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ABSTRACT Increasingly stringent fuel economy and emissions regulations have required the automotive industry to consider more fuel-efficient powertrains and alternative primary sources of transportation fuels. Powertrain electrification and hybridization have rapidly become part of the portfolio of all major automotive manufacturers, ranging from hybrid-electric, to plug-in hybrid-electric, to battery-electric vehicles, to hybrid-hydraulic and hybrid-mechanical solutions. The increased complexity of the powertrain systems associated with hybrid vehicles presents interesting control challenges and problems. This article presents a review of control problems associated with hybrid-electric vehicles (HEVs) and battery electric vehicles (BEVs).

KEYWORDS hybrid-electric vehicle, hybrid-electric powertrain, control, energy management.

1. HEV powertrains

A HEV powertrain contains at least two power sources: a primary engine – typically a combustion engine or a fuel cell fueled by a chemical fuel (in liquid or gaseous form), and a secondary power source that makes use of a Rechargeable Energy Storage System (RESS) that permits buffering the power demand of the vehicle so as to provide choices in the use of the power sources. While it is possible to design hybrid powertrains using secondary hydraulic or mechanical energy conversion and storage devices (hydraulic pump/motors and accumulators, mechanical flywheels), the majority of hybrid powertrains in use today employ electric machines and electrochemical energy storage devices (batteries and supercapacitors); thus, this brief review paper focuses exclusively on hybrid-electric vehicles (HEVs). Electric vehicles (EVs) can be viewed as a special case of HEVs in which no internal combustion engine is present, and many of the considerations that follow apply also to hydraulic and mechanical hybrids. HEVs may be classified according to their powertrain architecture, as shown in Figure 1.

A series HEV powertrain employs an Electric Machine (EM) to propel the vehicle, while using an Internal Combustion Engine (ICE) coupled to a second EM as an electrical generator set. In a series HEV, the electrical generator set can provide power directly to the electric traction system, via an electrical DC bus, or can charge an RESS (battery, for example), or can perform both functions. Motive power to the vehicle is delivered by the primary EM. Thus, a series HEV blends electrical power from a RESS with electrical power generated by an ICE-powered generator set to provide motive power to the vehicle. Deciding how much electrical power to draw from each of the two power sources to meet the power demand of the vehicle is an important control objective. A further feature of interest is the ability to recover some of the kinetic energy of the vehicle during braking events by using the traction EM in generator mode to recharge the RESS.

A parallel HEV powertrain blends mechanical power from the ICE and one or more EM(s) through appropriate mechanical coupling and transmission elements to deliver motive power to the vehicle, or to recharge the RESS. In a parallel HEV powertrain the same EM is used to provide power to the vehicle (motor mode), and to provide energy to the RESS (generator mode); in the latter case, the RESS can be re-charged either by providing power from the ICE in excess of that required by the vehicle, or by converting the kinetic energy of the vehicle into electrical power through the braking action of the EM.

A third configuration, the one that is most commonly found among passenger vehicles in commercial production today, is the power-split HEV, in which the benefits of both series and parallel HEVs are achieved, most commonly by using one or more planetary gear sets to couple two EMs – to the ICE on one side, and to the driveline on the other.

Regardless of architecture, HEV powertrains enable fuel savings and emissions reductions by operating in a variety of modes that include: load leveling, regenerative braking, engine start-stop, and transmission optimization [1, 2].

