Review of optimization strategies for system-level design in hybrid electric vehicles

Review of Optimization Strategies for System-Level Design in Hybrid Electric Vehicles

Emilia Silvas, Theo Hofman, Nikolce Murgovski, L. F. Pascal Etman, and Maarten Steinbuch, *Senior Member, IEEE*

***Abstract*—The optimal design of a hybrid electric vehicle (HEV) can be formulated as a multiobjective optimization problem that spreads over multiple levels (technology, topology, size, and control). In the last decade, studies have shown that by integrating these optimization levels, fuel benefits are obtained, which go beyond the results achieved with solely optimal control for a given topology. Due to the large number of variables for optimization, their diversity, and the nonlinear and multiobjective nature of the problem, a variety of methodologies have been developed. This paper presents a comprehensive analysis of the various methodologies developed and identifies challenges for future research. Starting from a general description of the problem, with examples found in the literature, we categorize the types of optimization problems and methods used. To offer a complete analysis, we broaden the scope of the search to several sectors of transport, such as naval or ground.**

***Index Terms*—Coordination methods, driving cycle, hybrid electric vehicles (HEVs), multilevel optimal design, optimization methods, powertrain design.**

I. Introduction

Current challenges for newly developed vehicles, as strict legislations on CO_2 or the foreseen future lack of oil, are addressed in various transportation sectors, with hybrid powertrains, as viable solutions. Having more than one source of power, hybrid powertrains give birth to a large design space for the physical system and increase the complexity of the control algorithm. The coupling (dependence) between the parameters of the physical system (e.g., topology) and the parameters of the control algorithm transforms the problem into a multilevel problem (as depicted in Fig. 1) that, if solved sequentially, is by definition suboptimal [1]. Therefore, the physical system and the control algorithm should be designed in an integrated manner to obtain an optimal system design.

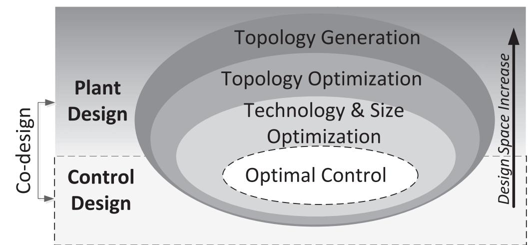

Fig. 1. Hybrid electric vehicle (HEV) system-level design (SLD) and its multilayers.

Because of the large dimensions of the design space, computer simulations of dynamical systems, e.g., for different architectures and component sizes, have become more important as a preliminary step to building prototypes [2]. Computer simulations significantly speed up the control synthesis of a given design and topology. However, even with computer systems, the problem of finding the optimal vehicle design that provides the best control performance is typically intractable. Obviously, it is not feasible (costwise or timewise), given a design space, to build all possible vehicles and evaluate which configuration and parameters provide the best performance for control. Moreover, even when designing the control algorithm, due to the nonlinear, mixed-integer, and multidimensional (several states) characteristics of HEVs control problem, the simulations require large computational times. Ergo, it is not timewise feasible to simulate all combinations (i.e., brute force searches) of the design variables [3]. Instead, optimization-based frameworks for plant and control synthesis of HEVs are being developed. Starting from the optimal control and continuing to the optimal sizing, different optimization algorithms were used to obtain the maximum powertrain energy efficiency and/or the minimum total cost of vehicle ownership.

Based on examples from recent literature, in this paper, we introduce the general problem of optimally designing an HEV. Then, we summarize the common challenges in this design problem and present the different methods and frameworks that have been developed to improve the design of HEVs. The focus of this overview is on frameworks that include the codesign of HEVs, i.e., concurrent plant (as topology or size) and control optimization.

The remaining sections of this paper are organized as follows. After a description of HEV topologies is given in Section II, the system-wide optimization problem is described in Section III. Section IV discusses existent methodologies used for integrating the plant and control optimization, together with the used optimization algorithms. In Section V, these

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E. Silvas was with the Control Systems Technology Group, Department of Mechanical Engineering, Eindhoven University of Technology, Eindhoven 5612, The Netherlands. She is now with the Netherlands Organization for Applied Scientific Research (TNO) Technical Sciences, Helmond 5700, The Netherlands (e-mail: emilia.silvas@tno.nl).

T. Hofman, L. F. P. Etman, and M. Steinbuch are with the Control Systems Technology Group, Department of Mechanical Engineering, Eindhoven University of Technology, Eindhoven 5612, The Netherlands (e-mail: t.hofman@tue.nl; l.f.p.etman@tue.nl; m.steinbuch@tue.nl).

N. Murgovski is with the Department of Signals and Systems, Chalmers University of Technology, Gothenburg 412 96, Sweden (e-mail: nikolce.murgovski@chalmers.se).

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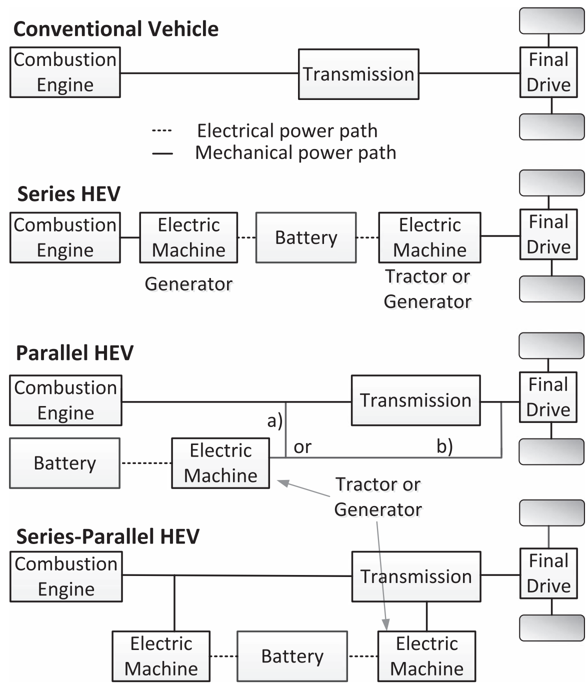


Fig. 2. Main topology classes in vehicles: conventional (solely fuel driven) and hybrid electric [series, parallel, and series–parallel (with one or more planetary gear systems)]. Here, dotted lines represent electrical links, and solid lines represent mechanical links.

algorithms are discussed and compared, and in Section VI, the conclusions are drawn.

