Optimal Energy Management of Series Hybrid Electric Vehicles With Engine Start–Stop System

Boli Chen®, Member, IEEE, Xiao Pan®, and Simos A. Evangelou®, Senior Member, IEEE

Abstract—This article develops energy management (EM) control for series hybrid electric vehicles (HEVs) that include an engine start–stop system (SSS). The objective of the control is to optimally split the energy between the sources of the powertrain and achieve fuel consumption minimization. In contrast to existing works, a fuel penalty is used to characterize more realistically SSS engine restarts, to enable more realistic design and testing of control algorithms. This article first derives two important analytic results: 1) analytic EM optimal solutions of fundamental and commonly used series HEV frameworks and 2) proof of optimality of charge sustaining (CS) operation in series HEVs. It then proposes a novel heuristic control strategy, the hysteresis power threshold strategy (HPTS), by amalgamating simple and effective control rules extracted from the suite of derived analytic EM optimal solutions. The decision parameters of the control strategy are small in number and freely tunable. The overall control performance can be fully optimized for different HEV parameters and driving cycles by a systematic tuning process while also targeting CS operation. The performance of HPTS is evaluated and benchmarked against existing methodologies, including dynamic programming (DP) and a recently proposed state-of-the-art heuristic strategy. The results show the effectiveness and robustness of the HPTS and also indicate its potential to be used as the benchmark strategy for high-fidelity HEV models, where DP is no longer applicable due to computational complexity.

Index Terms—Closed-form solution, energy management (EM) control, hybrid electric vehicle (HEV), optimal control, Pontryagin’s minimum principle (PMP), rule-based control.

NOMENCLATURE

| CS | Charge sustaining. |
| DP | Dynamic programming. |
| EFC | Equivalent fuel consumption. |
| EM | Energy management. |
| FCM | Fuel consumption model. |
| HEV | Hybrid electric vehicle. |
| HPTS | Hysteresis power threshold strategy. |
| ICE | Internal combustion engine. |

PL | Propulsion load. |

PMP | Pontryagin’s minimum principle. |

PS | Primary source. |

SOC | State of charge. |

SS | Secondary source. |

SSS | Start–stop system. |

WLTP | Worldwide harmonized light vehicles test Procedure. |

I. INTRODUCTION

The HEVs are regarded as an essential stage of transportation electrification toward addressing the global concerns of environmental pollution caused by emissions. In popular architectures, the HEV embodies a combination of an ICE and a battery-driven electric motor. As such, HEVs can profit from a freely optimized power split between the two energy sources for improving fuel economy compared to conventional vehicles. In addition, modern HEVs are usually equipped with an engine SSS, which automatically shuts down and restarts the ICE, thereby enabling a further reduction of idling fuel consumption and emissions.

The problem of finding a fuel-efficient power split for HEVs, known as the EM control problem, has drawn considerable attention in the past decade. A comprehensive overview of existing EM techniques, from rule-based to optimization-based, can be found in [1]–[4]. Most of the existing EM approaches are optimization-based, such as DP [5], quadratic programming (QP) [6], PMP [7], [8], equivalent consumption minimization strategies (ECMS) [9], [10], extremum seeking [11], and model predictive control [12]–[15]. More specifically, DP is able to guarantee global optimal solutions in general optimization problems, and however, it is computationally intensive and therefore limited to highly simplified models [16]. The ECMS is derived using the PMP, which results in a computational efficient local optimization algorithm at the expense of weakened optimality, especially when the model complexity increases [9], [10]. Model predictive control offers a computationally efficient alternative to global optimal control in yielding near-optimal solutions with less simple models. Moreover, stochastic and data-driven optimization (machine learning) methodologies are continually emerging and have become effective and important means to formulate model-free EM control strategies [17]–[21]. For further improvement of the HEV fuel efficiency, engine ON/OFF control needs to be embedded into EM control design to account for SSS dynamics and therefore to avoid inefficient engine idling operation.

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Boli Chen is with the Department of Electronic and Electrical Engineering, University College London, London WC1E 6BT, U.K. (e-mail: boli.chen@ucl.ac.uk).

Xiao Pan and Simos A. Evangelou are with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, U.K. (e-mail: xiao.pan17@imperial.ac.uk; s.evangelou@imperial.ac.uk).

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The vast majority of the literature assumes the SSS to be ideal with no extra cost for engine restarts [7], [22]–[24], which may lead to EM strategies that force the engine to a very rapid succession of starts/stops. To prevent this unnecessarily inefficient behavior, Sciarretta et al. [25], Nuesch et al. [26], and Schori [27] proposed an enhanced SSS modeling framework in the context of conventional heuristic or numerical optimization of parallel HEV EM, where the fuel required to accelerate the engine from rest to idle speed is considered so that fast ICE start/stop transitions are penalized and avoided as a consequence.

Although optimization-based EM strategies can be easily tackled offline, they are usually not feasible for onboard computation units of modern HEVs due to computational and memory limitations. However, due to the simplicity in implementation and ease of understanding of their operating principles, rule-based strategies are more prevalent among commercial HEVs. Rule-based EM strategies are usually characterized by Boolean or fuzzy rules, which are described as a set of rules that compute the control signals based on preestablished thresholds over the controlled variables [23], [28], [29]. The thermostat control strategy (TCS) and power follower control strategy (PFCS) are the two most conventional rule-based techniques, yet their fuel economies are not optimized. The operational rules behind them are load following and load leveling mechanisms that have been extensively used in rule-based EM techniques of HEVs. Nonetheless, the conventional TCS and PFCS are outdated for modern HEVs where the SSS is becoming ubiquitous and very efficient these days, allowing the engine to be turned off and on with very low fuel consumption penalty. Although the recently proposed exclusive operation strategy (XOS) [23] and optimal primary source strategy (OPSS) [29] dramatically improve the optimality of the existing rule-based approaches, their performance still falls behind optimization-based benchmarks by some margin.

Previous work of Chen and Evangelou [30] has proposed an innovative rule-based control strategy for series HEVs that bridges the gap between rule- and optimization-based methods. This strategy can emulate the globally optimal solution to the EM problem with simple and effective rules, which are extracted from the closed-form optimal EM solution for a simplified vehicle/powetrain model. However, the investigation in [30] is of limited scope since it does not consider the impact of the SSS, and furthermore, it provides an analysis; consequently, a control design, on the basis that battery CS operation (for a whole mission), is strictly guaranteed, without an investigation into the optimality (in terms of fuel economy) or otherwise of the CS operation.

