Supervisory Power Management Control Algorithms for Hybrid Electric Vehicles: A Survey

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***Abstract*—The growing necessity for environmentally benign hybrid propulsion systems has led to the development of advanced power management control algorithms to maximize fuel economy and minimize pollutant emissions. This paper surveys the control algorithms for hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs) that have been reported in the literature to date. The exposition ranges from parallel, series, and power split HEVs and PHEVs and includes a classification of the algorithms in terms of their implementation and the chronological order of their appearance. Remaining challenges and potential future research directions are also discussed.**

***Index Terms*—Hybrid electric vehicles (HEVs), plug-in HEVs (PHEVs), supervisory power management control algorithms.**

I. Introduction

A. Motivation

FOSSIL fuels are an unsustainable resource: our planet has only a finite number of deposits. Two thirds of the oil used around the world currently goes to power vehicles, of which half goes to passenger cars and light trucks [1]. Widespread use of alternative powertrains is currently inevitable, and many opportunities for substantial progress remain. Concerns about climate change and the U.S. dependence on foreign oil are among the factors driving the development of alternatives to traditional vehicle powertrains and have led to significant investment in enhancing the propulsion portfolio with new technologies [2]. Hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs) have attracted considerable attention due to their potential ability to reduce petroleum consumption and greenhouse gas (GHG) emissions. This capability is mainly attributed to the following: 1) the potential for downsizing the engine; 2) the capability of recovering energy during braking, and thus, recharging the energy storage unit (e.g., battery or ultracapacitor); and 3) the ability to minimize engine operation at speeds and loads where fuel efficiency is low. In addition, hybridization, which typically refers to the power requirements for the electric motor or the degree of electrification, of conventional powertrain systems allows elimination of near-idle engine operation, thus enabling direct fuel economy enhancement.

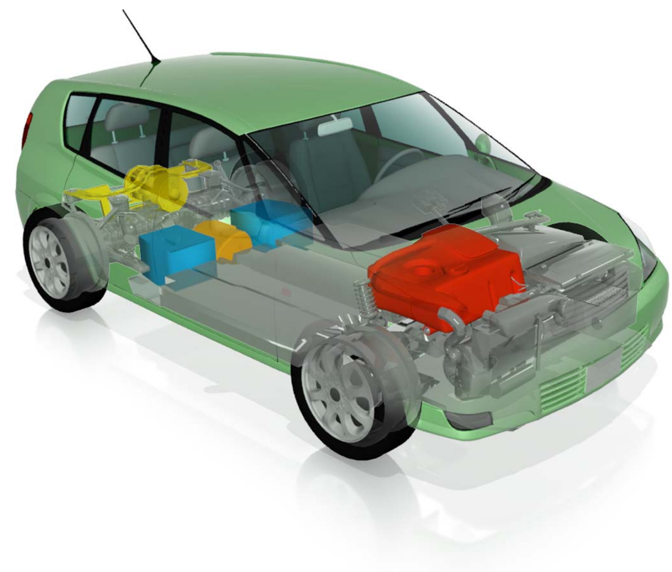

Fig. 1. HEV configuration showing the engine (red), the inverter (orange), the battery (light blue), and the electric machines (yellow).

A typical HEV (see Fig. 1) consists of the fuel converter (internal combustion engine), the inverter, the battery, and the electric machines (motor and generator). Depending on their architecture, HEVs fall into one of several categories: 1) parallel; 2) series; or 3) power split. In parallel HEVs, both the engine and the motor are connected to the transmission, and thus, they can power the vehicle either separately or in combination. The series HEV, in which the electric motor is the only means of providing the power demanded by the driver, is the simplest HEV configuration. Finally, the power split HEV can operate either as a parallel or a series HEV, combining the advantages of both.

HEVs may be also classified based on the degree of hybridization as either 1) micro HEVs, 2) mild HEVs, or 3) full HEVs. In micro HEVs, or start/stop vehicles, the engine is turned off during braking or at stop to avoid idling operation, and the starter motor is used to start the engine when the driver presses the accelerator pedal. A mild HEV is essentially a conventional vehicle with an oversized starter, also allowing the engine to be turned off whenever the car is coasting, braking, or stopped and quickly restart whenever the driver presses the accelerator pedal. The motor is often mounted between the engine and the transmission, substituting for the torque converter, and it can be used to supply additional power when

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accelerating. Micro and mild HEVs include only some of the features of HEVs and therefore usually achieve only limited fuel savings. In contrast, full HEVs, also called strong HEVs, have larger electric machine and battery. The electric machine (in motor mode) can power the vehicle separately if necessary and regenerate energy (in generator mode) from braking and store it in the battery.

Depending on the driving mode, e.g., cruising or braking, either a positive or a negative torque is demanded from the powertrain. The power available from the electric machine is regulated by adjusting its torque such that it can be either positive or negative depending on the operating mode. In the motor mode, the electric machine contributes power to the driveline by drawing electrical energy from the battery. In the generator mode, the electric machine absorbs power from the driveline and charges the battery. In cruising, the power demanded from the powertrain is expressed by a positive amount of torque, given a fixed engine speed. In braking, the power is expressed by a negative torque. The generator absorbs the maximum possible amount as determined by the system's physical constraints. If residual braking energy remains, the friction brakes handle this. For the next 20–30 years, the gasoline HEV offers a promising path to cost-effective reduction in fuel use. Relative to conventional spark-ignition and diesel engines, gasoline HEVs are projected to offer increasing efficiency gains and a narrowing price premium [3].

The power management control algorithm in HEVs and PHEVs determines how to split the power demanded by the driver between the thermal and electrical subsystems so that maximum fuel economy and minimum pollutant emissions can be achieved. Developing the control algorithm in HEVs and PHEVs constitutes a challenging control problem and has been the object of intense study for the last 15 years.

B. Contribution of This Paper

The research reported in the literature to date has aimed at enhancing our understanding of power management control optimization in HEVs and PHEVs. While much progress has been made, some improvements have been incremental, and there has been considerable repetition of a limited number of basic concepts. It appears that the current state of the art is now at a point where new and significantly different approaches are needed.

This paper has two main objectives: to summarize the results of major power management control algorithms for HEVs and PHEVs that have been reported in the literature to date and to discuss a potential research direction. The contribution of this paper is the collection and review of the HEV/PHEV power management control literature. The algorithms described cover the time period from 1998 to the present, and they are distinguished by the HEV or the PHEV architecture in which they were implemented and their approximate chronological order.

Any such effort has obvious limitations. Space constraints limit the description of algorithm details, and thus, extensive discussions are included only where they are important for understanding the fundamental concepts or explaining significant departures from previous work. In all cases, objectivity has been a high priority.

C. Organization of This Paper

The remainder of this paper proceeds as follows. Section II formulates the power management control problem and presents major control algorithms to derive the control policy. Section III is devoted to parallel HEVs, their classifications, and the associated power management control algorithms. Series and power split HEVs are covered in Sections IV and V, respectively. Section VI focuses on PHEVs and their control algorithms. Finally, Section VII includes a discussion of potential opportunities for future research.

II. Power Management Control Problem

A. Problem Formulation

Here, we formulate the power management control problem and present the control algorithms that can be used to derive the optimal control policy. References of various research efforts that have used these algorithms in various HEV/PHEV configurations are provided in the following sections. In our notation, random variables are denoted by uppercase letters, and their realizations are denoted by lowercase letters. Subscripts denote time; for example, X_t denotes a random variable at time t, and x denotes its realization.

The HEV is considered as a system whose state evolves over time. At time t, $t = 1, 2, \ldots, T$, the state of the system X_t takes values in a finite state space $\mathcal{S} \subset \mathbb{R}^n$, $n \in \mathbb{N}$. We also consider a finite control space $\mathcal{U} \subset \mathbb{R}^m$, $m \in \mathbb{N}$, from which control actions, i.e., U_t, are chosen. The initial state of the system X_0 is a random variable taking values in the system's state space, i.e., $\mathcal{S}$. The evolution of the state is imposed by the discrete-time equation $X_{t+1} = f(X_t, U_t, W_t)$, where the input from the environment, i.e., W_t, is the disturbance in our system (driver's power demand, i.e., P_{driver}) at time t. Furthermore, the system output is generated according to $Y_t = h(X_t, V_t)$, where V_t is the error from the sensors. However, the system's state X_t can be completely observed.

Assumption 1: The input from the driver W_t and the error from the sensors V_t are two sequences of independent random variables, which are independent of the initial state X_0 and take values in the finite sets $\mathcal{W}$ and $\mathcal{V}$, respectively.