II. Hybrid Electric Vehicles

Conventional vehicles run on internal combustion engines, consuming fuel to deliver the required power. In addition to providing a useful work, conventional vehicles are encountered with dissipative energy, such as the braking energy, aerodynamic drag losses, tire friction losses, and engine idling losses. In this topology, emission reduction possibilities exist, such as lighter materials and more improved designs, but are limited. For instance, while reducing further the aerodynamic drag or the tire losses is possible, braking and idling losses will always be significant in conventional vehicles. Nevertheless, the sizing of the combustion engine will always be decided by the power it needs to provide. To circumvent this limitation, various hybrid architectures have been developed, where each architecture has its advantages and disadvantages.

Hybrid vehicles combine two or more technology principles to produce, store, and deliver power. Current market hybrid vehicles typically combine a combustion engine and an electric machine (EM), as power converters, and they are referred to as HEV's. This hybridization allows a wide variety of topologies for the configuration of the powertrain.

Three categories of topologies may be distinguished: *series*, *parallel*, and *series–parallel*, as illustrated in Fig. 2. These topologies, as well as their applicability to various transportation sectors, have been researched intensively in recent years and are described in detail in survey papers such as [4]–[9] and books [10]–[13]. In an HEV, depending on its topology and component technologies, an EM can function as a *tractor* (delivering positive torque and speed to propel the vehicle) or as a *generator* (producing energy, from either the engine or from regenerative braking, to charge the battery).

Series HEVs perform best in stop-and-go driving since there is no mechanical link between the combustion engine and the wheels. This way, the engine can be run at its most efficient point also in varying vehicle speeds. Moreover, because there is no mechanical connection between the combustion engine and the wheels, this configuration is rather flexible with regard to the physical location of the various components in the powertrain. This makes the series topology highly suitable for application with restricted (re)design space.

When a series HEV is used in highway or interurban driving, high powers need to be transmitted to the wheels from the EM. Hence, large electrical machines are needed to achieve high vehicle speeds. In addition, this topology requires a double energy conversion for delivering the required power, which induces efficiency losses. In this configuration, the size of the traction EM is deducted from the vehicle's required performance (such as the acceleration requirement). Thus, the sizing of the powertrain reduces to finding the optimal sizing of the battery and the power generating group (combustion engine/generator).

In parallel HEVs, the combustion engine and the EM are both connected to a mechanical transmission, and they can generate power independently of each other. The EM can be connected before or after the transmission, as shown in Fig. 2 with (a) and (b). Moreover, the HEV can switch between the power sources given the driving conditions. In this configuration, there is no separate generator. Whenever generating power is possible and needed (e.g., energy recuperated from braking), the EM functions as a generator.

Parallel HEVs have a direct mechanical connection between the engine and the wheels. This leads to smaller energy losses (as they do not require the dual energy conversion as the series topology) but less flexibility in the mutual positioning of the powertrain components compared with the series HEV drivetrain as well.

Series–parallel HEVs have an extra direct mechanical connection between the generator and the traction motor via the transmission. These architectures combine the benefits from both series and parallel HEVs. They are usually constructed with one or more planetary gear sets (PGSs) and require at least two EMs. PGSs are transmission elements with three connectivity points (ring, sun, and carrier). These transmission elements eliminate the need of a traditional stepped (manual or automatic) gearbox and other transmission components.

Due to their increased flexibility in operating the components (as in series HEVs) and the presence of mechanical links (as in parallel HEVs), series–parallel HEVs can lead to a reduced fuel consumption for a wide variety of applications [14]. However, at the same time, they come at a higher price and require more complex control strategies.

Except these three HEVs categories, others can be also found in literature or practice, e.g., the dual-mode hybrid and the four-quadrant transducer. These mostly vary in the construction of the transmission components and will not be addressed here. See [15]–[19] for more information.

The efficiency of hybrid topologies varies according to the conditions under which they are driven. The design choice for one or other architecture depends on the (intended) mission of the vehicle and the tradeoff between cost and performance. Given the pros and cons of the serial, parallel, and series–parallel topologies, these are each predominantly used in certain transportation sectors. Serial topologies are currently most often found in buses [20]–[24], battery electric vehicles [25] with range extenders, boats [26], heavy vehicles (military), locomotives [27]–[30], and other in-urban vehicles, such as taxis or passenger vehicles [31]–[33], whereas parallel topologies and series–parallel are very common in passenger vehicles [34]–[38].

Due to the high cost and complexity of series–parallel topologies, the parallel topologies are, at the moment, the most commonly produced type of HEVs. Consequently, the parallel hybrids dominate the literature on supervisory control strategies for HEVs [36], [39], [40].

For different applications, dedicated research has been conducted on technologies for hybrid components and storage devices (as batteries, supercapacitors, or flywheels). Overviews of electric motor drives and storage devices are well presented in [5] and [41]–[46]. The requirements of each application determine the suitability of a certain technology, as well as the required dimensions of the respective hybrid component. In fact, determining the technology and dimension of a particular powertrain component represents also a discrete choice. This makes the optimal design of the powertrain of a hybrid electrical vehicle a discrete programming problem in terms of topological connectivity, technologies, and dimensions of the HEV powertrain components.

In the first research effort on HEV development, the various options (topology, type, size) were investigated for a restricted set of discrete design choices (e.g., a battery versus fuel cells or three dimensions for the same Li-ion battery). The limited search space already provided novel hybrid powertrain configurations with a lower fuel consumption than conventional vehicles. Recent research papers on HEV development increase the scale of the optimization problem, in an effort to further improve the HEV performance. Typically, one seeks to formulate and solve a system-wide optimization problem covering the various components and disciplinary aspects involved in the HEV powertrain design.

In the following, these approaches for design and control of HEVs will be presented and analyzed, with their pros and cons. We address the design of HEVs alone, without considering their effect on infrastructures (charging, traffic/transport, communication). For details on cooptimization of both HEVs and infrastructure, see [47]–[50].

III. Problem Statement for System-Wide Optimal Design

A hybrid vehicle contains multiple interconnected subsystems, which, themselves, consist of several subsystems. When an HEV is built, it is desired to minimize both operational and component/design costs.

