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The Role of ITS in PHEV Performance Improvement

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***Abstract*— Driving patterns have great impact on fuel economy or power split control decisions of PHEV (Plug-in Hybrid Electric Vehicle) energy management. In this paper, a statistical approach was used to analyze real world velocity profiles to gather traffic information such as average speed, speed limits, segment length, etc. A Markov chain model was developed to make use of such information for generation of random velocity profiles that are representative of real world driving scenarios.**

The velocity profiles generated using the Markov chain models are used to calculate vehicle fuel economy by means of a validated through the road parallel PHEV model and ECMS (Equivalent Consumption Minimization Strategy) control strategy. The end goal of the research is to find mathematical, statistical or heuristic relationships between road events and the performance of PHEV energy management.

I. Introduction

Various researchers have pointed out that driving patterns such as road type and traffic condition, trend and style, and vehicle operation modes have various degrees of impact on vehicle fuel consumption [1], [2], [3], [4], [5], [6]. The research related to intelligent vehicle power control has tried to find ways to incorporate the online driving pattern information into control strategies [7], [8], [9], [10], [11], [12], [13]. In [6], 62 driving pattern parameters were selected to describe the dimensions of urban driving and factorial analysis was used to reduce the initial 62 parameters to 16 independent driving pattern factors based on their effects on emissions and fuel consumption. For driving pattern analysis, driving pattern recognition approach was used in [7], [8], [9] to define different driving modes. In [7] [9], Artificial Neural Network (ANN) based driving pattern recognition was conducted while in [8] Lin et al. used a simple rule-based control strategy to recognize the Representative Driving Profiles.

Statistical analysis based approach was proposed by Gu et al. [10], they developed a simple algorithm that can be easily implemented in real time. In [11] and [12], an intelligent energy management agent (IEMA) based on driving pattern recognition was used for parallel hybrid vehicles. 40 out of the 62 parameters from [7] with seven new parameters were used for the driving pattern recognition. In [13], an intelligent system was developed to predict the current traffic conditions and neural learning for predicting the driving environment, such as road type and traffic congestion. The developed intelligent system was then used for vehicle power management.

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External systems like traffic information systems and traffic modeling approaches were used for prediction of the driving patterns [14]. Similar to [10], a statistical analysis and clustering approach was used in [15] for driving cycles. It first divided the driving cycles into segments called kinematic sequences and then clustering approach was used to separate those kinematic sequences into groups based on statistical information. The paper also proposed an approach to generate the driving cycles by choosing the kinematic sequences from the existing database randomly following distributions obtained from the kinematic sequences. For long and regular driving cycles, the approach may be effective and appropriate. However, it may not be adequate enough to generate short and more precise driving cycles. Markov chain modeling is an effective way to generate a representative driving pattern in a statistical way. In [16], Markov chain modeling was used for the velocity profiles generation based on observations from some standard driving cycles.

In this paper, with real world driving data available from a PHEV fleet, a systematic statistical approach was carried out, and then Markov chain modeling was used based on the clustering results. Furthermore, traffic information was used as the constraints for the stochastic velocity generation model. With traffic information, more precise velocity profiles were generated for different driving patterns under different traffic density conditions.

Given the complexity of plug-in hybrid electric vehicle architecture, the control strategy algorithm is required to perform multi-objective optimization of fuel economy, all-electric range, total emissions, battery life, ease of implementation, along with the constraints related charging issues and availability, battery aging, expected performance. Energy management algorithms can be broadly divided into analytical (e.g. dynamic programming, Pontryagin principle, equivalent consumption minimization strategy) and empirical (rule-base, fuzzy logic, artificial neural networks) approaches. Ideally, a priori detailed knowledge of the trip is required for optimal solution, but clearly this is not a practical scenario and a trade-off between optimality and level of information is needed. This paper is focused on ECMS and builds on methodology and results presented in [17]. As confirmed also by [18], the presented control strategy requires very limited information about the trip to obtain near-optimal performances, thus being suitable for online implementation. In order to increase the level of available trip information, some authors ([19], [14]) have developed tools to characterize driving pattern based on GPS,