Assumption 1 imposes a condition yielding that the state X_{t+1} depends only on X_t and U_t [4]. That is, the evolution of the HEV state can be modeled as a controlled Markov chain and is represented by a conditional probability, i.e., $P(X_{t+1}|X_t, U_t)$.

In our formulation, a state-dependent constraint is incorporated; that is, for each state, i.e., $X_t = x$, there is a nonempty and closed set $\mathcal{C}(x) := \{u | X_t = x\} \subset \mathcal{U}$ of feasible control actions. We denote the set of admissible state/action pairs $\Gamma := \{(x, u) | x \in \mathcal{S} \text{ and } u \in \mathcal{C}(x)\}$ such that it is a measurable subset of $\mathcal{S} \times \mathcal{U}$. For each state of the system $X_t = x$, we define the Borel measurable functions $\mu : \mathcal{S} \to \mathcal{U}$ that map the state space to the control action space defined as the control law. When the system is at state $X_t = x$, the controller chooses action according to the control law $u = \mu(x)$.

Definition 1: Each sequence of the measurable functions μ is defined as a stationary control policy of the system $\pi := (\mu(1), \mu(2), \ldots, \mu(|\mathcal{S}|))$, where $|\mathcal{S}|$ is the cardinality of the system's state space $\mathcal{S}$.

Let Π denote the set of the collection of the stationary control policies $\Pi := \{\pi | \pi = (\mu(1), \mu(2), \ldots, \mu(|\mathcal{S}|))$. The stationary control policy π operates as follows. At each stage t, the controller observes the state of the system, i.e., $X_t = x \in \mathcal{S}$; an action, i.e., $u = \mu(x)$, is realized from the feasible set of actions at that state, and an uncertainty, i.e., W_t, is incorporated in the system. At the next stage, i.e., $t+1$, the system transits to the state $X_{t+1} = x' \in \mathcal{S}$, and a transition cost, i.e., $c_t : \mathcal{S} \times \mathcal{C}(x) \times \mathcal{S} \rightarrow \mathbb{R}$, $c_t(X_{t+1}|X_t, U_t)$ is incurred. The one-stage expected cost function of the system, i.e., $k : \Gamma \rightarrow \mathbb{R}$, is given by $k(X_t, U_t) = \sum_{x' \in \mathcal{S}} P(X_{t+1} = x' | X_t = x, U_t) \cdot c_t(X_t = x' | X_{t-1} = x, U_{t-1})$. A stationary policy depends on the history of the process only through the current state, and thus, to implement it, the controller only needs to know the current state of the system. The advantages for implementation of a stationary policy are apparent as it requires the storage of less information than required to implement a general policy. Thus, a stationary policy is attractive in automotive-related applications where computational and storage power is limited on board a vehicle.

B. Offline Power Management Control Algorithms

1) Optimization Criteria: Stochastic optimal control of complex dynamic systems is a ubiquitous task in engineering. The problem is formulated as sequential decision making under uncertainty, where a controller is faced with the task of selecting actions in several time steps to efficiently achieve the system's long-term goals. Sequential decision models are mathematical abstractions representing situations in which decisions must be made in several stages while incurring a certain cost at each stage. A key aspect of these problems is that each decision may influence the circumstances under which future decisions will be made. Thus, the decision maker must balance her/his desire for low present cost to avoid future situations where high cost is inevitable. The completed period of time, which is denoted by T, over which the system is observed is called the *decision-making horizon* and can be either finite or infinite. For the finite decision-making horizon problem, the objective is to derive the optimal control policy that minimizes the following total expected cost criterion:

$$J(x_0) = \mathbb{E}^{\pi} \left[\sum_{t=0}^{T-1} k(X_t, U_t) + k_T(X_T) \right] \tag{1}$$

where k_T is the terminal cost function.

In the infinite-horizon problem, the objective is to minimize the total cost over an infinite number of stages, i.e.,

$$J(x_0) = \lim_{T \to \infty} \mathbb{E}^{\pi} \left[\sum_{t=0}^{T} k(X_t, U_t) \right]. \tag{2}$$

The assumption of an infinite number of stages is never satisfied in practice. However, it is a reasonable approximation for problems with a finite but very large number of stages, as, for example, in the HEV power management control problem where we are interested in optimizing HEV efficiency over the long-term driver's driving style and commute. The optimal control policies are typically stationary, as described in the previous subsection. Infinite-horizon problems require a more sophisticated analysis than the finite-horizon problems because we need to analyze limiting behavior as the horizon tends to infinity. This is a nontrivial analysis, and it can often reveal significant obstacles. There are four principal optimization classes that can be used in the infinite-horizon minimization problems [5]: 1) stochastic shortest path problems; 2) discounted problems with bounded cost per stage; 3) discounted and undiscounted problems with unbounded cost per stage; and 4) average cost per stage problems. In the first three classes, the objective is to derive a control policy to minimize the total expected cost associated with the initial state $X_0 = x_0$ over an infinite number of stages, i.e.,

$$J(x_0) = \lim_{T \to \infty} \mathbb{E}^{\pi} \left[\sum_{t=0}^{T} \gamma^t \cdot k(X_t, U_t) | X_0 = x_0 \right] \tag{3}$$

where the cost is guaranteed under various assumptions on the problem structure and the discounted factor $\gamma \in (0, 1]$. The meaning of this factor is that future costs matter less than the same costs when incurred at the present time. In the stochastic shortest path problems, the discounted factor is equal to 1; however, it is assumed that there is a special cost-free termination state in which once the system reaches that state, it remains there at no further cost. In the third class of these problems, the discounted factor may or may not be less than 1, and the cost per stage may be unbounded. Finally, in the fourth class, the long-run expected average cost per unit time is considered, i.e.,

$$J = \lim_{T \to \infty} \frac{1}{T+1} \mathbb{E}^{\pi} \left[\sum_{t=0}^{T} k(X_t, U_t) \right] \tag{4}$$

which does not depend on the initial state, and it is well defined under certain assumptions.

2) DP: Dynamic programming (DP) [6] has been widely employed as the principal method for analysis of sequential decision-making problems, e.g., deterministic and stochastic optimization and control problems, Markov decision problems, minimax problems, and sequential games. While the nature of these problems may vary widely, their underlying structure is similar and has two principal features: an underlying discrete-time dynamic system whose state evolves according to given transition probabilities that depend on a decision at each time and a cost function that is additive over time. The objective is to derive an optimal policy that minimizes an optimization criterion. DP relies on a very simple idea, i.e., the principle of optimality [6], which states that "An optimal policy has the property that whatever the initial state of the system and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision." For an intuitive distance analogy taken from [5], suppose that the shortest route from New York City to Las Vegas passes through Chicago. The principle of optimality states the rather obvious fact that the Chicago to Las Vegas portion of the route is also the shortest route for a trip that starts from Chicago and ends at Las Vegas. Thus, DP gradually computes an optimal policy backward in time: deriving first the optimal policy for the "tail subproblem" involving the last stage and then extending the optimal policy to the tail subproblem involving the last two stages and continuing in this manner until an optimal policy for the entire problem is derived.

Although DP can yield a global optimal solution in closed form, the associated computational requirements are often overwhelming, and for many problems, a complete solution by DP is impossible. The reason lies in what Bellman [6] referred to as the "curse of dimensionality," namely, the exponential increase in the computational requirements as the problem's size increases. The computational requirements are proportional to the number of possible values of states; thus, for complex problems, the computational burden may be excessive. In addition, DP algorithms require the realization of the conditional probabilities of state transitions and the associated costs, implying *a priori* knowledge of the system dynamics. Nonetheless, DP is the only generally rigorous approach for sequential decision-making problems under uncertainty, and even when it is computationally prohibitive, it serves as the basis for other suboptimal approaches. A rigorous treatment of the decision-making problems and their solution with DP using the preceding optimization criteria can be found in [7]–[10].

C. Online Power Management Control Algorithms

Although DP can provide the optimal solution in both the deterministic and stochastic formulations of the power management control problem, the computational burden associated with deriving the optimal control policy prohibits online implementation in vehicles, and it can grow intractable as the size of the problem increases. To address these issues, research efforts have been concentrated on developing online power management algorithms. The main aspects of these algorithms are concerned with the self-sustainability of the electrical path, which must be guaranteed for the entire driving cycle, and the fact that limited *a priori* knowledge of the future driving conditions is available.