This present article works on bridging the gap between rule- and optimization-based EM strategies in the more general context with the SSS considered, by proposing a novel heuristic strategy for EM control of series HEVs with SSS. The series HEV architecture, on which this article focuses, is a common arrangement for modern HEVs [31] and involves a number of products in the market, such as the Nissan Note e-Power, VIA Motors products, and numerous other extended-range electric vehicles. The main contributions of the work are summarized as follows.

1) Fundamental analysis with an HEV model without engine SSS that considers the main physics of the EM problem for series HEVs is conducted and feasible fundamental solutions of the optimal EM for series HEVs are found (this is a generalization of the work in [30]).

2) Fundamental analysis with an HEV model with an ideal (lossless) engine SSS, which additionally to the model features in contribution 1, captures the basic physics of the SSS, is conducted and feasible fundamental solutions of the optimal EM for series HEVs with SSS are found.

3) Fundamental analysis proves that CS operation is a necessary condition to reach globally optimal fuel economy in series HEVs.

4) By using simple and effective control rules that are inspired by the fundamental analysis and solutions of the optimal EM in contributions 1) and 2), as well as by the CS operation optimality result in contribution 3), a novel heuristic strategy, the HPTS, is proposed for the EM control of series HEVs with a more realistic SSS for which engine restarts are associated with a fuel penalty. An analytic solution of the optimal EM is not feasible in this case.

5) The performance of the HPTS is evaluated and benchmarked against DP solutions and a recently developed state-of-the-art rule-based method. Moreover, the influence of the penalty fuel for engine restarts is further investigated by simulation.

The remainder of this article is structured as follows. Section II introduces the vehicle model and the formulation of the EM problem. A theoretical derivation of the optimal EM solutions is presented in Section III, and from the analysis, the HPTS is proposed. Section III also includes the analysis that proves the optimality of CS operation. Simulation results and discussion are presented in Section IV. Finally, concluding remarks are given in Section V.

II. MODELING OF THE SERIES HEV AND PROBLEM FORMULATION

The vehicle model is developed based on the series HEV system (without the engine SSS) described in [8]. In particular, the ICE and the electric machines are approximated by steady-state efficiency maps, while the power converter, inverter, and transmission system are modeled by constant efficiency factors that consider the possible energy losses. This vehicle model captures the essential physical characteristics of the powetrain components with a relatively low dynamic order, thereby being widely applicable for HEV analysis and control design [32]–[34]. In the following, the overall vehicle system is briefly introduced with particular emphasis on the modeling of the engine SSS, which has not been considered sufficiently in the past.

The series HEV powetrain architecture is sketched in Fig. 1. As it can be noticed, the power outputs from the
primary source (PS) and the secondary source (SS) branches are combined electrically at the dc link. Then, the total power is delivered to the driving wheels included in the PL branch, which is an inverter-driven electric motor/generator, mechanically connected to the wheels with a transmission system characterized by a fixed drive ratio $\xi$. The inverter and transmission are modeled as constant efficiency terms $\eta_i$ and $\eta_t$, while the efficiency of the motor/generator, $\eta_m$, is described by a static efficiency map of the load torque and the angular speed, as shown in Fig. 2.

By virtue of the series architecture, it is reasonable to assume the load power $P_{PL}$, a known signal, as it is independent of the EM (power split) between the two energy sources [36]. Given a driving cycle and the steady-state efficiencies $\eta_i$, $\eta_t$, and $\eta_m$, $P_{PL}$ may be determined by

$$P_{PL} = \begin{cases} P_{\text{drive}} & \forall P_{\text{drive}} \geq 0 \\ \left( P_{\text{drive}} - P_h \right) \eta_i \eta_m \eta_t & \forall P_{\text{drive}} < 0 \end{cases}$$

(1a)

where $P_{\text{drive}}$ is the power at the driving wheels requested to follow the driving cycle and $P_h$ is the mechanical braking power directly applied to the wheels. Furthermore, $P_{\text{drive}}$ can be evaluated by Newton’s laws of motion as follows:

$$P_{\text{drive}} = \nu (ma + F_T + F_D + mg \sin \theta)$$

(2)

where $\nu$, $a$, and $m$ are the speed, acceleration, and mass of the vehicle, respectively, $F_T = f_T mg$ and $F_D = f_D v^2$ are the resistance forces, respectively, due to tires and aerodynamics drag, and $\theta$ is the road slope associated with the speed profile. By considering that the mechanical braking power is dissipated and $P_{SS\text{min}}$ is the maximum charging power of the SS, it is possible to always freely choose $P_h$ such that $P_{PL}$ in (1b) for $P_{\text{drive}} < 0$ is given as follows:

$$P_{PL} = \max \left( P_{\text{drive}} \eta_i \eta_m \eta_t, P_{SS\text{min}} \right) \forall P_{\text{drive}} < 0 $$

(3)

to maximize energy regeneration and hence fuel economy.

Consequently, it is reasonable to decouple the EM problem of a series HEV into two steps: 1) compute $P_{PL}$ requested by a driving cycle by (1a), (2), and (3) and 2) find an appropriate power split (for $P_{PL}(i > 0)$ between the two energy sources subject to the power balance at the dc link (see (12) described later in Section II-C).

### A. Primary Source Branch

As shown in Fig. 1, the engine branch is formed by an ICE, a permanent magnet synchronous generator, and an ac–dc rectifier, which are connected in series. The overall efficiency of this branch is simply the product of individual component steady-state efficiencies. The present work is based on the PS branch efficiency map shown in Fig. 3 [36]. The mechanical separation from the wheels allows the primary source branch to be constantly operated along the trajectory of the most efficient torque–speed operating points. In such a case, the fuel mass rate $q_f$, as shown in Fig. 3, can be fit approximately as a linear function of the branch output power $P_{PS}$. The dynamic equation of the fuel mass $m_f$ is therefore given by

$$m_f = q_{f0} + \alpha_f P_{PS}$$

(4)

in which $q_{f0}$ acts as the idling fuel mass rate and $\alpha_f$ is the coefficient of power transformation.

