Dossier

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Electronic Intelligence in Vehicles

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Dossier

Electronic Intelligence in Vehicles
Intelligence électronique dans les véhicules

Intelligent Energy Management for Plug-in Hybrid Electric Vehicles: The Role of ITS Infrastructure in Vehicle Electrification

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Résumé — Gestion énergétique intelligente pour véhicules électriques hybrides rechargeables : rôle de l'infrastructure de systèmes de transport intelligents (STI) dans l'électrification des véhicules — Le désir de réduire les émissions de carbone issues des sources de transport a conduit durant la dernière décennie au développement de nouvelles technologies de propulsion, axées sur l'électrification des véhicules (comprenant les véhicules électriques hybrides, hybrides rechargeables et sur batteries). Ces technologies de propulsion, en même temps que les avancées en matière de télécommunication et de puissance de calcul, présentent le potentiel de rendre les véhicules particuliers et commerciaux plus efficaces sur le plan énergétique et plus écologiques. En particulier, les algorithmes de gestion énergétique sont partie intégrante des véhicules rechargeables et sont très importants pour atteindre les bénéfices de performances. Les performances optimales des algorithmes de gestion énergétique dépendent fortement de la capacité à prévoir la demande énergétique du véhicule. Les informations disponibles concernant l'environnement (température, humidité, vent, qualité de route, etc.) et le trafic (densité du trafic, feux de circulation, etc.) sont très importantes en termes de fonctionnement d'un véhicule à efficacité optimale. Le présent article passe brièvement en revue certaines technologies actuelles susceptibles d'aider à atteindre cet objectif d'efficacité optimale. En plus des informations disponibles issues des systèmes d'informations télématiques et géographiques, la connaissance de la demande de chargement projetée des véhicules sur le réseau électrique est nécessaire pour construire un dispositif de commande de gestion énergétique intelligent pour les futurs véhicules hybrides rechargeables et électriques. L'incidence du chargement de millions de véhicules à partir du réseau électrique pourrait être significative, sous forme d'une charge accrue des centrales électriques, des lignes de transmission et de distribution, des émissions et de l'aspect économique (des informations sont données et discutées dans le cas des USA). En conséquence, ces effets doivent être pris en considération d'une manière intelligente en commandant/programmant le chargement par l'intermédiaire d'un dispositif de commande répartie basé sur la communication.

Abstract — Intelligent Energy Management for Plug-in Hybrid Electric Vehicles: The Role of ITS Infrastructure in Vehicle Electrification — *The desire to reduce carbon emissions due to transportation sources has led over the past decade to the development of new propulsion technologies, focused on vehicle electrification (including hybrid, plug-in hybrid and battery electric vehicles). These propulsion technologies, along with advances in telecommunication and computing power, have the potential of making passenger and commercial vehicles more energy efficient and environment friendly. In particular, energy management algorithms are an integral part of plug-in vehicles and are very important for achieving the performance benefits. The optimal performance of energy management algorithms depends strongly on the ability to forecast energy demand from the vehicle. Information* *available about environment (temperature, humidity, wind, road grade, etc.) and traffic (traffic density, traffic lights, etc.), is very important in operating a vehicle at optimal efficiency. This article outlines some current technologies that can help achieving this optimum efficiency goal. In addition to information available from telematic and geographical information systems, knowledge of projected vehicle charging demand on the power grid is necessary to build an intelligent energy management controller for future plug-in hybrid and electric vehicles. The impact of charging millions of vehicles from the power grid could be significant, in the form of increased loading of power plants, transmission and distribution lines, emissions and economics (information are given and discussed for the US case). Therefore, this effect should be considered in an intelligent way by controlling/scheduling the charging through a communication based distributed control.*

NOMENCLATURE

ACC-LA	Adaptive Cruise Control Look-Ahead
BM	Blended Mode
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimization Strategy
EV	Electric Vehicle
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GPS	Global Positioning System
HEV	Hybrid Electric Vehicle
ISO	Independent System Operator
IT	Information Technology
ITS	Intelligent Transportation Systems
ORCED	Oak Ridge Competitive Electric Dispatch
PEV	Plug in Electric Vehicle
PHEV	Plug in Hybrid Electric Vehicle
RPD	Road Power Demand
SOC	State of Charge
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle

Symbols

θ	Road inclination
ρ	Air density
ϕ	Wind angle of attack
A	Front surface area
C_{drag}	Drag coefficient
$C_{rolling}$	Road friction coefficient
C_{room}	Heat capacity at constant pressure in the cabin room
g	Gravity acceleration
m	Vehicle mass
M	Air mass in the cabin room
T_{room}	Cabin room temperature
V_t	Vehicle speed
V_w	Wind speed

INTRODUCTION

Public awareness of climate change and of the importance of energy savings is increasing and governments are encouraging the use of renewable energy. A clear correlation can be observed between vehicle density (cars per 1 000 inhabitants) and a country's GDP (Gross Domestic Product); this suggests that as densely populated countries such as China, India and Brazil achieve higher economic status, it can be expected that the demand for personal transportation will increase accordingly. Today, this demand can be directly translated into increased demand for petroleum, a fact that is hardly compatible with current data on oil production. Plug-In Electric Vehicles (PEVs, whether hybrid or battery-only) are receiving a great deal of interest in the United States due to their energy efficiency, convenient and low-cost recharging capabilities and reduced use of petroleum. Recent improvements in lithium batteries technology are making PHEVs (plug-in hybrids) in particular a viable solution to reduce cost, petroleum consumption and emissions from the transportation sector. PHEVs aim at bridging the gap between pure electric vehicles and conventional vehicles using a hybrid electric powertrain [1]. Similar to a Hybrid Electric Vehicle (HEV), a PHEV is powered by two energy sources, gasoline and electricity. In a HEV, the battery is charged using the engine and regenerative breaking and the battery state of charge is maintained around a constant value throughout the driving cycle. The improvement in fuel economy of HEV is achieved by the optimization of power split between battery and engine. A PHEV has greater battery capacity than a HEV and the ability to charge the battery from external sources such as the power grid, solar power, etc. The external charging ability allows the PHEV battery to be depleted during the vehicle operation and be charged when the vehicle is plugged-in, thus using electrical energy as a transportation fuel and displacing gasoline.