A. Driving Cycle

To evaluate the fuel consumption of an HEV, a drive cycle Λ is necessary. This is a series of data points, i.e.,

$$\Lambda(t) = \begin{bmatrix} v(t) \\ s(t) \end{bmatrix}, \text{ with } t \in [t_0, t_f] \tag{1}$$

with $v(t)$ representing the speed of a vehicle over time, $s(t)$ representing the slope (gradient) of the road, and $[t_0, t_f]$ representing the driving cycle length. The drive cycle represents the type of driving conditions in which the HEV is used. It is the main determinant for the fuel consumption and the design (such as dimensioning of components) of the vehicle.

Driving cycles, which can be either measured or artificially created, vary across applications, countries, and organizations. Driving cycles are used to assess the performance of HEVs in different ways, as, for example, fuel consumption and pollution emissions [51]–[53]. In the literature, most driving cycles assume $s(t) = 0$. This is an important assumption for heavier vehicles, where the contribution in the total power demand, for $s(t) \neq 0$, becomes significant.

B. Plant and Control Optimization Problem

The HEV efficiency and cost are dependent not only on the components (their connections, technologies, and sizes) but also on the control algorithm used. The varying parameters defining topology, sizing, and control inputs constitute the design variables (denoted by $\mathbf{x}$) in the optimal design problem, for both the plant and the control of an HEV, i.e.,

$$\begin{aligned} \min_{\mathbf{x}_c, \mathbf{x}_p(t)} \quad & \mathbf{J}\left(\mathbf{x}_p, \mathbf{x}_c(t), \Lambda\right) \\ \text{s.t.} \quad & g_j\left(\mathbf{x}_p, \mathbf{x}_c(t)\right) \leq 0, \quad j = 1, 2, \ldots, m \\ & h_l\left(\mathbf{x}_p, \mathbf{x}_c(t)\right) = 0, \quad l = 1, 2, \ldots, e \\ & \dot{\xi}(t) = f\left(\xi(t), \mathbf{x}_p, \mathbf{x}_c(t), t\right) \\ & \xi(t_0) = \xi_0 \\ & \xi(t_f) = \xi_f. \end{aligned} \tag{2}$$

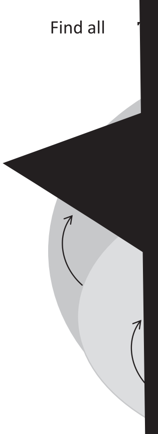
Here, $\mathbf{x}_p \in \mathbb{R}^n$ and $\mathbf{x}_c(t) \in \mathbb{R}^z$ denote the design variable vectors with n independent plant variables and z independent control variables, respectively; m is the number of inequality constraints; e is the number of equality constraints; $\mathbf{J}$ is the cost function; and ξ are the states of the dynamical system, e.g., the state of charge (SOC) of the electric buffer.

Note that, for ease of understanding, vectors are marked in bold, i.e., $\mathbf{x}$ is a vector of design variables, where each variable is denoted by x. Moreover, $(\cdot)_p$ represents a plant-related variable (such as battery sizing), whereas $(\cdot)_c$ represents a control-related variable (such as engine torque).

In cases where ξ denotes the battery SOC, the final state conditions

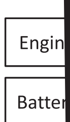
$$\xi_f = \xi_0 \tag{3}$$

$$\xi_f = \xi_{\min} \tag{4}$$



[redacted]

Fig. 3. SLD [redacted]



[redacted]

The most commonly employed objective functions $J_i(\mathbf{x}) : \mathbb{R}^k \to \mathbb{R}^1$ are

$$J_1 = \int_{t_0}^{t_f} \dot{m}_f(t)dt \quad J_4 = \int_{t_0}^{t_f} \mathrm{NO}_x(t)dt$$

$$J_2 = \Psi_m + \Psi_i + \Psi_b \quad J_5 = \int_{t_0}^{t_f} \mathrm{HC}(t)dt$$

$$J_3 = -m_0 + m_b \quad J_6 = \int_{t_0}^{t_f} \mathrm{CO}(t)dt. \tag{9}$$

Herein, J_1 represents the CO_2 reduction, or the overall fuel consumption; J_2 is the hybridization cost, i.e., the summed cost of the motor Ψ_m, cost of the inverter Ψ_i, and cost of the battery Ψ_b. J_3 is the payload weight of the vehicle (on-board passengers or cargo) m_0 plus the weight of the battery m_b. J_4, J_5, and J_6 are the nitrogen oxide (NO), hydrocarbon (HC), and carbon monoxide (CO) emissions.

The multiobjective character of the HEV SLD problem (fuel, costs, etc.) requires dedicated multiobjective optimization algorithms/solvers, or reformulation of the problem into a single objective formulation. The latter, which is referred to also as *scalarization* of the cost function, is often used and represents a choice of the designer.

There are multiple methods for objective function scalarization [55]. The weighted sum formulation is equal to

$$f(\mathbf{J}, \mathbf{w}) = w_1 J_1 + w_2 J_2 + \cdots + w_k J_k \tag{10}$$

with $\mathbf{w}$ being a vector of weight parameters, with

$$w_1 + w_2 + \cdots + w_k = 1. \tag{11}$$

The weights are adjusted such that a certain preference for the optimization targets is imposed. This scalarization is used, for example, in [56, Ch. 3], where

$$f(\mathbf{J}, \mathbf{w}) = (w - 1)\hat{J}_1 + w\hat{J}_2 \tag{12}$$

is proposed (with $\hat{J}$ representing the normalized[1] value of J) or in [57], where

$$f(\mathbf{J}, \mathbf{w}) = w_1\hat{J}_1 + w_2\hat{J}_5 + w_3\hat{J}_6 + w_4\hat{J}_4 \tag{13}$$

is used.

As aforementioned, when an HEV is built, it is desired to minimize both operational and component/design costs. The SLD problem is a challenge given that different optimization functions depend on different system levels. For example, minimizing the cost of electrification, J_2 is typically used for powertrain component sizing (since J_2 does not depend on the control algorithm). On the other hand, J_1 is always used as objective for the control algorithm design, but it also depends on the component sizing. What the possible optimization schemes are and how the HEV design problem has been addressed so far are discussed next.

[1]The authors define a normalized value $\hat{J} = (J/J^N) \in [0, 1]$, where J^N is estimated as the largest possible value of J within the search space.

