



Performance Evaluation of Hybrid Electric Vehicle Powertrain Systems

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Peer Review Information	Abstract
<i>Submission: 18 Jan 2020</i> <i>Revision: 02 Feb 2020</i> <i>Acceptance: 17 March 2020</i> Keywords <i>hybrid electric vehicle, powertrain, performance evaluation, energy management, regenerative braking</i>	Hybrid electric vehicle (HEV) performance depends on the interaction of powertrain topology, component efficiency, regenerative braking, battery utilization, and supervisory energy management. This paper presents a compact and reproducible methodology for evaluating series, parallel, and power-split HEV powertrains under identical driving demand. The method combines a longitudinal vehicle model with quasi-static energy conversion models, a charge-sustaining supervisory control layer, and common key performance indicators covering equivalent fuel consumption, regenerative energy recovery, cycle-level fuel-to-wheel efficiency, traction capability, and battery state-of-charge constraints. A representative 1500 s urban-highway composite profile is used only as an illustrative case study; it is not presented as regulatory or experimental test data. Under the stated assumptions, the illustrative power-split system produced the lowest equivalent fuel use, followed by the parallel and series configurations. The main contribution is not a claim of vehicle certification performance, but a step-by-step evaluation framework that can be implemented in MATLAB/Simulink, ADVISOR, AVL Cruise, GT-SUITE, or an equivalent simulation environment and subsequently validated using chassis-dynamometer or on-road measurements.

Introduction

[12] K. Song, X. Wang, F. Li, M. Sorrentino, and B. Zheng, "Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability," *Energy*, vol. 205, 118064, 2020. DOI: 10.1016/j.energy.2020.118064. Hybrid electric vehicles combine an internal-combustion engine with one or more electric machines and an electrochemical energy-storage system so that traction power can be supplied through multiple energy paths. The architecture may be arranged as series, parallel, or power-split, and each arrangement produces a different balance among mechanical complexity, conversion losses, regenerative capability, engine operating flexibility, and control difficulty. Early reviews

established that configuration and supervisory control are inseparable design variables because the same engine, motor, and battery can produce different fuel-economy and drivability outcomes when connected or controlled differently [1]. Later comparative work showed that optimal-control concepts such as dynamic programming, Pontryagin's minimum principle (PMP), and the equivalent consumption minimization strategy (ECMS) can be interpreted through a common energy-management framework [2].

Performance evaluation is therefore more demanding than comparing rated engine and motor powers. A useful methodology must impose the same vehicle mass, road-load model, driving cycle, environmental assumptions, accessory demand, initial battery state of charge

(SOC), and end-of-cycle SOC constraint on every candidate. It must then track energy from the fuel tank and battery to the wheels, including regenerative braking and conversion losses. Reviews of HEV modeling emphasize that longitudinal vehicle dynamics, component efficiency maps or surrogate models, battery SOC dynamics, and supervisory logic should be integrated rather than assessed independently [3]. More recent studies also demonstrate that learning-based energy management can improve online decision making [4,5], while battery aging and power-source durability can materially change the definition of an optimal solution [6,11,12].

The objective of this paper is to define a practical methodology for comparing HEV powertrain systems at the concept or early-development stage. The framework is architecture-neutral, reproducible, and suitable for simulation-first studies. It focuses on four questions: whether the powertrain can meet traction demand; how much fuel-equivalent energy is required; how effectively braking energy is recovered and reused; and whether the battery is operated within defined SOC and power limits. The literature cut-off is 2020, as requested, and all cited references in the paper were published no later than that year.

Literature Review

Bayindir et al. classified the principal HEV configurations and emphasized the importance of electronic control in coordinating the engine, electric machine, storage system, and transmission [1]. Serrao et al. compared DP, PMP, and ECMS and showed why globally optimal offline solutions are valuable as benchmarks for implementable real-time strategies [2]. Enang and Bannister subsequently reviewed HEV modeling and control approaches, highlighting the need to match model fidelity to the intended control and evaluation objective [3]. These works collectively support a methodology in which architecture, component models, and energy management are evaluated as one coupled system rather than as isolated subsystems.