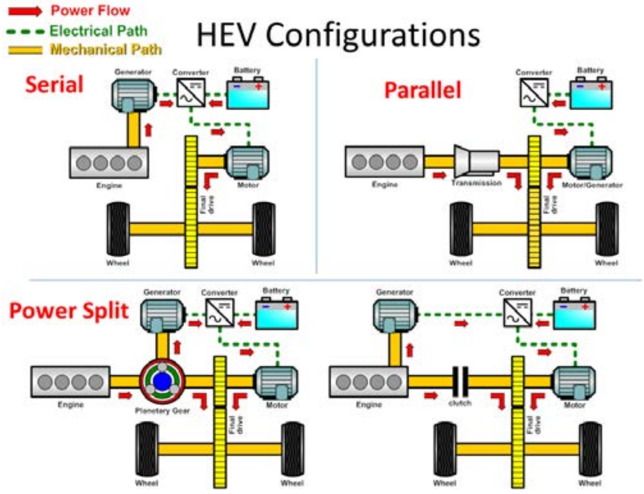


Figure 1 Hybrid powertrain configurations (after [1])

All of these functions benefit from the availability of a RESS and of bi-directional power converters, that is the electric drive system(s) that can serve both motor and generator functions.

2. HEV operation

A HEV is considered charge sustaining if the RESS is recharged only by power supplied by the ICE or by regenerative braking. If, on the other hand, the vehicle is designed to deplete energy stored in the RESS during the course of a trip, ending the trip with a lower state of stored energy than at the start and requiring re-charging from the electrical grid, the vehicle is called charge depleting, and is commonly referred to as a Plug-in HEV (PHEV). PHEVs can in turn be subdivided into blended-mode PHEVs, in which stored electrical energy and fuel chemical energy are used jointly to achieve minimum overall energy use, and Extended-Range Electric Vehicles (EREVs), in which electrical energy is used exclusively to power the vehicle, until a lower bound is reached, at which point the vehicle uses both ICE and EM(s) to behave like a charge-sustaining hybrid. In principle, any of the architectures of Figure 1 can be used in any of these modes. A Battery-Electric Vehicle, or BEV, is an extreme case of an EREV, in which the vehicle is not equipped with an ICE. Miller [2] provides an excellent overview of the technology underlying each of the powertrain architectures mentioned so far.

3. Control Problems in X-EVs

Let us refer to the general case of a hybrid or electric vehicle as an X-EV, with the X- in X-EV representing any of the architecture discussed so far: X- = H, PH, ER, or B. X-EVs enable multiple configurations and operating modes of the powertrain, presenting a number of interesting control problems above and beyond those that are already present in non-hybrid powertrains (e.g.: engine and transmission control). In general, the control architecture of a HEV is hierarchical, with a higher-level (supervisory) controller that manages the power flows and mode changes (e.g.: from electric to hybrid in an EREV) to meet the vehicle fuel economy, emissions, performance and drivability requirements. Figure 2 depicts a hierarchical control architecture in use in a prototype PHEV.

In a X-EV, two problems are especially important: *optimal energy management*, that is the ability to optimize the energy use of a vehicle during a trip; and *mode switching*, that is, the ability to select the appropriate operating mode and to smoothly switch between modes. The higher-level controller issues set-points to lower-level controllers that are used to manage the ICE, the EM(s), the mechanical transmission system, the brake system, and the RESS, as well as other auxiliary functions in the vehicle. In this article we primarily consider the higher-level controller, and focus on two problems that are especially relevant to HEVs: optimal energy management, and mode switching. In addition, we also consider the battery controller (often called battery management system or BMS), which while being a low-level control, is very specific to X-EVs.