1) MPC: Model predictive control (MPC) relies on prediction models to obtain a control action by solving an online optimization problem over a finite horizon. It is often used in constrained regulatory related control problems of large-scale multivariable systems, where the objective is to operate the system in a certain desired way. In MPC, the control policy is derived by solving online an iterative finite-horizon optimization problem of a plant model. At time t, the current state of the system is sampled, and control strategy is computed for a relatively short time horizon N, i.e.,

$$J = \min_{U_t \in \mathcal{U}} \sum_{t=k}^{k+N-1} l(X_t, U_t)$$
$$\text{s.t.} \quad X_{t+1} = f(X_t, U_t, W_t), \quad X_t \in \mathcal{S}; U_t \in \mathcal{U} \tag{5}$$

where $l(X_t, U_t)$ is a cost function. Wang and Boyd [11] determined that the main shortcoming of MPC is that it can be only used in applications with slow dynamics, where the sample time is measured in seconds or minutes, and they described a collection of methods for improving the speed of MPC using online optimization. They suggested that future research should investigate a formal stability analysis and performance guarantee.

2) Pontryagin's Minimum Principle and ECMS: One of the principal procedures in solving optimization problems is to derive a set of necessary conditions that must be satisfied by any optimal solution. These conditions become sufficient under certain convexity conditions on the objective and constraint functions. Optimal control problems may be regarded as optimization problems in infinite-dimensional spaces, and thus, they are substantially difficult to solve [12]. The minimum principle, which is formulated and derived by Pontryagin [13] in the 1950s, states that any optimal control, along with the optimal state trajectory, must solve the so-called Hamiltonian system, which is a two-point boundary value problem, plus the maximum condition of a function called the Hamiltonian. The mathematical significance of the minimum principle lies in the fact that minimizing the Hamiltonian is much easier than the original control problem, which is an infinite-dimensional one. This leads to closed-form solutions for certain classes of optimal control problems.

The optimal control problem is formulated by considering the HEV as a continuous-time dynamic system $\dot{x}(t) = f(x(t), u(t))$, $0 \le t \le T$. According to the minimum principle, if, for any given initial state $x(0)$, the control trajectory $\{u^*(t) | t \in [0, T]\}$ is optimal with corresponding state trajectory $\{x^*(t) | t \in [0, T]\}$, then, for all $t \in [0, T]$

$$u^*(t) = \arg\min_{u \in \mathcal{U}} \left[k\left(x^*(t), u\right) + \nabla_x J^*\left(t, x^*(t)\right)' f\left(x^*(t), u\right) \right] \tag{6}$$

where $k(x^*(t), u)$ is the cost function, and $J^*(t, x^*(t))$ is the optimal cost-to-go. A rigorous treatment of the formulation of Pontryagin's minimum principle in optimal control problems can be found in [12] and [13].

Power management control algorithms based on the minimum principle usually consist of an instantaneous optimization problem that accounts for storage system state-of-charge (SOC) variation through the equivalent fuel consumption (EFC). The latter is evaluated by considering average energy paths leading from the fuel to the electrical energy storage. Kim *et al.* [14] introduced this concept in 1999 by presenting a power management control strategy in which consumed battery energy is converted to an EFC amount. The fuel consumption is then minimized by selecting optimal combinations of control variables, e.g., gear ratio, motor torque, and throttle. In 2000, Paganelli *et al.* [15] introduced the instantaneous EFC minimization strategy (ECMS), which allows the battery SOC to be taken into account. Although ECMS was intuitively developed, various researchers, as shown in the following sections, have used Pontryagin's minimum principle to analytically derive the ECMS. The Hamiltonian can be interpreted as the sum of the actual fuel consumption in the engine and of a term that has

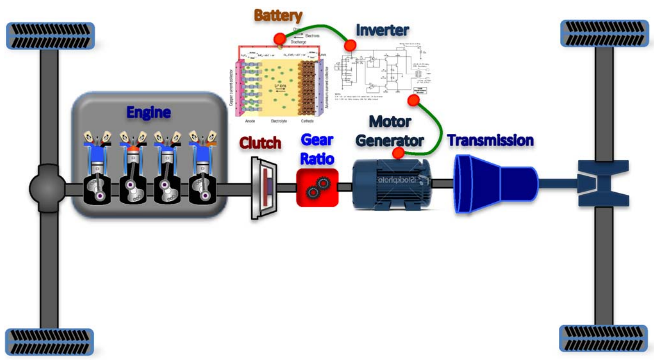

Fig. 2. Pretransmission parallel HEV configuration.

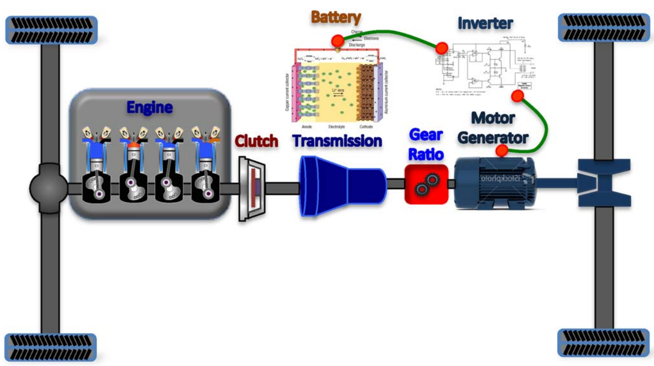

Fig. 3. Posttransmission parallel HEV configuration.

the same units and is related to the use of the battery power. This additional term represents the virtual consumption associated with the battery use and is related to the future fuel consumption due to the use of the battery at the present time.

III. Parallel HEVs

In parallel HEVs, both the engine and the motor are connected to the transmission, and thus, they can power the vehicle either separately or in combination. Current commercialized parallel configurations use a single small (< 20 kW) electric motor and a small battery pack as the electric motor is not designed to solely power the vehicle from launch. Parallel HEVs can use a smaller battery pack as they rely more on regenerative braking and the engine can also act as a generator for supplemental recharging; thus, they are more efficient for highway driving than in urban stop-and-go conditions or city driving. There are two architectures in parallel HEVs: the pretransmission parallel architecture (see Fig. 2) and the posttransmission parallel architecture (see Fig. 3). In a pretransmission architecture, the electric machine can start the engine; thus, a starter/alternator is not necessary, and there are some savings associated with the reduced weight. On the other hand, in the posttransmission architecture, the regenerative braking efficiency is maximized due to the physical location of the motor. There are also fewer to no spinning losses through the transmission in this case.

The first research efforts in modeling and control of parallel HEVs appeared in the late 1990s. Powell *et al.* [16] introduced various HEV dynamic models and highlighted many of the important control-related issues. Zoelch and Schroeder [17] presented one of the first methods to optimize the power split and transmission gear ratio in a parallel HEV over a given driving cycle. Kolmanovsky *et al.* [18] reviewed some emerging approaches at that time for the energy management of advanced powertrain configurations and presented a case study including a parallel HEV. Rizzoni *et al.* [19] developed the QSS-Toolbox for the analysis, design, and control of HEVs. This toolbox can be used in conjunction with a commercial computer-aided engineering tool to design optimal HEV powertrains, control algorithms, and parameter tuning and perform simulations [20]. Butler *et al.* [21] presented a toolbox developed at Texas A&M University for modeling, simulation, and analysis of electric vehicles (EVs) and HEVs. Chan *et al.* [22] published an overview of HEV technologies and a simple commercialization roadmap for the industry.

A. Rule-Based Power Management Control Algorithms

Since 1998, significant efforts have focused on optimizing the power management control in parallel HEVs employing some heuristic approaches. Baumann *et al.* [23] proposed a method for design and development of HEVs based on a fuzzy logic controller. Salman *et al.* [24] presented another power management controller based on fuzzy logic to coordinate the operation of the HEV subsystems. He and Hodgson [25], [26] introduced one of the first models for simulation of parallel HEVs with a specific rule-based control strategy. The empirical HEV model and control schemes were capable of real-time evaluation of a wide range of parameters. Saeks *et al.* [27] proposed a decentralized adaptive control system for a motor/generator four-wheel-drive HEV designed to address unknown tire dynamics, changing road surfaces, and vehicle loading. Schouten *et al.* [28] presented a fuzzy logic controller to determine the split of the driver's power demand between the engine and the motor and used the powertrain system analysis toolkit (PSAT), which is known today as Autonomie[1] [29], to validate the effectiveness of the controller.

