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Effects of Different PHEV Control Strategies on Vehicle Performance

P. Tulpule* , V. Marano, G. Rizzoni
Center for Automotive Research, The Ohio State University

Abstract— **Foreign oil dependence, increased cost of fuel, pollution, global warming are buzz words of today's era. Automobiles have a large impact on increasing energy demand, pollution and related issues. As a consequence, many efforts are being concentrated on innovative systems for transportation that could replace petroleum with cleaner fuel, i.e. electricity from the power grid. The use of plug-in hybrid electric vehicles (PHEVs) can become a very important change in this direction, since such vehicles could benefit from the increasing availability of renewable energy. PHEVs requires new control and energy management algorithms, that are crucial for vehicle performance. This paper deals with evaluation of two modes, Electric Vehicle (EV) mode and Blended mode, for plug-in hybrid electric vehicles and their comparison with conventional and hybrid electric vehicle performance.**

In this paper two PHEV architectures are considered: through road parallel plug-in hybrid and series plug-in hybrid. Similar models have been developed to evaluate vehicle performance for conventional and hybrid architectures. Both PHEV architectures are analyzed with two different modes- EV and Blended; a modified version of ECMS (Equivalent Consumption Minimization Strategy) is used for both algorithms. Various standard as well as custom designed driving cycles are used in this analysis.

The paper provides quantitative analysis of the control algorithms to analyze their effects on fuel economy, use of electric energy, cost of operation, etc.; these results are compared with the simulations for hybrid and conventional vehicles. Some important relationships between fuel economy, design architectures and control strategies are shown and can be useful in the design of the optimal control algorithms for PHEVs. As shown in the results, the control problem for PHEVs is not limited to fuel economy but it also involves external factors, such as price of electricity, energy market and regulations, charging availability, battery life issues, etc.

I. INTRODUCTION

Effect of climate change and public awareness toward the importance of energy savings is increasing and governments are encouraging the use of renewable energy. The energy consumption of the US is very high as compared to that of European and Asian countries [1]; particularly, US citizens consume twice as energy per capita as Europeans and it is the largest consumer of the petroleum products. A clear correlation can be observed between vehicle density (cars per 1000 inhabitants) and the GDP (gross domestic product) [2] [3]; this suggests that as densely populated countries such as China, India, Brazil achieve higher economic status, it can be expected that the demand for personal transportation will increase accordingly, leading to significant increase in the demand of transportation fuels. Today, this demand can be directly translated into increased demand for petroleum, a fact that is hardly consistent with current data on oil production. The energy market in US can be classified into four sectors, transportation, residential, commercial, and industrial. The transportation sector is the main contributor to the total energy consumption along with the electric power generation. It is also important to note that [4] the energy efficiency of the transportation sector is the lowest of all other sectors (around 20%) and that approximately 62% of the petroleum is imported, and it is used almost exclusively for transportation.

PHEVs have gained interest over the past decade due to their energy efficiency, convenient and low-cost recharging capabilities and reduced use of petroleum. The energy management algorithms for PHEVs are crucial for vehicle performance; the capability to operate in pure electric mode and to recharge the battery from an external source increases the complexity of the energy management problem, compared to hybrid electric vehicles. This paper considers the issues of PHEV energy management and gives an application of ECMS algorithm adapted to the PHEV requirements.

The PHEV control problem is similar to the hybrid vehicle control, with the main difference being that the batteries used for PHEV applications are almost completely depleted (usually 95-25 % SOC) and then charged from external sources (not from the onboard APU). These constraints create many difficulties in the optimization; in particular, the performance depends not only on the driving pattern, but also on initial battery SOC. As shown in the paper, trip length and initial SOC are key factors to determine fuel economy: while conventional and hybrid vehicles have a constant mpg at increasing distance over the same driving pattern, results for PHEVs show a decrease in fuel economy at increasing distance.

Given a driving pattern, for trips shorter than the AER (all electric range, number of miles that can be run in pure electric mode), a PHEV presents the same fuel economy of a pure electric vehicle; for much longer trips (AER negligible with respect to the total trip) a PHEV tends to the same fuel economy of a hybrid electric vehicle.

