

## **An investigation on the effect of driver style and driving events on energy demand of a PHEV**

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### **Abstract**

Environmental concerns, security of fuel supply and CO<sub>2</sub> regulations are driving innovation in the automotive industry towards electric and hybrid electric vehicles. The fuel economy and emission performance of hybrid electric vehicles (HEVs) strongly depends on the energy management system (EMS). Prior knowledge of driving information could be used to enhance the performance of a HEV. However, how the necessary information can be obtained to use in EMS optimisation still remains a challenge. In this paper the effect of driver style and driving events like city and highway driving on plug in hybrid electric vehicle (PHEV) energy demand is studied.

Using real world driving data from three drivers of very different driver style, a simulation has been exercised for a given route having city and highway driving. Driver style and driving events both affect vehicle energy demand. In both driving events considered, vehicle energy demand is different due to driver styles. The major part of city driving is reactive driving influenced by external factors and driver leading to variation in vehicle speed and hence energy demand. In free highway driving, the driver choice of cruise speed is the only factor affecting vehicle energy demand.

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*Keywords: Energy consumption, power management, PHEV, vehicle performance, simulation*

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### **1 Introduction**

Environmental concerns, security of fuel supply and CO<sub>2</sub> regulations are driving innovation in the automotive industry towards electric and hybrid electric vehicles. Fuel economy and emission performance of hybrid electric vehicle (HEV) strongly depends on the energy management system (EMS).

Definition of terminology used:-

1. Drive cycle: Vehicle speed - time data is referred as drive cycle.
2. Driver style: Driver has own characteristic way in driving vehicle like starting, stopping and cruising. In the process they can be efficient, inefficient, aggressive and calm. For a given condition, the variation in vehicle performance due to the driver behaviour is called as driver style.

3. Driving events: Route data is divided into city and highway driving. These are called as driving events.
4. Specific energy: Specific energy (Wh/km) is the vehicle energy required to travel one kilometre.

This paper focuses on the effect of driver style and driving events on EMS optimisation for HEVs. It also gives an outline of how driving events and driver style information can be used as a future cost in EMS.

The key objectives in the design of an EMS are [1, 2]

- A. Maximise fuel economy and minimise emissions
- B. Achieve good driving performance
- C. Maintain state of charge (SOC)
- D. Strive for optimal performance under all conditions
- E. Perform in real time and
- F. Minimise system cost

## 1.1 Drive cycles

For a given drive cycle or a set of drive cycles, it is possible to deliver optimal results like high fuel economy, low emission and maintain desired state of charge (SOC). Legislative drive cycles (LDC) are commonly used for EMS optimisation [3, 4]. In real world driving, vehicles are not driven in LDC. Hence their performance may not be optimal.

Real world drive cycles are more transient in comparison to LDC. They are used for vehicular emission inventory calculation and emission modelling based on time (per day, month and year) and region (urban, rural and national level)[5, 6]. Some examples are ARTEMIS, EMPA and TRAMAQ. They are also used for vehicle durability assessment and study.

Alternatively, EMS can be designed with reduced drive cycles dependence [7, 8]. The basic assumption is that the driver behaviour can be approximated with a Markovian process. The EMS is optimised over various drive cycles in an average sense. The transition probabilities are determined using LDC and real world drive cycles. The weakness in this model is that the transition of events like urban and highway driving do not happen randomly. They are fixed for a given route. Only their characteristics like

traffic may vary over time. Hence drive cycle for a given route is not a series of random events as represented by Markov driver. In real world driving they do not represent the actual future cost.

Instantaneous fuel economy optimisation technique like ECMS are used in [9, 10]. In this method tuning parameters adapt to the current driving conditions or SOC. It assumes that future driving conditions will be similar to the current conditions. Such an approach will lead to sub optimal results in maintaining the desired SOC and fuel economy.

The current research challenge is focused on the last three objectives of EMS (D-F). To make EMS deliver optimal results for varied driving conditions.

An adaptive EMS using PI controller with the basic assumption that the past speed profile provides a good representation of the future drive cycle is presented in [11]. The corrective action for deviation in SOC is taken by PI controller at the end of the trip, assuming the speed profile in the next trip will be same. This method may make EMS highly sensitive without understanding the root cause for the variation.

In pattern recognition method [12, 13] a pre-determined control action is taken based on the pattern match. Each time this window considered for pattern match is only a small part of the future cost. Thus the complete future cost is not studied leading to undesired performance. This method is also sensitive to the recognition of the initial pattern of the drive cycle set.

