Analysis of Electric Vehicle Usage of a Hyundai Santa Fe Fleet in Hawaii

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Abstract
Here we report the analysis of vehicle usage of a fleet of 15 Hyundai Santa Fe electric-sport-utility-vehicles (e-SUVs), which was tested in Honolulu, Hawaii, from July 2001 to June 2003. The 15 vehicles were dispatched to the Hickam Air Force Base (HAFB), City and County (C&C) of Honolulu, Hawaiian Electric Co. (HECO), and the Hawaii Electric Vehicle Demonstration Project (HEVDP) office for field evaluation. More than 25,000 trips were recorded using on-board data acquisition systems in all vehicles during the two-year period, representing a total driving distance of more than 255,000 km. We used a systematic approach to conduct driving cycle analysis (DCA) from the second-by-second trip data. Detailed breakdown of the driving cycles in terms of driving patterns was generated and summarized as functions of vehicle operating time and mileage for each vehicle over the evaluation period. In this paper, we illustrate how to analyze the vehicle usage from such a DCA and the real-life data in the database. The vehicle usage analysis (VUA) includes frequency and extent of vehicle operation in addition to the DCA. We intend to correlate vehicle performance via DCA and VUA for comparison among different operating organizations to allow us develop a more effective fleet operation in the future.

Keywords
driving cycle analysis, fleet operation, field testing, vehicle usage analysis, on-board data acquisition

1. INTRODUCTION
Vehicle usage analysis (VUA) is very useful and critical to the understanding of fleet operation efficiency, and it can also improve experience with electric vehicle (EV) operation. Such an analysis is typically conducted using statistical methods (e.g., [Weijer, 1997; Riemersma et al.; Kelly et al, 2001; Frey et al., 2002]). The statistical approach often lacks the utility that can correlate among events to provide time-dependent and intuitive understanding of the consequence in performance from sequential events of vehicle operation. It is also limited by its inability to conducting detailed driving cycle analysis (DCA), especially those in the real-life operation, or to providing a comprehensive comparison among individual events on a common basis.

Recently, we have developed a unique approach [Liaw et al., 2002; Liaw, 2004] to allow detailed DCA. The advantage of our approach is the ability to systematically breakdown the trip into sections of sequential driving periods, which we called “driving pulses,” that permit us to recognize a unique driving pattern associated with each pulse. Each driving pulse is defined as an active driving period between two subsequent stops. The average speed and distance driven between the two stops were calculated for each driving pulse. Using the average speed and distance driven of each pulse for all the pulses recorded in the database, we then constructed a dispersion plot to reveal the distribution of the average speed and driving distance in the collection of driving cycles. From such a dispersion plot, we used a unique fuzzy logic technique to recognize the driving pattern for each pulse. By doing so, we were able to summarize a trip with a series of pulses, each associated with a unique driving pattern. We called this type of expression of trip information in a graphic format a “trip composition,” which displays the sequential variation of driving patterns with the time and distance traveled.

The trip composition can be normalized to represent the driving pattern changes with respect to percentage of traveling time or distance. In this fashion, we demonstrated that any trip could then be compared side-by-side with other trips or standard driving schedules analyzed with the same fuzzy logic technique to reveal their similarity or difference in the driving cycle.

We can further summarize the trip composition for a vehicle over a certain period of time to yield a historical summary of how the vehicle was driven daily, weekly, monthly, yearly, or over its lifetime. This is the basis for extending the analysis of vehicle usage from single trip to the entire service life of operation of the vehicle. This capability will enable us to conduct a life cycle analysis (LCA) of vehicle performance with its usage pattern, thus impacts from various driving conditions in the active driving regime can be derived. Furthermore, the trip composition summary provides a common basis for side-by-side comparison based on operating conditions, vehicle operators and their driving habits, locations, or usage patterns.