Furthermore, the SSS allows the ICE to be switched OFF without idling loss. However, some amount of fuel is consumed to turn on the ICE again. In this work, this penalty fuel usage is modeled by a constant term $m_p = K q_{f0} kg$, which is equivalent to the amount of fuel consumed by idling the ICE for $K$ seconds. Moreover, the delay of restarting the engine is neglected as it mainly affects the driving comfort rather than fuel economy. To integrate the SSS dynamics into
the FCM (4), let us introduce the binary engine OFF/ON state
$s \in \{0, 1\}$ and the jump set $S \triangleq \{s|s^+ \neq s\}$, with $s^+$ the next
value of the state. As such, ICE operation can be characterized
in terms of $s$ and $P_{SS}$: 1) the engine is switched off when
$s = 0$ and $P_{SS} = 0$; 2) the engine is idling when $s = 1$ and
$P_{SS} = 0$; and 3) the engine produces propulsive power when
$s = 1$ and $P_{SS} > 0$. Finally, the FCM in the presence of the
SSS may be described by the following hybrid dynamical
system:

$$
\begin{align*}
\dot{m}_f = q_{f0} s + a_f P_{SS}, & \quad \text{if } s \notin S \\
\dot{s} = 0
\end{align*}
$$

(5)

and

$$
\begin{align*}
\dot{s}^+ = s + u_s, & \quad \text{if } s \in S \\
m_f^+ = m_f + m_p(1 - s)
\end{align*}
$$

(6)

where $u_s \in (-1, 1)$ is the SSS control signal.

B. Secondary Source Branch

The battery is modeled as a series connection of an ideal
temperature source and an ohmic resistance, and therefore, the
battery voltage $V_b$ is defined by $V_b = V_{oc} - i_b R_b$, where
$V_{oc}$ is the open-circuit voltage of the battery, $i_b$ is the battery
current assumed positive during the discharge phase, and $R_b$
is the internal resistance. By considering the battery power
$P_b = V_b i_b$, $i_b$ can be solved with respect to $V_{oc}$, $R_b$, and $P_b$
as follows:

$$
i_b = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4 P_b R_b}}{2 R_b}.
$$

(7)

The battery SOC represents the only state variable, governed by
SOC = $-i_b/Q_{max}$, where $Q_{max}$ is the battery capacity.
Instead of using a nonlinear mapping between SOC and the
open-circuit voltage, $V_{oc}$ is reasonably approximated by a
constant voltage, which is compatible with the usual aim
of CS battery management, by which the SOC is narrowly
constrained. Furthermore, by combining the battery with the
bidirectional dc/dc converter, the SS output power is obtained by

$$
P_{SS} = \eta_{dc}^{sign(P_{SS})} P_b
$$

(8)

where $\eta_{dc}$ is the efficiency of the dc/dc converter. Substituting
the algebraic solution of $i_b$ [obtained by applying (8) in (7)],
the dynamic behavior of the SS can be described by the
differential equation of SOC with respect to $P_{SS}$ only as

$$
SOC = \frac{-V_{oc} + \sqrt{V_{oc}^2 - 4 P_{SS} R_b/\eta_{dc}^{sign(P_{SS})}}}{2 R_b Q_{max}}.
$$

(9)

C. Overall Model and EM Problem

In view of (5), (6), and (9), the overall system dynamics are
expressed by the hybrid system given by

$$
\dot{x} = f(x, u) = \begin{pmatrix}
\dot{m}_f = q_{f0} s + a_f P_{SS} \\
\dot{s} = -\frac{V_{oc} + \sqrt{V_{oc}^2 - 4 P_{SS} R_b/\eta_{dc}^{sign(P_{SS})}}}{2 R_b Q_{max}}
\end{pmatrix}
$$

(10)

if $s \notin S$ and if $s \in S$

$$
x^+ = g(x, u) = \begin{pmatrix}
m_f + m_p(1 - s) \\
SOC \\
\dot{s} = s + u_s
\end{pmatrix}
$$

(11)

where $x = [m_f, SOC, s]^T$ and $u = [P_{PS}, P_{SS}, u_s]^T$ represent
the state variables and control inputs, respectively.

The EM control aims to minimize the overall fuel consumption $m_f$
by an appropriate power split between $P_{PS}$ and $P_{SS}$,
which satisfies the dc-link power balance

$$
P_{HL} = s P_{PS} + P_{SS}.
$$

(12)

Moreover, the operation of both energy sources is subject to

$$
SOC_{min} \leq SOC \leq SOC_{max}
$$

(13)

$$
0 \leq P_{PS} \leq P_{PS_{max}}
$$

(14)

$$
P_{SS_{min}} \leq P_{SS} \leq P_{SS_{max}}
$$

(15)

where $SOC_{min}$ and $SOC_{max}$ are the SOC operational limits
and $P_{PS_{max}}$ and $P_{SS_{max}}$ are the maximum propulsive power
PS and SS can deliver, respectively. The main characteristic
parameters of the vehicle model are summarized in Table I,
where the power limits are chosen to emulate the energy
sources for a nonplug-in HEV.

### III. EM Strategies Based on the Fundamental Analysis of Fuel Efficiency Optimization

This section aims to provide a fundamental analysis to show
the nature of optimal EM solutions using two variants of the
presented vehicle model, both of which have been used for
the design of EM strategies in the literature: 1) without engine
SSS and 2) with an ideal engine SSS ($m_f = 0$). The analytic
solutions yield some fundamental principles that are used to
go beyond the treatment of models 1) and 2) and construct a
new heuristic control strategy, the HPTS, for the more realistic
model (10) and (11). Further analysis is carried out to justify
the optimality of the CS operation in terms of fuel efficiency.
which is linked to the control design and results presented in this article.