Besides analyzing the control strategies on standard driving cycles, this paper deals with customized driving cycles; a proper combination of known driving cycles has been adopted to analyze real world situations, such as going to work, running errands, etc. The performance of different control strategies and architectures was evaluated by comparing total electrical energy consumption, fuel economy, cost of operation etc. with comparable conventional and hybrid

*Corresponding Author: Pinak Tulpule, The Ohio State University, Columbus, Ohio. email: tulpule.1@osu.edu

electric vehicles.

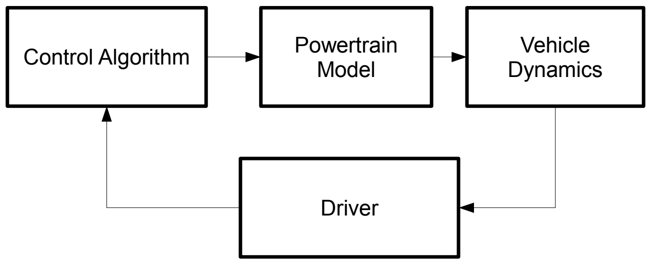

Fig. 1. Block Diagram of the simulator

The paper is organized as follows: Section II explains the models used in this analysis; Section III gives details of the control algorithms; Section IV describes methodology and simulation approach; Section V presents some results and discussion; and Section VI gives the conclusion.

II. VEHICLE MODEL

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 emissions for a particular driving pattern. The simulators were constructed using quasi-static models for drivetrain components with forward-looking 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 forward-looking model also includes a driver model: a PID controller that compares the vehicle speed with the desired vehicle speed (driving cycle) and generates acceleration and brake commands [5]. 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 1.

This modeling method was used to create four drivetrain models (Conventional, Hybrid, and two PHEVs) for a sport utility vehicle. It is worth noting that the hybrid version of the analyzed vehicle currently exists at The Center for Automotive Research at The Ohio State University and that the models for several components were validated starting from road testing. The same vehicle parameters were used to develop all other models. The hybrid vehicle is a through road parallel hybrid and consists of an engine coupled to the front wheels along with a belted starter alternator (BSA), and a traction motor to drive the rear wheels. Starting from this validated model, a PHEV version has been developed by increasing the battery capacity and adapting the control strategy as explained in the following section. A second PHEV model was developed for a series powertrain architecture. The series architecture consists of a 106KW rear electric motor and a 40KW generator in the front. Details of the models are given in Table I.

The supervisory control algorithms were developed for each of the vehicle architectures. The control of the conventional vehicle is simple - applying all the demanded torque to the engine; in case of Hybrid and PHEVs the computation of the optimum power split is performed by means of Equivalent Consumption Minimization Strategy (ECMS) [6].

TABLE I
VEHICLE CONFIGURATIONS.

Model	Mass (Kg)	Engine	Motor	Battery
Conventional	1660	3.4 L (138KW)	—	—
Hybrid (Parallel)	2050	1.9 L (103KW*)	67 KW	2.2 KWh, NiMH
PHEV (Parallel)	2130	1.9 L (103KW*)	67 KW	10 KWh, Li-ion
PHEV (Series)	2030	1.7 L (40KW**)	106 KW	10 KWh, Li-ion

* with use of B20 fuel
** Generator output power using gasoline engine.

III. PHEV CONTROL

The control problem for PHEVs follows the same concepts as hybrid vehicles control problem but with different constraints. As explained in the previous sections, PHEVs have larger batteries and the allowable SOC range can extend from $\sim 95\%$ to $\sim 25\%$. Thus, large amount of energy is available to assist the engine and displace the fuel energy allowing better use of the battery and increased all electric driving range. The control problem for PHEV is very similar to the hybrid and can be formulated in a similar fashion as follows:

$$x =: SOC \tag{1}$$
$$u =: P_{batt} \tag{2}$$
$$u^*(t) = \arg \min_{P_{batt}, P_{ICE}} (J(x, u, \dot{m}_f)) \tag{3}$$
$$P_{wheel} = P_{batt} + P_{ICE} \tag{4}$$

with the following constraints,

$$\begin{aligned} SOC_{min} \leq SOC(t) \leq SOC_{max} \\ T_{EMmin} \leq T_{EM}(t) \leq T_{EMmax} \\ T_{ICEmin} \leq T_{ICE}(t) \leq T_{ICEmax} \\ P_{battmin} \leq P_{batt}(t) \leq P_{battmax} \end{aligned}$$