In a couple of papers published in 2005, Langari and Won introduced another rule-based power management controller that is able to assess the driving conditions and vehicle operating mode [30], [31]. The controller consists of four components designed to identify the driver's driving style and distribute the power demanded by the driver to the engine and the motor, while maintaining the SOC of the battery within desired limits. He *et al.* [32] proposed a fuzzy logic controller with the intention to operate the engine efficiently. Boyali *et al.* [33] presented another heuristic control algorithm for the power split between the engine and the motor in a parallel HEV commercial van with front-wheel drive and manual transmission. Later that year, an architecture was introduced using the agent paradigm to bridge the asynchronous distributed computation and MATLAB environment [34]. Sundstrom *et al.* [35] developed

[1]Autonomie is a MATLAB/Simulink simulation package for powertrain and vehicle model development developed by Argonne National Laboratory. Autonomie provides a variety of existing forward-looking powertrain and vehicle models that can support the evaluation of new control functions in a math-based simulation environment.

a controller founded on rule- and mode-based optimal control strategies that optimize the gear shifting in a parallel HEV while maintaining low computational requirements and achieving low fuel consumption. Lawler *et al.* [36] presented a simulation study to explore the potential synergy between a homogeneous charge compression ignition (HCCI) engine and three HEV configurations. The goal of the proposed power management control strategy is to maximize the benefits of combining HCCI and HEV technologies.

Although heuristic approaches can yield power management control algorithms for operating the engine at the most fuel efficient speeds and loads, they cannot completely encompass all the potential fuel economy and GHG emission benefits of the various HEV architectures. A rigorous mathematical model and formal optimization procedures are necessary to derive globally optimal analytical solutions. There have been various methods proposed in the literature to achieve this objective, which can be implemented either offline or online.

B. Offline Power Management Control Algorithms

A significant amount of work has been proposed on optimizing the power management control in parallel HEVs using the deterministic formulation of DP, i.e., deriving the optimal control policy in an HEV for a given driving cycle. Lin *et al.* [37] used DP to compute the optimal control policy, i.e., the power split between the engine and the motor, and the gear shifting in a parallel HEV to minimize fuel consumption and selected emission species over a given driving cycle. The derived control policy was implemented in real time through rules resulting in near-optimal performance. Back *et al.* [38] proposed an approach to optimize engine and motor operation in a parallel HEV by predicting the driver's torque demand. The deterministic problem was addressed with DP, where MPC was used to implement the control policy in real time. An iterative algorithm using DP for offline optimization in a parallel HEV was proposed in [39] to handle the dimensionality of the problem formulation. Lin *et al.* [37] presented an analysis of the behavior of DP control policy using a near-optimal policy that can be implemented in real time. In this paper, the authors also discussed the tradeoffs between fuel economy and emissions. The following year, a comprehensive forward-looking hybrid vehicle simulation tool and its application to the design of a power management control algorithm using DP were presented in [40]. HE-VESIM, i.e., the HEV simulation tool, was developed at the Automotive Research Center of the University of Michigan to study the potential fuel economy and emission benefits of the parallel hybrid propulsion system for a medium-duty truck. To optimize the power split and gear selection using DP for each of six representative driving cycles in a parallel HEV truck, Lin *et al.* [41] presented a driving pattern recognition algorithm. The same year, Lin [42] published a summary of modeling and control strategy development for HEVs using DP in his dissertation. Although DP had been dominating the offline methods in optimizing the power management control in parallel HEVs, Won *et al.* [43] presented an algorithm based on a multiobjective nonlinear optimization problem formulation. The proposed control scheme assesses the amount of engine torque needed for generating propulsive power while ensuring that the battery's SOC is maintained within the desired range.

A couple of years later, Pu and Yin [44] proposed another DP-based algorithm. To overcome the curse of dimensionality, the control space is restricted, and control increments are carefully selected to balance computation accuracy and efficiency. Sundström *et al.* [45] examined the effects of hybridization ratio on fuel economy and emissions in a full HEV and a torque-assist HEV. Using DP to optimize the power management for different driving cycles, they found that the full HEV performs better than the torque-assist HEV at any hybridization ratio. DP was also used to solve the optimal control problem with the tailpipe emissions reduction as an objective in a parallel HEV [46]. As DP became a popular method for deriving offline the optimal control policy for the HEV power management control problem, Sundström and Guzzella [47] presented a generic DP code in MATLAB and made it publicly available. In another publication, Sundstrom *et al.* [48] used DP in a torque-assist parallel HEV to achieve an optimized hybridization ratio.

The deterministic formulation of DP has been used to benchmark the fuel economy of HEVs by providing the maximum theoretical efficiency that can be achieved over a given driving cycle. DP has been also extended to a stochastic formulation capable of deriving an optimal control policy for a family of driving cycles. Lin *et al.* [49] proposed a stochastic DP (SDP) approach using the discounted cost criterion where the one-stage cost was the weighted sum of fuel consumption, NO_x, and particulate matter emissions, with a penalty for SOC deviation. The control policy was derived offline by using the policy iteration method. The first attempt to use the shortest path formulation of the power management control problem using SDP was by Tate *et al.* [50]. The proposed approach provides a more natural formulation of the control problem as it allows deviations of battery SOC from a desired set point to be penalized only at the end of the trip. The method was illustrated on a parallel HEV truck model that had been previously analyzed using infinite-horizon SDP with the discounted cost criterion.

In the following year, Opila *et al.* [51] presented a method to account for drivability metrics in their proposed power management control algorithm, which also utilizes the shortest path SDP (SP-SDP) formulation. Tate summarized the findings on techniques for HEV controller synthesis mainly focusing on the SP-SPD formulation in his dissertation [52]. Subsequently, Tate *et al.* [53] used SP-SDP to address minimization of a weighted sum of fuel consumption and tailpipe emissions for an HEV equipped with a dual-mode electrically variable transmission. The unique aspects of the study included an electrically variable transmission and catalytic converter and a state-censoring technique to achieve short computation time. Their optimal solution was derived offline by solving a linear program. Liu *et al.* [54] used the stochastic formulation of DP to generate a power management control strategy and addressed engine soot emissions using an advanced engine-in-the-loop (EIL) setup. Coupling the real engine with the virtual driveline/vehicle enabled application of fast analyzers to characterize the impact of transient engine operation on emissions. The benefits of using the EIL for establishing drivability and soot emissions constraints were demonstrated through a study of a virtual parallel HEV for the high-mobility multipurpose wheeled vehicle (HMMWV) with a 6L V8 engine.

C. Online Power Management Control Algorithms

One of the first online control strategies in parallel HEV was reported in [55] aimed at evaluating all possible operating points that minimize a cost function consisting of fuel consumption and emissions while also maintaining the SOC within the desired range. The effectiveness and efficiency of the control strategy were evaluated in ADVISOR[2] over different driving cycles. Following their first paper on ECMS, Paganelli *et al.* [56] published a paper on ECMS that optimizes the power split and gear ratio in a paralled HEV while assigning a nonlinear penalty function for SOC deviation. Evaluation of the effectiveness of the proposed ECMS was conducted on the 2000 Chevrolet Suburban modified as a parallel HEV [57]. An alternative algorithm founded on optimal control theory and suitable for online implementation in parallel HEVs was developed in [58] and [59]. Although the proposed algorithm is computationally more efficient than ECMS, its performance is not competitive with ECMS. A couple of years later, Delprat *et al.* [60] introduced an efficient tool to evaluate minimal fuel consumption that overcame the computational burden drawback of other algorithms existing at that time.

In 2002, Paganelli *et al.* [61] published a paper on an ECMS-based algorithm to optimize fuel consumption with respect to the power split between the motor and the engine in a parallel HEV. Sciarretta *et al.* [62] proposed an ECMS algorithm in which EFC is evaluated under the assumption that every variation in SOC will be compensated in the future by the engine running at the current operating point. The EFC therefore changes both with the operating point and with the power split control, and its evaluation requires an additional inner loop in the instantaneous optimization procedure or storage of results in a lookup table. Musardo *et al.* [63], [64] presented an adaptive ECMS (A-ECMS) algorithm that periodically computes the equivalence factor and refreshes the control parameters based on the current driving conditions to maximize fuel economy for a parallel HEV. This proposed algorithm was evaluated under different driving cycles. While ECMS became the dominant control algorithm for online optimization of HEVs at that time, another approach based on game theory appeared in 2006 addressing the development and use of an integrated starter alternator for an HMMWV [65]. Wei *et al.* [66] used Pontryagin's minimum principle to develop an engine start–stop control strategy for reducing fuel consumption in a parallel HEV.

In 2007, Pisu and Rizzoni [67] compared three algorithms that can be implemented online, namely, a rule-based algorithm, an A-ECMS, and an $\mathcal{H}_\infty$ control. Relative to DP, they showed that A-ECMS outperforms the rule-based and $\mathcal{H}_\infty$ control algorithms. Salmasi [68] also presented an overall overview of power management control algorithms for parallel HEV architectures. Another overview was published in [69] comparing and classifying control algorithms according to their dynamic structure, complexity, applicability, and performance.