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TABLE I

STATISTICAL METRIC FOR DRIVING CYCLES

V_{mean}	Mean Velocity
$V_{run,mean}$	Mean Run Velocity
V_{max}	Maximum Velocity
a_{max}	Maximum Acceleration
d_{max}	Maximum Deceleration
a_{mean}	Mean Acceleration
d_{mean}	Mean Deceleration
a_{rms}	Root-Mean-Square of Acceleration
V_{std}	Standard Deviation of Velocity
a_{std}	Standard Deviation of Acceleration
$\% d_{time}$	Percent of Time Decelerating
$\% a_{time}$	Percent of Time Accelerating
$\% cruise_{time}$	Percent of Time Cruising
$\% a_{dist}$	Percent of Distance Accelerating
$\% d_{dist}$	Percent of Distance Decelerating
$\% cruise_{dist}$	Percent of Distance Cruising
PKE	Positive Kinetic Energy
D	Driving distance
T	Driving time

GIS and historical data. These driving patterns could be then used *i)* to tune control algorithms or *ii)* as predictions, resulting in improved performance of the energy management strategy and fuel economy, thus further proving the increasing importance of Intelligent Transportation Systems.

This paper deals with combining the ITS (Intelligent Transportation Systems) information with the PHEV energy management to find the relationship between velocity profiles and PHEV performance. The goal of the research is to find mathematical, statistical or heuristic relationships between road events and the performance of PHEV energy management. The task is divided into two groups, (i) relationship between road events, weather conditions and velocity statistical properties and (ii) relationship between velocity statistical properties and PHEV performance. In this paper, we focused on the second group of the study. The work related the first group is not included in this paper but can be found in [20].

The remainder of the paper is organized as follows. Statistical analysis of real velocity profiles along with Markov chain model-based velocity generation approach is presented in section II. PHEV model and simulator architecture is presented in Section III and IV, respectively. Section V gives simulation results followed by conclusion and future work in section VI.

II. STATISTICAL ANALYSIS OF REAL VELOCITY PROFILES

A systematic statistical analysis was carried out for the real driving velocities. The velocity profiles were divided into smaller segments, which are velocity profiles between two consecutive stops, and then the statistical analysis and clustering was performed based on the obtained velocity segments. A set of statistical characteristics adapted from [10], [15] was used to describe each velocity segment, as shown in Table I. Considering that the segment based velocity profiles were analized here, PKE (positive acceleration kinetic energy per unit distance) and $\%idle_{time}$ (percent of time idling) which were used in [21] were not used here. Instead, as pointed out in [15], driving distance and driving time were used.

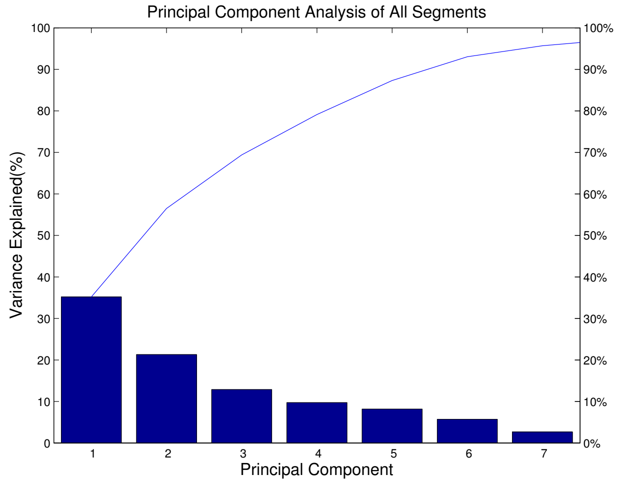

Fig. 1. Principal component analysis of all segments

With the proposed statistical metric each velocity segment (i) is represented by a 18 element vector, $DCSMV_{org,i\times 18}$ (Driving Cycle Statistical Metrics Vector). To reduce the dimension of the characteristic vector, Principal Component Analysis (PCA) was applied since the components of the vectors may be highly correlated. PCA involves a mathematical procedure that transforms the number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. Detailed description related to PCA analysis can be found in [21]. The accumulated variances shown in Figure 1 imply that the first 5 principal components determined from the PCA represent more than 90% of the information of the original vector.