where, T_{EM} is the electric machine torque, T_{ICE} is the engine torque, P_{ICE} is the engine power, P_{batt} is the battery power, E_{batt} is the total battery energy content, $J(u, x, \dot{m}_f)$ is the objective function. x is the state of the system which is taken as battery state of charge. The objective function J is taken as,

$$J = \int_0^{T_f} \dot{m}_f(t)dt \tag{5}$$

where, T_f is the length of driving cycle and $\dot{m}_f$ is the fuel consumption. In a PHEV energy optimization, the objective function might also consider the effects of battery energy consumption such as the electricity cost, overall emissions (from power generation and gasoline) etc.

PHEV control can be classified in two main categories: EV mode control and blended mode control. In EV mode control, the vehicle operates in charge depleting mode as long as the electric motor can supply the requested power and battery SOC is greater than a designed threshold. Once the battery depletes to SOC_{min} the controller switches to charge sustaining mode.

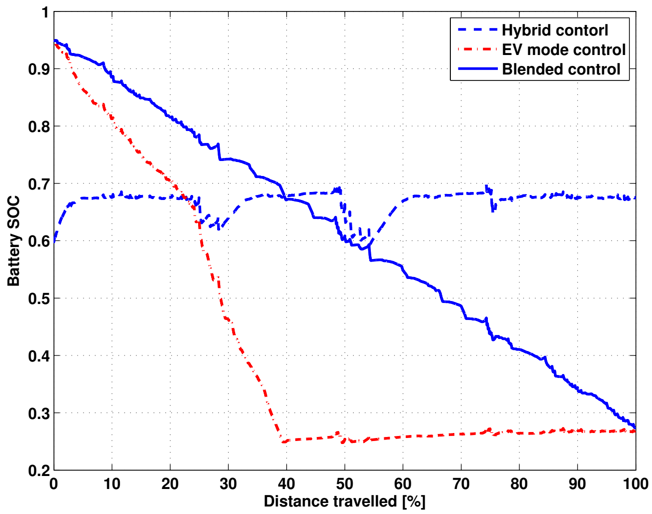

Fig. 2. Comparison of battery SOC profile for different control strategy.

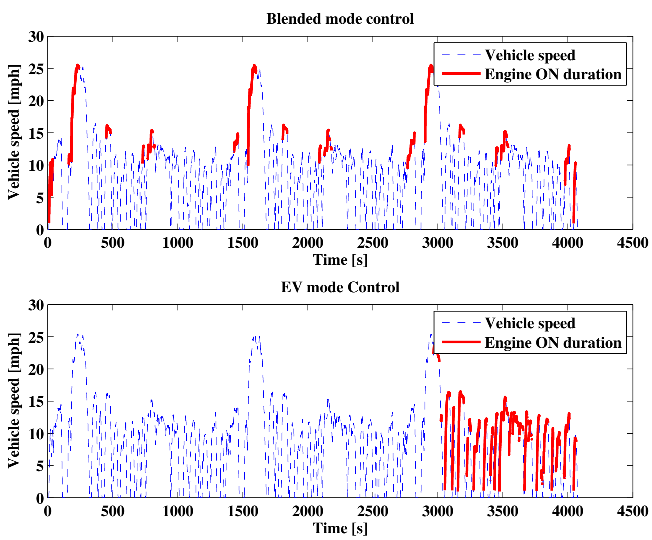

Fig. 3. Engine on time. Comparison of EV mode control and blended mode control for 3 UDDS cycles.

In blended mode control, the engine is used consistently with the electric motor during the entire driving trip. The power sharing between the motor and the engine is optimized such that the SOC decreases during the driving trip and reaches the minimum value only at the end of the trip. Figure 2 shows a comparison of SOC profiles for EV and blended mode control strategies along with the SOC for a hybrid architecture; Figure 3 shows the engine "on time" for these two modes. It is clear that the engine is used consistently in the blended mode control, while it is used extensively only at the end of trip for EV mode control.