In extension to the active driving regime, we believe that an effective evaluation of the electric vehicle use and its performance needs to include periods when the vehicle is on standby or when the battery is being charged. This approach is useful and important in the usage pattern analysis, because, for instance, under-the-shade or under-the-sun parking may lead to quite different thermal cycles that could affect battery performance. Therefore, the extent and frequency of the off-duty periods, both on standby and charging, will induce various impacts on the vehicle performance. To analyze these impacts from the standby and charging regimes, we think that, via statistical analysis in combination with the fuzzy logic approach, we can recognize vehicle usage patterns, in addition to the driving patterns, to facilitate and enable such an impact analysis. We began to pay attention to factors such as the percentage of time in use, frequency and extent of battery charging, etc., that could be used as key parameters to correlate with the vehicle performance. The correlation, for example, between battery life or energy utilization efficiency, with the vehicle driving and usage (including battery charging) patterns, can thus be derived.

This approach is unique and will be beneficial to future EV development and operation. We perceive that the potential benefits could include the developments of (1) a systematic analytical tool for engineers and vehicle developers to understand vehicle performance data collected in the real-life conditions, (2) a validation tool to allow evaluation of vehicle performance with data from the field testing, (3) a market analysis tool to afford assessment of vehicle design and performance from information collected in the field evaluation, and (4) a simulation tool to allow modeling of "what if" scenarios with a reliable engineering model to assess impacts from various real-life attributes, such as driving condition, driver habit, and the utilization of battery charging infrastructure. Vehicle performance analysis and fleet management will benefit greatly from this unique approach.

In this paper, we used a few illustrations with data collected in the field evaluation of the 15 electric-sport-utility-vehicles (e-SUV) fleet to demonstrate the feasibility of this unique approach and its applicability to other possible analyses and correlations.

2. DATA COLLECTION AND ANALYSIS

Fifteen e-SUVs, each equipped with a Panasonic nickel metal hydride (Ni-MH) battery pack and an Enova 60 kW Panther drivetrain, were prototyped by Hyundai Motor Company (HMC) in South Korea. The 15 vehicles were delivered to Honolulu, Hawaii, in July 2001, for a two-year field evaluation and demonstration under a Hawaii Electric Vehicle Demonstration Project (HEVDP), now HCATT, program. The vehicles were dispatched to the Hickam Air Force Base (HAFB), City and County of Honolulu (C&C), Hawaiian Electric Company (HECO), and HEVDP's office for field testing and operation. Each vehicle is equipped with an on-board data logger (see Figure 1), which communicates with the power control unit (PCU) and battery management unit (BMU) on the vehicle to log data in a second-by-second interval. Periodically, typically every two weeks or so, the data stored on the logger were transferred to a laptop computer for processing and uploading to the database in the laboratory for further analysis. Both trip and charging data were collected, including detailed data from the drivetrain and battery modules.

Fig. 1 Hyundai Motor Company's Santa Fe e-SUV and the onboard data logger used for data acquisition.

The data collected are summarized from the middle of July 2001 to June 2003, including more than 160,000 miles (255,000 km) and 25,000 trips. In our first year of effort, we focused on developing the DCA technique to analyze trip data. We developed a systematic approach [Liaw et al., 2002; Liaw, 2004] to analyze driving cycles using a fuzzy logic driving pattern recognition (FL-DPR) technique to characterize a trip with a compositional breakdown. More detailed description of the FL-DPR approach was reported in [Liaw et al., 2002; Liaw, 2004] and will not be repeated here. This approach allows us to analyze vehicle performance in a detailed manner, different from any conventional statistical analysis. For example, we were able to correlate different driving patterns with driving efficiency using the data collected in the field, unlike traditional approaches that have to rely on standard driving schedules using dynamometer testing. More interestingly, we can reveal variations from such a correlation in a trip data to show how different driving conditions affect the vehicle performance.

In this paper, we combined statistical analysis with our

FL-DPR technique to reveal and interpret how vehicle performance is related to vehicle operation under different conditions by the four organizations in the program. We correlated the vehicle performance to the usage and operating conditions to reveal the association of the usage patterns to vehicle performance.