Then k-means clustering approach was used to group the velocity segments into classes. Detailed description of k-means clustering was in [22]. Based on the PCA results, and trial and error method, two clustering result was better than other number of clusters. However, two clusters may not be the best grouping result, so deeper analysis with reduced order of statistical metric was carried out. Finally, a reduced order of statistical metric with only four variables gave much better clustering results with four clusters shown in Figure 2. The four variables were driving time, driving distance, maximum velocity and mean velocity. The sessions with negative silhouette values were deleted since they were not suitable to be grouped into any cluster. The resulting clusters with velocity profiles are shown in Figure 3.

In the clustering results, cluster 1 has relatively high velocity urban driving. Cluster 2 includes relatively low velocity urban driving, cluster 3 contains very low velocity driving such as moving vehicles in parking lots or when waiting for traffic lights, and cluster 4 includes typical highway driving. The grouped velocity profiles will be used for the stochastic velocity generation using Markov chain modeling approach.

A. Markov chain

In this paper, the Markov chain modeling approach given in [19] [23] was used to generate velocity profiles based on

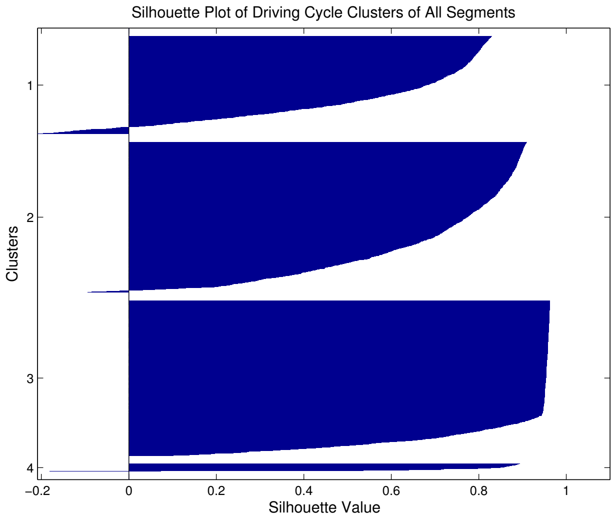

Fig. 2. Silhouette value for all segments

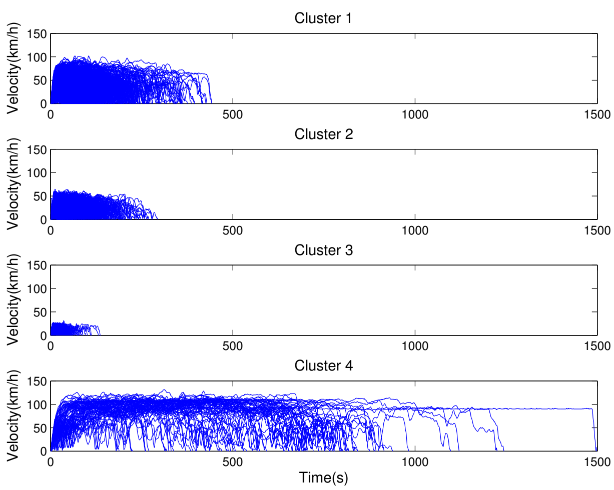

Fig. 3. Velocity profiles showing four clusters.

the observations from real world driving data available from the PHEV fleet. The Markov model is described in Equation (1), which shows that the next state of the system is only dependent on the current state.

$$P\{X(t+1) = j|X(t) = i\} = f(i,j) \quad (1)$$

Where, the state vector in the Markov chain is defined as $X_k = (V_k, A_k)$ where A_k is acceleration and V_k is velocity, and the probability distribution for a combination of A and V at the next step is given by the transition probabilities.