Obviously, the blended mode requires a priori knowledge of the driving pattern, thus needing sophisticated control algorithms, i.e. rule based algorithms, dynamic programming, as used in [7], [8], [9], [10]. [11] uses GPS information and historical traffic data to characterize the driving pattern and uses it for control strategy optimization.

ECMS:

In this study, the PHEV control was designed using a modified Equivalent Consumption Minimization Strategy (ECMS) algorithm. The ECMS solves the local optimization problem considering the total energy consumption, while maintaining the battery SOC constant. In other words the ECMS regulates SOC at a constant reference point with minimum fuel consumption.

The ECMS [6] [12] [13] is based on the fact that in a hybrid vehicle the energy consumption from the battery is replenished by running the engine. Therefore, battery discharging at any time is equivalent to some fuel consumption in the future. This equivalent fuel consumption is used as the objective function for control optimization. The input to the ECMS algorithm is total power demand at wheels, then the ECMS searches for the best power split between the engine and battery that minimizes the equivalent fuel consumption. The objective function for the ECMS is

$$J(t) = \int_0^{T_f} \dot{m}_{eq}(t)dt = \int_0^{T_f} \left(\dot{m}_{ice}(t) + \dot{m}_{batt,eq}(t)\right) dt \tag{6}$$

where, $\dot{m}_{ice}$ is the fuel consumption of the IC engine. The $\dot{m}_{batt,eq}(t)$ is the equivalent fuel consumed while charging/discharging the battery. While charging,

$$\dot{m}_{batt,eq}(t) = K_{eqf} \frac{P_{batt} * \eta_{total}}{Q_{lhv}} \tag{7}$$

and while discharging,

$$\dot{m}_{batt,eq}(t) = K_{eqf} \frac{P_{batt}}{\eta_{total} * Q_{lhv}} \tag{8}$$

where, K_{eqf} is the equivalence factor that acts as a weighting factor for the electric energy, η_{total} is the total efficiency of the electric drivetrain including the battery charge-discharge efficiency and the electric machine efficiency. Q_{lhv} is the lower heating value of gasoline. The equivalence factor is very important and it affects the optimum power sharing between the engine and the motor, and its optimum value is different for different driving patterns [13]. The objective function does not consider the battery SOC explicitly, so it cannot maintain the SOC within specified range. Therefore, a feedback correction is applied to the equivalence factor based on the SOC. The modified equivalence factor is calculated as,

$$K_{eqf} = EQF * K_P * K_I \tag{9}$$

where, EQF is the nominal equivalence factor; its value was determined by performing several simulation to obtain the best fuel economy and velocity tracking performance (2.4 for the parallel architecture and 2.1 for the series architecture) The K_P and the K_I gains are computed as follows [13]

$$x_1 = \frac{SOC(t) - SOC_{ref}/2}{\Delta SOC/2} \tag{10}$$
$$K_P = 1 - x_1^3$$
$$x_2(t) = 0.01 * (SOC_{ref} - SOC(t)) + 0.99 x_2(t - \delta t) \tag{11}$$
$$K_I = 1 + tanh(12 * x_2)$$

where, SOC_{ref} is the reference SOC for the ECMS algorithm and ΔSOC is the allowed range of SOC around SOC_{ref}.

EV mode control

The EV mode control has two stages - all electric and charge sustaining. The control algorithm selects the electric motor as long as the SOC is greater than $SOC_{min} + \Delta SOC/2$. The value of 25% is selected to maximize the useful capacity of the battery without affecting battery performance and life. When the SOC decreases below this value, the control algorithm switches to the ECMS for charge sustaining mode. Since the battery for the PHEV has a large capacity (compared to the maximum power demand) the ΔSOC is set to 4%, and SOC_{ref} is set to 27%.

Blended mode control

In blended mode control, the objective is to achieve the lowest limit of the SOC at the end of trip, when it is assumed that the total trip length is known. In this case, the battery SOC is reduced slowly throughout the trip and the SOC profile is optimally selected by principles from optimal theory like dynamic programming. In this paper, instead of using such a complex method, not implementable on board (due to high computational requirements), a simple strategy was used to compute the SOC profile. The battery SOC is linearly decreased with the distance traveled by the vehicle. The SOC computed in (12) is used as reference SOC for the ECMS algorithm in (10) and (11).

$$SOC_{ref}(t) = SOC_0 - \frac{D_{veh}(t)}{D_{total}} * (SOC_0 - SOC_f) \tag{12}$$

where, D_{veh} is the distance traveled by the vehicle.