3. RESULTS AND DISCUSSION

3.1 Fleet operation

Figure 2 summarizes the average mileage per month accumulated by each operating organization in the evaluation period. The patterns of operation in each organization varied through the entire period, revealing vehicle availability and/or change of usage patterns in each organization. In the months of March and June 2002, low mileage was recorded since most of the vehicles were called in for detailed testing and calibration with dynamometer and battery tester, and for maintenance and correcting problems with some parts and components. After March 2003, vehicles began to be called back for the final detailed testing and preparation for returning to HMC in Korea.

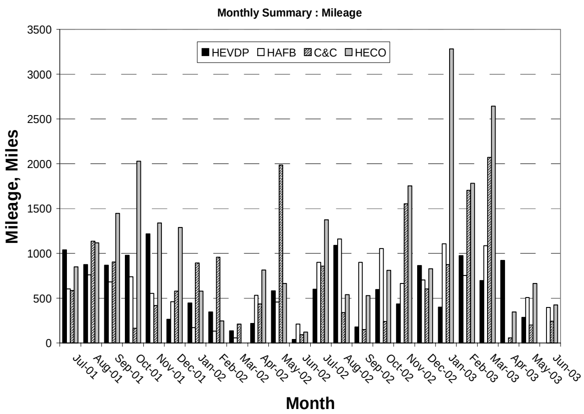


Fig. 2 Monthly summary of the average mileage driven in each organization during the test period.

Figure 3 reveals the monthly average number of trips made in each organization during the test period. Most of the mileage and trips were recorded by C&C and HECO, because the vehicles were primarily used by drivers that commute and operate the vehicles during the office hours. HAFB uses the vehicles primarily during the office hours for security patrol on the base and errands. HEVDP uses the vehicles usually for errands and occasionally for commute. As such, the trips made by C&C and HECO usually have more highway and rural driving mileage, in contrast to HEVDP and HAFB, which have more mix of short highway, urban and city driving patterns. In addition, HAFB trips are often constrained by the low speed limits on the base, thus slow in nature. The HEVDP trips are sporadic in nature due to irregular, spontaneous schedule of errands, occasionally mixed with commute trips. The diversity of the usage provides us an assembly of data with a wide range of operating conditions for comparison. Nonetheless, due to the unique geographical aspect of Honolulu on the island of Oahu, the driving habit of the drivers presumably is different (regardless of personality) from those of other geographic regions, which would induce local mix and, possibly, constraints, directly or indirectly, on the trip composition, as well as on the driving patterns. We believe that it is worth noting for the "Honolulu driving." Figure 4 summarizes the monthly average number of trips and accumulated hours of operation by each organization over the entire test period. HAFB achieved the highest average number of trips (215 trips per month), followed by HECO (170 trips per month). On the other hand, HECO has the highest average operation time; 44.89 hrs per month, followed by HAFB with 34.82 hrs per month. C&C made 115 trips and 28.61 hrs on average. HEVDP had 134 trips and 28.89 hrs, respectively. From Figure 4, we can derive the average trip duration

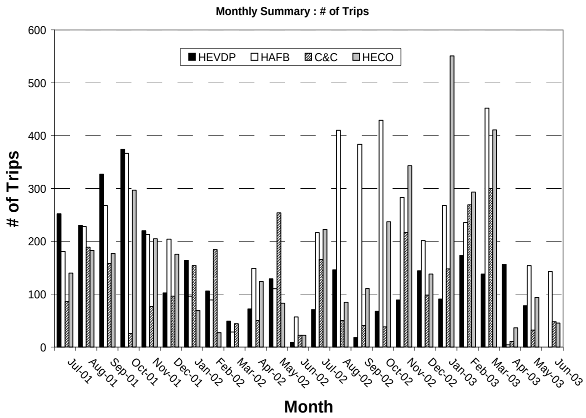


Fig. 3 Monthly summary of the average number of trips made in each organization in the test period.