Figure 1 shows that a typical US driver may benefit from a 50% reduction in total yearly operation costs [2]. In Figure 1, D1, D2 and D3 represent typical driving days for a US driver, wherein D1 represents a typical commute to work; D2 represents a commuting day plus evening errands; D3 mimics a weekend trip and the entire year is comprised of a suitably balanced mix of these representatives driving patterns.

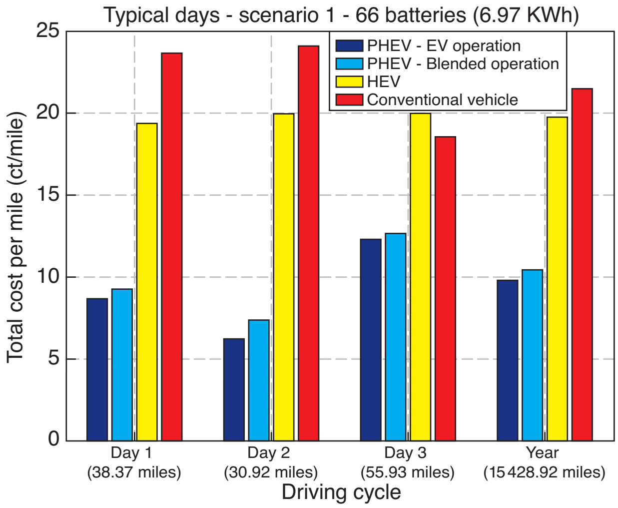

Figure 1

Comparison of PHEV with HEV and conventional vehicle based on operating cost for typical US driver [2].

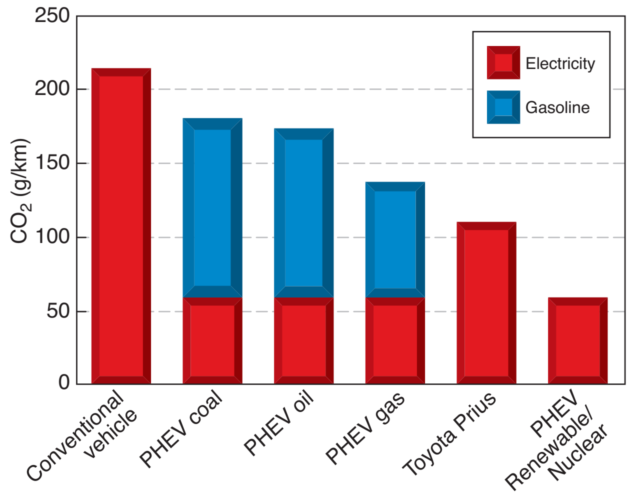

Figure 2

Vehicles CO_2 emissions comparison [3].

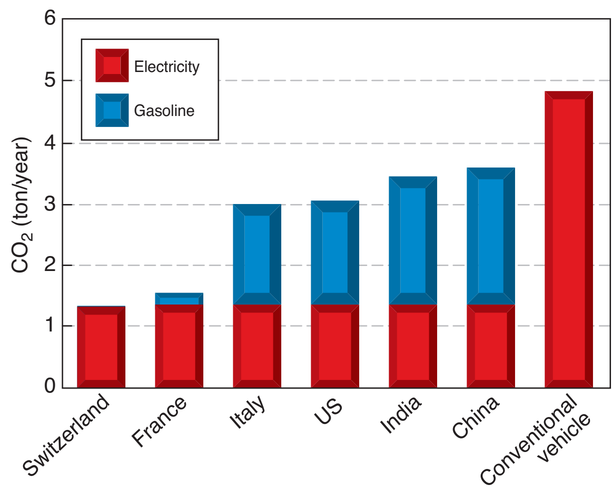

Figure 3

Effect of generation mix on CO_2 emissions [3].

In addition to fuel consumption and cost of operation, another important factor for a PHEV is the combined CO_2 emissions from vehicles and electric power plants. The total CO_2 emissions depend on the generation mix used to charge the PEV and therefore any results will depend on the regional power generation mix.

Figure 2 shows that CO_2 emissions related to the automotive sector could be decreased by PHEV and HEV use, in particular using a low-carbon source of energy (such as nuclear or renewable) to recharge PHEVs batteries, CO_2 emissions could be drastically reduced.

Figure 3 shows the impact of different generation mix on total CO_2 emissions, comparing annual per vehicle CO_2 emissions of a PHEVs charged with different countries' energy mix, *e.g*. in Switzerland the electricity is produced using hydroelectric and nuclear plants without emitting GHG therefore a PHEV will not produce pollutants emissions to recharge its batteries [3].

The paper is structured as follows: Section 1 "*Energy management of PHEVs*" gives an overview of control and optimization techniques employed in the energy management of plug-in hybrid vehicles; Section 2 "*Information Requirement*" describes the role of ITS in energy management, introducing the concept of an Intelligent Energy Management algorithm with access to GPS location of the vehicle along with expected route information, traffic conditions, current temperature and driving history of the vehicle; Section 3 "*Impact factor analysis*" discusses how different factors impact PHEV fuel economy and how different levels of predicted/available information can provide support to ITS-based control/optimization strategies; Sections 4 and 5 "*PEV charging*" and "*PEV impact on transformer*" present the impact of PEV charging on the grid, at higher level – power generation – and lower level – distribution networks, respectively. Finally, the section "*Closure*" summarizes the paper providing high-level considerations on the issues related to PHEV operation/charging and the potential role of ITS infrastructure.