From 2018 onward, data-driven control became increasingly prominent. Wu et al. applied deep Q-network reinforcement learning to continuous energy management in a power-split hybrid bus [4], and Han et al. used double deep Q-learning to improve energy management in a hybrid tracked vehicle [5]. These studies illustrate that advanced controllers can discover power-split policies that

are difficult to encode with fixed rules. However, learning-based results remain strongly dependent on the training cycle, reward function, constraints, and component model, so a fair performance-evaluation methodology must preserve common boundary conditions when different controllers or architectures are compared.

At the same time, research expanded the objective beyond instantaneous fuel economy. Li et al. developed a PMP-based adaptive strategy for a fuel-cell/battery hybrid system [6], while Xie et al. explicitly co-optimized battery sizing, depth of discharge, and energy management with battery degradation in the objective [11]. Song et al. likewise considered both fuel economy and power-source durability in a real-time PMP framework [12]. These contributions indicate that fuel consumption alone is insufficient for a complete evaluation, especially when a strategy obtains short-term fuel savings by using excessive battery throughput or aggressive SOC swings.

Two 2020 reviews provide a broader architecture-level perspective. Tran et al. surveyed electric and hybrid powertrain topologies together with integrated energy-management strategies [7], and Zhang et al. classified rule-based, optimization-based, and learning-based EMS approaches and discussed their relative real-time feasibility [8]. Zhuang et al. specifically reviewed HEV powertrain configuration studies and showed that topology selection has a first-order effect on fuel economy, efficiency, and drivability [9]. For connected vehicles, Oncken and Chen demonstrated that predictive information can be used in real-time model predictive powertrain control to improve forward-looking decisions [10]. The gap addressed here is a concise, stepwise evaluation procedure that uses these ideas to compare complete powertrain systems under one common test protocol.

Methodology

The proposed method is a simulation-first, controlled-comparison protocol. The same vehicle body, tire assumptions, route demand, accessory load, initial SOC, and ambient conditions are applied to each powertrain. Only the architecture-specific energy paths, component conversion efficiencies, and supervisory decisions are changed. Figure 1 summarizes the workflow.

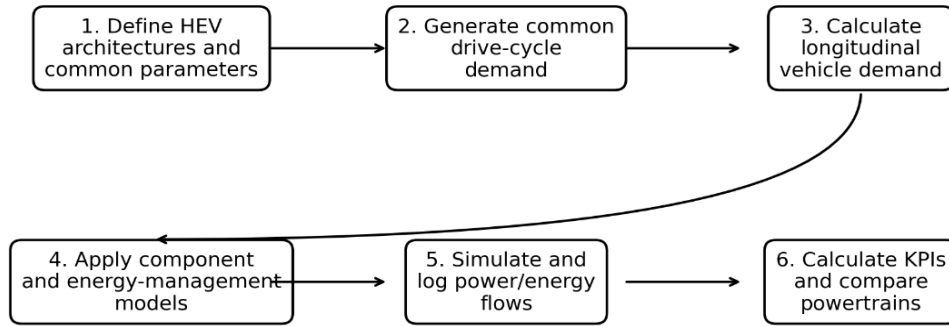


Figure 1. Step-by-step workflow for HEV powertrain performance evaluation.

Step 1 - Define candidate powertrains and common assumptions

Three HEV candidates are defined: series, parallel, and power-split. A conventional ICE vehicle is retained as a reference. In a series HEV the engine drives a generator and traction is electric; in a parallel HEV engine and motor can both transmit torque mechanically to the wheels;

in a power-split HEV a mechanical/electrical coupling device permits multiple power paths. The configuration definitions follow established topology classifications [1,7,9]. For a fair comparison, the illustrative case fixes the vehicle-level parameters shown in Table 1. Component values are representative engineering assumptions for methodology demonstration, not manufacturer data.

Table 1. Common vehicle-level assumptions used in the illustrative case study.