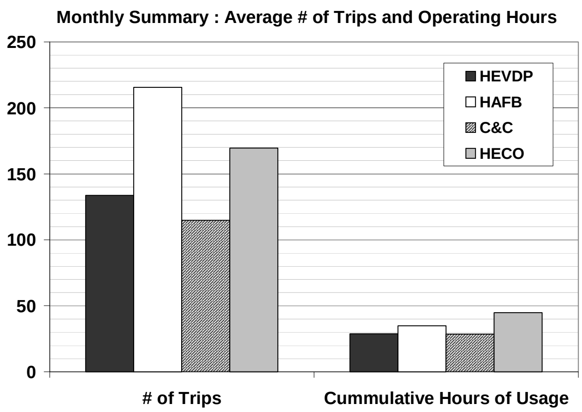


Fig. 4 Averaged number of trips and accumulated hours of operation per month achieved by each organization during the entire test period.

for each operating organization. From the monthly average mileage (later on in Figure 12), we can also derive the average trip distance. The results are shown in Figure 5. On average, HAFB trips are considerably shorter than those of the other three. This difference might be due to the nature of the trips made by HAFB, which are mostly for security patrol on a fixed route on the base. Typical trip duration is about 10-20 minutes, which is also typical for "Honolulu driving."

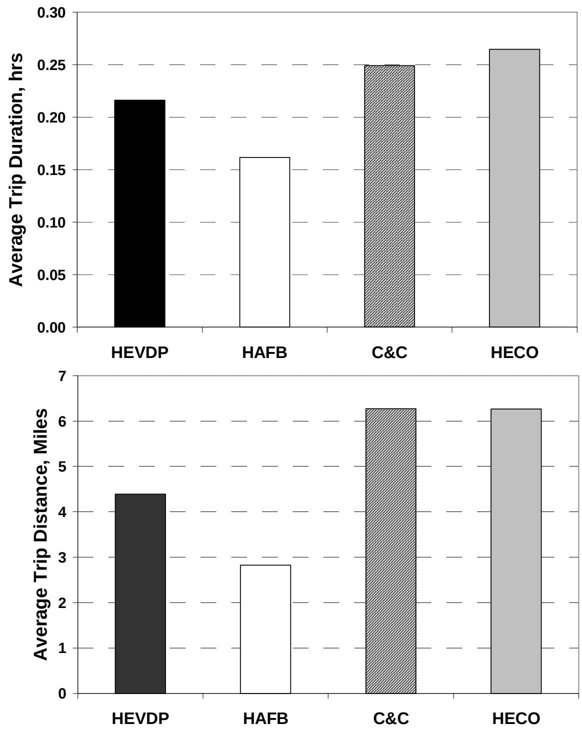


Fig. 5 Average trip duration and distance made by each operating organization over the test period.

3.2 Charging practice

In Figure 6, we show the monthly summary of number of charges by each organization during the evaluation period. The number of charges, in general, falls and rises with the number of trips and mileage; therefore, follows similar trends in Figures 2 and 3. It should be noted that the number of charges represents the frequency the on-board charger was plugged into the power outlets. It does not imply how many times the battery pack is being fully recharged. This is part of the issues need to be addressed to quantify how the charging infrastructure is being used and as part of the usage patterns of the vehicle operation.

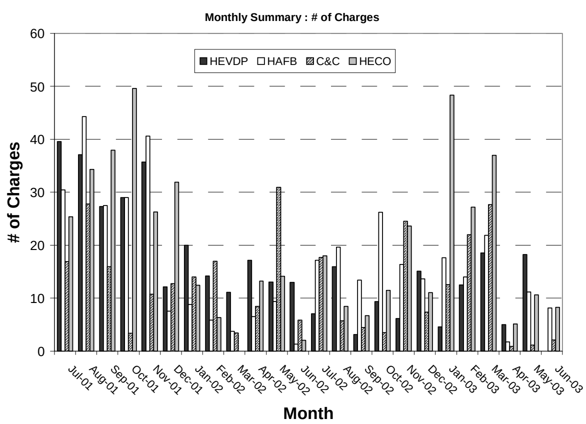


Fig. 6 Monthly summary of number of charges by each organization during the test period.