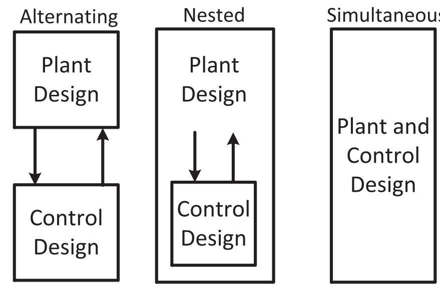


Fig. 5. Coordination architectures for SLD in HEVs.

IV. Published Hybrid Electric Vehicle Design Frameworks

In the context of HEV prototyping, a design framework is a methodology that uses existing optimization algorithms combined on multilevels to find the best design for given targets and constraints. This describes how and in which order the coupled optimization problems at the various levels are solved in an effort to solve the overall SLD problem. This relates to coordination methods in distributed multidisciplinary optimization (see, for instance, [58] and [59]), where the coordination method defines how the coupled disciplinary subproblems are solved to arrive at the system optimal solution.

For the plant and control design problem, there are basically three coordination architectures, as shown in Fig. 5.

1) *alternating* plant and control design, i.e., first, the plant is optimally designed. Using this outcome, the controller is optimally designed. Subsequently, the plant is optimized again, etc. The coordinator alternates between optimizing the plant and optimizing the control until the coupled variables have converged;
2) control design *nested* within plant design, i.e., every evaluation of a plant requires the full optimization of the controller design;
3) *simultaneous* plant and controller design (i.e., solving (2) all in one).

In the mid-1990s, when the hybrid vehicle market emerged, the plant design problem and the control design problem were treated completely independently [60]. Nowadays, in most literature and practice, a clear distinction is made between the plant and the control design variables and objectives, where (2) becomes the following codesign problem:

$$\min_{\mathbf{x}_p, \mathbf{x}_c(t)} \quad \mathbf{J}(\mathbf{x}) = \{J_p(\mathbf{x}_p, \mathbf{x}_c(t), \Lambda), J_c(\mathbf{x}_p, \mathbf{x}_c(t), \Lambda)\}$$
$$\text{s.t.} \quad \text{constraints as in (2).} \tag{14}$$

The plant cost function J_p and the control cost function J_c may contain any combination of the objectives from (9).

For the plant design problem, in the literature also, distinction is made between topology design and component sizing optimization. Usually, the component sizing problem is solved for a fixed topology. The choice of topologies to be analyzed has, so far, been mainly dictated by practical experience rather than by a topology optimization procedure. A computational tractable method for combined topology and component sizing optimization of the plant design is an open research question.

In the following, we give an overview of the currently employed methods for topology optimization of the HEV plant. Most of these methods aim at finding feasible topologies, not necessarily optimal topologies. Subsequently, in the forthcoming subsections, we survey methods for alternating, nested, and simultaneous plant and control design of HEV vehicles.

A. HEV Topology Generation or Selection

In practice, an HEV topology is often *selected* on the basis of criteria that derive from expert knowledge. In this approach, the set of rules forming the criteria can be derived from expert knowledge, availability of components on the market, other HEVs, and so on. The selected topology is very likely not optimal. Recent studies show that very small changes in known topologies, such as Toyota Prius or Chevrolet Volt, can lead to more efficient HEVs (with respect to cost or fuel) [61].

Another approach for arriving at a suitable topology is to evaluate at all possible topologies that can be constructed from a predefined fixed set of components. This is sometimes referred to as *topology generation*.

Usually, topology generation means the search for all feasible topologies $\mathbf{T}^f$ within a (large) set of possible topologies $\mathbf{T}^p$, given design constraints $\mathbf{c}$, i.e.,

$$\begin{aligned} \text{find all} \quad & \mathbf{T}^f \subseteq \mathbf{T}^p \\ \text{s.t.} \quad & \mathbf{c}(T^f) \leq 0. \end{aligned} \tag{15}$$

A method to solve (15) was proposed in [62], where $\mathbf{c}$ consists of functionality (i.e., power delivery, hybrid functions, and feasibility) and cost constraints. Each topology is modeled as an undirected connected finite graph, where each component is a node of the graph. Based on these nodes, a set of constraints are defined, and (15) is solved as a constraint satisfaction problem over finite domains [63]. In [62], this method is applied on a set of 16 powertrain components (including two PGSs, two EMs, and three clutches), searching for feasible series, parallel, and series–parallel HEV topologies. They show that the initial search space of $5.7 \cdot 10^{45}$ possible topologies is reduced to 4779 feasible topologies.

Another recent method by [64] to solve (15) aims at developing series–parallel topologies with one or multiple PGSs. This method models a topology as a bond graph and, similar to the previous method, uses constraints to arrive at feasible topologies. Using this method, in [65], the topology generation and optimization of a midsize passenger car is discussed. When series–parallel topologies with double planetary gears are used, in [66], a method to automatically model and exhaustively search for optimal topologies is proposed. The authors show, using Toyota Prius as a study case, that improved configurations (offering reduced fuel consumption) are found.

These studies show how the initial set of candidate topologies can be reduced in a systematic and complete way. At the same time, they highlight new challenges in defining and solving this kind of problems.

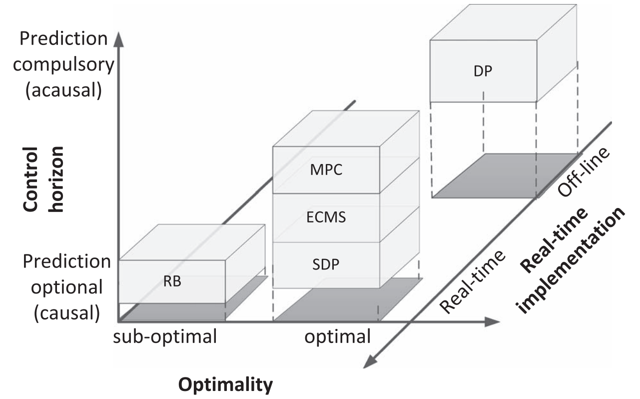


Fig. 6. Classification of energy management strategy categories: optimality, control horizon, and real-time implementation. RB : rule based, MPC : model predictive control, (S)DP : (stochastic) dynamic programming, and ECMS : equivalent consumption minimization strategy.

Once a topology has been decided on, codesign problem (14) is to be solved. Next, we distinguish sequential, alternating, nested, and simultaneous methods. *Sequential* is a special instance of the *alternating* coordination strategy (plant and control subproblems are solved only once, sequentially) and is also referred to as a design-first-then-control methodology.