Kermani *et al.* [70] proposed a power management control algorithm using Pontryagin's minimum principle. He formulated the Hamiltonian equation and solved the optimal control problem to minimize fuel consumption and CO_2 emissions. The following year, Kermani *et al.* [71] presented an MPC-based power management control algorithm. The effectiveness of the algorithm was compared with the one derived by solving the Hamiltonian equation. Yan *et al.* [72] presented an MPC-based control strategy that incorporates diesel engine transient characteristics for parallel HEVs. For HEV applications where the engines experience frequent transient operations, including start and stop, the effect of the engine transient characteristics on the overall HEV powertrain fuel economy becomes more pronounced. In their work, the engine transient characteristics were well accounted for by the HEV powertrain supervisory controller.

More recently, there has been an effort to develop power management control algorithms for HEVs by also including the battery's lifetime. Serrao *et al.* [73] formulated the power management control problem in HEVs by incorporating the aging of the battery. To explicitly quantify the battery aging, a model that correlates aging with SOC and charge/discharge rates was used. In the objective function of the problem formulation, fuel consumption and battery aging were considered, and the control problem was solved using Pontryagin's minimum principle. Ebbesen *et al.* [74] presented a power management control algorithm for a parallel HEV by modifying ECMS to include the battery's state of health in addition to fuel consumption. In both studies, it was found that there is a significant tradeoff between fuel economy and battery lifetime.

D. Learning and GPS-Enhanced Power Management Control Algorithms

Other research efforts for optimizing HEV efficiency reported in the literature have included features outside the aforementioned categories. Some of these power management control algorithms include a learning mechanism that aims to improve performance over time, whereas others incorporate the driver's driving style. Each individual driving style, e.g., stop-and-go driving, rapid acceleration, or braking, is different [75], and there are associated driving factors that have a major impact on fuel economy [76]. Jeon *et al.* [77] proposed a power management control strategy for a parallel HEV using driving pattern recognition to automatically select a control algorithm from a bank of six optimized representative driving modes using artificial neural networks (ANNs). Ichikawa *et al.* [78] presented a power management control algorithm based on online prediction of the future driving cycle using recorded data from prior driving. Chen and Salman [79] developed a learning strategy to maximize overall fuel economy while maintaining the battery SOC for parallel HEVs. The proposed strategy is based on a cost function that incorporates a learning scheme designed to fine-tune a penalty factor in real time based on driving style and conditions. Boyali and Guvenc [80] used neurodynamic programming to develop a power management

[2]ADVISOR is an advanced vehicle simulator developed by the National Renewable Energy Laboratory in 1994 to support the U.S. Department of Energy hybrid propulsion system program.

control algorithm that approximates the DP solution. Dextreit and Kolmanovsky [81] reported results of experimental comparisons of a rule-based control algorithm and an algorithm founded on game theory in a Land Rover Freelander 2 HEV prototype vehicle.

Sciarretta and Guzzella [82] published a comprehensive review of the various HEV architectures and power management control algorithms. They concluded that methods able to yield the global optimal solution, i.e., DP, can aim to provide the maximum theoretical efficiency and benchmark a given architecture. However, real-time controllers need to be simple and implementable with limited computation and memory requirements. To guarantee behavior that is sufficiently close to optimal, a real-time controller must be able to adapt to varying driving styles. Variation in fuel consumption for different driving styles can be up to 30% [83]; thus, developing a means of incorporating driver behavior into the power management controller can be beneficial. A paper discussing this issue was published the year following the paper of Sciarretta and Guzzella. Johannesson *et al.* [84] focused on incorporating external information such as destination route in the power management control algorithm, with information supplied by the vehicle navigation system, to improve fuel economy. Ambuhl and Guzzella [85] presented an ECMS-based algorithm using information received from a Global Positioning System (GPS). The algorithm used data on the upcoming topography of the road and the corresponding vehicle velocity to minimize fuel consumption. Zhang *et al.* [86] discussed the use of telematic technology to allow the controller of a parallel HEV to access information about future driving conditions, e.g., road grade, referred to as terrain preview. Huang *et al.* [87] developed a statistical approach to automatically distinguish driving styles in HEVs by periodically sampling them and extracting multiple statistical features to evaluate their significance. Li *et al.* [88] proposed the concept of an environmentally friendly HEV integrating three components, namely, clean energy powertrain, electrified chassis, and intelligent information interaction devices, to improve efficiency.

IV. Series HEV

A series HEV (see Fig. 4) is the simplest HEV configuration in which the electric motor is the only means of providing the power to the wheels demanded by the driver. The motor draws electric power in combination from the battery and from a generator run by the engine. The engine is typically smaller in series HEVs as it only has to meet on average the driver's power demand, and the battery pack is generally more powerful than the one in parallel HEVs to provide remaining peak driving power needs. The larger battery and motor, which are required by series HEVs, along with the generator, add to the cost, making series HEVs more expensive than parallel HEVs. While the engine in a conventional vehicle may inefficiently operate to satisfy the driver's power demand, e.g., stop-and-go driving, in a series HEV, the engine operates only at its most efficient speeds and loads as it is not coupled to the wheels. Thus, the engine is no longer subject to the driver's widely varying power demands and can operate in a narrow power range at near-optimum efficiency. As a result, series HEVs do not need a complicated multispeed transmission and clutch.

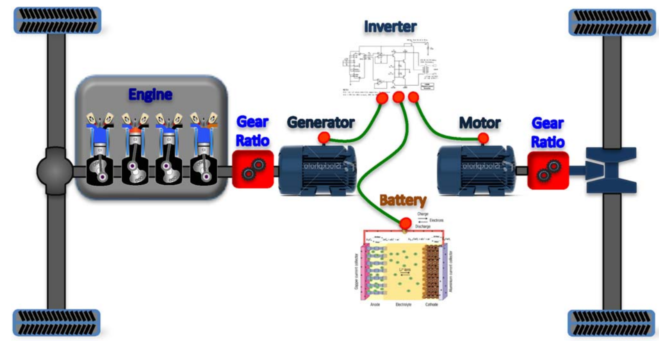

Fig. 4. Series HEV configuration.

Since series HEVs are superior in stop-and-go driving, they are primarily being considered for buses and other utility vehicles. Mckain *et al.* [89] evaluated the emissions and fuel economy of series hybrid electric buses and compared their performance with that of conventional natural-gas- and diesel-powered buses using the West Virginia University Transportable Heavy Duty Emissions Testing Laboratories to characterize emissions. In a paper designed to frame the problem in order to better tackle its challenges, Ceraolo *et al.* [90] presented an overview of series and parallel HEV architectures and the power management control problem.

Increased cooling demands in HEVs and additional hardware make it challenging to provide an effective cooling system that has minimal impact on fuel economy and cost. Typically, HEVs tend to have separate cooling systems for the hybrid and engine components due to their different requirements. The additional cooling system increases the hardware, cost, and weight and affects the vehicle fuel economy. Park *et al.* [91] studied the cooling performance requirements, parasitic power consumption, temperature stability, packaging, and operating mode for series heavy-duty HEVs.

Although electrification and hybridization can significantly improve fuel economy and reduce emissions in heavy-duty vehicles, the high cost associated with the components is a major concern. Cao and Emadi [92] proposed a new hybrid energy storage system for heavy-duty electric drive vehicles that can improve the battery's lifetime. In a series of papers, Lee and Filipi [93] and Lee *et al.* [94], [95] investigated the impact of advanced battery control strategies on the battery size and fuel economy for heavy-duty military vehicles. The objective of these control strategies is to ensure safe and robust operation covering infrequent extreme conditions. Excessive battery operation is moderated by adjusting the battery power upper and lower limits using the feedback of electrode-averaged lithium-ion concentration estimated by an extended Kalman filter. Simulation results yielded valuable information for battery sizing in terms of balancing the associated cost and fuel economy in heavy-duty HEVs demonstrating that it is possible to maximize capacity using smaller batteries.

A. Rule-Based Power Management Control Algorithms

The objective of the control problem formulation in the series hybrid configuration, in particular, is to operate the engine efficiently while maintaining the battery SOC within acceptable limits. Jalil *et al.* [96] proposed a rule-based control strategy using thermostat-type behavior to optimize the power management control in a series HEV. Yoo *et al.* [97] presented another rule-based control strategy for a series HEV with three power sources, namely, battery, supercapacitor, and engine generator.