For the sake of further analysis, let us first introduce some useful notations and definitions for the upcoming analysis. Consider \( T \) the total time of the driving mission. Two sets of time intervals \( \Phi \triangleq \{ t | P_{PL}(t) \geq 0 \} \) and \( \Psi \triangleq \{ t | P_{PL}(t) < 0 \} \) are considered such that \( \Phi \cup \Psi \) is the full time horizon \( \{0 \leq t \leq T \} \). The overall SOC variation over \( [0, T] \) is defined as \( \Delta SOC \triangleq SOC(0) - SOC(T) \). It is clear that

\[
\Delta SOC = \Delta_\Phi SOC + \Delta_\Psi SOC
\]

where \( \Delta_\Phi SOC \triangleq - \int_0^T (dSOC/dt) dt \) and \( \Delta_\Psi SOC \triangleq - \int_0^T (dSOC/dt) dt \leq 0 \). Moreover, \( \Phi \) can be divided into two subsets as \( \Phi = \Phi_d \cup \Phi_c \) with \( \Phi_d \triangleq \{ t | P_{PL}(t) \geq 0, i_b(t) \geq 0 \}, \Phi_c \triangleq \{ t | P_{PL}(t) \geq 0, i_b(t) < 0 \} \). These subsets collect the battery discharging and charging intervals for all \( t \in \Phi \). Therefore,

\[
\Delta SOC = \Delta_\Phi SOC + \Delta_\Phi SOC + \Delta_\Psi SOC
\]

with \( \Delta_\Phi SOC < 0 \) and \( \Delta_\Psi SOC \geq 0 \). Finally, for brevity, the dependence of all variables on \( t \) is dropped in the following analysis.

A. Analysis for the Vehicle Model Without the SSS

Let us start by analyzing the powertrain system without the SSS, as the analytic solution is also instrumental for subsequently studying the optimal EM solution for the system with consideration of the SSS.

According to the power balance at the dc link (12), the input power signal \( P_{PS} \) of the FCM (4) can be replaced by \( P_{PS} = P_{PL} - P_{SS} \) (s is substituted as 1). By considering (4), the fuel consumption minimization problem, \( \min J = m_f(T) \), can be rewritten as

\[
\min J = \int_0^T q_{f0} dt + \alpha_f \int_0^T P_{PL} dt - \alpha_f \int_0^T P_{SS} dt
\]

which is equivalent to

\[
\min_{P_{SS}} J = - \alpha_f \int_0^T P_{SS} dt
\]

(17) as \( \int_0^T q_{f0} dt + \alpha_f \int_0^T P_{PL} dt \) is constant for a given driving cycle and independent of the EM control. The EM control problem of a series HEV is now formulated as an optimization problem with only one dynamic state, SOC, and a single control input, \( P_{SS} \), subject to the SOC operational limits (13) and the energy source power limits

\[
\max(P_{PL} - P_{SS\text{max}} + P_{SS\text{min}}) \leq P_{SS} \leq \min(P_{SS\text{min}}, P_{PL})
\]

(18) which is obtained by combining (12), (14), and (15). Based on the optimal solution for \( P_{SS} \), the fuel usage, \( m_f(T) \), can be evaluated \textit{a posteriori}. To address this optimization problem, constrained and unconstrained arcs need to be pieced together. Based on the state constraints (13), the optimal solution is the result of different combinations of the following possible arcs.

1) State Constraints Not Active: According to the PMP, a candidate for an optimal control input \( P^*_{SS} \) for minimizing (17) is found if \( P^*_{SS} \) minimizes the Hamiltonian

\[
H = -\alpha_f P_{SS} + \begin{cases} 
-V_{oc} + \sqrt{V_{oc}^2 - 4P_{SS} R_b/\eta_{dc}}, & P_{SS} \geq 0 \\
-V_{oc} + \sqrt{V_{oc}^2 - 4P_{SS} R_b/\eta_{dc}}, & P_{SS} < 0
\end{cases}
\]

(19)

which includes the costate \( \lambda \). The dynamics of the costate are described by

\[
\dot{\lambda} = -\frac{\partial H}{\partial SOC} = 0
\]

(20)

which implies that the optimal costate \( \lambda \) is constant. By taking the partial derivative of \( H \) with respect to \( P_{SS} \), we obtain

\[
\frac{\partial H}{\partial P_{SS}} = -\alpha_f - \frac{\lambda}{\eta_{dc} Q_{max} \sqrt{V_{oc}^2 - 4P_{SS} R_b/\eta_{dc}}}, \quad P_{SS} \geq 0
\]

\[
\frac{\partial H}{\partial P_{SS}} = \frac{\lambda}{\eta_{dc} Q_{max} \sqrt{V_{oc}^2 - 4P_{SS} R_b/\eta_{dc}}}, \quad P_{SS} < 0
\]

If \( \lambda = 0 \), \( \partial H/\partial P_{SS} = -\alpha_f < 0 \), which is independent of the input. Hence, the Hamiltonian is minimized at the maximum value of the input as follows:

\[
P_{SS}^{*} = P_{SS\text{max}}.
\]

(21)

If \( \lambda > 0 \), it is immediate to show that \( \partial H/\partial P_{SS} < 0 \), \( \forall P_{SS} \) (with \( P_{SS\text{min}} < V_{oc}^2/4R_b \)), and the optimal control input follows (21). If \( \lambda < 0 \), the second-order derivative of \( H \) with respect to \( P_{SS} \)

\[
\frac{\partial^2 H}{\partial P_{SS}^2} = \begin{cases} 
\frac{2\lambda R_b}{\eta_{dc} Q_{max} V_{oc}^2 (V_{oc}^2 - 4P_{SS} R_b/\eta_{dc})^{3/2}}, & P_{SS} \geq 0 \\
-\frac{2\lambda R_b}{\eta_{dc} Q_{max} (V_{oc}^2 - 4P_{SS} R_b/\eta_{dc})^{3/2}}, & P_{SS} < 0
\end{cases}
\]

is always positive. As such, \( H \) is formed by two convex segments continuous at \( H(0) = 0 \), and the global minimum of \( H \) depends on the minima of the functions representing both segments of \( H \). By solving the algebraic equation \( \partial H/\partial P_{SS} = 0 \) for \( P_{SS} \geq 0 \) and \( P_{SS} < 0 \), respectively, we obtain

\[
P_{SS}^{*} = \frac{1}{4R_b} \left( \frac{\eta_{dc} V_{oc}^2}{\alpha_f^2 Q_{max}^2 \eta_{dc}} \right)^{1/2}, \quad \text{if } P_{SS} \geq 0
\]

(22a)

\[
P_{SS}^{*} = \frac{1}{4R_b} \left( \frac{\eta_{dc} V_{oc}^2}{\alpha_f^2 Q_{max}^2 \eta_{dc}} \right)^{1/2}, \quad \text{if } P_{SS} < 0
\]