Kutter[14] demonstrated the requirement for adaptive EMS in situation were the actual speed profile deviate from the originally predicted speed profile after a period of time. This is similar to change in destination planned in the midway. In such situation, almost balanced SOC is achievable only by having adaptive EMS.

In the quest to develop optimal and adaptive EMS, various driving data are used. Use of upcoming driving data like velocity and elevation with EMS are found beneficial [15].

Similarly Kessels[16] shows that use of static vehicle speed and road elevation helps to improve result. In this study, a very simple drive cycle is constructed out of NEDC and an imaginary

elevation. As in most studies, the actual benefit in real world driving was not studied to make a meaningful conclusion.

In recent research work, the most commonly used sources to get driving data like speed profile is to use ITS data. Use of ITS data in EMS is far better than relying on LDCs.

Gong used WisTransPortal data for drive cycle modelling using historic traffic information for power management study of PHEV. Vehicle speed – time series aggregate data for 10 weekdays was used to develop a freeway driving cycle[17].

As part of ITS, WisTransPortal supported by the university of Wisconsin – Madison, data is collected from detectors placed along the road to measure volume, speed and occupancy for purposes of corridor-based performance analysis and freeway management. Each detector records data at five minute intervals. From this aggregate data, volume speed and occupancy for a region is generated[18]. So, ITS vehicle speed data is aggregate data of various vehicle type and driver styles. Use of such data in EMS as future cost will be advisable only in situations where vehicle type and driver style have relatively less influence for example driving during peak traffic time.

Prior knowledge of driving information is required to enhance the full potential of HEV. But how the necessary information can be obtained to use in EMS optimisation still remains as a challenge.

Previous research has shown that speed profiles and sometimes road elevations can be considered in future cost estimation in EMS. But each driver has their own style of driving for a given situation. A review on the study of driver style is discussed in the next section.

## 1.2 Driver style

Driver style has a significant bearing on fuel consumption and emissions [19-24]. A lot of work is focused towards improving driver style by providing driver assist both in conventional vehicles [25] and HEVs [26, 27]. To date, little is understood about considering driver style in control strategy optimization of HEV. Normally PI or PD controllers are used as the driver [11,

28]. Thus variation in energy demand due to real world driving style is neglected.

Phuc *et al* proposed a torque distribution strategy for a parallel HEV, which incorporates driving characteristics by interpreting accelerator pedal operation during vehicle following conditions [29]. For driver using large accelerator pedal position, the required motor torque is reduced to avoid engine operation in low efficiency areas. This strategy is questionable, as reducing performance may not be acceptable to the driver.

The effects of driver behaviour during vehicle cruising on control strategy was presented in [30]. Two drivers were compared for fuel economy. It was concluded the smoother acceleration pedal movement in cruise driving could reduce the fuel consumption and show less switching between operating points of the hybrid vehicle.

Johannesson [31] used a driver model with fixed acceleration and deceleration values and hence lacked scope to make control strategy adaptive to driver or address variation due to individual drivers.

In intelligent energy management agent (IEMA) presented [13], driver behaviour was classified based on average acceleration and standard deviation of acceleration over a specific driving range. For the effect of driver variability, the idea is to compensate a factor of  $\pm 10\%$  of total torque distribution in control strategy. EMS was proposed based on pattern recognition method as discussed in section 1.1.

## 1.3 Objectives

For optimal performance in real world driving advance knowledge about driving information is required. Vehicles are not driven in any specific standard drive cycles whilst driving from destination A to B. ITS data is a better option but the aggregate data do not reflect the effect of vehicle type and driver style. Each driver has a different style for a given driving event. EMS devices control strategy is based on vehicle demand to achieve optimal performance and maintain the required SOC. The objective of this work is to study the effect of,

1. Driver style on vehicle energy demand for a given vehicle and route.
2. Driving event like city and highway driving on vehicle energy demand.

Control strategy optimisation is not considered in this study. This study will help in developing a method to gather knowledge about driving information for EMS in real world driving.

## 2 Methodology

Real world driving data of three different driver styles are used to study city driving and highway driving. Audi Duo is converted to a plug-in HEV (PHEV) of parallel architecture to study the vehicle energy demand by simulation. Vehicle specification is given in table 1.