1 ENERGY MANAGEMENT OF PHEVS

Energy management algorithms for PHEVs are crucial for vehicle performance. Energy management strategies in a PHEV are similar to those employed in HEVs, with the

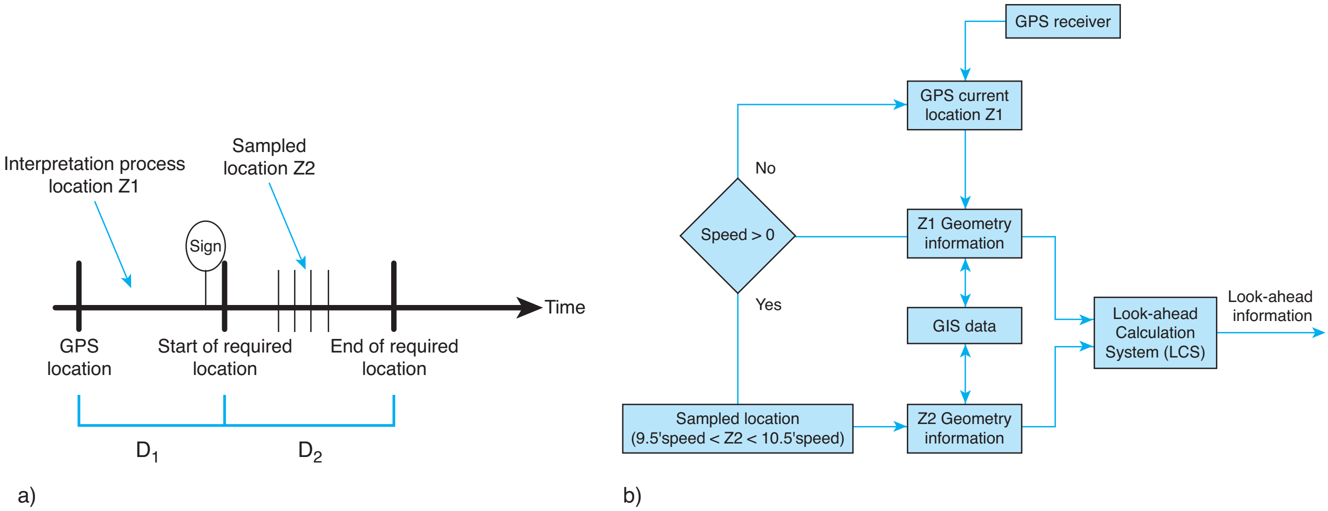

Figure 4

Look-ahead prediction method. a) Sampling locations. b) Calculation system [18].

additional degree of freedom corresponding to the ability to deplete the battery pack to obtain electric tractive power in significant quantities, coupled to the possibility of recharging the pack [4].

PHEV performance can be affected by uncertain factors such as road conditions, environmental conditions and driver behavior. One of the most important challenges for the development of PHEV control strategy is the synchronization of multiple energy sources and conversion of power flow control for both the mechanical and electrical paths in optimal fuel efficiency and battery areas [5]. The control strategies in a PHEV can be classified in two main groups as follows:

– numerical optimization such as Dynamic Programming (DP) and stochastic optimal control. DP is a methodology that can compute the optimal solution, but it is practically impossible to implement on a vehicle since it requires whole future driving cycle information [6]. Gong *et al*. [7] proposed a novel approach to optimal power management of PHEVs in the charge-depletion mode with driving cycle modeling based on the historic traffic information. The DP algorithm was applied to reinforce the charge-depletion control such that the SOC drops to a specific terminal value at the end of the driving cycle. Only fuel consumption is considered for the current stage of the study. They used a simulation for several standard driving cycles with two trip models used for the proposed method and the results showed improvement in fuel economy compared with a rule-based control and a depletion sustenance control for most cases. Furthermore, the results showed much better consistency in fuel economy compared with rule-based and depletion sustenance control. Moura *et al*. [8] examined the problem of optimally splitting driver power demand between the engine and electric machines in a PHEV. They used stochastic dynamic programming to optimize PHEV power management over a distribution of drive cycles, rather than a single cycle. Also, they controlled the charge depletion over aggressive charge depletion followed by charge sustenance. Finally, the impact of variations in relative fuel-to-electricity pricing on optimal PHEV power management has been examined. Bashash *et al*. [9] used the stochastic optimal control method and optimized a PHEV charging the combined effects of total energy cost, battery health, electricity pricing and PHEV driving patterns. The charge patterns obtained through this optimization were substantially different from those optimized for energy cost or battery health alone. As can be seen from the recent research studies, DP also requires a large amount of memory and computational power to perform the optimization [10];
– heuristic and knowledge-based online optimization such as rule based algorithms [11-13], fuzzy logic [14-16] and equivalent consumption minimization strategy [17] can on the other hand be implemented on board of a vehicle. The heuristic and knowledge-based algorithms do require some information to perform optimization but it is typically less information than that required by DP. In order to the best way is a trade-off between information requirements and algorithm performance by making adaptive of heuristic and knowledge-based algorithms [18]. Khayyam *et al*. [18] show that if the vehicle could make intelligent predictions about the look-ahead future road, the greatest fuel savings

strategy would be achieved. Look-ahead prediction method get sampling locations of slopes and a look-ahead calculation system that employs the GPS and GIS information. Figure 4 shows the algorithm and calculation system.

One of the look-ahead system illustrations can be seen on vehicle air conditioning system enhanced with look-ahead system [19]. Based on the study and using the road ahead environment weather conditions (wind, temperature, etc.) and road information (slope, bend, etc.), the vehicle fuel consumption can be intelligently decreased. These achievements can be utilized by using the Information Technology (IT). IT enables elements within the transportation system vehicles, roads, traffic lights, message signs, etc., to become intelligent by embedding them with microchips and sensors and empowering them to communicate with each other through wireless technologies.

Heuristic and knowledge-based online optimization techniques do require some information to perform offline optimization or tuning of the parameters but it is typically less than that required by dynamic programming. As one might imagine, there is a trade-off between information requirements and algorithm performance.

For instance, the EV mode control is a simple method with two stages – charge depleting (all electric) and charge sustaining. The control algorithm selects only the electric motor as long as the battery State of Charge (SOC) is greater than a threshold value. Once the SOC reduces below this value, the control algorithm switches to charge sustaining (PHEV behaving like a HEV). In blended mode control, the objective is to achieve lower limit of SOC only at the end of trip. The battery SOC is reduced slowly throughout the trip and the SOC profile followed in this control can be optimally selected by principles from optimization theory, like dynamic programming. This method can provide better fuel economy but at the cost of higher information requirement.