(22b)

at which the two quadratic functions reach their minima. If \( \lambda \in (-\alpha_f Q_{max} V_{oc}/\eta_{dc}, 0) \), both optimal control inputs shown in (22a) and (22b) are positive, which implies that the minimum of \( H \) within the domain \( P_{SS} < 0 \) is \( H(0) \), and therefore, the global minimum of \( H \) is obtained at (22a). Similarly, for \( \lambda \in (0, -\alpha_f Q_{max} V_{oc}/\eta_{dc}) \), it can be inferred that both solutions shown in (22a) and (22b) are negative. Hence, the global minimum of \( H \) is obtained when \( P_{SS} \) follows (22b). Finally, if \( \lambda \in [-\alpha_f Q_{max} V_{oc}/\eta_{dc}, -\alpha_f Q_{max} \eta_{dc} V_{oc}] \), the optimal control shown in (22a) is negative and in (22b) is positive.
As such, \( H \) is monotonically increasing for \( P_{SS} \geq 0 \) and monotonically decreasing for \( P_{SS} < 0 \), which yields \( P_{SS}^* = 0 \). By taking into account the control constraints (18), the optimal input \( P_{SS}^* \) is given as follows:

\[
P_{SS}^* = \begin{cases} 
\min(P_{SS_{\max}}, P_{PL}) & \forall \lambda \in [0, \infty) \\
\min\left(P_{SS}^*, P_{SS_{\min}}, P_{PL}\right) & \forall \lambda \in \left(-\frac{\alpha_f Q_{\max} V_{oc}}{\eta_{dc}}, -\frac{\alpha_f Q_{\max} V_{oc}}{\eta_{dc}}\right) \\
\min(0, P_{PL}) & \forall \lambda \in \left(-\infty, -\frac{\alpha_f Q_{\max} V_{oc}}{\eta_{dc}}\right) \\
\min\left(\max\left(P_{SS}^*, P_{PL} - P_{PS_{\min}}, P_{SS_{\min}}\right), P_{PL}\right) & \forall \lambda \in \left(-\infty, -\frac{\alpha_f Q_{\max} V_{oc}}{\eta_{dc}}\right)
\end{cases}
\]

(23)

where, for brevity, we denote \( P_{SS}^* \) and \( P_{SS}^- \) the solutions given in (22a) and (22b), respectively. As it can be seen, there exist four possible optimal modes of operation depending on the value of \( \lambda \). The numerical calculation of the closed-form control solution for a given \( P_{PL} \) profile involves identifying the constant operating power of the SS, which is equivalent to finding the costate \( \lambda \). Given an SOC(0) in conjunction with \( P_{PL} \), \( \lambda \) can be identified by a simple parameter searching approach that ends when the SOC(T) is fulfilled. It is noteworthy that \( P_{SS}^* \) is constant unless a control constraint (18) is reached. Moreover, when \( P_{PL} < 0 \) (i.e., \( t \in \Psi \)), it can be seen in all cases shown in (23) that the optimal input is simply expressed as

\[
P_{SS}^* = P_{PL}
\]

(24)

unless \( \max(P_{SS}^*, P_{PL} - P_{PS_{\min}}, P_{SS_{\min}}) < P_{PL} \) (which is a special case of the fourth case in (23)), and in such a case

\[
P_{SS}^* = \max\left(P_{SS}^*, P_{PL} - P_{PS_{\min}}, P_{SS_{\min}}\right).
\]

(25)

The latter is a nontypical case where significant battery charging is required such that the ICE will be active even during the braking phase to boost the battery charging power.

2) State Constraints Active: By operating the SS at \( P_{SS}^* \), the unconstrained optimal state trajectory, \( \text{SOC}(t, P_{SS}) \), may violate the state constant (13) during the operation. The optimal solution in such cases can be found by invoking a recursive scheme [37]. Suppose that at some time \( t = t_p \), the state constraint is exceeded the most in the unconstrained optimal trajectory, and the problem is then split in two subproblems with boundary conditions \{SOC(0), SOC(t_p)\} and \{SOC(t_p), SOC(T)\}, if SOC(t_p) = SOC_{max} in the case the upper state constraint is exceeded; otherwise, SOC(t_p) = SOC_{min}. By following the same approach used for the unconstraint case, it is immediate to find the optimal costate and the associated control solution for both problems. From the jump conditions of the PMP, \( \lambda \) is discontinuous at \( t_p \), \( \lambda(t_p^+) < \lambda(t_p^-) \) if the upper bound is reached, and \( \lambda(t_p^+) > \lambda(t_p^-) \) if the lower bound is reached. Once the solution for a subproblem is found, such properties can be utilized to facilitate the searching of \( \lambda \) for the other subproblem. If the constraint is still violated in any of the two subproblems, the procedure is repeated until all state constraints are met.

To illustrate the above recursive solution searching mechanism, a numerical example with HEV parameters given in Table I is shown in Fig. 4. The HEV is requested to follow a segment (WL-L) of a standard driving cycle (that will be properly introduced later in Fig. 10) with the associated \( P_{PL} \) profile as shown in Fig. 4, and the boundary conditions of SOC set to SOC(0) = 79.8% and SOC(T) = 79.8%. As it can be noticed, in the unconstrained optimal state (SOC) trajectory, the SOC constraint is exceeded the most at \( t = 337 \) s, where the boundary value problem is subsequently split into two subproblems. By repeating the global search of \( \lambda \) for both subproblems, a piecewise constant \( \lambda \) is found. Since the SOC constraint is fulfilled by the resulting state trajectories in both phases, the recursive algorithm ends and the optimal solution is found.

To further clarify the closed-form control solution (23), another example is carried out by utilizing a simple but representative \( P_{PL} \) profile. As it can be seen in Fig. 5, by following a simple \( P_{PL} \) profile, the optimal power-split profiles are found by DP for vehicle parameters given in Table I with a fixed terminal SOC(T) at 0.65. To emulate different scenarios in (23) (last three cases in (23) except Case I which is a subsolution of Case 2), initial SOC cases are set to: 0.64, 0.5775, and 0.54, which are associated with the three different cases of \( \Delta_{SOC} > 0 \) (solution Case 2), \( \Delta_{SOC} = 0 \) (solution Case 3), and \( \Delta_{SOC} < 0 \) (solution Case 4), respectively. The subcase of Case 4 shown by (25) may occur if SOC(0) is set to a further lower value (more charge is required to meet the terminal SOC condition by the end of the mission). Under these circumstances, the SS is charged throughout the mission at a constant power below
the negative \( P_{PL} \) value (this subcase is not shown in Fig. 5). The numerical (DP) results in Fig. 5 verify the closed-form solution (23), indicating that for an optimal EM (during the propulsive phase \( \Phi \)), the SS is operated at a load leveling fashion unless a control or a state limit is reached (e.g., during the period \( t \in [0, 5] \) in Case 2). As a consequence, once the PS is active, its power output \( P_{PS} \) follows the trends of the \( P_{PL} \) profile but with a fixed power difference that is equal to \( P_{SS}^* \).