Parallel architecture - Application of ECMS

The above explained ECMS algorithm is applied to the simulation model of through-road parallel hybrid with belted-starter alternator. This architecture has three degrees of freedom (ICE power, EM power and BSA power) and optimum power split between engine, electric motor and BSA is computed by the ECMS. As explained in [5], the ECMS searches for the best combination of ICE, EM and BSA power to minimize the equivalent fuel consumption as shown in (6). The battery power in (7, 8) is computed as,

$$P_{batt} = P_{EM} + P_{BSA} \tag{13}$$

Series architecture - Application of ECMS

In series hybrid, the power is supplied by engine-generator and battery, therefore the ECMS control strategy is used to select best power split between generator power and battery power. One of the advantages of this architecture is that the engine can be always operated in its best operating region. Therefore, at a given power split, the engine operating point is selected such that the engine operates at its best efficiency point [12].

The two control algorithms implemented on the two PHEV architectures, along with conventional and hybrid architectures give a total of six different models/controls: Conventional, Parallel hybrid, Parallel PHEV with EV mode control, Parallel PHEV with Blended mode control, Series PHEV with EV mode control, Series PHEV with Blended mode control.

IV. Methodology and Simulation

The vehicle architecture models and the control algorithms were simulated for different standard driving cycles and data on fuel economy, electrical energy consumption and battery energy utilization was analyzed. In the case of PHEVs, standard driving cycles do not provide enough information to estimate fuel economy for real world driving needs, thus typical driving patterns and days have been identified and used as input for the study. The custom driving cycles are generated as a combination of standard driving cycles as shown in Table II [14], resulting in 15,428 miles/year. For a complete analysis it is also important to consider different charging availability as shown in Figure 4, i.e. how often it is possible to recharge the battery: controlled charging (once a day, overnight) and uncontrolled charging (charging is possible whenever the vehicle is parked). Clearly, through uncontrolled charging better fuel economy can be achieved, but at the price of reduced battery life. It is assumed in this work that charging takes place only during off-peak hours, without the option of charging during the day. The capability to include charge-at-will operation will be included in future work.

V. Results and analysis

The models were analyzed for fuel economy on different driving cycles. Figure 5 shows the improvement in fuel economy; it is important to note that the fuel economy for the hybrid configuration is calculated as miles per gallon gasoline equivalent while for PHEVs the fuel economy is the combination of gasoline in mpg (the bars of Figure 5) and electric energy consumed from the battery (numbers over the bars in Figure 5). As expected, the results show a substantial reduction in the fuel consumption for PHEVs; for a complete energy analysis, the electricity needed to recharge the battery to its initial condition needs to be considered, as shown in Figure 7.

Analysis of Fig 5 shows that the PHEV provides better mileage for urban driving but the fuel economy improvement is smaller for highway driving (two standard driving cycles are driven for multiple times to generate these graphs). All

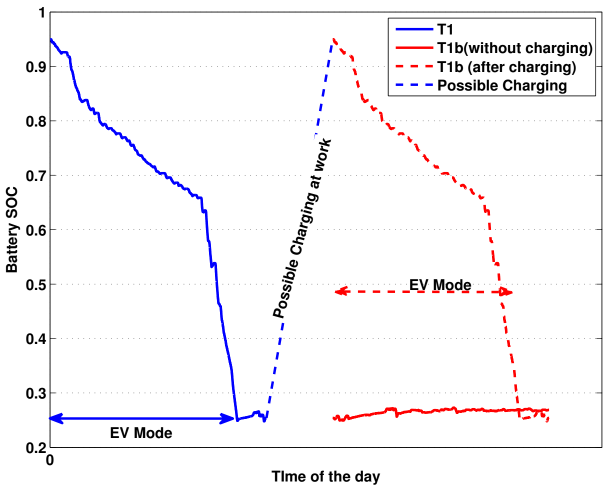

Fig. 4. Hypothetical case where battery is charged at work in the afternoon.