B. Offline Power Management Control Algorithms

Optimization of fuel economy in series HEVs was a major theme of reports in the literature in the first decade of the 2000s. The first application of DP in the power management control problem for HEVs appeared in 2000. Brahma *et al.* [98] presented a control algorithm for a series HEV using the deterministic formulation of DP, deriving the optimal control policy for a given driving cycle, the Federal Urban Driving Schedule in this case. Tate and Boyd [99] introduced a different approach using convex optimization to address the power management control problem. In particular, they addressed the problem of finding optimal engine operation in a pure series hybrid vehicle over a fixed driving cycle subject to a number of constraints related to components, e.g., engine, battery, and motor. In their approach, the authors formulated optimization of fuel consumption as a nonlinear convex optimization problem, which was then approximated as a linear program.

Konev *et al.* [100] proposed another interesting power management control algorithm aiming at ensuring gradual operation of the engine-generator unit along the steady-state optimal operating points. In the proposed approach, HEV operation is modeled as a random process. The algorithm attempts to minimize the probability of discharging or overcharging the battery beyond a predetermined SOC target. The probability is estimated based on the statistics derived from the past history of the SOC. Pérez *et al.* [101], following [98], used DP to minimize fuel consumption with respect to the power split between the engine and the energy storage unit in a series HEV. Wang *et al.* [102] proposed a power management control strategy using support vector machines (SVMs). SVM is a technique in the field of statistical learning originally developed for classification problems. Their approach included setting up an operation database of different load sequences, initial SOC, and vehicle speed; applying a fast Fourier transform on load sequences to select characteristic features and generate a new database; and, finally, training SVM to produce the controller classifier.

C. Online Power Management Control Algorithms

During typical driving cycles, most of the engine operating time is occupied by transients rather than steady-state conditions [103]. Emissions during transient operation are extremely complicated and vary significantly with each particular driving cycle [104]. Engine operating points, during the transient period before their steady-state value is reached, are associated with different specific fuel consumption rates [105]. To address transient engine operation, Barsali *et al.* [106] proposed an online control algorithm for a series HEV relying on adaptable overall parameters to characterize the driving schedule and any sudden changes in driving mode. Since the publication of this paper, as was the case in parallel HEVs, ECMS and MPC have been the dominant approaches to address the power management control problem online in series HEVs. Pisu and Rizzoni [107] developed an ECMS to optimize the power management for a series hybrid electric heavy-duty truck with two energy storage systems, namely, a battery and an ultracapacitor. Serrao and Rizzoni [108] proposed an analytical solution based on Pontryagin's minimum principle for the optimal power management control problem in a series hybrid electric refuse collection truck. The equivalence factors that allow for the transformation of electrical energy into future fuel consumption must be determined with optimization techniques and are related to the driving cycles that the vehicle follows. Therefore, the factors that minimize the fuel consumption over an urban cycle are different from those that would be needed in a highway cycle. Gao *et al.* [109] implemented a control strategy that requires tuning of fewer control parameters than ECMS. The proposed control strategy is compared with the thermostat control strategy and the power follower control strategy using ADVISOR.

More recently, Serrao *et al.* [110] have presented a formal analytical derivation of ECMS for energy management in a series HEV based on Pontryagin's minimum principle. The paper focused on single-degree-of-freedom systems, e.g., series or parallel, in which the battery power can be used as the only control variable for the power split control problem. The optimal control problem essentially was formulated as an instantaneous optimization problem. The Hamiltonian can be interpreted as the sum of the actual fuel consumption in the engine and of a term that has the same units and is related to the use of the battery power. This additional term represents the virtual consumption associated with the battery use and is related to the future fuel consumption due to the use of the battery at the present time, as intuitively explained in the first papers on ECMS, namely, [15] and [56].

Around 2009, various researchers appear to have started exploring MPC for the power management control problem. Classical MPC formulations do not necessarily provide a systematic way to deal with model uncertainties and disturbances, which are often completely neglected in the prediction model. Robust MPC schemes that take into account the presence of disturbances are primarily based on the min–max approach, where the minimized target cost function is computed over the worst possible disturbance realization. Nominal controllers that neglect the effects of disturbances may lead to poor performance when implemented in real processes, whereas robust controllers provide control laws that are often too conservative. Ripaccioli *et al.* [111] presented an MPC-based control algorithm to optimize the power management online using mixed-integer quadratic programming. Cairano *et al.* [112] proposed an energy management control strategy for a series HEV. The strategy maximizes the pointwise powertrain efficiency by selecting the steady-state engine operating point for a given power request. To account for the transitions between different operating points, a control algorithm uses the battery to smooth out these transitions. The control policy was integrated with the powertrain control software in the engine control unit of a prototype vehicle and tested over the urban dynamometer driving schedule and US06 driving cycles. Ripaccioli *et al.* [113] extended this work and demonstrated the use of stochastic MPC (SMPC) in a series HEV. The power demanded by the driver was modeled as a Markov chain trained from a given family of driving cycles. A linear model was used with SMPC to derive an optimal control policy (engine power). Simulation results over the new European driving cycle (NEDC) demonstrated the effectiveness of the proposed approach. The approach was then enhanced with online learning capabilities of the transition probability matrix and demonstrated on standard and real-world driving cycles [114].

More recent publications have proposed different approaches for the online optimization of the power management control problem in series HEVs. The growing demand for making intelligent systems that can learn how to improve their performance while interacting with their environments has led to significant research on computational cognitive models. Computational intelligence, or rationality, can be achieved by modeling a system and the interaction with its environment through actions, perceptions, and associated costs [115]. Li *et al.* [116] proposed an approximate DP-based control strategy using an online learning method for a parallel HEV. Johri and Filipi [117] proposed a policy iteration approach to overcome the DP curse of dimensionality for a system with large state space. Using ANNs to approximate the cost-to-go function and applying reinforcement learning, the controller is able to improve its performance over time. Although the effectiveness of the power management control algorithm was validated through simulation in a series hydraulic hybrid vehicle, the algorithm could probably be also successfully applied in a series HEV. Another proposed online control approach addressed this problem by modeling HEV operation as a controlled Markov chain [118]. The stochastic optimal control problem was treated as a dual constrained optimization problem using the average cost criterion. It was shown that the control policy yielding higher probability distribution to the states with low cost and lower probability distribution to the states with high cost is an optimal control policy, which is defined as an equilibrium control policy.

V. Power-Split HEVs

The power split HEV (see Fig. 5) combines the advantages of both series and parallel configurations; series HEVs are more efficient at lower vehicle speeds, whereas parallel HEVs are more efficient at high speeds. The power split HEV costs higher than a parallel HEV as it needs two electric machines acting as both a motor and a generator and a larger battery pack. The "power split" name comes from the power split device (PSD), which is a planetary gear set that replaces the traditional gearbox and acts as a continuously variable transmission with a fixed gear ratio. The PSD allows the smaller of the two electric machines to act as a starter for the engine, thereby eliminating another component of a traditional gasoline engine. Rotation speeds of the electric machines and the engine are interdependent, and the speed of one of the electric machines will always change when the speed of either of the other two is varied. Thus, the engine can both power the vehicle directly, as in the parallel drivetrain, and be effectively disconnected from the wheels so that only one of the electric machines acting as a motor propels the vehicle, resembling a series HEV. A power split HEV operates more as a series HEV at a lower vehicle speed, whereas at a high vehicle speed, the engine takes over, and energy loss is minimized, resembling a parallel HEV.

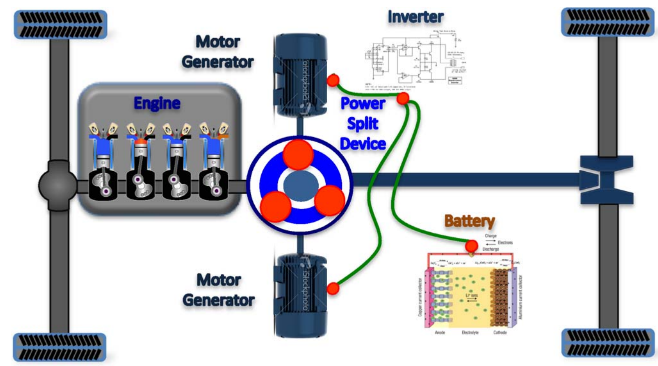

Fig. 5. Power-split HEV configuration.

Liu *et al.* [119] developed a dynamic model in MATLAB/Simulink of the Toyota hybrid system (THS), i.e., the first commercial power split HEV, with special attention given to PSD. The model is suitable for model-based control and system analysis. Meisel [120] presented a power split analysis of the energy flow for the second-generation THS and the two-mode transmission, including the kinematics of these power split transmissions whereby the speeds of all the planetary gears and electric machines were considered.