**B. Analysis for the Vehicle Model With the Lossless SSS**

In this section, the SSS is integrated with no penalty fuel \( (m_f = 0) \), as commonly assumed in EM studies (see, e.g., [7], [33], [38]). In such a case, the new Hamiltonian \( \forall t \) is

\[
H = \begin{cases} 
H_1 = q_f + \alpha_f (P_{PL} - P_{SS}) \\
\quad \quad + V_{oc} + \sqrt{V_{oc}^2 - 4P_{SS} R_b / \eta_{dc}^{\text{sign}(P_{dc})}} \\
\quad \quad - \lambda \frac{2R_b Q_{max}}{P_{SS} < P_{PL}} \\
H_2 = \frac{V_{oc} + \sqrt{V_{oc}^2 - 4P_{PL} R_b / \eta_{dc}^{\text{sign}(P_{dc})}}}{2R_b Q_{max}} \\
\quad \quad - \lambda \frac{P_{SS} - P_{PL}}{P_{SS} < P_{PL}} \\
\end{cases} 
\]

(26)

The dynamics of the costate remains the same as (20). The minimum of the Hamiltonian with respect to the control input \( P_{SS} \) can be found by identifying the minimum of the two candidates \( H_1 \) and \( H_2 \) of the piecewise Hamiltonian (26) and selecting the minimum between the two candidates [27], [38]. For the sake of further analysis, let \( H_1^* \) and \( H_2^* \) denote the optima of \( H_1 \) and \( H_2 \), respectively. The minimum for the second candidate \( H_2 \) is trivial

\[
H_2^* = H_2, \quad P_{SS}^* = P_{PL} 
\]

(27)

since the expression \( H_2 \) does not depend on the control variable \( P_{SS} \). In accordance with the results (without the SSS) shown previously, the following analysis for the present case of SSS is carried out individually for all the four cases presented in (23).

1) \( \lambda \in [0, \infty) \): Due to the fact that \( H_1 \) is monotonically decreasing as \( P_{SS} \) increases (e.g., consider that \( \partial H_1 / \partial P_{SS} < 0 \)) and \( P_{SS} < P_{PL} \), it can be inferred that \( H_1 > H_2 \) for all feasible \( P_{SS} \). Therefore, the associated optimal control solution shown in (23) remains as the optimum under such circumstances, and the optimal Hamiltonian, \( H^* \), is

\[
H^*(P_{SS}) = \begin{cases} 
H_1^* = H_1(P_{SS_{\text{max}}}), & \text{if } P_{PL} > P_{SS_{\text{max}}} \\
H_2^*, & \text{if } P_{SS_{\text{max}}} \geq P_{PL}. 
\end{cases} 
\]

(28)

2) \( \lambda \in (- \alpha_f Q_{\max} \eta_{dc} V_{oc}, 0) \): The minimum of \( H_1 \) by applying the unconstrained optimal control input \( P_{SS}^{**} \) (defined in (22a)) is

\[
H_1^* = q_f + \alpha_f P_{PL} - \alpha_f \eta_{dc} V_{oc}^2 \\
\quad \quad - \frac{\lambda^2}{4R_b Q_{\max}^2} V_{oc} \\
\quad \quad - \frac{\lambda}{2R_b Q_{\max}}. 
\]

(29)

The minimum of the switching Hamiltonian \( H \) may be identified by assuming \( \dot{H} = H_1^* - H_2^* \), which is a quadratic and concave function with respect to \( P_{PL} \) (\( H_1^* \))(\( P_{PL} \)) that is linear and \( H_2^* \) (\( P_{PL} \)) that is convex. The maximum value of \( \dot{H} \), \( \dot{H}_{\text{max}} \), can be identified by first solving the equation \( \partial H / \partial P_{PL} = 0 \), yielding \( H_{PL} = P_{SS}^{**} > 0 \) from which it is immediate to obtain \( \dot{H}_{\text{max}} = \dot{H}(P_{PL}) = q_f > 0 \). Hence, the equation \( \dot{H} = 0 \) has two real roots \( P_{PL}^1(\lambda) \) and \( P_{PL}^2(\lambda) \) (the superscript “-” stands for the smaller root, while “+” represents the greater one), which result in a power interval \( \Sigma_1 = \{P_{PL} | P_{PL}^1 < P_{PL} < P_{PL}^2\} \), and for \( P_{PL} \in \Sigma_1 \), it holds that

\[
\dot{H} > 0 \Rightarrow H_1^* > H_2^*. 
\]

(30)

Expression (30) gives the region where \( H_2^* \) is the minimum of the switching Hamiltonian; otherwise, \( H_1^* \) is the minimum. A singularity may occur when \( P_{PL} \) equals \( P_{PL}^1 \) or \( P_{PL}^2 \) as both minimum candidates adopt the same value. In this case, either \( H_1^* \) or \( H_2^* \) can be selected, and the preference could depend on the emphasis placed on other aspects, including NOx emissions, driver comfort, engine noise, and SSS cost (response lag and additional fuel required to restart the engine). The present work focuses on the fuel efficiency of EM, which is directly influenced by the engine start fuel cost [as modeled in (5) and (6)]. In this context, \( H_1^* \) should be chosen at the singularity to minimize the number of engine ON/OFF switches.