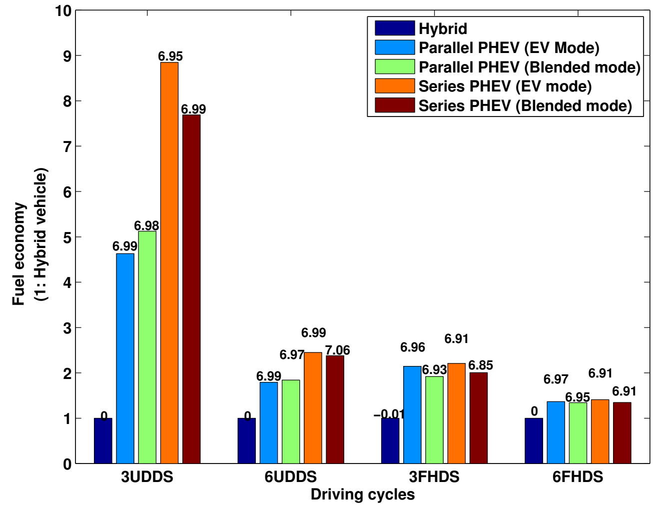

Fig. 5. Fuel economy comparison for different cycles and models.[* mpgge for Hybrid vehicle.][Number over each bar shows net electric energy used from the battery in KWhr.]

the test results for the PHEVs are obtained by setting the initial SOC at 95% and lower SOC limit set to 25%. The numbers over the bars show the net energy consumed from the battery. The results clearly show the dependence of the fuel economy on driving distance.

Although the series PHEV performs better than a hybrid, it provides less improvement over a parallel hybrid vehicle for highway driving. This effect is caused in part by the small size of the battery as it cannot supply the required power while maintaining the battery SOC profile. Therefore, the engine-generator is operated for more time and also the effective efficiency from engine to wheels is less in series hybrid as compared to the parallel hybrid. Therefore, the combined effect is reduced fuel economy for series hybrid. The results of fuel consumption show that the blended mode control is better as compared EV mode control. However, improvement in fuel economy shown in this paper is smaller

TABLE II

DRIVING AND CHARGING EVENTS

T1	UDDS+US06 (trip to work after full charge)
T1b	US06+UDDS (trip to home after work). Initial SOC is the final SOC of previous trip
T2	UDDS (errands). Initial SOC is the final SOC of previous trip
T3	UDDS + HWFET + HWFET + HWFET + HWFET + UDDS (this assumes the vehicle is only recharged at the end of the day)
C1	Overnight charging after T1b
C2	Overnight charging after T2
C3	Overnight charging after T3

Simulated typical days

	Events	Frequency
D1	T1-T1b-T2-C2	3 days/week, 48 weeks/year (tot. 144 days/year)
D2	T1-T1b-C1	2 days/week, 48 weeks/year (tot. 96 days/year)
D3	T3-C3	2 days/week, 48 weeks/year + 7days/week, 4 weeks/year (tot. 124 days/year)

because the SOC profile has not been optimized with off line optimization methods. Although these algorithms do not give the optimum solution, they can be easily implemented onboard at low computational cost. Work is currently underway to assess the optimality of these control strategies with respect to the dynamic programming.

In all the comparisons it can observed that, as the vehicle travels longer distances or it is running at higher velocities, the improvement in the PHEV fuel economy is lower. Therefore, it might be better to use hybrid control for long distance trips to reduce the battery depth of discharge while achieving good fuel economy.

A Similar analysis was performed to assess PHEV performance in real world scenarios, by using the driving patterns described in Section IV. Sample results are shown in Figure 6. Results on fuel economy show consistent improvement as one goes from conventional to hybrid to PHEVs. The overall performance of blended mode control is better than EV mode control. These results also show that for highway driving (T3 cycle) the fuel economy improvement is less as compared to hybrid.

The numbers over the bars in Fig. 6 show the net energy used from the battery in KWhr. So the better fuel economy in PHEV is achieved through use of electrical energy: the PHEV control strategy depletes the entire battery by consuming almost 7 KWhr of energy to maximize the use of electricity instead of gasoline.