A. Rule-Based Power Management Control Algorithms

The power split HEV is a complex system, and very few heuristic approaches have been reported. Rizoulis *et al.* [121] analyzed the power split configuration of Michigan Technological University's FutureTruck, and a rule-based control strategy was proposed to operate the engine efficiently. Kessels *et al.* [122] proposed a control algorithm that does not require the knowledge of the driving cycle, yielding a suboptimal solution to the power management control problem. The algorithm is implementable in multiple HEV configurations.

B. Offline Power Management Control Algorithms

Using the model developed earlier [119], Liu and Peng [123] published another paper on implementing two power management control algorithms in THS. The first algorithm was based on the stochastic formulation of DP, and the second one was based on ECMS. Dextreit *et al.* [124] presented a control algorithm for power split HEVs based on game theory. In their approach, HEV operation is viewed as a noncooperative game between the driver and the powertrain. The paper illustrates the development of a game theory solution and compares the effectiveness of the efficiency of the approach with rule- and DP-based algorithms in terms of the design procedure, the resulting fuel consumption, and the computational effort required to construct and implement the solution.

Opila *et al.* [125] used SP-SDP to develop a power management control algorithm on Ford's highly datailed series–parallel vehicle model over large numbers of real-world driving cycles and compared it with a controller developed by Ford for a prototype vehicle. The driving cycle data used for simulation consisted of two sets of 100 driving cycles derived from actual driving trips made by 87 different drivers at the University of Michigan Transportation Research Institute (UMTRI). Results showed that the SP-SDP–based controller yielded a 2%–3% improvement in fuel economy compared with Ford's baseline power management controller. A couple of years after their first paper [125], Opila *et al.* [126] proposed another algorithm based on SP-SDP for improving both fuel economy and drivability. The controller was evaluated with Ford's vehicle simulator over the Federal Test Procedure and NEDC driving cycles, and explicit tradeoffs between fuel economy and drivability were quantified.

C. Online Power Management Control Algorithms

For power split HEVs, it seems that MPC has been the most popular online approach to develop a power management control algorithm. Borhan *et al.* [127] presented a power management control algorithm based on MPC for power split HEVs. In their approach, they formulated a nonlinear optimization problem and linearized the governing equations of the powertrain dynamics at each point in time. A receding-horizon linear MPC strategy was used to determine the power split ratio. The proposed MPC-based controller is predictive in nature, adapting to changes in the powertrain operating point and external disturbances and systematically tuned with low parameter sensitivity. The following year, Borhan *et al.* [128] published another paper proposing an NMPC-based control algorithm for power split HEVs. The fuel minimization problem was converted to a finite-horizon optimal control problem with an approximated cost-to-go, using the relationship between the Hamilton–Jacobi–Bellman equation and Pontryagin's minimum principle. PSAT was used to validate the effectiveness of the control algorithm. On the same note, Borhan *et al.* [129] and Borhan and Vahidi [130] formulated a nonlinear constrained optimal control approach consisting of two different cost functions and a linear time-varying MPC algorithm with a quadratic cost function. Finally, Kim *et al.* [131] proposed a power management control algorithm based on Pontryagin's minimum principle. A model corresponding to a THS was selected from the PSAT database for this study and was simulated over different driving cycles.

Path forecasting is used to obtain information about the route yet to be traveled to better optimize the charge/discharge cycle of the battery. This information-collecting capacity is yet to be fully realized in today's vehicles. Katsargyri *et al.* [132] proposed a receding-horizon control strategy for the onboard optimization of fuel consumption in power split HEVs. The control strategy depends on segmenting the virtual route so the optimization of the battery SOC set point can be rapidly performed. PSAT was used in this study, and the simulation results showed that the proposed control algorithm achieves significant success in obtaining near-optimal fuel economy as compared with DP. In the same year, Katsargyri *et al.* [133] presented another paper proposing a path-dependent power management control algorithm to improve fuel economy in power split HEVs. A key aspect of this approach addresses the accuracy of "route segment properties." This method divides the upcoming route into segments and notifies the driver about the optimal speed and route options available.

VI. PHEVs

The automotive industry has recognized that widespread use of alternative hybrid powertrains is currently inevitable and many opportunities for substantial progress remain. As such, more recently, PHEVs have held great intuitive appeal and have attracted considerable attention. PHEVs are hybrid vehicles with rechargeable batteries that can be restored to full charge by connecting a plug to an external electric wall socket. A PHEV shares the characteristics of both an HEV, i.e., having a battery, an electric motor, and an engine, and an all-electric vehicle, i.e., having a plug to connect to the electrical grid. PHEVs are particularly appealing in situations where daily commuting is within a small number of miles. Studies have shown that about 60% of U.S. passenger vehicles travel less than 30 mi each day [134]. Most PHEVs on the road today are passenger cars, but there are also versions of commercial vehicles, utility trucks, buses, and military vehicles.

Under the average mix of electricity sources in the United States, PHEVs can be driven with lower operation costs and fewer GHG emissions per mile when powered by electricity rather than by gasoline [135]. The main technical challenges for PHEVs are improving the energy storage capacity of lithium-ion batteries, demonstrating their reliability for automotive use, and reducing their cost. [3]. Tate *et al.* [136] presented an extensive study of the future opportunities for PHEVs and extended-range EVs (E-REVs). The authors concluded that, although HEVs and PHEVs have made progress in reducing fuel consumption and emissions, the HEV, in particular, is not the answer to energy and pollution challenges in the long term since the onboard energy still comes from petroleum. Instead, the HEV and the PHEV are merely stepping stones on the path to electrification. From an evaluation of the Regional Travel Survey, the authors draw the following conclusions: 1) more than 94% of vehicles operate at a power intensity higher than occurs in the urban and highway schedules; 2) E-REVs are ten times more likely to continue operating the whole day in EV mode than "an urban-capable PHEV derived from an HEV"; 3) E-REVs consume less than one half as much fuel as PHEVs in real-world driving; and 4) E-REVs can reduce startup emissions by 70%. The outcome of this study is that E-REVs should be viewed as a solution to the energy crisis and may be well worth the effort of pursuing the electrification capability.

More recently, Shiau *et al.* [137] have presented an optimization model based on integrated vehicle simulation polynomial metamodels, battery degradation data, and U.S. driving data. The proposed model identifies optimal vehicle designs and allocation of vehicles to drivers for minimum net life cycle cost, GHG emissions, and petroleum consumption under a range of scenarios. Wang *et al.* [138] proposed an approach to improve fuel economy and battery lifetime for EVs and parallel PHEVs with combination of an ultracapacitor and an energy-dense lithium-ion battery.

The implications of motor/generator and battery size on fuel economy and GHG emissions in a medium-duty PHEV were discussed in [139]. An optimization framework was developed and applied to two different parallel powertrain configurations, namely, pretransmission and posttransmission, to derive the optimal design with respect to motor/generator and battery size. The optimization framework was extended later on [140] to facilitate better understanding of the potential benefits from proper selection of motor/generator and battery size on fuel economy and GHG emissions. This understanding can contribute to appropriate sizing of these components and, in conjunction with an optimal power management control policy that includes the battery capacity and lifetime, can have significant implications in the overall PHEV cost. Wang and Cassandras [141] studied the problem of optimally controlling the charge and discharge rate of multiple nonideal batteries with the objective to maximize the minimum residual energy of the batteries at the end of a given time period. Investigating the same problem for a nonideal battery, it was shown that the optimal solution is of bang-bang with the battery always in recharging mode during the last part of the interval [142]. Li *et al.* [143] introduced a distributed supervisory controller to achieve battery component swapping modularity for PHEVs to provide users the ability to replace, or swap, batteries without redesign or recalibration of the system level controller.

Since the driver's driving style has major impact on battery lifecycle and capacity, a significant research effort has focused on developing a means of generating driving cycles to study their impact on the design and control of PHEVs. Gong *et al.* [144] developed a method for generating driving cycles with real-world driving properties for simulation and analysis of vehicles. Their method uses measured vehicle speeds from a number of vehicles to generate a Markov chain model. This effort was part of a larger project aimed at accounting for key factors such as vehicle patterns, vehicle characteristics, and market penetration of PHEVs. The data included measurements from nine actual PHEVs over the course of about two years. Lee *et al.* [145] investigated PHEV behavior during one day with synthesized representative one-day missions. The amounts of electric energy and fuel consumption were predicted to assess the PHEV impact on the grid with respect to the driving distance and different charging scenarios, namely, charging overnight and charging whenever possible. The representative cycles were synthesized using the extracted information from the real-world driving data in Southeast Michigan gathered by UMTRI. The real-world driving data include 4409 trips covering 830 independent days and temporal distributions of departures and arrivals. A year later, Lee *et al.* [146] extended this work on individual representative driving cycles, resulting in a proposed model that can capture departure and arrival time distributions with a small number of samples by statistically relating the distributions. Thus, representative real-world driving behavior is represented as a stochastic process and is statistically reconstructed.