Table1: Basic PHEV specification

Parameter	Specification
Vehicle mass	1450 kg
IC engine power	120 kW
Motor power	75 kW
Battery capacity	28 Ah
Transmission	Automatic
Initial SOC	0.9

### 2.1 Drive cycle data

Real world driving data for various drivers which was collected in the Sustainable Action on Vehicle Energy (SAVE) project at the WMG, University of Warwick is used in this study. Data was collected for a given vehicle and route for a mix of driving events - city and highway driving.

Based on extreme and mean fuel economy, three drivers are selected out of 20 drivers in this study. Driver 1 (D1) is observed to be highly efficient, steady and anticipative in driving, having the best fuel economy. Driver 2 (D2) is observed to have mean fuel economy. And finally driver 3 (D3) is highly inefficient, aggressive and reactive driving having the worst fuel economy.

The route considered is comprised of both highway and city driving. The initial 4.8 km and after 13.3 km is city driving. These regions are called as region A and C respectively. Region B, between A and C is highway driving.

In region A, speed limit is 18 m/s (40mph) having five round-about (R) as shown in figure 1. Similarly in region C, speed limit is 18 m/s having four traffic junctions (T) and one round-about. In between city driving is highway driving of 8.5 km. Region B having speed limit of 31 m/s (exact 70mph).

New European Driving Cycle (NEDC) is also used for comparison study. In this study NEDC is repeated till the study destination distance of 19.3 km is matched as shown in below.

### 2.2 PHEV modelling and simulation

The model is simulated using an in house package called Warwick Powertrain Simulation Tool for Architecture (WARPSTAR) [32]. WARPSTAR is a model based simulation suite built using MATLAB/Simulink. It offers the required flexibility and functionality for HEV modelling.

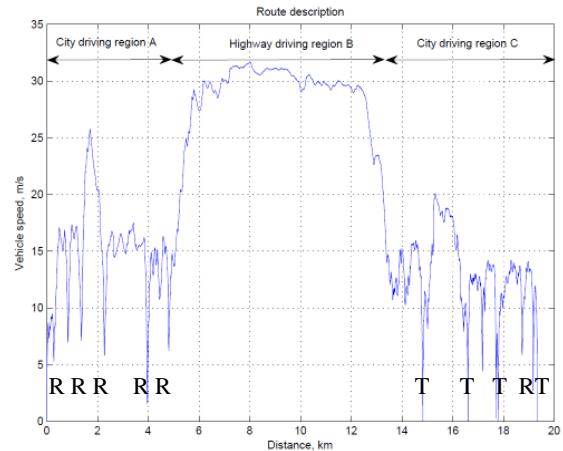


Figure1: Route description

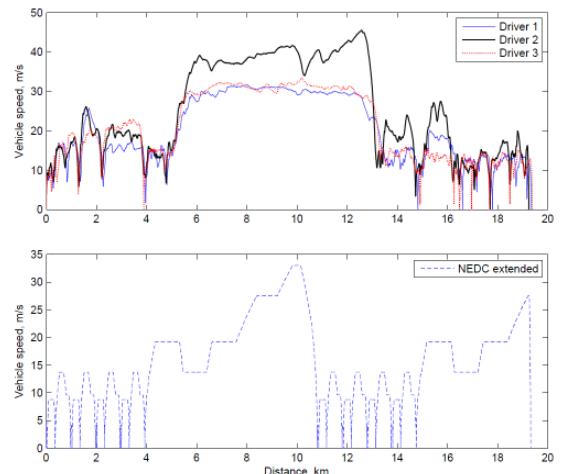


Figure2: Driver & NEDC extended vehicle speed

## 3 Results & Analysis

All three drivers were simulated using real world driving data for driving events like city and highway driving. In section 3.1, the effect of driver style and driving events on total vehicle energy demand, demand on electric motor and internal combustion engine (ICE) are analysed. The

implication on prior knowledge development for HEV is discussed in section 3.2.

### 3.1 Vehicle energy demand

All three drivers exhibit different total vehicle energy demand for a given route and vehicle as shown in table 2 and 3. Driver 2 requires 690 to 767 Wh more energy in comparison to driver 1 and 3. In terms of specific energy, driver 2 needs around 40 Wh/km more.

Table2: Total vehicle energy (Wh) demand comparison

Driver	D1	D2	D3	NEDC
Engine energy	935.9	1849.0	1034.0	881.4
Motor energy*	2130.0	1984.0	2109.0	2910.0
Total energy	3065.9	3833.0	3143.0	3791.4

\*Regenerative braking energy included

Fuel economy for extended NEDC is high, as engine is hardly used which is expected for the typical operation of a PHEV.