Parameter	Illustrative value	Purpose in model
Vehicle mass	1650 kg	Inertial demand
Drag coefficient / frontal area	0.29 / 2.2 m ²	Aerodynamic drag
Rolling resistance coefficient	0.011	Road-load force
Accessory electric load	0.6 kW	Auxiliary energy
Fuel lower heating value	8.9 kWh/L	Fuel-equivalent conversion
Cycle duration / distance	1500 s / 18.89 km	Common test demand
Maximum cycle speed	100 km/h	Traction requirement
Peak calculated wheel power	33.7 kW	Sizing check

Step 2 - Generate an identical driving-demand profile

The evaluation requires a speed-time trace that is identical for all powertrains. For the illustrative example, a 1500 s composite profile is generated from repeated stop-and-go urban segments followed by a highway segment. It covers 18.89 km, reaches 100 km/h, and produces 2.344 kWh of positive wheel energy and 0.424 kWh of available braking energy before regenerative and friction-brake losses. This profile is deliberately described as representative rather than as WLTP, FTP-75, or another regulatory schedule. In a formal validation study, the same workflow should be repeated with certified drive-cycle data and measured road-load coefficients.

Step 3 - Calculate longitudinal vehicle power demand

At each one-second time step, wheel demand is calculated from inertial, rolling-resistance, aerodynamic, and grade forces. With zero road grade in the base case, the tractive force and wheel power are computed as follows:

$$F_{tr} = m a + m g C_{rr} + 0.5 \rho C_d A_f v^2$$

$$P_w = F_{tr} v$$

Positive wheel power is traction demand, whereas negative wheel power is braking demand. The model is intentionally quasi-static: rotational inertia, shift transients, engine warm-up, thermal constraints, and detailed electrical dynamics can be added later if higher fidelity is required. This staged approach is consistent with the principle that model complexity should be matched to the evaluation purpose [3].

Step 4 - Model component energy paths and supervisory control

Each candidate is represented by effective conversion efficiencies for the active fuel-to-wheel path and for regenerative recovery. In a detailed implementation, these scalar values should be replaced by engine brake-specific-fuel-consumption maps, motor/generator efficiency maps, inverter losses, gear-dependent transmission efficiency, battery open-circuit voltage and internal resistance, and SOC-dependent power limits. The supervisory controller should then select engine on/off state, torque split, charging or discharging power, and regenerative braking subject to component constraints. Rule-based control provides a robust baseline, while DP can supply an offline lower-bound benchmark and ECMS/PMP can provide computationally efficient near-optimal strategies [2,8]. Predictive or learning-based controllers can be added as additional treatments, but they must receive the same demand and constraints [4,5,10].

For charge-sustaining comparison, the initial and terminal SOC should be matched within a small tolerance (for example, ± 0.5 percentage points). Fuel-equivalent correction must be applied if terminal SOC differs, otherwise a strategy can appear artificially efficient by simply depleting the battery. Battery current, C-rate, throughput, and temperature should also be logged where data are available, because aggressive battery use can trade fuel savings against life [11]. Durability-aware objectives can include an equivalent battery-aging cost or power-source degradation penalty [6,12].

Step 5 - Run the simulation and record energy flows

For every architecture the simulation is initialized with the same SOC and driven through the same speed profile. At each time step the following quantities are logged: demanded wheel power, engine fuel power, engine output power, motor electrical and mechanical power, battery charge/discharge power, regenerative braking power, friction braking power, SOC, and unmet traction demand. A simulation is rejected if it violates a component power limit or cannot track the prescribed speed within the allowed

tolerance. This prevents an undersized system from appearing efficient only because it failed to deliver the required performance.

Step 6 - Calculate performance indicators

The primary indicators are equivalent fuel consumption (L/100 km), cycle-level effective fuel-to-wheel efficiency, recovered braking energy (kWh), regeneration fraction, SOC change, peak battery power, and traction-demand tracking error. Equivalent fuel consumption is obtained by dividing total fuel energy by the lower heating value and normalizing by distance. A fuel-savings index is calculated relative to the conventional baseline. The cycle-level efficiency reported here is the ratio of positive wheel energy to fuel energy; because regenerated energy is reused, it is a system-level cycle indicator and should not be interpreted as a steady-state engine efficiency.

Step 7 - Validate and perform sensitivity analysis

Before drawing design conclusions, model outputs should be validated against published data, a high-fidelity simulation model, or physical measurements. At minimum, sensitivity runs should vary vehicle mass, road-load coefficients, regenerative efficiency, accessory load, battery capacity, and component efficiency assumptions. The ranking should also be checked on urban, highway, and mixed cycles because no single architecture is universally optimal. The 2020 literature shows that topology, controller class, prediction horizon, and durability weighting can all change the apparent optimum [7-12].