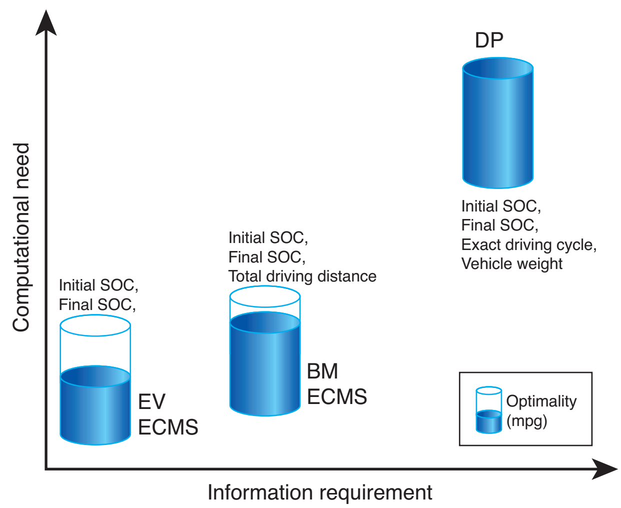

Figure 5

Comparison of the control strategies. DP: Dynamic Programming, BM ECMS: Blended Mode control using ECMS, EV ECMS: EV mode using ECMS. (ECMS: Equivalent Consumption Minimization Strategy).

A heuristic comparison of different energy management strategies with respect to online implementation and information requirements is graphically shown in Figure 5 [20].

ECMS is based on the fact that in general 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. For PHEV applications, the ECMS needs to consider also the energy coming from the grid: this effective fuel consumption is used as the objective function for control optimization while the input to the ECMS algorithm is total power demand. The ECMS searches the best combination between the engine and motor power, which minimizes the effective fuel consumption.

2 INFORMATION REQUIREMENT

Driving cycles and velocity profiles have great impact on PHEV performance in terms of overall energy consumption, fuel economy and emissions. Many researchers have suggested that road type and traffic condition, driving habits and vehicle operation modes have various degrees of impacts on vehicle fuel consumptions. Khayyam *et al.* [18] presented an Adaptive Cruise Control (ACC) system that reduces the energy consumption of the vehicle and improves its efficiency based on driving cycles and velocity. The Adaptive Cruise Control Look-Ahead (ACC-LA) system works as follows: it calculates the energy consumption of the vehicle under combined dynamic loads like wind drag, slope, kinetic energy and rolling friction using road data and it includes a look-ahead strategy to predict the future road frictions. The evaluation outcome indicated that the vehicle speed was efficiently controlled through the look-ahead methodology based upon the driving cycle and that the average fuel consumption was reduced by 3%.

In addition, incorporating knowledge derived from intelligent transportation systems about online driving pattern recognition and traffic and geographical information in control strategies is another path towards the optimization of PHEV energy management. The performance of the energy management algorithm is closely related to the power demand throughout the driving trip. The power demand depends on the road, weather conditions and velocity profile, which in turn is dependent on traffic and geography. The performance of energy management can be improved if it is optimized for the driving conditions and weather pattern. Therefore, information about the driving route, a weather forecast and traffic conditions are very important in guaranteeing optimal performance of the energy management strategy. Intelligent Transportation

Systems (ITS) allow the vehicle to communicate with other vehicles and the infrastructure to collect information about surrounding and expected events in the future, *e.g.* traffic condition, turns, road grade, rain, snow, temperature, etc. Such information is useful for the energy management algorithm optimization and plays crucial role in the fuel economy and battery utilization, as it can assist in designing algorithms such as stochastic dynamic programming, model predictive control, etc. ITS information can be utilized for long-term trip forecast as well as short-term velocity and power profile prediction. Static and dynamic information including road grade and road surface conditions, speed limits, traffic light locations and timing and real-time traffic flow speeds can be used to build a long term forecast of the overall trip to the destination. At the same time, information about the immediate surroundings, such as lane changing and turning decisions of the host and surrounding vehicles and estimation of waiting time for turning on red, left turns and stop sign queuing, is helpful for refining short term prediction of future driving profile. ITS information can improve vehicle energy efficiency and mobility with route planning. Road static information, real-time traffic flow, battery charging station locations and real-time prices and other information is useful in determining an optimal route for energy efficiency and short travel time. Figures 6 and 7 show a concept of such an intelligent energy management algorithm and its integration with ITS data.

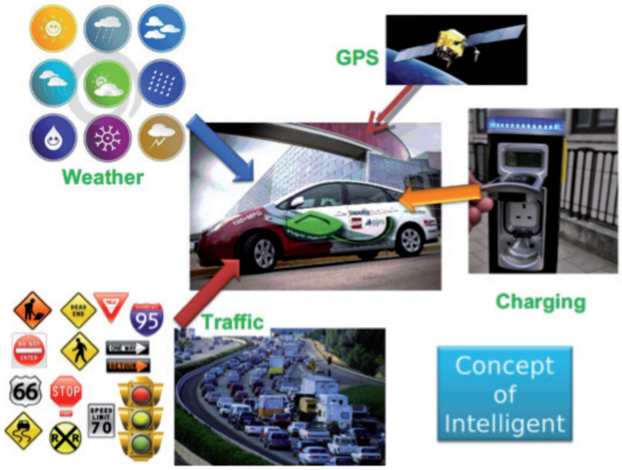

Figure 6

Concept of intelligent energy management for a PHEV.