Table3: Vehicle level fuel consumption

Driver	D1	D2	D3	NEDC
Fuel economy, mpg (UK)	119.70	60.26	90.43	641.4
Final SOC, %	0.63	0.64	0.63	0.54
Specific energy, Wh/km	158.85	198.60	162.85	196.45

#### 3.1.1 Initial city driving – region A

For initial city driving vehicle energy demand is compared including NEDC. NEDC of initial 4.8 km is considered as shown in figure 3.

Drivers' vehicle speed profile is varying from 0 to 25 m/s. All three drivers are driving at different speed at different points. These are a typical real world city driving conditions. Similarly for NEDC vehicle speed is varying from 0 to 20 m/s.

In city driving a driver's speed profile is highly transient and different to each other as shown in figure 3. But the vehicle net energy demand is fairly close to each other as shown in table 4.

Frequent stop-starts in NEDC do not have adverse effect on energy demand. This is due to the maximum use of electric motor which has high efficiency over wide speed range unlike in ICE.

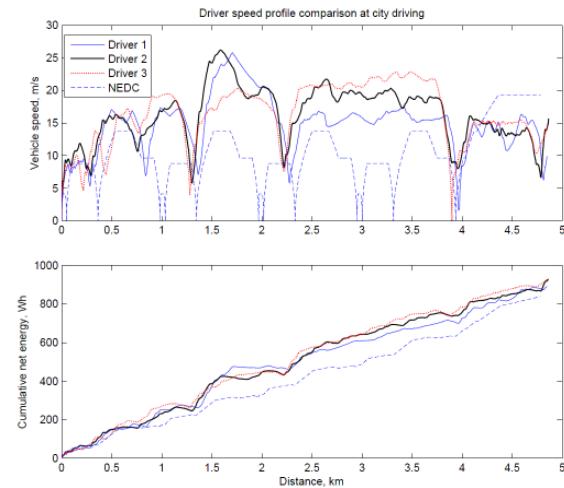


Figure3: Energy demand comparison at city driving-region A

Table4: Vehicle energy demand comparison in region A

Driver	D1	D2	D3	NEDC
Engine, Wh	19.39	63.46	0.85	9.10
Motor, Wh	873.60	864.90	930.80	930.80
Total, Wh	892.99	928.36	931.65	845.9
Specific energy, Wh/km	186.04	193.41	194.09	176.23
Final SOC, %	0.79	0.79	0.78	0.80

Normally in city driving electric motor is used predominantly. In this study ICE is used whenever vehicle speed exceeds 20 m/s. Normally in UK city driving speed limit is 18 m/s.

#### 3.1.2 Highway driving – region B

On highway drivers' speed profiles are fairly steady but their choice of speed is different. Driver 1 and 3 energy demand is similar as their high speed cruise is both around 30 m/s. Driver 2 exhibiting cruise speed of 40 m/s takes around 500 Wh more energy than other drivers.

This explains the major part of the difference in total energy demand between drivers. In terms of specific energy 60 Wh/km more is required for driver 2.

Table5: Vehicle energy demand comparison in highway driving - region B

Driver	D1	D2	D3
Engine, Wh	905.11	1662.54	1033.15
Motor, Wh	336.40	79.90	192.20
Total, Wh	1241.51	1742.44	1225.35
Specific energy, Wh/km	146.40	205.47	144.49

Usually in highway driving the engine or both engine and motor will be operating based on SOC and peak speed demand. In this study, only engine is working at cruise speed.

### 3.1.3 Final city driving – region C

After highway driving the remaining part is again city driving of 6 km. Like region A, in region C vehicle speed is highly transient and changing from 0 to 25 m/s. But in this case vehicle energy demand of all drivers is not same. For driver 2 it is higher by 231 and 176 Wh in comparison to driver 1 and 3 respectively.

Table6: Vehicle energy demand comparison in city driving - region C

Driver	D1	D2	D3
Engine, Wh	11.4	123.00	0
Motor, Wh	920.00	1039.20	986.00
Total, Wh	931.4	1162.20	986.00
Specific energy, Wh/km	155.23	193.70	164.33

## 3.2 Implication

In real world driving, vehicle speed profile is a function of driving events and driver style as shown in figure 1 and 2.