If \( P_{PL} > P_{SS_{\text{max}}} \), it is straightforward to show that the Hamiltonian is minimized at \( H_1^* \), as \( H^* = H_2^* \) is valid only when \( P_{PL} \leq P_{SS_{\text{max}}} \) [see (28)]. Let us now consider the case \( P_{PL} \leq P_{SS_{\text{max}}} \). When the unconstrained optimal control, \( P_{SS}^{**} \), is greater than \( P_{PL} \) (that is equivalent to \( P_{PL} < P_{PL}^2 \)), \( P_{SS}^{**} \) will be saturated by \( P_{PL} \) such that \( P_{SS} = P_{PL} \). Hence, the \( P_{PL} \) power region that yields \( P_{SS} = P_{PL} \) (i.e., \( H^* = H_2^* \), full electric mode) is \( \Sigma_1 = \{P_{PL} | P_{PL} \leq P_{SS_{\text{max}}} \} \). Therefore, the optimal solution for \( \lambda \in (- \alpha_f Q_{\max} \eta_{dc} V_{oc}, 0) \)
can be expressed as
\[ H^*(P_{SS}^*) = \begin{cases} H_2^*, & P_{PL} \in \mathcal{P}_{e,1} \\ H_1^* = H_1(\min(P_{SS}^*, P_{SS\text{max}})), & \text{otherwise.} \end{cases} \] (31)

By following in this section the same steps conducted previously, it is straightforward to derive the \( P_{PL} \) regions where \( H_1^* > H_2^* \) in the remaining two scenarios shown in (23): 1) \( \lambda \in [-\alpha_f Q_{\text{max}} V_{oc}/\eta_{dc}, -\alpha_f Q_{\text{max}} \eta_{dc} V_{oc}] \) and 2) \( \lambda \in (-\infty, -\alpha_f Q_{\text{max}} V_{oc}/\eta_{dc}) \). Without loss of generality, let us assume that the condition (30) is valid in case 1) for \( P_{PL} \in \mathcal{P}_{e,2} \) and in case 2) for \( P_{PL} \in \mathcal{P}_{e,3} \). Thus, the optimal solution in both scenarios can be expressed as
\[ H^*(P_{SS}^*) = \begin{cases} H_2^*, & P_{PL} \in \mathcal{P}_{e,2} \\ H_1^* = H_1(0), & \text{otherwise.} \end{cases} \] (32)

for \( \lambda \in [-\alpha_f Q_{\text{max}} V_{oc}/\eta_{dc}, -\alpha_f Q_{\text{max}} \eta_{dc} V_{oc}] \) and
\[ H^*(P_{SS}^*) = \begin{cases} H_2^*, & P_{PL} \in \mathcal{P}_{e,3} \\ H_1^* = H_1(\max(P_{SS}^*, P_{PL} - P_{PS\text{max}}, P_{SS\text{max}})), & \text{otherwise.} \end{cases} \] (33)

for \( \lambda \in (-\infty, -\alpha_f Q_{\text{max}} V_{oc}/\eta_{dc}) \).

A graphical representation of the optimal solutions is shown in Fig. 6 for different values of costate \( \lambda \) (horizontal axis) and load power \( P_{PS} \) (vertical axis). As it can be seen, the optimum \( H^* \) selects the minimum among the two candidates, \( H_1^* \) and \( H_2^* \) (with the regions of different colors in Fig. 6 specifying where each candidate has the lowest value), and when \( H_1^* = H_2^* \), \( H_1^* \) is selected under the provision of minimizing ICE start-stop events. The left plot in Fig. 6 denotes the solution without including the control constraints on \( P_{PS} \) (and \( P_{PS} \) as a consequence). In this case, the two solution regions are separated by two borders (shown as thick solid lines), on which \( H = 0 \) (singularity). In particular, for \( \lambda \in (-\alpha_f Q_{\text{max}} \eta_{dc} V_{oc}, 0) \), the upper and lower borders, respectively, denote \( P_{PL} = P_{PS}^* \) and \( P_{PL} = P_{PS}^* \) as they have been previously defined in Section III-B. The left plot in Fig. 6 is also overlaid with lines that show the control constraints (obtained by (14) and (15) or (18)). By including these control constraints in the problem, the practical solution is shown in the right plot of Fig. 6, which verifies the closed-form solution described by (28) and (31)–(33).

In conclusion, the optimal solution \( P_{SS}^* \) that minimizes the piecewise Hamiltonian (26) is formed by the four segments, as shown in (28) and (31)–(33). Each segment is a piecewise function that merges a section of (23), obtained in the absence of the SSS, with \( P_{SS}^* = P_{PL} \) (except for \( \lambda \geq 0 \) where the control law is unique i.e., the first line of (23) and (28)). Depending on the \( P_{PL} \) branch power demand \( P_{PL} \), the optimal control policy may switch between the two pieces of the solution within one segment. As with the previous no SSS case, the unconstrained closed-form solution can be found explicitly by numerically identifying \( \lambda \), which determines the switching threshold and the optimal SS operating power. If a state constraint is violated in the unconstrained solution, the recursive algorithm described in Section III-A2 can be utilized to iteratively find the optimal solution.

Similar to the previous case without the SSS in Fig. 5, example DP solutions for the present case are shown in Fig. 7 for the same \( P_{PL} \) profile, vehicle parameters, and target SOC(T) at 0.65. Fig. 7 shows that the three representative analytic solutions cases (31)–(33) ((28) is not shown since it is a subsolution of (31)) are precisely followed. The optimal power profiles indicate that during the propulsive phase \( \Phi \), the powertrain is operated in pure electric mode at low load requirements. Once \( P_{PL} \) reaches the switching threshold, the PS is activated and the powertrain is operated in ICE only or hybrid mode with the SS being charged/discharged at a constant power as with the behavior in no SSS case.

The presence of the switching threshold, therefore, represents a fundamental difference of the present case solution to the solution of the case with no SSS, derived in Section III-A. With no SSS, only one parameter is needed to reconstruct the solution, the constant power at which the SS power levels off once the ICE is on; for example, in Cases 2–4 in Fig. 5, it levels off at a positive value, zero, and a negative value; see also the parameter \( P_{SS,\text{in}} \) in the context of Case 2 in [30]. In contrast, with the SSS present, two parameters are required to reconstruct the solution, the constant power at which the SS power levels off once the ICE is on, as before, and the switching threshold.

C. Hysteresis Power Threshold Strategy (HPTS)

By using insights gained from the preceding solutions presented in Sections III-A and III-B, the HPTS is developed in this section to address the most realistic case, where the penalty fuel for the engine reactivation is involved, for which analytic solutions are not feasible.