$$P(A_{k+1} = a_{k+1}, V_{k+1} = v_{k+1}|a_k, v_k) = p_{k,k+1} \quad (2)$$

Detailed procedures of using Markov chain model for our PHEV fleet real world velocity data was included in [21]. In Equation (3), $m_{i,j}$ is the number of occurrences of the transition from v_i to v_j for a certain acceleration rate, and $m_i = \sum_{j=1}^{n} m_{i,j}$ is the total number of times v_i has occurred at the acceleration rate.

$$p_{i,j} = \frac{m_{i,j}}{m_i} \quad (3)$$

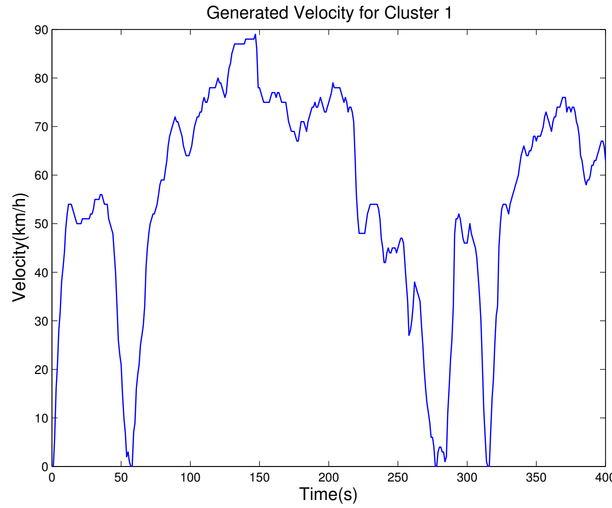

Fig. 4. Generated Velocity Profile for Cluster 1

Apart from the transition probabilities some traffic information like speed limit and segment length can also be added into the model. To accurately generate velocity profiles representing different traffic conditions, information like average speed, speed limits, segment length will be integrated into the Markov chain model for velocity generation. Detailed description of the combined model is in the following paragraphs.

Assuming that the whole trip has N segments which can be obtained from ITS, a stochastic velocity profile is generated for each segment based on Markov chain model. During the generation process following steps are performed till all segments are generated

1) The speed limit was checked to limit the generated velocity at each step.
2) Idle period was generated following the idle time distribution which was collected from the real world driving data
3) The mean value of this velocity profile was compared to the average velocity of the segment to check whether the average velocity is acceptable. If unacceptable, generate velocity profile for this segment, otherwise go on for the next segment.
4) The process was carried out until all the segments were finished.

B. Sample data

So far, almost one year driving data of a PHEV has been considered for this study. The collected 530 cycles were divided into more than 4000 segments. Based on the four clusters obtained, Markov chain model can be used for each cluster for velocity generation. Detailed work about the velocity data process and velocity generation were shown in [21]. One example case of generated velocity profile for cluster 1 using the corresponding probability transition matrix is presented in Figure 4. Similarly, velocity profiles for other clusters can be generated in the same way.

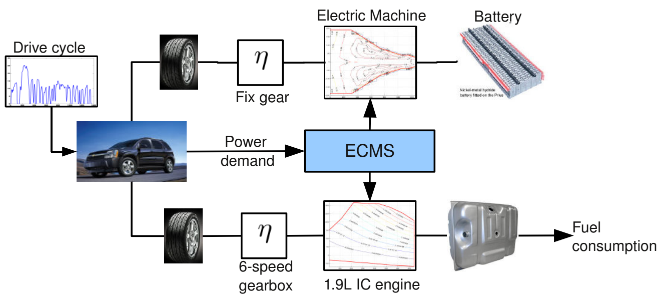

Fig. 5. Powertrain architecture and simulator used in this study [17].

TABLE II
SIMULATOR DETAILS

Vehicle	Chevrolet Equinox mid-size SUV
Total Mass	2090 Kg
Engine	1.9L Diesel, 4 cylinder, 103kW, 17.5:1
Rear axle Motor	67 kW peak, 3ph AC Induction motor
Transaxle	6 speed automatic
Traction Battery	9kWh GAIA Li-ion battery. Nominal voltage 270V
Gear shifting	Look up table controller
Engine, EM models	Fuel consumption map and Efficiency maps
Simulator	Backward Quasi-static simulator built using Matlab/Simulink
Energy management	Equivalent Consumption Minimization Strategy.

