49] is primarily focusing on developing such an integrated approach to enable early prediction of battery life for traction and storage applications.

5. Conclusion

To conduct driving or duty cycle analysis using real-life vehicle test data is difficult and challenging. Successful driving cycle analysis, on the other hand, can greatly benefit technology development, as we explained above. We showed that comprehensive driving cycle analysis could be achieved with unique fuzzy logic pattern recognition (FL-PR) technique. The contribution from this FL-PR technique is the ability to construct a driving cycle profile (DrCP) based on percentage time and/or distance traveled. The DrCP 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 effective force for vehicle propulsion (or battery life, which is feasible but not presented herein). This FL-PR approach could be extended to systematically analyze impacts from traffic or road condition, and derive useful vehicle usage information to assist fleet management or battery performance and life prediction. We also showed that we could use this FL-PR technique to analyze duty cycles and identify useful stress factors to define vehicle usage profile that can be used to correlate battery degradation in the future. Our ultimate goal is to use real-life data and laboratory testing to establish a realistic model for battery performance and life prediction.

Acknowledgements

The authors would like to express their gratitude to the U.S. Department of Transportation and the Hawaii Center of Advanced Transportation Technologies (HCATT), previously known as Hawaii Electric Vehicle Demonstration Project (HEVDP), administered by the High Technology Development Corp. (HTDC) of the State of Hawaii, for funding support. Their appreciation also went to Mr. Thomas L. Quinn, Director of HCATT, who is supportive to this work. They would like to thank Hyundai Motor Company of South Korea for significant engineering and technical support of the demonstration project in roadworthy evaluation and on data acquisition system. Special thanks went to Jin Hun Cho, Ki Ho Yoo, Chae Mo Yang, and Jun Hyuck Seo for their instrumental assistance and technical support on the data acquisition system. Many others on the HMC management team, particularly Dr. Chul-Soo Kim, are also much appreciated for their substantial commitment and support. The authors would also like to send their appreciations to Enova Systems, Inc., especially Dr. Don Kang, Todd Martin and a few others, for providing significant contributions to vehicle maintenance and test facility operation. They would also like to express their gratitude to many people in the Hickam Air Force Base, Hawaiian Electric Company, and the City and County of Honolulu, who assisted in the vehicle operation and data collection. In addition, they would like to thank Mr. Carl Perazzola, Michael Mead, and their staff in the U.S. Air Force Advanced Power Technology Office (APTO, Robins Air Force Base, GA) for providing follow-on funding. Finally, they thank all their co-workers, including Keith P. Bethune, Benoit Dailliez, Alea Teeters, Morgan Bonnet, and Eloi Beaudrouet for their contributions to the success of the data collection and analysis.