Figure 7 displays the monthly average number of charges and accumulated hours of charging performed by each organization. The average number of charges performed by HEVDP and HECO (each has three vehicles) suggests that the users plugged in for opportunity recharge for each vehicle at a frequency once 1-2 days in their charging practice. The number of charges and charging duration observed in C&C (27.13 times per month and 12.4 hrs, three vehicles) and HAFB (43.3 times per month and 16.5 hrs, 6 vehicles) are noticeably lower than the other two (e.g., versus HECO's 49.50 times per month and 19.6 hrs, respectively, the highest among all), suggesting that they did not charge the battery as frequently as the others, and about once every 2-4 days. Therefore, all four operating organizations practiced very differently in utilizing vehicles and charging infrastructure.

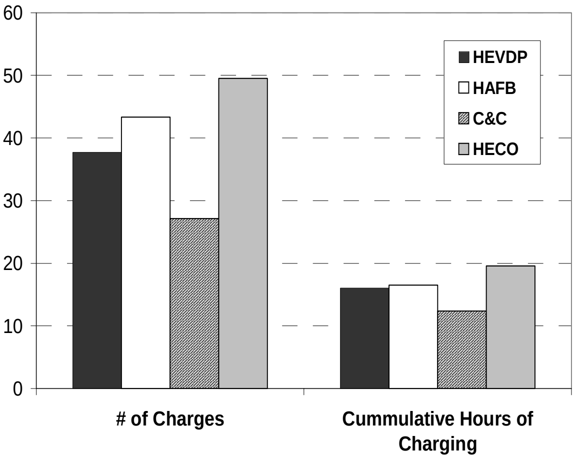


Fig. 7 Monthly average number of charges and accumulated hours of charging by each operating organization.

Disparity in the charging practice and vehicle operation is further observed in Figure 8. Three attributes are used for comparison: the average charge duration, the ratio of the charge duration against operating hours, and the number of trips made per charge. HEVDP led the charge duration versus operation time ratio (0.555), and with a longer average charge duration (0.425 hrs) and lower number of trips per charge (3.54), indicating that they tended to leave the vehicles in recharge more and use

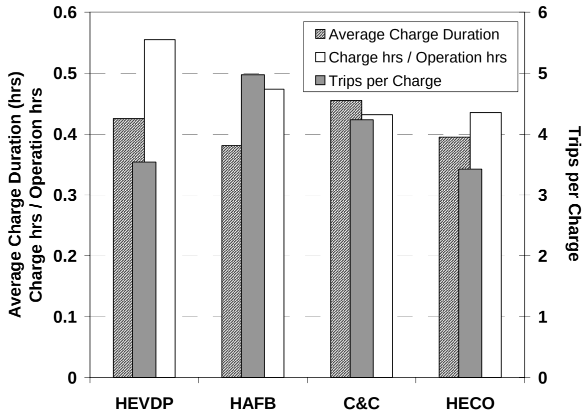


Fig. 8 Average charge duration, the ratio of charge time versus accumulative operating hours, and the number of trips made per charge performed by each operating organization.

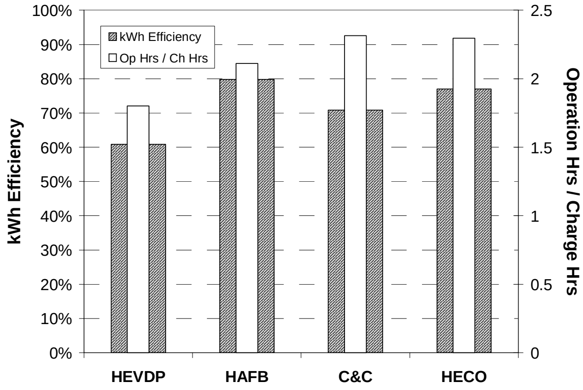


Fig. 9 The percentage of kWh consumed in vehicle driving versus the kWh provided in the charging (kWh efficiency) and the ratio of operation hours versus charging time in each organization.