B. Design-First-Then-Control Strategy for HEV Design

The design-first-then-control strategy is the simplest strategy one can envision; the coupling between the plant design and control design problems is neglected. Mainly due to its decentralized manner, this strategy has been a pioneer when approaching HEV design. The control problem is approached for a fixed plant, i.e., fixed (a)–(c) layers in Fig. 3.

The development of the control algorithm, i.e., the energy management system (EMS) of an HEV powertrain, consists of finding the set points of the power converters that can deliver the driver's required power in an "optimal" way. Optimality is defined in terms of fuel consumption [J_1 from (9)], but may also include pollutant emissions [J_4 and J_5 from (9)], drivability, or performance criteria related to the battery (e.g., life degradation or charge). This optimal control problem, which is given by

$$\begin{aligned} \min_{\mathbf{x}_c(t)} \quad & J_c\left(\mathbf{x}_p, \mathbf{x}_c(t), \Lambda\right) \\ \text{s.t.} \quad & \text{constraints as in } (2) \end{aligned} \tag{16}$$

has been approached by two main categories of methods as depicted in Fig. 6: optimization-based and rule-based (RB) methods.

The strategies based on rules, either heuristics [67] or fuzzy logic [39], [68], [69] are based on expert knowledge translated into Boolean rules, to make the power sources work in their most efficient regions. These algorithms are easy to implement, and they do not require high computation times. However, they cannot offer any proof of optimality of the solution found. They may require significant tuning effort and may change significantly for each topology. This disadvantage has motivated

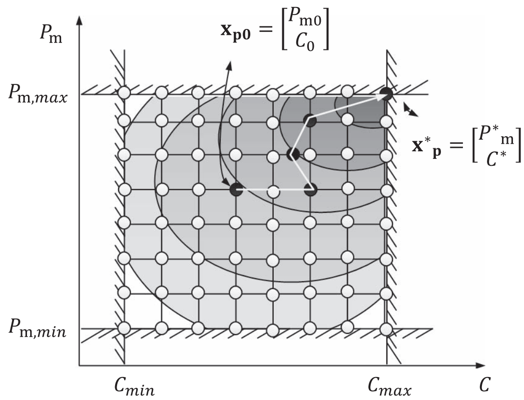


Fig. 7. Design space exploration using (light gray dots) exhaustive search, an (dark gray points) optimization algorithm, and the interpolation contour lines of the cost function.

the investigation and the applicability of rigorous optimization algorithms.

There exist a wide variety of optimization algorithms for controller design. Two categories may be distinguished: real-time-implementable [70] or offline algorithms [71]. Dynamic programming (DP) is widely used for offline optimization, and DP typically serves as a benchmark for evaluating other (real-time) algorithms [72]–[77]. There exist also optimization-based algorithms that can be online implementable. These are mostly based on the equivalent consumption minimization strategy (ECMS) [40], [78]–[83], stochastic DP (SDP) strategies [84]–[88], or model predictive control (MPC) strategies [89], [90]. Reviews of EMS can be found in review papers such as [91]–[97]. Benchmark comparisons are given in [98] and [99], where several algorithms are implemented and compared for controlling the plug-in Chevrolet Volt HEV. Note again that all these energy/power control algorithms are derived for an *a priori* defined HEV. Therefore, the dependence between the system design and the control algorithm design is not taken into account. However, this coupling exists, e.g., the dimension of the battery will influence the optimal control problem. To overcome this limitation, attempts to design better systems have been developed using design-and-control methodologies (in either an alternating, nested, or simultaneous fashion).

C. Alternating, Nested, and Simultaneous Coordination Schemes

For each topology, to find the set of optimal $\mathbf{x}_p^*$ with a nested coordination scheme, various authors [98], [100]–[106] have used exhaustive search in the plant design optimization problem, combined with a rule based or DP for control design. With exhaustive search, also referred to as brute force search, the design space is gridded, and for each grid point, the cost function is evaluated [107]. This is depicted in Fig. 7 for the parallel topology in Fig. 4, where the hybridization potential is analyzed in terms of fuel consumption for $\mathbf{x}_p^{\text{pr}} = [P_m \;\; C]^T$.

Using the values of the cost function at each point, the shape of this function can be interpolated, and a design can be chosen. For the sake of clarity, we depict this for two plant design variables only. If more design variables are included, the visualization and interpretation of results will be difficult. Then, Latin hypercube sampling can be used to explore the cost function in all the feasible design spaces [108].

In [100], such a nested exhaustive search framework is used to compare four topologies (a conventional HEV, a start–stop HEV, a full-parallel HEV, and a power-split HEV), for a passenger car application given different driving cycles. Due to hybridization and engine downsizing, the authors present more than 33% CO_2 decrease for the full-parallel and power-split (similar to Toyota Prius) HEVs. In [104], focusing on the transmission selection, three full-parallel hybrid electric drivetrain topologies are investigated. In [102], *one-variable-at-a-time* exhaustive search is used for the component sizing optimization loop, and DP is used for the control algorithm. Considering a series-hybrid microbus, $\mathbf{x}_p^s = [P_{e+m1} \quad C]^T$ is defined, with P_{e+m1} representing the generating group power (i.e., the combined generator motor and engine) and C representing the battery capacity. With a fixed battery pack, the generating group of the series architecture, i.e., P_{e+m1}, is varied in size, and the possibility of downsizing or upsizing the engine is analyzed. Once a value was found for P_{e+m1}, this is fixed, and the variation on the battery pack sizing is investigated. We refer to this as one-variable-at-a-time exhaustive search, since, when mapping this problem to the previous example in Fig. 7, the authors vary one variable at a time, resulting in only one row/column, and repeat this process for all design variables.

The exhaustive search strategy is simple and insightful but only works for a limited number of plant design variables. The computational burden quickly grows, for increasing number of plant variables. The computational time may be expressed as $T = T_a \cdot \prod_{i=1}^{N} g_i$, with N being the number of plant design variables, T_a being the time in which the optimal control problem is solved, and g_i being the number of grid points for variable i. The grid needs to be sufficiently dense to guarantee a reasonable accurate interpolation between the grid points. Alternatively, for increasing number of plant variables, one may consider to use a Latin hypercube design exploration with a radial basis of Kriging type of surrogate model for the interpolation.