A. Parallel PHEVs

Although the power management control problem in PHEVs can be simplified by operating the vehicle in all-electric mode until the lower SOC limit is reached before engaging the engine, this approach has been shown to be inefficient. Thus, there have been various research efforts aimed at developing power management control algorithms for optimizing PHEV operation. Karbowski *et al.* [147] used DP to optimize the power management in a pretransmission parallel PHEV. Several driving cycles were analyzed, and each of them was repeated multiple times to assess the impact of driving distance. O'Keefe and Markel [148] explored two power management control strategies for PHEVs using DP, namely, an EV-centric control strategy and an engine-motor blended control strategy. The results demonstrated that for urban driving, fuel consumption was minimized by maximizing electrified operation. Gong *et al.* [149], using DP, proposed a power management control algorithm that divides the entire driving cycle into segments and calculates fuel consumption and SOC for various vehicle speeds and accelerations. Yang *et al.* [150] presented another study using a DP-based algorithm for a parallel PHEV and showed simulation results over the NEDC driving cycle. Gong *et al.* [151] presented an approach to optimize the power management in a parallel PHEV by modeling driving cycles based on historic traffic information. They used a solution derived by DP to reinforce the charge-depletion control such that the SOC drops to a specific terminal value at the end of the driving cycle.

B. Series PHEVs

To overcome the problem of battery overdischarge and associated damage resulting from inaccurate estimates of the SOC in series PHEVs, Li *et al.* [152] defined a new quantity called the battery working state, which is based on both battery terminal voltage and SOC. Simulation results indicate that the proposed algorithm was effective in ensuring that the engine operates in the vicinity of its maximum fuel efficiency region while preventing the battery from overdischarging.

More recently, Patil *et al.* [153] have proposed a framework using DP for simultaneously optimizing the charging and power management of a series PHEV. The results show that addressing these two optimization problems simultaneously can provide valuable insights for certain combinations of daily driving scenarios, grid generation mixes, and optimization objectives. In one of the example cases considered, the grid produces higher CO_2 per unit energy between 3 A.M. and 8 A.M. This simultaneous control strategy responds by refraining from completely charging the PHEVs' battery in the early morning from the grid and judiciously increasing battery charging by the engine while driving. Patil *et al.* [154] presented an approach using a backward-looking powertrain model to implement the deterministic formulation of DP that aims to evaluate state constraints before selecting the optimal paths, thus resolving the associated DP computational challenges.

C. Power Split PHEVs

As in HEVs, DP has been used to explore the maximum theoretical efficiency in power split PHEVs. The study by

Bin *et al.* [155] is an example of using modified DP for power split PHEVs. Bashash *et al.* [156] simultaneously investigated the minimization of battery degradation and fuel/electricity costs via an optimization of the charge pattern for the power split PHEV. Two competing optimization problems were solved. The stochastic formulation of DP was used to derive the optimal control policy, and the driver's power demand was modeled as a Markov chain. The result of this optimization process is a family of optimal solutions in the form of a Pareto frontier showing the balance between total energy cost and battery resistance growth. The authors concluded that the optimal charging rate is near 1C, implying that faster charging would be better. On a similar note, Moura *et al.* [157] explored the quantification of the tradeoffs between power management algorithm design and battery energy capacity. A year later, the authors proposed a power management control algorithm for power split PHEVs using the stochastic formulation of DP [158]. In their approach, they explicitly investigated the tradeoffs between fuel consumption and electricity use in a PHEV and explored the potential benefits of controlled charge depletion over aggressive charge depletion followed by charge sustaining mode, while at the same time considering the impact of variations in relative fuel-to-electricity pricing on optimal PHEV power management.

Sharer *et al.* [159] analyzed the potential improvements in fuel economy for a power split PHEV for three charge-depleting power management control algorithms verus all-electric control strategy followed by charge-sustaining operation. Karboski *et al.* [160] used DP to compare the three PHEV configurations, i.e., parallel, series, and power split PHEV configurations. They concluded that fuel economy can vary for each configuration and highly depends on the nature of the route. Kum *et al.* [161] proposed an approach to quantify the SOC level with respect to the remaining trip with the aim to adjust control policy. Bashash and Fathy [162] presented an optimization framework aimed at minimizing the total cost of energy, including fuel and electricity, for a given PHEV powertrain configuration, electricity price, and trip schedule, over the course of a finite time. Yu *et al.* [163] developed a trip-oriented control algorithm to optimize fuel economy by adjusting the ration between the thermal and electrical paths of the powertrain. Chen *et al.* [164] used an online power management control algorithm using neural networks, trained on six driving cycles, that manage the power distribution between the engine and the battery.

VII. Outlook and Future Direction

There is a solid body of research now available that has aimed at enhancing our understanding of power control optimization in HEVs and PHEVs. Many different approaches have been proposed to address the fundamental vehicle system performance challenges using both offline and online analytical algorithms. Serrao [165] has recently presented a comparative analysis of the power management control problem in HEVs. DP, ECMS, and MPC have been the dominant methods used in the literature to obtain closed-form solutions based on analytical models of some or all of the subsystems. The biggest remaining uncertainties are related to external factors, including the driver's driving style, the surrounding traffic environment, and the driving terrain. It appears that future research studies need to be devoted to considering the vehicle as part of a larger system, which can be optimized at an even larger scale. Such large-scale optimization will require the acquisition and processing of additional information from the driver and conditions outside the vehicle itself. This is likely to require addition of new sensors and/or better utilization of information generated by existing sensors. However, the processing of such multiscale information will require significantly new approaches in order to overcome the curse of dimensionality. One particular area where new sensors will be needed is in vehicle-to-vehicle communication (see Fig. 6). It seems clear that the availability of this information has the potential to reduce traffic accidents and ease congestion by enabling vehicles to more rapidly account for changes in their mutual environment that cannot be predicted by deterministic models. Likewise, communication with traffic structures, nearby buildings, and traffic lights should allow for individual vehicle control systems to account for unpredictable changes in local infrastructure.

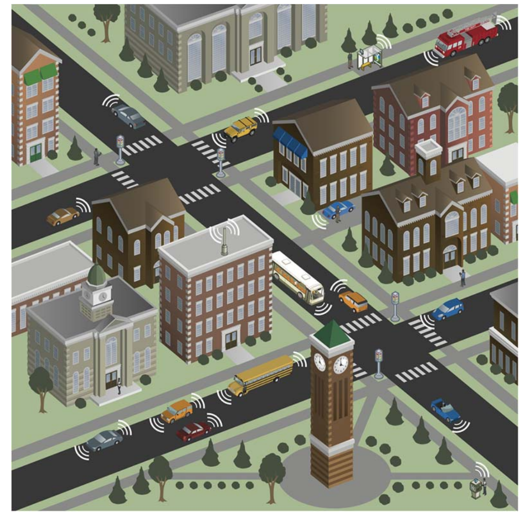

Fig. 6. Vehicles able to communicate with each other and to communicate with infrastructure, e.g., buildings and traffic lights.

Recognition of the necessity for connecting vehicles to their surroundings is gaining momentum. Many stakeholders intuitively see the benefits of multiscale vehicle control systems and have started to develop business cases for their respective domains, including the automotive and insurance industries, government, and service providers. The main focus is on safety and how accidents could be potentially prevented by developing multiscale systems based on vehicle-to-vehicle and vehicle-to-infrastructure communications to alert drivers. Thus, we can assume that these technologies will be available in a few years. The question is whether we could take advantage of these technologies and optimize the power management control in HEVs and PHEVs. What if we would consider the problem of optimizing fuel economy and emissions for a fleet of vehicles rather than a single vehicle, thus eliminating the uncertainty related to traffic? What would be the appropriate conceptual approaches for modeling and optimization?

Investigating a new optimization framework that considers a fleet of vehicles could aim to compute the most efficient

Fig. 7. Information systems to the driver.

vehicle speed in centralized locations and communicate this with driver information systems to the driver (see Fig. 7) to avoid congestion, thus improving overall efficiency and reducing emissions in conventional vehicles. In HEVs and PHEVs, the power management controller would have to account for limited uncertainty about surrounding traffic and commute and be able to optimize fuel economy, pollutant emissions, as well as battery lifetime and range. The detailed investigation of these issues could provide policymakers with unique new tools to assess the implications in promoting the development of technologies and infrastructure in new directions.

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