References

[1] E. Ericsson, Transportation Res. Part D 5 (2000) 337–354.
[2] E. Ericsson, Transportation Res. Part D 6 (2001) 324–345.
[3] F. An, M. Ross, Society of Automotive Engineers (SAE) Technical Paper 930328, 1993.
[4] F. An, M. Barth, G. Scora, Society of Automotive Engineers (SAE) Technical Paper 972646, 1997.
[5] F. An, M. Barth, Society of Automotive Engineers (SAE) Technical Paper 981902, 1998.
[6] F. An, F. Stodolsky, D. Santini, Society of Automotive Engineers (SAE) Technical Paper 1999-01-2929, 1999.
[7] M. Barth, M. Todd, Transportation Res. Part C 7 (1999) 237–259.
[8] H.Y. Tong, W.T. Hung, C.S. Cheung, Atmos. Environ. 33 (1999) 2323–2335.
[9] K.L. Butler, M. Ehsani, P. Kamath, IEEE Trans. Vehicular Tech. 48 (1999) 1770–1778.
[10] Z. Rahman, K.L. Butler, M. Ehsani, Society of Automotive Engineers (SAE) Technical Paper 1999-01-1151, 1999.
[11] J.Q. Hansen, M. Winther, S.C. Sorenson, Sci. Total Environ. 169 (1995) 129–139.
[12] C. Young, M. Smith, T. Younglove, M. Barth, Proceedings of the 10th CRC On-Road Vehicle Emissions Workshop, San Diego, CA, 2000.
[13] N. Dembski, Y. Guezennec, A. Soliman, Society of Automotive Engineers (SAE) Technical Paper 2002-01-0069, 2002.
[14] M. Ergeneman, C. Sorusbay, A. Goktan, Int. J. Vehicle Des. 18 (1997) 391–399.
[15] J.H. Kent, G.H. Allen, G. Rule, Transportation Res. 12 (1978) 147–152.
[16] D.J. Simanaitis, Automotive Eng. 85 (1977) 34–43.
[17] M. André, Sci. Total Environ. 334–335 (2004) 73–84.
[18] J.-H. Tsai, H.-L. Chiang, Y.-C. Hsu, B.-J. Peng, R.-F. Hung, Atmos. Environ. 39 (2005) 6631–6641.
[19] K.J. Kelly, A. Rajagopalan, Benchmarking of OEM Hybrid Electric Vehicles at NREL, NREL/TP-540-31086, National Renewable Energy Laboratory, August 2001.
[20] K.J. Kelly, M. Mihalic, M. Zolot, Presented at the 17th Annual Battery Conference on Applications and Advances, Long Beach, California, January 14–18, 2002, 2002 (NREL/CP-540-31306).
[21] J.C. Bezdek, S.K. Pal (Eds.), Fuzzy Models for Pattern Recognition, IEEE Press, New York, 1992.
[22] S. Mitra, S.K. Pal, Fuzzy Sets Syst. 156 (2005) 381–386.
[23] S.A. Kalogirou, Prog. Energy Combust. Sci. 29 (2003) 515–566.
[24] R.J. Kuo, Eng. Appl. Artif. Intell. 13 (2000) 249–261.
[25] M.B. Gorzalczany, Inform. Sci. 120 (1999) 69–87.
[26] P. Billaudel, A. Devillez, G. Villermain Lecolier, Int. J. Approx. Reason. 20 (1999) 1–20.
[27] P.K. Modi, S.P. Singh, J.D. Sharma, Eng. Appl. Artif. Intell. 20 (2007) 481–491.
[28] C.H. Cai, D. Du, Z.Y. Liu, Poster Presentation at the IEEE International Conference on Fuzzy Systems, St. Louis, 2003.
[29] S. Piller, M. Perrin, A. Jossen, J. Power Sources 96 (2001) 113–120.
[30] C.C. Chan, E.W.C. Lo, W.X. Shen, J. Power Sources 87 (2000) 201–204.
[31] P. Singh, C. Fennie, U.S. Patent 6,011,379, January 4, 2000.
[32] P. Singh, R. Vinjamuri, X. Wang, D. Reisner, J. Power Sources 162 (2006) 829–836.
[33] B.Y. Liaw, K.P. Bethune, C.S. Kim, Proceedings of the 19th Electric Vehicle Symposium (EVS-19), Busan, Korea, October 13–17, 2002.
[34] B.Y. Liaw, J. Asian Electric Vehicles 2 (2004) 551–556.
[35] M. Dubarry, M. Bonnet, B. Dailliez, A. Teeters, B.Y. Liaw, J. Asian Electric Vehicles 3 (2005) 657–663.
[36] U.S. Environmental Protection Agency (EPA), 2006. <http://www.epa.gov/otaq/emisslab/methods>.
[37] K. Takei, K. Kumai, Y. Kobayashi, H. Miyashiro, N. Terada, T. Iwahori, T. Tanaka, J. Power Sources 97–98 (2001) 697–701.
[38] PNGV Battery Test Manual, Revision 2, Idaho National Engineering Laboratory, US Department of Energy, DOE/ID-10597, August 1999.
[39] D.P. Abraham, J. Liu, C.H. Chen, Y.E. Hyung, M. Stoll, N. Elsen, S. MacLaren, R. Twesten, R. Haasch, E. Sammann, I. Petrov, K. Amine, G. Henriksen, J. Power Sources 119–121 (2003) 511–516.
[40] J. Shim, R. Kostecki, T. Richardson, X. Song, K.A. Striebel, J. Power Sources 112 (2002) 222–230.
[41] A. Urbina, T.L. Paez, R.G. Jungst, B.Y. Liaw, J. Power Sources 110 (2002) 430–436.
[42] H. Wenzl, I. Baring-Gould, R. Kaiser, B.Y. Liaw, P. Lundsager, J. Manwell, A. Ruddell, V. Svoboda, J. Power Sources 144 (2005) 373–384.
[43] M. Dubarry, V. Svoboda, R. Hwu, B.Y. Liaw, Electrochem. Solid-State Lett. 9 (2006) A454–A457.
[44] M. Dubarry, V. Svoboda, R. Hwu, B.Y. Liaw, Capacity Loss in Rechargeable Lithium Cells during Cycle Life Testing: The Importance of Determining State of Charge, Journal of Power Sources (2007), doi:10.1016/j.jpowsour.2007.06.185.
[45] M. Dubarry, V. Svoboda, R. Hwu, B.Y. Liaw, J. Power Sources 165 (2007) 566–572.
[46] R.G. Jungst, G. Nagasubramanian, H.L. Case, B.Y. Liaw, A. Urbina, T.L. Paez, D.H. Doughty, J. Power Sources 119–121 (2003) 870–873.
[47] B.Y. Liaw, R.G. Jungst, G. Nagasubramanian, H.L. Case, D.H. Doughty, J. Power Sources 140 (2005) 157–161.
[48] M. Dubarry, B.Y. Liaw, Development of a Universal Modeling Tool for Rechargeable Lithium Batteries, Journal of Power Sources (2007), doi:10.1016/j.jpowsour.2007.06.157.
[49] M. Dubarry, V. Svoboda, R. Hwu, B.Y. Liaw, A Roadmap to Understand Battery Performance in Electric and Hybrid Vehicle Operation, Journal of Power Sources (2007), doi:10.1016/j.jpowsour.2007.06.237.