In recent years, the use of optimization-based multilevel design, (introduced already for different applications [109]–[111]) has seen an increased interest. By using an optimization algorithm for the plant design problem, one seeks to reduce the number of cost function evaluations, compared with exhaustive search (see, for example, Fig. 7), with a better exploration of the design space in the design region of interest.

The SLD problem is usually nonlinear and often also has mixed-integer characteristics. In the literature about multilevel optimization of HEV, a wide variety of algorithms have been selected for the plant optimum design. One may distinguish between derivative-free and gradient-based algorithms. Examples of derivative-free algorithms include the following: Dividing Rectangles (DIRECT) [122], [139]; particle swarm optimization (PSO) [56], [130]; genetic algorithms (GAs) [20], [51], [140]–[142]; and simulated annealing (SA) [123], [143]. Papers that use a gradient-based algorithm include sequential quadratic programming (SQP) or convex optimization (CO) [133], [136], [137], [144].

TABLE I
CLASSIFICATION OF SEVERAL FRAMEWORKS FROM EXISTING LITERATURE, AS A FUNCTION OF *COORDINATION METHODS* AND *ALGORITHMS* USED FOR SIZING AND CONTROL DESIGN [ECMS : EQUIVALENT CONSUMPTION MINIMIZATION STRATEGY, (S)DP : (STOCHASTIC) DYNAMIC PROGRAMMING, SQP : SEQUENTIAL QUADRATIC PROGRAMMING), SA : SIMULATED ANNEALING, PSO : PARTICLE SWARM OPTIMIZATION, RB : RULE BASED, SADE : SELF-ADAPTIVE DIFFERENTIAL EVOLUTION, DS : DOWNHILL SIMPLEX METHOD]

ALGORITHMS		COORDINATION METHODS
Component Sizing	Control	
		Sequential
Fixed	RB	Parallel HE Truck [112]
	ECMS	Parallel Small HEV [40], Through-the-road Parallel Midsize HEV [113]
	SDP	Mid-size Series-Parallel HEV [87]
	DP	Parallel HE Truck [112]
		Nested
Exhaustive Search	RB	Large-size passenger parallel HEV [114], Medium-Duty Parallel HE Truck [101], Small passenger HEV with CVT [37], Torque-Assist Midsize HEV [115], Parallel HE Truck [3]
	ECMS	Fuel Cell HE Truck with two in-wheel EMs [103]
	DP	Passenger HEV (Parallel [36], [116], Torque-Assist [115], Large Parallel [104], Compact Parallel [98], Several vehicles [100]), Heavy-Duty HE [108]. HE microbus [102]
SQP	RB	PNGV passenger HEV [117]
	DP	Parallel HE Class 8 Truck [118]
DIRECT	RB	Parallel passenger HEV [119], Parallel HEV [6], Mid-size HE SUV [120] Mid-size parallel HE SUV [121], Parallel passenger HEV [122]
SA	RB	Parallel passenger HEV [6], [119], [122], Series HE Commercial City Bus [123]
DS	RB	Series passenger PHEV [124]
SADE	RB	PNGV parallel passenger HEV [125]
Single / Multi-Objective GA	RB	Parallel passenger HEV [119], [122], Parallel HEV transit bus [20], Fuel-cell HEV [126], Parallel HEV [6], Hybrid and Electric Submarine [127]
	SQP	Hybrid and Electric Submarine [128]
	DP	Parallel Class 8 HE Truck [129]
PSO	RB	Parallel passenger HEV [6], [57], [119]
	DP	Midsize Parallel HEV [56], [130] Torque-assist and Parallel passenger HEV [131], Parallel Class 8 HE Truck [129], Series HEV [132]
		Simultaneous
Convex Opt.	Convex Opt.	Series PHEV Bus [133]–[136] Parallel PHEV [137], Series HEV [132]
		Alternating
SQP	ECMS	Mid-size passenger HEV [138]

When in the system design process separate plant and controller optimization subproblems are considered, a coordination method between these two optimization layers is needed. Based on the coordination schemes defined in Fig. 5, in Table I, a classification of several frameworks from existing literature is shown. This table tabulates the type of algorithm for the plant design problem, the type of algorithm for the control design problem, and the coordination strategy to arrive at the system optimal solution. One may notice that recent studies use either nested, simultaneous, or alternating coordination methods to reach an optimal design. The structure in Table I indicates also the evolution of the strategies used. Methods have evolved from sequential to mostly nested plant and controller design. Quite recently, also the simultaneous and alternating coordination schemes have been proposed for use in HEV frameworks, which may provide computational advantages compared with the nested scheme.

Vehicle simulation packages, such as Advanced Vehicle Simulator (ADVISOR) [145] or Powertrain System Analysis Toolkit [146], containing RB algorithms for HEV control, have facilitated the fast development and simulation of design frameworks. For instance, using an RB control algorithm nested within multiobjective GA (having UDDS as input driving cycle) [51], in [20], the sizing of a parallel hybrid bus is discussed for multiple objectives, i.e., J_1, J_4, J_5, and J_6 from (9). In addition to the benefits for design, the following are highlighted: 1) The increase of population size of the algorithm will result in improved accuracy of results; 2) no user-supplied weights of each objective must be provided; and 3) more driving cycles must be used to improve this methodology and the design. This is addressed in [127] and [128], where the same strategy is applied to find the optimal design of a hybrid submarine, investigating three different topologies for four different driving cycles. This study shows that multiobjective GA can handle a very large design problem, with 16 objective functions and a nine-dimensional design space, with both discrete and continuous design variables.

One clear drawback in these studies is the use of RB algorithms for controller design, which is suboptimal. An alternative is to use, for example, an evolutionary algorithm such as PSO in combination with DP for optimizing the control strategy, as used in [56] and [130]. In this novel framework, DP ensures finding the optimal control policy for every population point candidate selected by PSO in the outer loop. The authors use this framework to optimally size and control a parallel passenger HEV and compare its results with previously developed frameworks, which use SQP in the outer loop (plant design) and RB algorithms in the inner loop (controller design). It is shown that RB algorithms are less fuel efficient (by 11% for this case) and lead to a more expensive system (by 14%) than optimal solutions obtained by PSO.