Results

Table 2 reports the output of the illustrative quasi-static case defined above. These values are generated by the stated assumptions and are included to demonstrate how the proposed methodology produces comparable KPIs; they are not claimed as measured performance of any production vehicle. The conventional reference uses no regenerative recovery. The HEV cases recover different fractions of the 0.424 kWh braking-energy opportunity and convert the recovered electrical energy back to wheel work with architecture-specific assumptions.

Table 2. Illustrative architecture-level results from the common simulation protocol.

Powertrain	Recovered braking energy (kWh)	Eq. fuel use (L/100 km)	Reduction vs ICE	Cycle-level efficiency
Conventional ICE baseline	0.000	6.30	-	22.1%
Series HEV	0.246	4.79	23.9%	29.1%

Parallel HEV	0.263	4.35	30.9%	32.0%
Power-split HEV	0.280	4.12	34.6%	33.8%

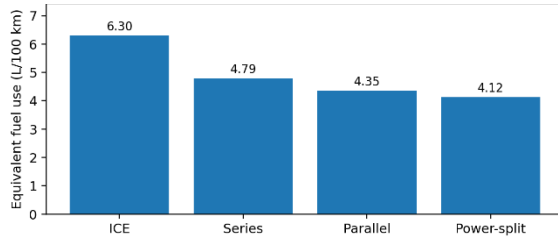


Figure 2. Equivalent fuel-use comparison for the illustrative common-cycle simulation.

The power-split case achieves the lowest equivalent fuel use at 4.12 L/100 km, a 34.6% reduction relative to the conventional baseline. The parallel architecture follows at 4.35 L/100 km, while the series arrangement reaches 4.79 L/100 km. The ranking is physically consistent with the simplified assumptions: the power-split model combines high regenerative utilization with a relatively efficient fuel-to-wheel path, whereas the series model experiences an additional electrical conversion chain. The result also illustrates why topology cannot be evaluated from component ratings alone; energy-routing efficiency and control opportunities determine how often each component operates near an efficient region [7,9].

The numerical differences should not be generalized beyond the test assumptions. If a city cycle contains more braking events, the value of regenerative capability increases; if sustained highway operation dominates, the direct mechanical path of a parallel system may become more attractive. Likewise, a controller that aggressively discharges the battery may reduce short-cycle fuel use but fail a charge-sustaining comparison. This is why the proposed protocol requires terminal-SOC correction, common cycle inputs, and sensitivity analysis. Advanced ECMS/PMP, MPC, or learning-based strategies can be inserted into the same framework and compared against an offline benchmark without changing the KPIs [2,4,5,10].

Conclusion and Discussion

This paper has presented a step-by-step methodology for evaluating hybrid electric vehicle powertrain systems using a common simulation protocol. The central requirement is controlled comparability: each candidate must experience the same road-load demand, speed trace, accessory load, initial battery condition, and performance constraints. The methodology then links longitudinal dynamics, architecture-

specific energy paths, component efficiency models, supervisory energy management, battery constraints, and common KPIs. This approach is supported by the progression of HEV research from topology and classical energy management [1-3] to learning-based control [4,5], durability-aware optimization [6,11,12], integrated topology studies [7,9], broad EMS classification [8], and predictive connected-vehicle control [10]. The illustrative case demonstrates how the framework can generate a transparent ranking without presenting simulated values as experimental facts. Under the chosen assumptions, power-split, parallel, and series HEVs reduced equivalent fuel use relative to the conventional baseline, with the power-split arrangement giving the best cycle-level result. The result should be interpreted as a methodology demonstration rather than as a universal architecture verdict. A different driving cycle, component map, battery size, control policy, thermal state, or aging penalty can change the ranking. For a full research study, the next level of fidelity should replace constant efficiencies with experimentally derived maps, use standard regulatory cycles, impose engine emissions and battery thermal limits, and validate the model against dynamometer or on-road data. Statistical repetition across multiple cycles and uncertainty bands for road load and component efficiency should then be reported. The same framework can also be extended to plug-in hybrids by adding grid electricity, charge-depleting/charge-sustaining phases, and utility-factor weighting. In this form, the methodology provides a defensible basis for early-stage design selection and for later controller benchmarking without changing the fundamental evaluation logic.

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