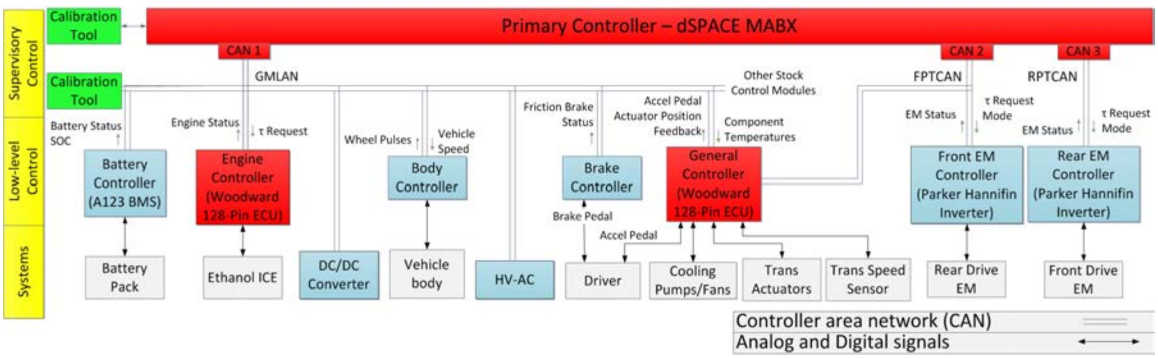


Figure 2 Hierarchical structure of a HEV controller
(courtesy: The Ohio State University EcoCAR 2 Team [3])

4 Optimal energy management

The optimal energy management problem in a X-EV consists of finding the control *u(t)* that leads to the minimization of a performance index *J* over the time horizon $t_0 - t_f$, corresponding to a driving cycle, or trip; the problem is subject to constraints that are related:

i) to physical limitations of the actuators and the energy stored in the RESS; and
ii) to the requirement to maintain the RESS state of energy within prescribed limits (in a charge-sustaining X-EV), or to track a specified RESS stored energy trajectory (in charge-depleting X-EVs).

Let $L(\cdot)$ be a suitable function of the system states and inputs that accounts for the quantities we wish to minimize, for example, fuel consumption, or emissions of carbon dioxide. Then, we define the cost function

$$J\left(x(t),u(t)\right)=\int_{t_0}^{t_f} L\left(x(t),u(t),t\right)dt \qquad (1)$$

which is to be minimized for every trip. In general, the exact driving cycle, or profile, associated with a trip is not completely known; thus, a causal solution to this problem is impossible to achieve without making some assumptions. Various approaches to solve (1) have been proposed over the years; we cite: i) Dynamic Programming (DP); ii) local optimization solutions as surrogates of a global solution; iii) Pontryagin's Minimum Principle (PMP); and iv) rule-based methods. Onori et al. [4] provide a comprehensive overview of the problem, as well as detailed examples. We briefly review approaches i), ii), and iii).

4.1 Global optimization by Dynamic Programming

If the driving cycle, represented by the vehicle instantaneous velocity over time, *v(t)*, is known, it is possible to cast (1) in such a form that a DP solution is possible. For example, in a charge-sustaining X-EV one can find the sequence of inputs that minimizes the trip fuel consumption, while sustaining the desired state of charge of a battery and meeting the speed profile of the vehicle. In this problem, the input is the power supplied by the battery to the electric machine, and the state of charge of the battery, SOC, is the only state; all other subsystems (engine, electric drives, transmission, etc.) are modeled via quasi-static efficiency models that can be represented by algebraic equations (e.g.: Willans lines, [5]), or by maps. The vehicle velocity profile, *v(t)*, is converted to a vehicle power request, $P_{REQ}(t)$, knowing the vehicle load characteristics (aerodynamic, inertial, rolling and drivetrain friction, and road grade). In turn, the power required to meet a specific load profile is the sum of the power delivered by the ICE and EM, $P_{REQ}(t)=P_{ICE}(t)+P_{BAT}(t)$. So, for example, we seek the control input, $P_{BAT}(t)$, that corresponds to the minimum fuel consumption, that is: $\min_{\{P_{ICE}(t),P_{BAT}(t)\forall t\}}\int_{t_0}^{t_f}\dot{m}_f(t)dt$, while delivering the requested vehicle power. The problem has physical constraints in the actuators (maximum and minimum power that can be delivered by ICE and EM), as well as the requirement for the control policy to be charge-sustaining, which is translated into the additional condition $SOC(t_0)=SOC(t_f)$. While this is only a sketch of the problem formulation (see [4] for a detailed treatment), it should be clear that it is possible to find a DP solution. If the vehicle is charge depleting, the problem can be similarly formulated with $SOC(t_f)<SOC(t_0)$

In practice, this approach requires complete information of the vehicle velocity profile, and DP is not an implementable, causal solution to the X-EV energy management problem. It is, however, a very useful tool to establish a benchmark for a problem, or as an aid in developing a rule base [4]. Stochastic DP methods have been proposed to circumvent the need to know the driving cycle exactly (see e.g.: [6]).