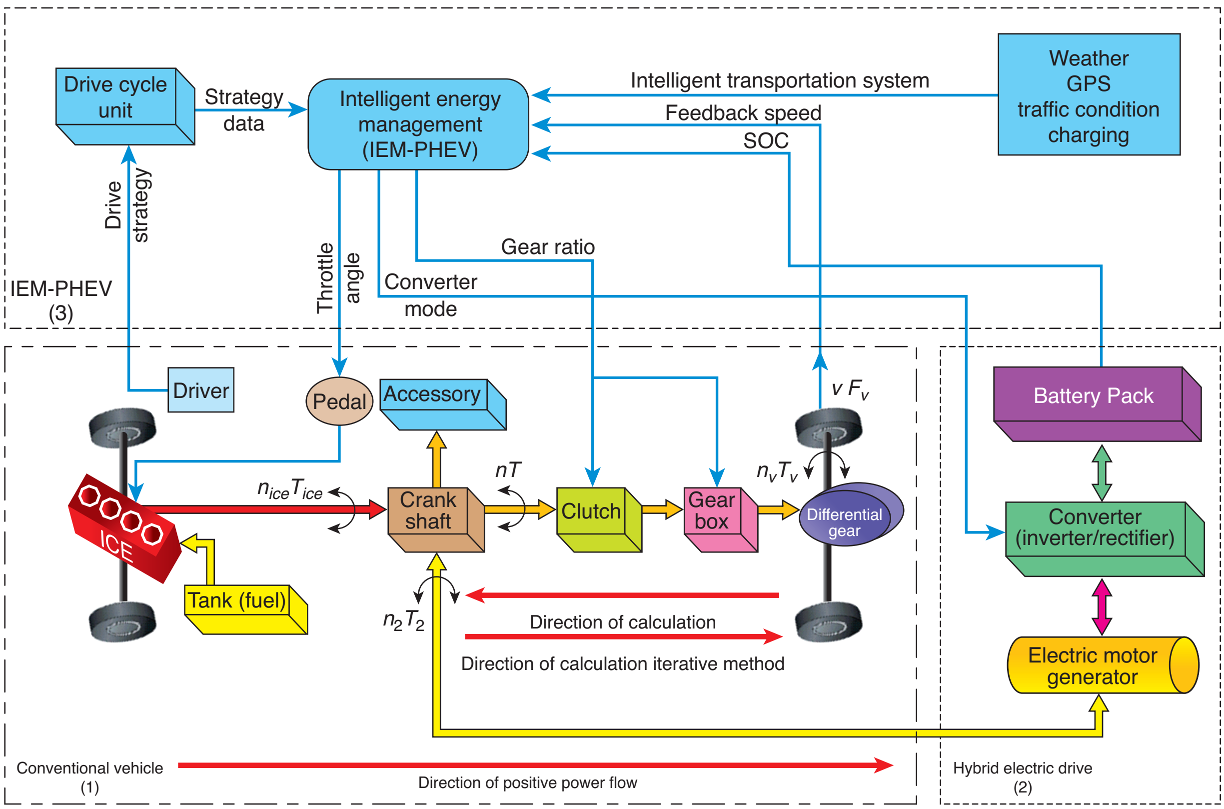

Figure 7

Schematics of intelligent energy management for a PHEV.

An intelligent energy management algorithm will have access to GPS location of the vehicle along with expected route information, traffic conditions, current temperature and driving history of the vehicle. Based on this information the vehicle energy management algorithm will forecast the traffic condition and power demand from the vehicle. The algorithm will then optimize its decisions to optimally select battery usage and reduce fuel consumption, emissions, etc. In this way an intelligent energy management strategy will adapt itself to the changing weather and traffic conditions to give best performance.

It is worth noting that the future information about the weather, velocity profile and PHEV charging is not exact and complete *i.e.* it is not possible to predict exact velocity profile for complete driving trip but it is possible to predict the velocity profile in statistical sense *i.e.* prediction of average velocity, average acceleration, idle time, stop time etc. It is also possible to predict the availability of charging station, cost of electricity etc., to control the battery state of charge and charging. Such quantities can be calculated from trip information, GPS, communication with the infrastructure etc.; also many conditions can be predicted for weather, *e.g.* temperature, rain, snow etc. The task of predicting all such quantities and use them to perform energy management optimization is clearly overwhelming. One objective of this article is to suggest the most important factors that affect the performance of the energy management system. For example, the velocity profile depends on the road events and traffic conditions such as a traffic light, stop sign, pedestrian crossings, etc. Similarly, the initial SOC is a function of charging habits and infrastructure availability. We call the systematic analysis of these conditions Impact Factor Analysis and describe it in the next section.

3 IMPACT FACTOR ANALYSIS

The research described here is centered on real world driving data from a PHEV fleet operated by Center for Automotive Research at The Ohio State University. This database currently contains more than 100 000 miles of vehicle data throughout the year with many different variables such as longitude, latitude and altitude from GPS, vehicle velocity, coolant temperature, fuel consumption, battery SOC, current etc., from vehicle CAN bus, along with time and date. The GPS data is sufficiently accurate so that it can be used to exactly locate the vehicle on the road and also determine the lane. This data is used in this analysis to find the velocity traces during road events and then perform the statistical analysis.

In this process, an impact factor knowledge base has been constructed, with important information on which factors have the largest impact on performance and which factors are most important for subsequent development of energy management strategies in optimizing fuel economy. Using these tools, a generalized sensitivity analysis will be conducted to delineate and prioritize variables, configuration/sizing and control parameters, usage pattern, etc. according to performance benefits. The initial part of this task is to intelligently reconstruct a real world dynamic transportation map from both the static data (GPS, GIS, Mapping, etc.) and dynamic data (V2I, V2V information exchange/broadcast) for the purpose of PEV energy management optimization. The critical task is to identify what information can be used to improve fuel economy and to determine the requirements on this information.

Different events are defined for weather, road, driving and charging conditions *e.g.*, traffic lights, stop signs, turns, lane changing, driving in snow, rain, temperature effect, charging availability, charging power, etc. A more elaborate list is given in Table 1. Initially, the impact of the single events on the velocity profile is analyzed. The goal is to determine how such events affect velocity profile of the vehicle and how this information can be used to optimize the PHEV energy management strategy [21]. Similarly, the effects of ambient temperature, humidity and air density on PHEV energy utilization and fuel economy are analyzed [21].

TABLE 1

Impact factors [21]

Weather conditions	Road and traffic	Charging
Snow	Intersections (stop signs, yield signs, turns)	Availability (at home, workplace)
Rain	Road grade	Policy (controlled, uncontrolled)
Fog	Traffic light (numbers, stop time, distance between lights, synchronized?)	Charging power (Level I, Level II)
Wind	Traffic density	Electricity cost
Ice	Pedestrian crossing	
Temperature	Ramps Speed limits	

The temperature also affects tire pressure and the rolling resistance of the tire, which is inversely proportional to the tire temperature, *e.g.* a relative increase of 26°C in the temperature decreases the rolling resistance coefficient by 0.003 units. This impact of temperature on rolling resistance results in changes in energy demand of the vehicle due to change in temperature by assuming constant tire pressure and air density. The results of these two analyses are shown in Figure 8ab. Figure 8a shows that increase in temperature from –25 to 50°C causes 23% reduction in air density which reflects into 5% decrease in the energy demand in urban driving and 10% reduction in energy demand for highway driving. The relative increase in the temperature of 26°C in