the vehicle less than the others. HAFB's charge duration is the lowest (0.381 hrs) among the four, but with the highest number of trips per charge (4.97), and a moderate ratio of charge time versus operation hours (0.474), indicating that HAFB tended to frequently use the vehicle for short trips (also suggested in Figures 4 and 5). C&C has the longest average charging duration (0.456 hrs) and the lowest ratio of charging time versus operation (0.432), with a good number of trips per charge (4.23), indicating that C&C operated the vehicles frequently with longer trips (Figure 5), mostly for commutes, and did not charge often (Figure 7); but, when the vehicle was in charging, it dwelled in long recharges (Figure 8). On the other hand, HECO used the vehicles with the least number of trips per charge (3.43), with moderate charge duration (0.395 hrs) and a relatively lower charge versus operation ratio (0.436). HECO operated vehicles often for long trips (Figures 4 and 5), and with frequent recharge (Figure 7); however, the long duration of trips resulted in fewer trips between recharge (Figure 8).

The diversity in fleet operation, vehicle usage, and charging practice results in variations of impacts on vehicle performance. An example is shown in Figure 9, where the kWh efficiency (i.e., the percentage of the kWh consumed in driving versus the kWh used in charging) and the ratio of accumulative hours of operation against the charging duration are displayed for each organization. We found the following aspects worth noting: First, the trend in the figure seems to suggest that the higher the operation versus charging time ratio, the better the kWh efficiency; which might explain why HEVDP's usage pattern (e.g., partially due to attributes in Figure 8) resulted in a lower kWh efficiency. In addition, the correlation between charging practice, as revealed in Figure 7, and the kWh efficiency is stronger than the relation between operation (Figure 8) and the kWh efficiency. Thus, the practice of less-frequent-charging and more-frequent-use in driving employed by HAFB and HECO tends to give better kWh efficiency.

This result might suggest that by minimizing self-discharge loss during the standby idling and by avoiding inefficient trickle charging (i.e., minimizing kWh loss due to the gas recombination) in long charging duration (Figure 8) - two major shortcomings often experienced with the Ni-MH battery systems, the HAFB and HECO's style of operation could lead to better efficiency. This aspect is better illustrated in Figure 10, where the kWh for operation and charging per hour are displayed. The kWh energy consumption under different driving conditions did not introduce too much variation in the overall kWh consumption in operation. HAFB's consumption is however slightly higher than the others. The charging practice in C&C was, surprisingly, consuming more

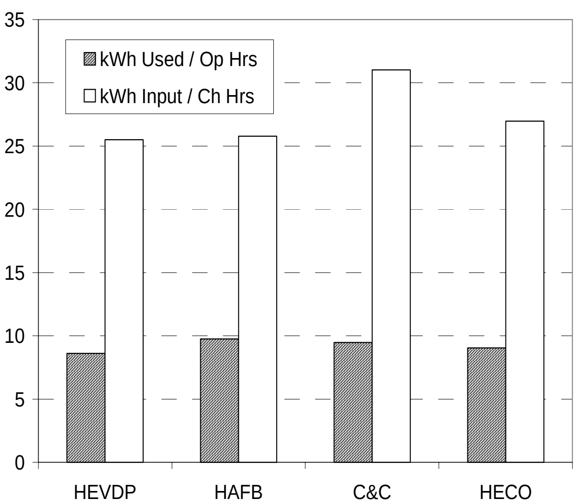


Fig. 10 The kWh energy used per operating hour and the kWh energy input per charging hour exercised by each organization.

kWh per charging hour, which is probably due to a longer trickle charging. This result might have undermined the kWh efficiency (Figure 9) for C&C.