4.2 Local optimization by equivalent fuel consumption minimization

A heuristic approach that has met with success is to solve (1) as a local optimization problem, wherein $\int_{t_0}^{t_f}\min_{\{P_{ICE}(t),P_{BAT}(t)\forall t\}}\dot{m}_f(t)dt$ is used as an approximation for $\min_{\{P_{ICE}(t),P_{BAT}(t)\forall t\}}\int_{t_0}^{t_f}\dot{m}_f(t)dt$. This approach gives rise to the *Equivalent fuel Consumption Minimization Strategy* (ECMS) [7], which accounts for the use of stored electrical energy, in units of chemical fuel use (g/s), such that one can define an "equivalent fuel consumption" taking into account the cost of the electrical energy used to produce $P_{BAT}(t)$ by way of the fuel that must be used at a future time to replenish the stored electrical energy in the RESS. The equivalent fuel consumption is defined in (2).

$$\dot{m}_{f,eq}(t)=\dot{m}_f(t)+\dot{m}_{eq}(t)=\dot{m}_f(t)+s(t)\frac{E_{batt}}{Q_{LHV}}S\dot{O}C(t) \qquad (2)$$

In (2), $\dot{m}_{f,eq}$ is the equivalent fuel consumption, $\dot{m}_f$ is the actual chemical fuel consumption, $\dot{m}_{eq}$ is the virtual fuel consumption corresponding to the use of electricity stored in the battery (to be replenished in the future), E_{BAT} is the energy capacity of the battery, Q_{LHV} is the lower heating value of the chemical fuel, and s(t) is the equivalence factor that assigns a cost to the use of electricity. Then, the global minimization problem of (1), with $L(\cdot) = \dot{m}_{f,eq}$, becomes the problem of finding $\int_{t_0}^{t_f} \min_{\{P_{ICE}(t), P_{BAT}(t) \forall t\}} \dot{m}_{f,eq}(t) dt$. This approach, which can be easily implemented, has been used widely and has been shown to closely approximate the global optimal solution if sufficient knowledge of the vehicle driving cycle is available. The method does requires empirical calibration and tuning of the equivalence factor, *s(t)*, the optimal value of which is dependent on the driving cycle. Such calibration could be automated by using a predictor to generate a short-horizon estimate of the driving cycle, and an adaptor to generate an appropriate *s(t)* [8].

iii) Optimization by Pontryagin's minimum principle

Pontryagin's minimum principle (PMP) can also be employed to solve the x-EV energy management problem [4]. If, again, the fast dynamics of the system are neglected, the state equation is:

$$\dot{x}(t) = f(x,u,t) = -\frac{1}{E_{BAT}} I_{BAT}(x,u,t) \quad (3)$$

where $x = SOC$ is the state of charge of the battery, E_{BAT} is the energy capacity of the battery, and I_{BAT} is the instantaneous battery current. If the input is the power requested of the battery, $P_{BAT}(t)$, which in turn determines the engine power request, $P_{ICE}(t)$, and hence the fuel consumption, then the Hamiltonian function can be defined to be:

$$H(x(t), P_{BAT}(t), \lambda(t)) = \dot{m}_f(P_{BAT}(t)) - \lambda(t) \cdot f(x(t), P_{BAT}(t), t) \quad (4)$$

In (4), $f(\cdot)$ is given by equation (3), and the control $P_{BAT}(t)$ is that which minimizes equation (4) at each time instant is:

$$P^*_{BAT}(t) = \arg\min_{P_{BAT}} H(x(t), P_{BAT}(t), \lambda(t)) \quad (5)$$

The co-state variable, $\lambda(t)$, is the solution of:

$$\dot{\lambda}(t) = -\lambda(t) \frac{\partial f(x(t), u(t))}{\partial x} \quad (6)$$