The frameworks that solve the plant design problem using stochastic algorithms such as PSO, GA, or SA, or using deterministic search algorithms such as DIRECT, can handle nonlinear cost function and constraints, searching the design space globally. However, when the cost function behaves smoothly and has only few local minimizers, a derivative-based algorithm will offer a faster solution to the optimization problem. In addition, a larger number of plant variables can be addressed in that case.

The typically used J_1 cost function from (9) is multimodal (with many local minima), and, sometimes, noisy and discontinuous [122]. To ensure the receivability of the global optimum, in [22], [133], [144], and [147], the HEV design problem is formulated as a convex optimization problem, with proposed convex component models and integer control signals obtained by heuristics. Comparative studies of the gradient-based and derivative-free algorithms for HEVs optimal design are presented in [121]. Furthermore, comparisons between only the derivative-free algorithms for HEVs optimal design can be found in [122] and [119]. Choosing one optimization algorithm, to find the optimal solution to each design layer, is not straightforward; it depends strongly on the problem setup and will briefly be described next.

V. Trends in Optimal System-Level Design for Hybrid Electric Vehicles

An important driver for optimization approaches in HEV vehicle design is the legislative restrictions, which have become increasingly tight during the last two decades. Emission regulations have evolved from Euro 1 in 1993 to Euro 6 in 2014 (changing both permissiveness, e.g., CO_2 levels, and focus, e.g., from CO_2 to NO_x or PM). The number of yearly publications on HEV optimization approaches has steadily grown (see Fig. 8). Within the hybrid vehicle research publications area, the plant and control design areas have also grown in recent years.

When defining an optimization problem, its target is a formal transposition of vehicle manufacturer preferences on the constructed system. In turn, the manufacturer tries to meet all legislative restrictions and create a vehicle competitive on the market, appealing to customers and financially beneficial. In

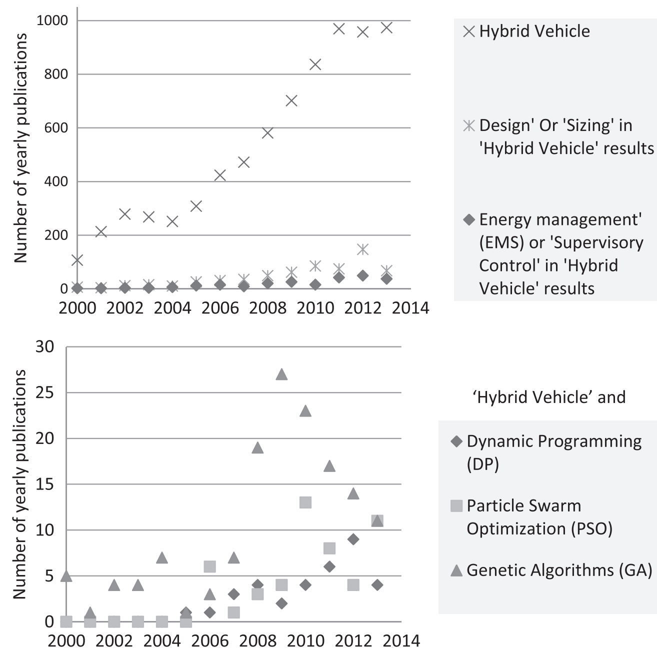


Fig. 8. Research trends in hybrid vehicles design and optimization algorithms used. The curve shows the number of papers in the Google Scholar database containing the keywords *hybrid vehicle* and the keywords in the legends as parts of their title.

this frameup, the challenge to have a general problem definition is even bigger, since these dependencies are changing over time (e.g., emissions regulations). These challenges have led to constant development of control algorithms for HEVs (named either supervisory control or EMSs). In Fig. 8, one can see an ascending trend in the use of DP as a control algorithm. In fact, DP is used as a benchmark comparison for the development of other algorithms (real time implementable).

For solving the problem of optimal system design, there is no universally accepted or widely used algorithm (as, for example, in control design DP). The trend in algorithms selection, for component sizing, is to use evolutionary optimization algorithms. Among these, most commonly used optimization algorithms are GA and PSO, as shown in Fig. 8. Furthermore, multiple research papers report the computational inefficiency of exhaustive search, which leads to its inapplicability for large multidimensional design spaces.

Another trend is the increased focus on the driving cycles used in the HEV optimization problem formulation. Each manufacturer will design a car suitable for certain road types (road, e.g., highway, in-city, and interurban, off-road, ship, rail, or air) and applications (e.g., heavy-duty vehicle, passages, and bus), which will use a specific driving cycle. These range from high-speed highway driving on flat road to city driving with altitude variations, and all the variations in between [148], [149]. The ideal HEV should be fuel efficient in all situations in which it is used. In most cases, designers/researchers choose to vary the driving cycle in the design step of the hybrid vehicle to have a more efficient vehicle (in terms of energy) [103], [131], [150], [151]. In addition, synthetic cycles can be constructed to be shorter (enabling thus faster simulations or larger design space explorations) but more representative of the actual driving cycles [152]. In this direction, the methods based on Markov chain theory show promising results, as presented in [52] and [153]–[155].

Depending on the shape of the optimization function, as well as the types of constraints, an optimization algorithm may prove to be better than others. Typically, the road types and applications dictate a choice of topology, eliminating layers (a) and (b) in Fig. 3.

In [122] and [129], different optimization algorithms, for the sizing loop (plant design), are compared to find the optimal design for one topology. For the control, one algorithm is used in all cases. At the expense of larger batteries, GA reaches a design with 7% reduced fuel consumption. Next, a design that does not require engine downsizing is reached with the PSO algorithm, where the 5% fuel consumption is achieved with a smaller EM. Without continuing with this analysis, one must be aware that these results are sensitive to how the algorithms are tuned (such as maximum number of function evaluations and to what supervisory control algorithm is used).

In the case of a strong nonlinear optimization function, the algorithms that use the gradient of the function, such as SQP, often converge to a local minimum. To avoid premature convergence and local optima, one can start from different initial points, i.e., $\mathbf{x}_{p0}$, or use a global optimization algorithm, such as GA, PSO, or another. Population-based evolutionary algorithms, such as GA, PSO, and SA, will have, overall, more function evaluations then gradient-based algorithms, since, at each iteration (*generation*), they will evaluate J for multiple starting points x_{p0} (often named *population*).