Figure 11 shows the analysis of the monthly average use of kWh input and output in each organization. Interestingly, the subtle difference in charging practice exercised by HEVDP and C&C versus HAFB and HECO, as discussed in Figure 7, also reflects a similar subtleness in Figure 11 between the two groups of practice. Although the data in Figure 11 may have shown a direct influence on the results of Figure 9, the presentation illustrates the benefit from the practice of charging by HAFB and HECO, which achieved a more effective use of the kWh energy than the other two. HAFB and HECO did not plug in for charging as often as the other two until the capacity of the pack was low. As a result, a higher kWh efficiency was achieved.

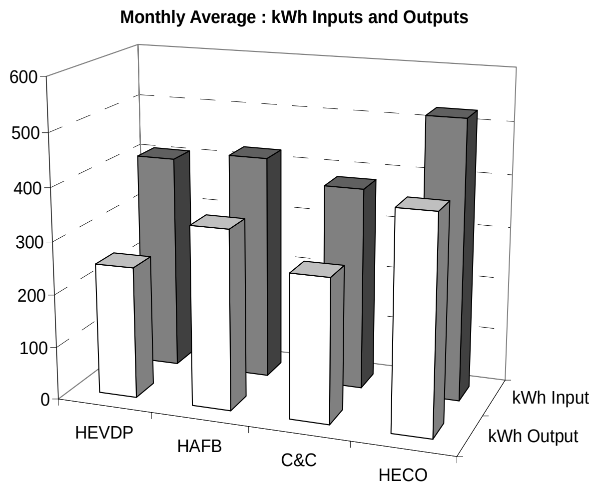
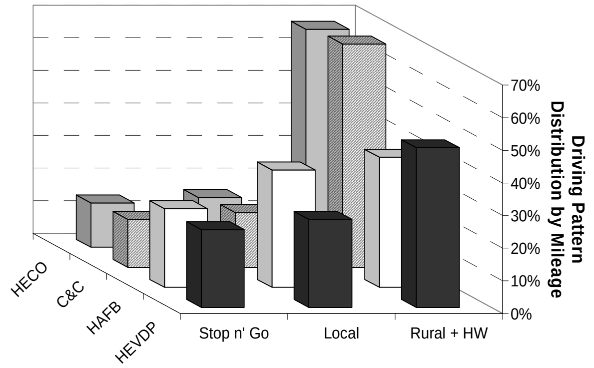


Fig. 11 Monthly average kWh input and output for each organization.

3.3 Driving cycle impacts

The variations in kWh efficiency in Figure 9 have been related to fleet operation and charging practice, and some important correlation has been found. It's not so clear, however, that how driving cycles can affect the kWh efficiency. We therefore analyzed the driving cycles of the vehicles operated by each organization to find out if there is any relevancy. Figure 12 shows the driving pattern distribution based on mileage in the driving cycles performed by each organization. The distribution indicates that HEVDP and HAFB operated the vehicles in a more balanced distribution with considerable portions of stop-n-go city and local (urban and suburban) driving, and the average mileage was relatively low. C&C and HECO used the vehicles more in the rural and highway driving conditions. High monthly average mileage thus resulted.



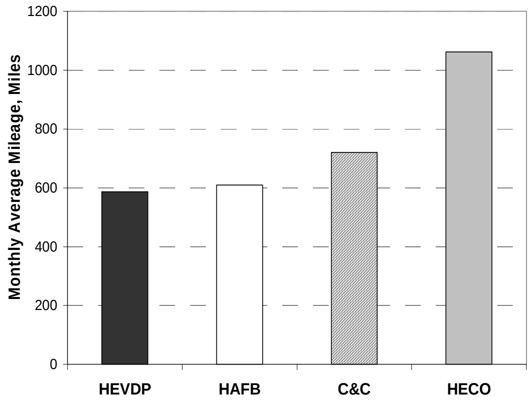


Fig. 12 Summary of monthly driving pattern distribution by mileage and average mileage operated by each organization.