Equations 3 and 5, with boundary conditions $x(t_0)$ and $x(t_f)$, can be solved numerically; in [9, 10] it is shown that the co-state $\lambda(t)$ is related to the *equivalence factor* of equation (2), confirming that the intuitive ECMS solution is in fact the PMP solution, providing that the equivalence factor (or co-state) is time-varying and satisfies

$$H(t,x,u,\lambda) = \dot{m}_f + \lambda(t)\dot{x}(t) \quad \text{and}$$

$$s(t) = -\lambda(t) \frac{Q_{LHV}}{E_{BAT}} \quad (7)$$

The PMP solution is also cycle-dependent, as the optimal initial condition for the co-state is dependent on the driving cycle. This dependence on the driving cycle, whether expressed in terms of an equivalent fuel consumption in the ECMS solution, or as the initial condition of the co-state in the PMP solution, is an unavoidable consequence of the fact that the fuel consumption of a vehicle is strongly dependent on the driving conditions, which affect the vehicle load.

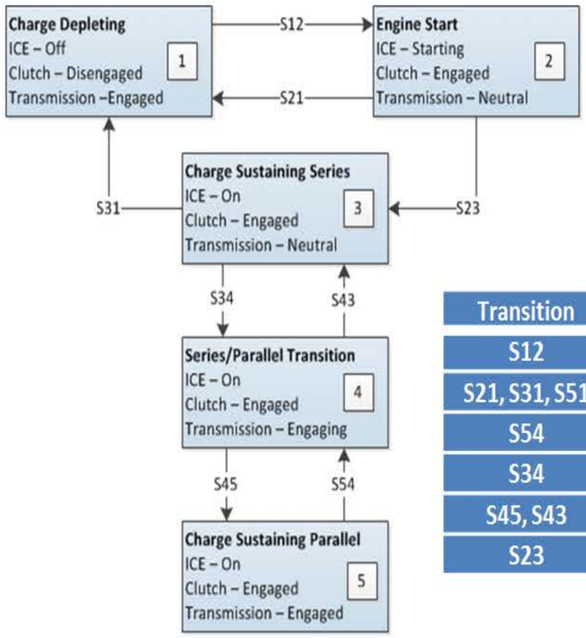
The basic concepts outlined above continue to be the subject of further development; for example, integrating available trip information available from navigation and geographical information systems into predictive energy management algorithms, and considering battery aging as a cost in the optimization function are but two of the research areas being pursued.

5 Mode switching

X-EV architectures permit multiple operating modes to exploit the design and control flexibility available in the powertrain. Some examples: a X-EV could operate in pure EV mode, or in hybrid mode (whether series, parallel, or power-split); could use special control algorithms during regenerative braking events to provide maximum energy recovery without adversely affecting brake and vehicle stability control systems; and could implement special start-stop control strategies that minimize fuel consumption at idle without adversely affecting engine cold- or warm-start emissions, and without inducing unwanted transient vibrations [11]. Figure 3 depicts an example of a state flow diagram that could be implemented in a finite state machine. Mode switching can result in *driveability* problems [12], that is in undesirable transient response characteristics during mode changes. An X-EV can, in this context, be represented as a hybrid system [13].

6 Battery management systems

The most common RESS in hybrid vehicle is the electrochemical battery. A hybrid or electric vehicle uses a battery pack that is typically composed of modules, which are in turn comprised of battery cells connected in series and parallel. Battery



Transition	Condition
S12	$SOC < SOC_{min}$
S21, S31, S51	$SOC \geq SOC_{min}$
S54	$V_x < V_{highway}$
S34	$V_x \geq V_{highway}$
S45, S43	Transition Complete = 1
S23	Engine Start Complete = 1