In case of hybrids the electricity used from the battery is generated by the engine, thus the quantity of gasoline needed to recharge the battery can be known with some approximations. In case of PHEVs the electricity needed to recharge the battery can come from different sources like coal, gas, wind, etc. depending on where, and when the vehicle is charged (electric energy generation mix varies with location and time). Its cost is variable, thus making the analysis of PHEV more complex and function of factors

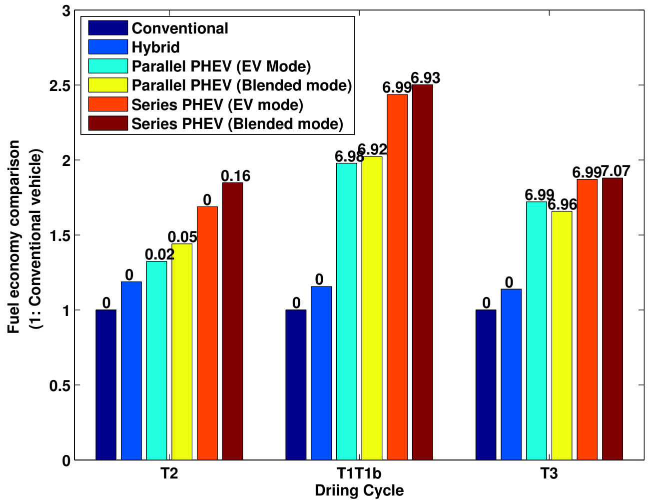

Fig. 6. Net electrical energy consumption and fuel economy comparison for different cycles and models.[mpgge for Hybrid vehicle.] [Number over each bar shows net electric energy used from the battery in KWhr.]

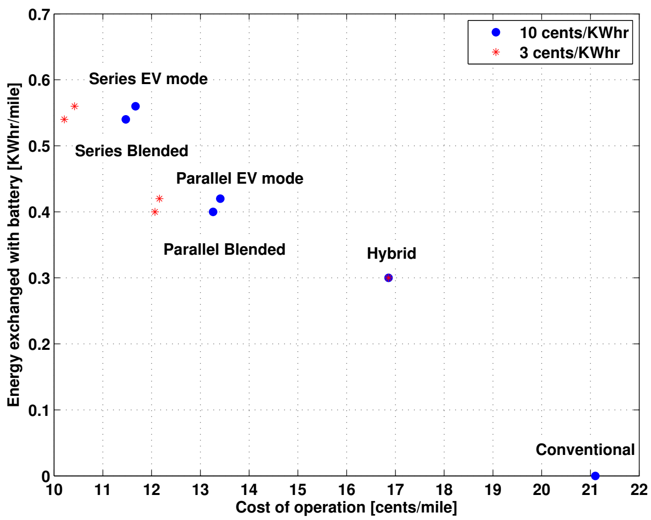

Fig. 7. Battery energy and cost analysis.

that are external to the vehicle. In this paper a typical year is analyzed starting from the driving cycles shown in Table II; in order to take into account the electricity and the gasoline needed over the year, an economic analysis has been performed. The electricity prices are considered to be 10.4 cents [15] and gasoline price is taken to be 4$/gallon. The results are plotted in Figure 7 along with the total electric energy exchanged with battery per mile over the year. This energy considers not only the difference between initial and final state of charge but also the energy exchanged during charge sustaining mode (total charging and discharging energy). It is clear that series configurations show better fuel economy but at the same time show higher usage of battery. This will affect battery performance and life. The figure shows that the blended mode control can be a good trade-off by providing lower cost of operation and lower energy exchanged with the battery. It is clear that an optimal trade-off must be found between cost of operation and battery life (investment cost).

VI. Conclusion

The paper presents an ECMS based control method for PHEVs. This approach does not require extensive offline optimization or driving pattern information, except the total trip distance. The results show that no architecture is optimum in all circumstances, and it gives a perspective on characterizing the strategies for particular driving patterns. Different architectures and control strategies were implemented and compared both on standard and customized driving cycles representing real world data. Besides showing expected improvement in fuel economy for PHEVs, the results also show that complete analysis on PHEV performance needs to consider external factors such as battery life, charging availability, energy cost, etc. The models and algorithms presented in this paper can be extended to study the interaction between driving patterns, the power grid, charging availability, different charging scenarios and the vehicle performance.

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