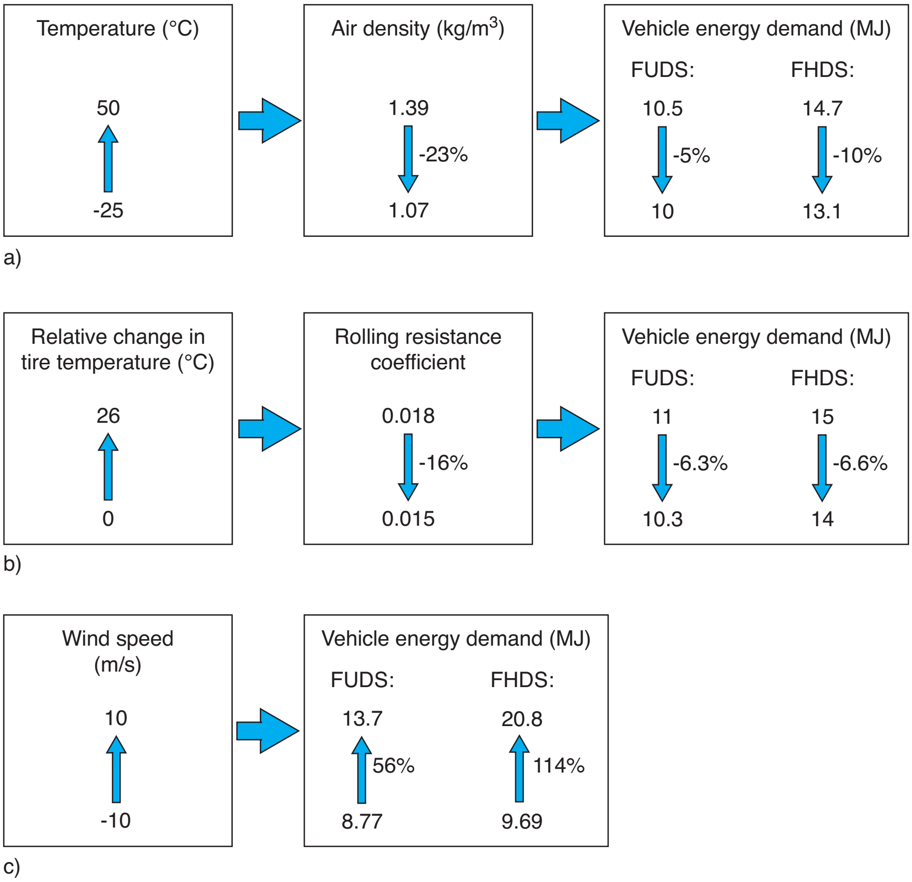

Figure 8

Impact of temperature on vehicle energy demand due to a) air density, b) rolling resistance coefficient, c) impact of wind speed on vehicle energy demand.

tire temperature decreases the rolling resistance coefficient by 16% which reflects in the decrease in vehicle energy demand by approximately 6.5% in urban and highway driving. As shown in Figure 8c, the change in wind direction (negative speed means that wind is flowing in direction of vehicle motion) causes large change (56% in urban and 114% in highway driving) in the energy demand from the vehicle. Also, it is observed that a change in wind speed from 5 to 10 m/s changes the energy demand by 21% and 16% for urban and highway driving, respectively.

Next, a specific route is considered to find the important velocity statistics *e.g.*, average velocity, maximum acceleration, stop time, etc. which have large impact on the fuel consumption. Figure 9 shows how the optimal value of the ECMS tuning factor is affected by driving patterns. This optimal factor for each velocity trace is compared with eighteen statistical values of the respective velocity trace to perform a regression analysis. The sample results provided here show optimum tuning factor *versus* average acceleration for all the road events along with linear functions.

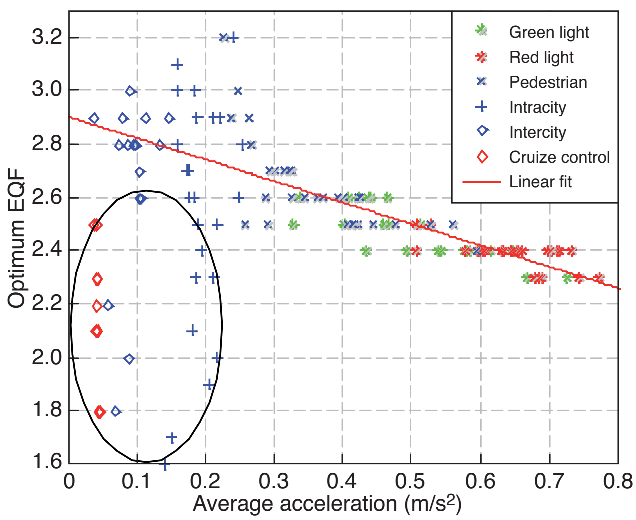

Figure 9

Optimal equivalence factor *versus* average acceleration. Black circle represents cruise control velocity profiles.

The figure can be used as relationship between average acceleration and the optimal tuning factor of the employed control algorithm, such that if the average acceleration for a velocity profile is known, then the optimal tuning factor can be determined.

Such results will help in integrating ITS with the energy management by collecting the data about average acceleration for different road events and tuning controller online. Results show that the knowledge about vehicle driving pattern in the form of road grade, velocity profiles, trip distance, weather characteristics and other exogenous factors, can be used to improve the performance of the energy management strategy and fuel economy, thus further proving the increasing importance of ITS infrastructure.

4 PEV CHARGING

PEVs utilize power by plugging into an electric power source and stored in rechargeable battery packs and they have been called vehicle to grid (V2G). PEVs significantly increase the load on the grid, much more than you would see in a typical household. Due to the characteristics of electric power generation (inefficient at managing peak loads), transmission and distribution, experts have identified local distribution as a likely part of the chain to be adversely affected by unregulated PEV charging. Clement-Nyns *et al*. [22] proposed some the impact of vehicle to grid on distribution grid. These issues can be addressed by using smart grid electricity. A smart grid focuses on electrical and information infrastructure and it encompasses three major areas:

- demand management,
- distributed electricity generation,
- monitoring and control.

Grid monitoring and control is required to ensure that electric generation matches the demand. If supply and demand are not in balance, generation plants and transmission equipment can shut down which, in the worst cases, can lead to a major regional blackout. The development V2G can be facilitated nationwide by ITS wireless and V2G play important roles in ITS. ITS and V2G each promise to save scores of billions of dollars to the US annually, improve the environment, health and quality of life and make the US more energy independent, robust, competitive and safe. Khayyam *et al*. [23] demonstrated that the intelligent controllers (connected with ITS information) could monitor and control the electrical grid when connected and recharging PEV batteries. In order to, the study examined the distribution of electricity in the power grid of a large-scale city so that PEVs can tap into the system. The electricity grid for the large-scale city was modeled and it could be shown that the vehicle electrification can play a major role in helping to stabilize voltage and load. The smart grid model used two intelligent controllers:

- fuzzy load controllers;
- fuzzy voltage controllers.