Figure 3 State diagram illustrating mode switching in a PHEV (courtesy: The Ohio State University EcoCAR 2 Team [3])

management systems are necessary to provide charge balancing, cell protection, state of charge and state of health estimation, and other functions related to the management of the stored energy. A good overview of battery systems and associated control problems may be found in [14]. Two important problems related to battery management are state of charge (SOC) and state of health (SOH) estimation. SOC estimation is a necessary component of any battery management system. The SOC of battery is defined by the following equations, in which x is the SOC, Q_{BAT} is the battery capacity in ampere-hours, and η the battery charging/discharging efficiency:

$$\dot{x}(t) = \frac{\eta}{Q_{BAT}(t)} \cdot I_{BAT}(t)$$

$$x(t) = x(t_0) + \frac{1}{3600 \cdot Q_{BAT}(t)} \int_{t_0}^{t_f} I_{BAT}(\tau) \cdot d\tau \quad (8)$$

In practice, there are two problems with using current integration (also called *Coulomb counting*) to estimating SOC: i) errors in numerical integration accumulate and may cause significant bias error in the estimate; and ii) the actual capacity of the battery is unknown during vehicle operation, as it changes over time due to battery aging. A second SOC estimation approach consists of correlating the battery open-circuit voltage to the SOC, but this approach also suffers from significant uncertainty, as the open-circuit voltage-SOC correlation curves are only accurate in stationary conditions (constant temperature, with battery at rest). SOC estimation has been the subject of much research, and has seen the use of Kalman filters, extended Kalman filters, particle filters, and other estimation approaches [14]. The SOH of a battery degrades over time due to two principal factors: *capacity fade*, and *power fade* (which can also be thought of as *conductance fade* caused by an increase in the internal resistance of the battery). These phenomena are the result of complex electrochemical interactions that are specific to battery chemistry. The ability to estimate the capacity and resistance of a battery during actual operation is a very important aspect of battery management. As in the case of SOC estimation, no direct measurement is possible outside of controlled laboratory conditions, hence estimation algorithms must be employed [15]. It is important to observer that SOC and SOH estimation algorithms operate on two completely different time scales, as the SOC of a battery fluctuates over time windows of minutes or hours, while the SOH changes very slowly over time, with measurable changes occurring over periods of months or years.

7 Summary and future directions

In summary, the control of X-EV powertrains is a rich subject for control theoreticians and practitioners, presenting topics related to optimization and optimal control (for energy management, battery aging), hybrid control (for drivability), adaptive and predictive control, and, estimation. Further, the electrification of ground vehicles presents interesting opportunities to integrate vehicles with the electric power and communication networks infrastructures. The following paragraphs describe two such opportunities.

7.1 Vehicle-grid interaction

As the penetration of plug-in vehicles, PHEVs and BEVs, increases, their impact on the electric power grid cannot be neglected; consideration of increased electric power demand and of the timing of vehicle charging must be included in the control/optimization of the electric power grid.

The electric grid and the transportation system are the two largest sectors that produce greenhouse gas emissions. When large numbers of vehicles are electrified and draw power from the electric grid, it is important to aim for reduced overall greenhouse gas emissions, rather than just shifting emissions from tailpipes to power plant stacks. Controlling the charging of plug-in vehicles to alleviate the impact to the grid has been studied, including the idea of using plug-in vehicles as ancillary services to the grid, possibly with significant renewable power sources connected to the grid. Modeling and simulating this integrated system requires information on detailed grid load profiles, power generation pricing and carbon emissions, wind statistics, vehicle usage statistics. In addition, charging control must balance multiple factors: grid stability, fully-charging all vehicles, minimizing data collection and communication, and overall system carbon emission minimization.

7.2 Intelligent Transportation Systems

X-EVs, as well as conventional vehicles, will benefit from the ability to analyze traffic and geographical 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 energy management [16, 17]. There are significant opportunities to achieve significant fuel savings and emissions reduction by considering the large-scale interactions of vehicles with one another and with the infrastructure, further exploiting the flexibility inherent in X-EVs.

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