III. VEHICLE SIMULATOR

The simulator considered in this study builds upon an energy-based model developed in Matlab/Simulink environment designed for the Challenge-X student competition. The simulator and the component models were validated against the experimental data during the three years of the competition [24]. The vehicle simulators were developed to perform the energy analysis of the vehicle. The main purpose of these simulators is to analyze fuel consumption and battery usage for a particular driving pattern. The simulator is a quasi-static model for drive train components with backward model of the vehicle. The quasi-static models do not consider transient response of vehicle components and use static efficiency maps and fuel consumption maps for the engine and the motor. The control algorithm accepts these commands and selects the optimum power split between the engine and the battery. The general architecture of the simulator is shown in Figure 5. The component specifications of the vehicle power train are given in Table II.

IV. PHEV ENERGY MANAGEMENT

The velocity profiles generated as discussed in the previous section are then used for PHEV energy management performance analysis. The goal of this study was to compare PHEV fuel economy and electric energy consumption for different (but equivalent in terms of distance and number of stops) velocity traces. The results provide some insights into the effect of different driving conditions on PHEV performance. PHEV energy management strategy is based on Equivalent Consumption Minimization Strategy (ECMS) as given in [17]. The ECMS is used in blended mode control where the battery SOC decreases gradually such that it reaches the minimum allowed value only at the end of the trip. This control is implemented by considering a reference SOC profile that linearly decreases with the driving distance. This strategy was proved to be near optimal in [17] but it requires prior knowledge of total distance between two charging events.

V. RESULTS

The developed simulator is used to study the impact of driving profiles in fuel economy and optimality of ECMS. The PHEV simulator has an all-electric range (AER) of approximately 16 miles; therefore, to properly assess the performance of the energy management algorithm in blended mode control, the total trip distance is chosen to be 50 miles. Out of the 50 miles only the initial 5 miles of trip is synthetically generated using Markov chain models for a route in Columbus, OH as shown in Figure 6.

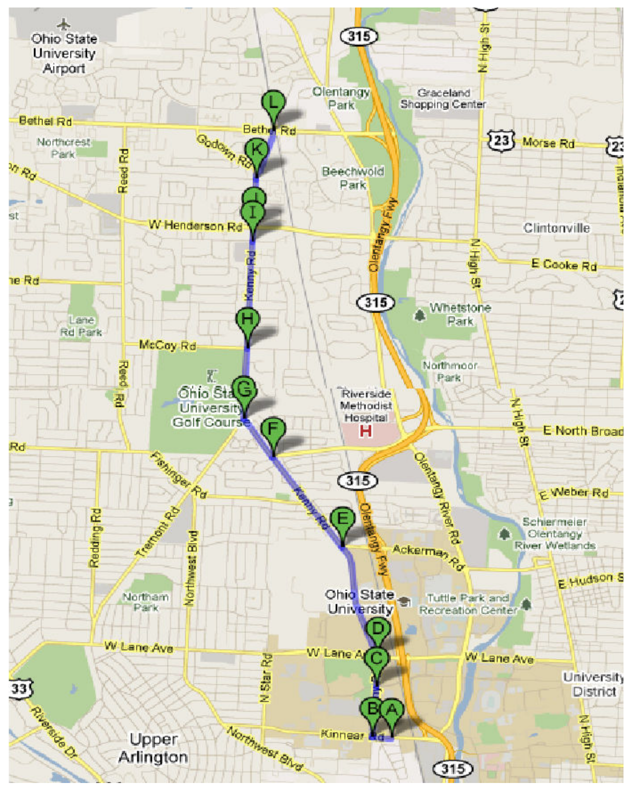

Fig. 6. A route from CAR to bethel road showing location of traffic lights.