In this study, intelligent controllers optimized the grid stability of load and voltage for connection vehicle to grid. The results showed that the smart grid model could respond to any load disturbance (V2G and others) in less time, with increased efficiency and improved reliability compared to the traditional grid.

Local distribution grid load pattern may change and some power lines, substations can become overload quickly. The charging load can increase the emissions from the power generators based on the generation mix of the power grid. The increase can be very high so that the net emission (tailpipe + power grid) could be larger than that of the conventional vehicles.

PEV charging is performed when the vehicle is stopped. So the charging time and duration is dependent on the user. Vehicle charging is reflected as a load or demand on the grid, so it is necessary to study the effect of vehicle on the grid and the effect of different level of market penetration of PEVs into the automotive sector. As the number of vehicles increases the charging demand may exceed the grid capacity or may cause severe constraints on its operation. The time and location of the vehicles determine whether the effect of the PEV charging will be on local grid or regional power system. PEV charging may require more generation capacity, more transmission and distribution capacity to meet the electrical power demand. One possible behavior, which could be rewarded by appropriate electricity pricing policies, would see PEVs being charged primarily at night, with reduced effects on the grid. But in general, charging time during the daytime is a very important factor in determining the fuel consumption, emissions and cost of electricity for a PHEV, as illustrated in Figure 10. This figure shows the result of a study performed using the ORCED model for generation dispatch in the Virginia-Carolina control region [24]. The time of charging decides which generators will be used to satisfy the increased demand; for example, evening charging would increase natural gas combined-cycle generation while night time charging would increase coal-fired power generation, with clear implications with respect to cost and emissions.

Thus, time-of-charging can have a significant impact on the emissions and the generation associated with electricity used as a transportation fuel. From the figure, it is clear that in most cases the power plants used to satisfy incremental loads in the early evening are gas combined cycle and gas turbine power plants. The evening scenarios have the majority of the generation coming from these plants, while in the nighttime charging scenarios most of the added generation comes from coal. Although night charging will result in minor impact on the grid, it is worth noting that the energy mix for night charging has a higher coal-fired plant content.

Therefore, apart from the optimization of energy management of PHEVs it is also important to intelligently control the charging behavior. If all vehicle controllers independently

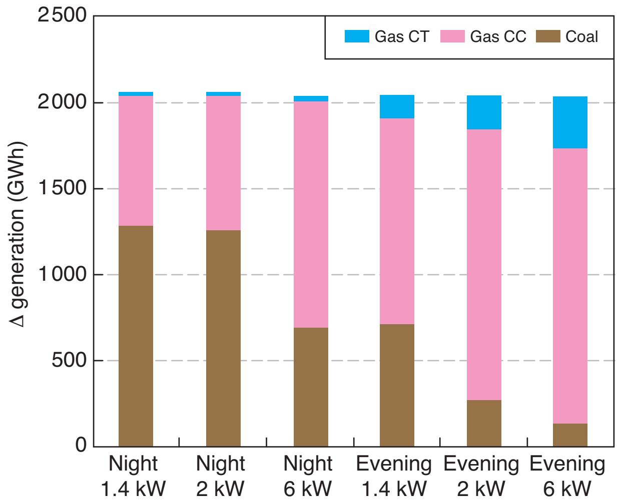

Figure 10

Effect of charging time on generation mix [24].

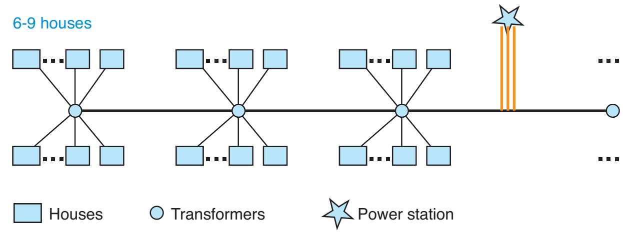

Figure 11

Topology of power grid and houses in US.

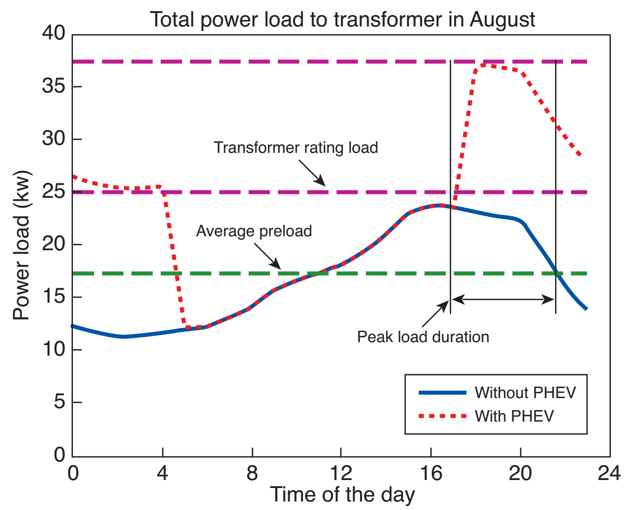

Figure 12

PEV load on the transformer. Red dotted line shows increased demand from PEV charging.

decided to charge without any external signal, grid stability could be compromised. Therefore, it is necessary to provide a centralized charge-enabling control to each vehicle. This control could be provided by the grid operator (*e.g.*: an Independent System Operator, or ISO). The concept of "Smart Charging" relies on communication interface between the power grid and the vehicle to control the charging time and avoid diverse effect on the power grid. Each vehicle is equipped with a communication interface, either a wireless link, Internet connection etc. This interface provides the commands to the vehicle and also it sends signals back to ISO. The signals may include power availability in the vehicle battery, power usage history, power absorbed from and supplied to the grid, etc.

5 PEV IMPACT ON TRANSFORMER

The characteristics of electric power generation, transmission and distribution in the US are such that experts have clearly identified local distribution as the most likely component of the chain to be adversely affected by unregulated PEV charging. A lot of research has been done to study the PEV charging impact. Authors in [25] gave an extensive review of PHEV development and deployment related questions including the PEV impact on the electric grid. The objective of the paper is to understand what level of PEV market penetration the current grid would be capable to handle. Although quite much work has been pointed to study the impact of PEV to grid, a detailed study of PEV charging impact on to the local distributed transformer system has not been performed.