Driving events are not random or probabilistic phenomena as considered in Markov driver model. They are fixed to a location or route. For a given driving event, vehicle speed changes due to traffic and driver variation.

The importance of driver style is demonstrated with the speed profile in figure 2 and energy demand results in table 2.

### 3.2.1 City driving

In city driving, vehicle speed is low but highly transient as shown in figure 3. So prediction is difficult due to various external factors like

traffic, traffic signal and driver. The major part of city driving is reactive driving.

During regions A and C, city driving conditions are fairly similar. But the vehicle energy demand for a given driver is not same. In region C after 16 km, vehicle speed is restricted due to traffic and signal. The influence of these external factors are significant but cannot be predicted in exact sense. Also variation due to the driver can be expected even driving exactly the same route again.

Reactive driving, role of the driver, uncertainty of traffic and signal makes the prediction of exact vehicle speed to use in EMS for control strategy optimization not possible. By seeing speed profiles at region A and C, the use of average vehicle speed or range does not reflect the complete picture. Use of specific energy range for a given driver and event appears to be the better option.

Vehicle energy demand range observed for all drivers and events in this study is shown in table 7. For driver D2 it is a very specific value which will make for the EMS easier devising the control strategy.

Table7: Specific energy (Wh/km) comparison of drivers

Driver	D1	D2	D3
City driving	155 – 186	193 – 194	164 – 194
Highway driving	146	205	144

In control strategy, use of the electric motor in city driving helps in negating the effect of transient speed as explained in 3.1.1. This is due to the high efficiency over wide speed range of electric motors. So ideally operation of only electric motor is preferred in city driving. The control strategy and component sizing goes hand in hand. Sizing battery and motor as a function of real world driving to ideally cover all transient operations will help in improving HEV performance.

### 3.2.2 Highway driving

In highway driving, vehicle speed is high and relatively steady. The cruise speed depends entirely on the driver choice. Usually uncertainties in highway driving are comparatively fewer.

In this study, a wide variation in energy demand is observed for highway driving among drivers. The reason is entirely due to the driver's choice of cruise speed. Higher cruise speed leads to high

energy demand. Transport departments can take note of this to work on speed limits to improve CO<sub>2</sub> emissions. Again as in city driving, energy demand for highway cruising can be a range instead of a specific value as shown in table 7. However the highway energy demand range is expected to be a narrower range due to relatively steadier speeds.

With the help of individual driver's historic data or accepting the driver's choice, the vehicle cruise speed and hence the vehicle energy demand might be predicted for highway driving.

Live ITS or other traffic data can be used as secondary information to refine the estimation. But ITS aggregate data cannot serve as a drive cycle itself.

It is worth remembering that the real world data used in this work is of the same vehicle and given route, and still a wide variation in energy demand is observed both in city and highway driving.

Similarly use of fixed acceleration, deceleration and vehicle speeds will mislead the EMS when it comes to real world driving. Such a representation neglects driver style leading to non-optimal future cost estimation.

Overall, vehicle speed profiles for city driving cannot be predicted and driver style has an influence. In highway driving, driver choice of cruise speed has a significant impact. It is not possible to maintain or sustain SOC, with only vehicle speed as prior knowledge. Driver style knowledge is crucial too.

With the above knowledge, vehicle energy demand and mode of EMS operation like electric, ICE and hybrid can be planned for the complete route with fair accuracy.

Unlike in the current production PHEV where the mode of operation is predetermined, EMS can take decision on optimal mode of operation based on events, driver style and anticipated vehicle energy demand.

## 4 Conclusions and future work

To achieve optimal performance of HEV prior knowledge about driving information is required. For that one of the challenges is how this prior knowledge can be developed and used.

This study was carried out to understand the effect of driver style and driving events on vehicle energy demand and the following conclusions are made.

- Driver style and driving events like city and highway driving both affects vehicle energy demand. Hence both have to be considered in developing prior knowledge.
- In city driving, prediction of vehicle speed profile is not possible due to reactive driving. Also average vehicle speed and range do not reflect the complete picture. Traffic, traffic signal and driver style has a significant effect on energy demand.
- In highway driving, the choice of cruise speed by the driver has the major impact on vehicle energy demand.

In future work, variation in energy demand at repetitive trip for a given route and driver will be studied. Use of specific energy range for future demand estimation has to be investigated further. Finally an effective use of this prior knowledge developed in adaptive EMS will be investigated.

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