The length of the trip segment is about 5 miles with 10 traffic lights, and the speed limit of 45 mph. Segment lengths between traffic lights were obtained from Google map [25]. To assess the impact of traffic density on PHEV performance, four traffic conditions were assumed. In high traffic density situation, the PHEV was assumed to stop at all traffic lights and 5 extra stops caused by other traffic events, and the average velocities for each segment were relatively small ranging from 10-30 mph depending on the segment length. In low traffic density situation, the PHEV was assumed to stop at only 4 randomly chosen traffic lights, and the average velocity for each segment were relatively high ranging from 30-40 mph depending on the segment length. Two more traffic situations between these two were defined as well with 7 and 10 stops, respectively. The decreasing number of stops indicates the decreasing traffic density and the four different conditions are shown in Figure 7. In order to have statistically significant dataset, fifteen velocity profiles were generated for each traffic density condition.

All scenarios were analyzed using the PHEV simulator described in the previous section. An optimal equivalence factor was found for each velocity profile using iterative procedure such that the final SOC is equal to the reference SOC. The optimal fuel economy for each velocity profile is calculated by considering only the fuel consumption; this approach is valid because all velocity profiles reach the same final state of charge so that net electricity consumption is the same for all cycles. It should be noted that the purpose of this study is to compare the impact of different velocity profiles on PHEV performance; since net electricity consumption for all cycles is constant, equivalent miles per gallon is not relevant. Figure 8 shows the results for minimum fuel consumption for different traffic densities; it can be noted that the number of stops within a fixed distance is less important as compared to the velocity profile. These results signify that small changes in the velocity profiles can significantly change the fuel economy performance of a PHEV. It is worth noting that these results are based on the optimal equivalence factor for each case; simulations have shown that if the controller has no availability of real time driving data and it is tuned just based on standard driving cycles (e.g. UDDS) the resulting fuel economy is 5 - 10% lower.

The optimal equivalence factor for different driving cases is shown in Figure 9. The figure shows that different velocity profiles have different optimal equivalence factors although there is a general trend that lower traffic densities require higher equivalence factor. The large deviation of equivalence factor around the average value suggests that the optimal equivalence factor strongly depends on statistical properties of velocity profiles along with the traffic density.

In order to identify which statistical properties of velocity profile have larger impact on the optimal equivalence factor, a regression analysis was performed. Initially, a linear regression is used to find out the direct relationships between the velocity statistics as given in Table I and the equivalence factor. The regression coefficients are shown in Figure 10. This figure gives a general idea about the importance of acceleration parameters and overall distribution of acceleration throughout the driving cycle on the equivalence factor. The % time spent in cruising and stopping is inversely proportional to the time spent in acceleration and deceleration. Therefore, these results suggest that the driving behavior is more important than the velocity of the vehicle, i.e. stop and go traffic with different average, maximum velocities may lead to same equivalence factor.

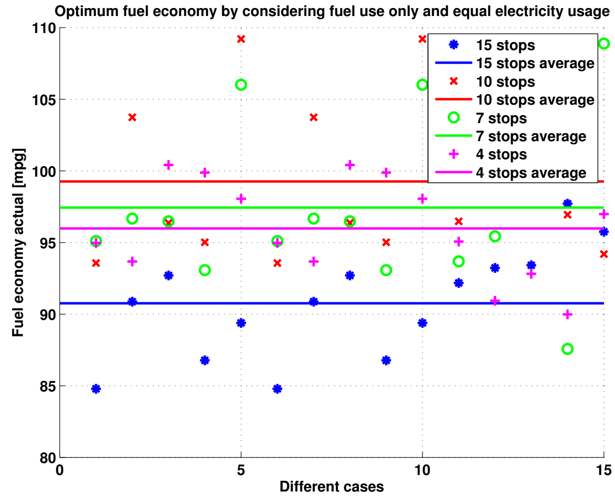

Fig. 8. Effect of driving profiles on fuel economy.