Figure 13 shows the efficiencies achieved with respect to the breakdown of organization and driving pattern. The overall average drive efficiency achieved by HAFB is quite exceptional and higher than those made by the other three. Particularly, the drive efficiency in the stop-n-go city and local driving regimes in the HAFB driving performance is extraordinarily better than the others, which contributes substantially to the overall performance efficiency. The driving habit contribution (Figure 13) to the kWh efficiency (Figure 9) is therefore demonstrated by the unique driving practice of the HAFB fleet.

4. CONCLUSION

We have derived vehicle utilization patterns from 15 HMC Santa Fe e-SUVs operated by four different organizations under a two-year evaluation and demonstration project in Honolulu, Hawaii, from July 2001 to June 2003. We showed how to analyze the fleet operation in terms of vehicle use in driving and battery charging practice, showing different patterns among the fleets operated by different operators. Despite different driving cycles experienced in the vehicles by different operators, detailed analysis revealed that the different operation and utilization patterns could result in different en-

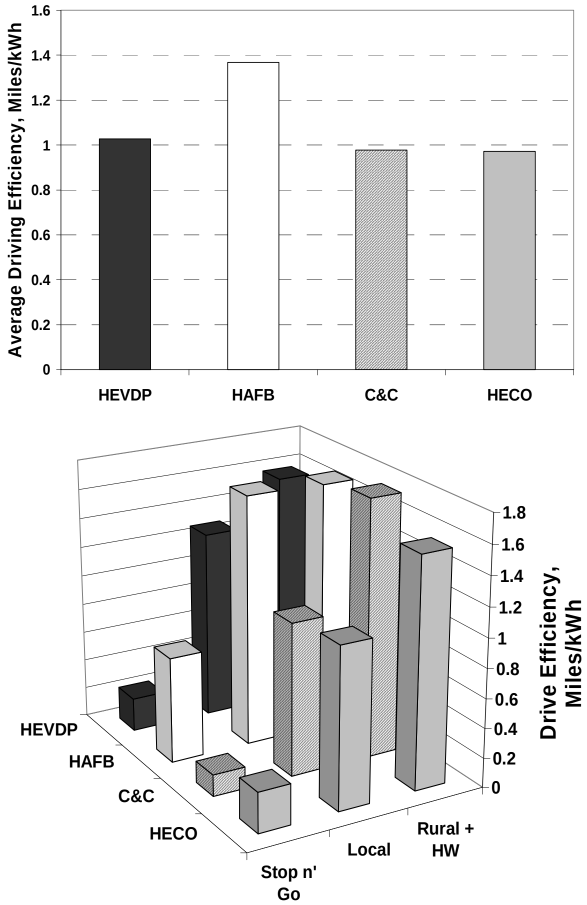


Fig. 13 Summary of the overall drive efficiency and the associated efficiency as a function of driving pattern distribution at each organization.

ergy utilization efficiencies. We found that more active and frequent utilization of the vehicles in driving, with shorter charging time, could enhance the kWh utilization efficiency. We further analyzed the effect from driving cycles with different attributes of driving patterns using a unique driving cycle analysis developed in the project. Correlation of drive efficiency with driving patterns can be derived.

Acknowledgements

The authors would like to thank Hyundai Motor Co., the U.S. Department of Transportation, the U.S. Air Force under the Other Transaction Agreement DTRS56-99-T-0017 with Hawaii's High Technology Development Corporation, and the State of Hawaii, for supporting this work. Significant engineering support from HMC on the data acquisition system, particularly by Drs. Chul-Soo Kim, Kil-Young Youn, and Mr. Seo Junhyuck, is greatly appreciated. The Enova Systems, Inc., particularly Mr. Todd Martin, has provided substantial engineering and staffing support to maintain the vehicles. We would also like to thank Hickam Air Force Base, especially Mr. Patrick Lindo, Hawaiian Electric Company, and the City and County of Honolulu, those who have put in tremendous effort in operating the vehicles and assisting with the data collection.

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(Received April 13, 2005; accepted May 28, 2005)