This section presents a study performed to find the impact of PEV charging on the local distribution transformer. The findings of this study may assist in determining the most suitable local/regional charging strategies for PEVs. Currently, in the US electric power to single-occupancy home residence is provided by a transformer that typically feeds several units (4-10 houses depending on the transformer size), as shown in Figure 11. Based on the existing design, the total power load is less than the maximum limit of the transformer, which means that the transformers can work safely, without overheating and meet their intended design life of at least 20 years. However, with more and more PEVs to be used in the future, will residential transformers still be able to meet the new load demand without undue reduction in their life? Currently, there are three levels of charging rates for PEVs: Level I to Level III. For the purpose of illustration, we consider Level-II charging, which delivers up to 6.6 kW at 220 V.

Transformer life is a complicated function of electrical load and ambient temperature. Generally, heat is the biggest

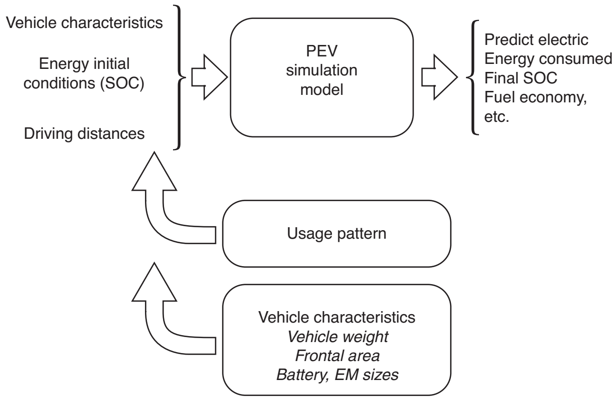

Figure 13

Energy analysis model-diagram.

enemy of transformer life. One simple rule of transformer safe use of to set a limit to peak load duration, based on some empirical tables or maps, such that during a day the transformer load cannot exceed some value, which is determined by the preload level. Figure 12 takes a 25-kVA transformer for example. In this case, we assume that just two PHEVs are charged at night with Level II charging. A simple estimate shows that the average preload for the 25-kW transformers is about 75%. Based typical industry guidelines, to meet its design life goals, peak load (about 37.5 kW) should not exceed 3 hours for the transformer.

As pointed out in [26], aging, or deterioration of insulation, is a time function of temperature, moisture content and oxygen content. For the modern oil preservation systems, the moisture and oxygen contributions to insulation deterioration can be minimized, leaving insulation temperature as the controlling parameter [26]. So the aging model is developed based on hot-spot temperature estimation as presented by [26]. Hot-spot temperature can be estimated by transformer thermal model based on heat transfer theory. Then, the hot-spot temperature can be estimated given know ambient temperature and load. In [27], a detailed discussion of the impact of different numbers of PEVs on a 25-kW transformer was presented. A transformer thermal model was used for the aging estimation given the load and ambient temperature.

The diagram of the energy analysis model is shown in Figure 13. Electric energy consumption and fuel economy of the PEV fleet are estimated based on the stochastic inputs like vehicle weight, generated velocities, initial SOC, etc. The complete model also includes driving pattern recognition to identify different types of driving cycles and estimate performance like fuel economy and emission. Two PEV models were considered *(Tab. 2)*, a plug-in hybrid electric vehicles (similar to the GM Chevy Volt) and an electric vehicle (similar to the Nissan Leaf) [27]. The required charging load of PEVs was generated from a Monte Carlo based mass simulation model based on the vehicle model parameters and customer driving patterns.

TABLE 2

PEV specifications

	Battery capacity (kWh)	Curb weight (pounds)	Frontal area (m^2)
Chevrolet volt (PHEV)	16	3 781	2.27
Nissan leaf (EV)	24	3 500	2.16

From the data provided by an electric utility, a set of raw data of power load for year 2009 was available for study. The empirical data indicates that a typical 25-kVA transformers feeding 6 homes has average load of 10.2 kW, peak load of 25.97 kW and minimum load of 0.1976 kW. PEV charging rate was set to be level 2 of the SAE J1772 standard, about 6.6 kW (220 V, 30 A) in average.

Table 3 shows preliminary estimation of transformer insulation life for different scenarios (different plugging-in time and different number of connected PEVs). The charging time required for each PEV is not a firm value, but a stochastic value, function of the daily driving pattern and initial state of charge.

TABLE 3

Expected transformer insulation life for different scenarios (6.6 kW)

Cases with Monte Carlo SOC	2 PEV (years)	4 PEV (years)
All vehicles plugged-in at 7 pm	14.41	0.0432
All vehicles plugged-in at 12 am	OK	0.5148
Randomized PEV charging (Frequency 30 min)	OK	13
Randomized PEV charging (Frequency 15 min)	OK	20.7
PEV charging – evenly averaged between 7 pm and 6 am	OK	OK

Results show that PEV charging has great impact on the transformer life without intelligent regulation. Without any control, just 2 PEVs (connected at the same time) would reduce transformer life (design life is 20 years); on the other hand, a proper control strategy would be able to minimize the impact on transformer life even for more aggressive cases, like 4 PEVs. Obviously a PEV without any intelligent control cannot guarantee that the transformer will not be overloaded for an excessive period of time. It should be expected that in the future intelligent PEVs will have access to this information from the utility companies *via* a communication link and will be able to make decisions about charging time and power considering the limitations of the local distribution system.

CONCLUSION

Advances in GPS, telecommunication and portable computing devices will change many aspects of vehicle energy management. This article suggests that in the future we will see fuel-efficient, environment- and traffic-aware vehicles that integrate ITS and telematic systems with electrified propulsion technology to achieve optimal energy management.

Further, the impact of PEVs on the power grid cannot be neglected when large numbers of these vehicles are introduced in the market; thus, consideration of increased electric power demand and of the timing of vehicle charging must be included in the control/optimization process. In the future, it will become necessary to analyze information in real time to quantify the effects of infrastructure, environment and traffic flow on vehicle fuel economy and emissions and to permit the application of forecasting and optimization methods for the energy management of plug-in electric and hybrid vehicles.

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