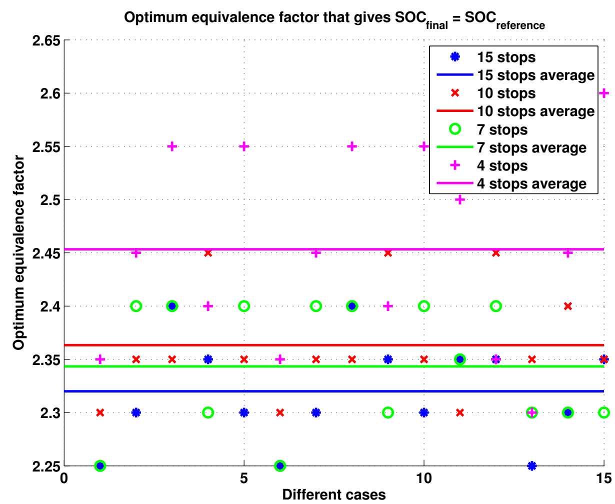

Fig. 9. Effect of driving profiles on equivalence factor.

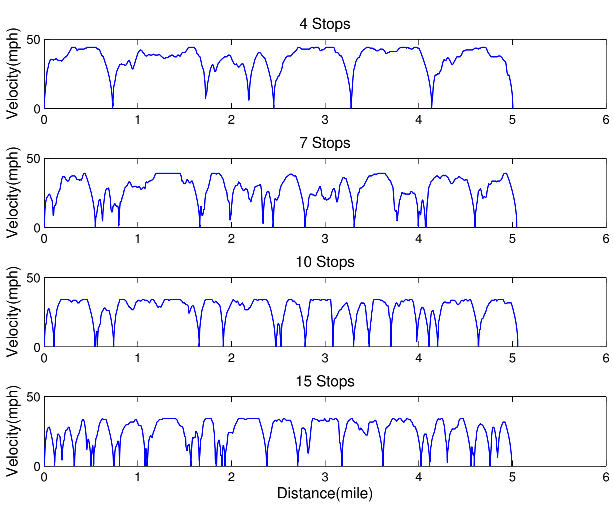

Fig. 7. Velocity profiles showing different traffic density conditions.

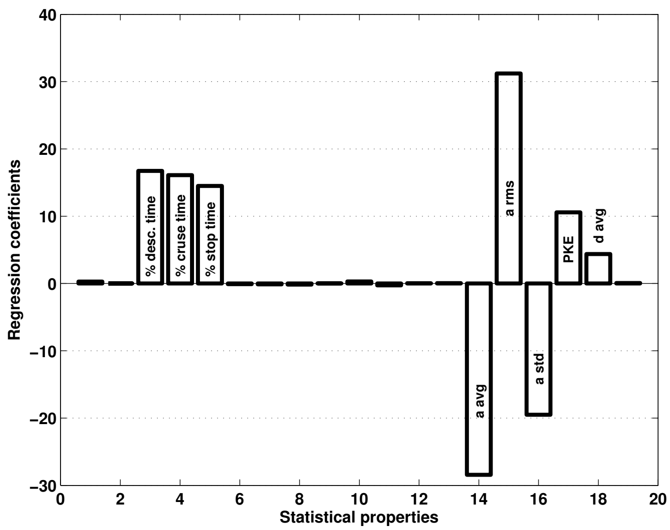

Fig. 10. Regression analysis results to show the relation between velocity statistics and equivalence factor.

VI. Conclusion

This paper presents a preliminary study of equivalence factor and fuel economy for different driving conditions. The study is performed by means of synthetic driving cycles generated using real world driving data and using Markov chain modeling. A specific route is assumed in this paper to reduce the variability in the velocity profiles and the study is performed in simulation using a PHEV model with equivalent consumption minimization strategy. The preliminary results show that the driving profiles have impact on the PHEVs fuel consumption and the optimum equivalence factor for ECMS. A regression analysis is performed to identify different factors affecting the optimal equivalence factor. The results show that acceleration statistics such as average acceleration, RMS acceleration, etc. have largest impact on the equivalence factor as compared to the velocity statistics such as mean velocity, maximum velocity, etc.

The end goal of the research is to find mathematical, statistical or heuristic relationships between velocity profiles, driving habits and PHEV energy management and performance. This study is the first step to show the need of detail analysis to find optimal equivalence factor and its dependence on the driving profiles to improve PHEV performance. Future work includes more accurate regression models (quadratic, nonlinear, etc.) based on analytical solutions and a method to predict the equivalence factor using ITS trip information.

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