Summarizing, different tricks must be made when one desires to use a certain kind of optimization algorithm for subproblem solving: 1) When convex optimization is used, the convexification of the optimization problem is required to guarantee finding the global optimum; 2) when SQP is used, for the original problem (nonconvex), the initial point x_{p0} can be varied to test the reach of local or global minimum; and 3) when evolutionary algorithms are used, various parameters have to be tuned (e.g., population size). In addition, as stated earlier, it is important what coordination strategy is used, and which decomposition paradigm (overviews of such paradigms are found in [156] or [157]).

Designing an HEV with explicitly considering the coupling between the plant and its control has proved more promising than sequential design. These novel design approaches (nested or simultaneous) were investigated for the main components of the propulsion, i.e., electric motor, battery, and combustion engine. Following this trend of combining the plant and control design, in the future, more components can be considered as variables in the design process. Examples can include auxiliary units, e.g., air conditioning system or the power steering system, as considered in [3], [158], and [159]. With the inclusion of more components as variables, the design problem becomes more difficult to define and handle.

VI. Conclusion

This paper has reviewed the current state of design of hybrid vehicles, including architecture, sizing components, control algorithm, and methods of finding the optimal SLD. Although, at first glance, there seem to be three major classes of HEV topologies to chose from (*serial*, *parallel*, and *serial–parallel*), current market vehicles prove that minor design changes can lead to significant improvements in fuel consumption, costs of electrification, performance, and generated emissions. These small changes, such as the addition of a clutch or resizing the battery, cause many changes in different design levels (both at the subsystem level and at the system level). Thus, the interaction between components is becoming increasingly important, and neglecting it in the design step leads to loss of potential after hybridization.

Starting with sequential designs, usually made in a topdown manner, a transition to coupled plant and control designs has commenced in the last decade, the most popular variant being controller design nested within plant design. These approaches prove clear advantages but also introduce several challenges in solving this optimization problem. Sequential design is simple and intuitive, but neglects the influence of the plant design on the controller design. The plant is designed without taking the controller into account. Subsequently, the controller is designed using the given design as is.

Bilevel optimization frameworks take the coupling between plant and controller designs into account. One may distinguish a nested and an alternating formulation. Often used, nested optimization poses more challenges on finding a global optimal solution at the system level and creates a shift toward multidisciplinary design. Even so, recent studies have shown that HEV designs with significantly lower fuel consumption and emissions can be found. These are opportunities to be further investigated.

By analyzing existing publications, we can conclude that using optimization algorithms, to solve different optimization layers, has proven beneficial for design. These could be further used, in more extended coordination methods to include the selection of topologies and technologies. For instance, these extended coordination methods might include the following: 1) (simultaneous topology and sizing design) alternating with controller design; 2) controller design nested with respect to simultaneous topology and sizing; 3) topology alternating with sizing alternating with control; or 4) simultaneous topology, sizing, and control design.

To substantially reduce the computational burden, one can introduce approximations of the original problem (e.g., the convexification of the problem or metaheuristic models), can shorten the driving cycle used for design, or can use parallel computing. Driving cycles used as input for the control algorithm (energy management strategy) should be build short, more realistic, and more representative of realistic driving types.

How to address, in an (more) automatic way, multiple topologies with a large variety in the components types and numbers remains an open question. Furthermore, the topology automatic construction and optimization problems create challenges in the control algorithm development, which has to handle various topologies in an automatic way. To solve the SLD problem and find an HEV that can be market competitive, one may define the optimization targets to include, in addition to fuel, also costs, emissions, or performance aspects. Easy-to-use methodologies must be developed, to help developers, and the industry in general, to reach better designs in the early steps of the HEV development process.

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Emilia Silvas received the B.Sc. degree in automatic control and computer science from Politehnica University of Bucharest, Bucharest, Romania, in 2009 and the M.Sc. degree in systems and control and the Ph.D. degree from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2011 and 2015, respectively.

Since 2016, she has been a Research Scientist with the Netherlands Organization for Applied Scientific Research (TNO), Helmond, The Netherlands, working in the areas of cooperative vehicle systems and mobile robots. Her research interests include advanced control, system identification and modeling, machine learning techniques, and optimal system design.

Theo Hofman was born on September 5, 1976. He received the M.Sc. (with honors) and Ph.D. degrees in mechanical engineering from Eindhoven University of Technology, Eindhoven, The Netherlands, in 1999 and 2007, respectively.

From 1999 to 2003, he was a Researcher and a Project Manager with the Research and Development Department, Thales Cryogenics B.V., Eindhoven. From 2003 to 2007, he was a Scientific Researcher with Drivetrain Innovations B.V. (Punch Powertrain in 2013 onward), Eindhoven. From 2007 to 2009, he was a Postdoctoral Fellow with the Control Systems Technology (CST) Group, Department of Mechanical Engineering, Eindhoven University of Technology, where he has been an Assistant Professor since 2010. His research interests include the development of model-based system design methods for dynamical systems (including discrete topology design) with applications to powertrain systems.

Nikolce Murgovski received the M.Sc. degree in software engineering from University West, Trollhättan, Sweden, in 2007 and the M.Sc. degree in applied physics and the Ph.D. degree in signals and systems from Chalmers University of Technology, Gothenburg, Sweden, in 2007 and 2012, respectively.

He is currently an Assistant Professor with the Department of Signals and Systems, Chalmers University. His main areas of interest include optimization and optimal control in the automotive area.

L. F. Pascal Etman received the M.S. and Ph.D. degrees in engineering mechanics from Eindhoven University of Technology, Eindhoven, The Netherlands, in 1992 and 1997, respectively.

He is currently an Associate Professor with the Control Systems Technology Group, Department of Mechanical Engineering, Eindhoven University of Technology. His research interests are in multidisciplinary optimization and systems engineering methods for modeling, design, and development of complex engineering products and manufacturing systems.

Maarten Steinbuch (S’83–M’89–SM’02) received the Ph.D. degree from Delft University of Technology, Delft, The Netherlands, in 1989.

Since 1999, he has been a Full Professor with the Control Systems Technology Group, Department of Mechanical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands. His research interests are in the modeling, design, and control of motion systems and automotive powertrains.

Prof. Steinbuch is the Editor-in-Chief of *IFAC Mechatronics* and the Scientific Director of the Centre of Competence for High Tech Systems of the Federation of Dutch Technical Universities.