When engine start fuel cost, \( m_r \), is enabled, \( m_{r=K_q f_0} \) is added to the base fuel consumption as long as the transition \( S_{n-1} \triangleq \{ s | s = 0, s^+ = 1 \} \) is detected. Application of the optimal EM solution derived for a lossless SSS to this case may result in fast engine ON/OFF switching dynamics...
when $P_{PL}$ fluctuates around switching power thresholds, thus leading to a significant increase of fuel usage. The HPTS attempts to address this issue and to approximate the global optimal solution with consideration of $m_p$ by combining the control policies extracted from the analytic solutions obtained previously with a newly designed switching logic for ICE ON/OFF control. The overall control scheme is graphically shown in Fig. 8.\(^1\)

As it can be noticed, the principles of HPTS are defined in Fig. 8, while it is clear that outside the hysteresis zone, the hysteresis dynamics dictate the operation in the hysteresis zone (which may happen in practice due to control discretization) and (31)–(33) (in which $\Delta P_{PS}$ a tuneable constant parameter; thus, the SS is always operated at a constant power $-\Delta P_{PS}$ when the ICE is active. This operation is inspired by the analytic solution (23) and (31)–(33) (in which $\Delta P_{PS}$ is in fact a constant that depends on $\Delta SOC$ and is found analytically), and it introduces an additional degree of freedom (the tuneable parameter $\Delta P_{PS}$) compared to the conventional load following (exclusive operation) strategy ($\Delta P_{PS} = 0$) used in [23]. Depending on the sign and value of $\Delta P_{PS}$, when the ICE is activated, the SS may be discharged to cover the unfulfilled power demand ($\Delta P_{PS} < 0$), charged by the PS to absorb the excess PS power ($\Delta P_{PS} > 0$), or idling ($\Delta P_{PS} = 0$ and the mode falls into the PS-only mode).

In order to reduce the incidence of ICE ON/OFF transitions, a hysteresis switching scheme for ICE ON/OFF control is also developed, as shown in Fig. 9. The hysteresis dynamics are assigned in relation to the engine ON/OFF state $s$, giving

$$P_{SS} = (1 - s)P_{PL} - s\Delta P_{PS}, \quad P_{PS} = s(P_{PL} + \Delta P_{PS}) \quad (34)$$

and

$$s = \begin{cases} 0, & \text{if } P_{PL} \leq P_{PS,th} \\ 1, & \text{if } P_{PL} > P_{PS,th} \\ s(t^-), & \text{otherwise} \end{cases}$$

where $t^-$ represents the time instant before $t$ and $P_{PS,th}$ and $P_{PS,max}$ are two separate tuneable power thresholds. The hysteresis dynamics dictate the operation in the hysteresis zone in Fig. 8, while it is clear that outside the hysteresis zone, the $P_{SS}$ and $P_{PS}$ expressions in (34) fall back, respectively, to those in the yellow and green zones in Fig. 8.

Operation outside the primary region triggers the emergency rules, which aim to prevent the SOC constraints violation (which may happen in practice due to control discretization) and also define the power split for extremely large power demand ($P_{PL} > P_{PS,max}$). More specifically, when SOC reaches or goes beyond its limits ($SOC \geq SOC_{max} \lor SOC \leq SOC_{min}$), the SS power is set to maximum (min($P_{SS,min}$, $P_{PL}$)) or minimum (max($P_{PL} - P_{SS,max}$, $P_{SS,min}$)) operating power to

\(^1\)Operation in the bottom-right and top-left corners, shaded as red and blue regions, by the defined rules is only possible in transient conditions (short time) to avoid draining or overflowing the SOC. The latter can be naturally avoided by assigning more mechanical brakes so that, for example, $P_{PL} = 0$ (see (1b)).
force the SOC immediately back into the main operational zone, as inspired by the PMP analysis in Section III-A2 and Fig. 4. In particular, with the operational policy for \( SOC \leq SOC_{\text{min}} \), the PS can be triggered on (enabling the hybrid mode) even during braking.

The design of the HPTS amounts to finding optimally tuned values for \( E_{PS,\text{th}} \), \( T_{PS,\text{th}} \), and \( \Delta P_{PS} \) that minimize the fuel consumption \( m_f \) while maintaining the CS condition

\[
\Delta SOC = 0. \tag{35}
\]

Condition (35) is sought because it is naturally optimal as will be shown next in Section III-D, which is also a major contribution of this article. The global tuning nature of the control requires access to the whole driving cycle in advance (as is the case with DP and ECMS) so that the tunable parameters can be tuned separately for each driving cycle. This allows for the rules of the HPTS to be tailored for all driving cycles rather than having compromised control policies that may excel on some driving cycles but behave less well on others. Thus, HPTS can be used to obtain benchmark solutions, and also, it can be implemented in practice when the driving profile is known or can be estimated.

### D. Fuel Economy Evaluation

The EFC is a measure of the fuel economy that has been widely used in the literature for evaluating overall fuel economy. It allows the comparison of the overall fuel economy by considering the actual fuel consumption as well as the shortage/surplus of final SOC. In this section, we prove that the optimal EFC of a driving mission is achieved for the two equivalence factors \( S_{d,\text{efc}} \) and \( S_{c,\text{efc}} \) (for battery discharging and charging, respectively) represent the correlation of the electrical energy and the fuel chemical energy required when following a driving cycle. Hence, to proceed with the assessment of an EMS, \( S_{d,\text{efc}} \) and \( S_{c,\text{efc}} \) have to be identified \textit{a priori} for each driving cycle and each vehicle model. In brief, the identification method proposed in [25] requires a sweep of the power-sharing factor \( \Delta u_{\text{efc}} = P_{PS}/P_{PL} \), \( \forall t \in \Phi \) within the range \([1 - \Delta u_{\text{efc}}, 1 + \Delta u_{\text{efc}}]\), with \( \Delta u_{\text{efc}} \) selected such that either the upper or the lower bound for the SOC is not violated during the operation. The overall electrical and fuel energy consumptions for a specific value of \( u_{\text{efc}} \) while undergoing a given drive cycle are computed by

\[
E_e = \int_0^T i_b V_{oc} dt \quad \text{and} \quad E_f = \int_0^T qHV m_f dt
\]

and are plotted against each other for different values of \( u_{\text{efc}} \). Such a plot is separated into two segments intersecting at \( u_{\text{efc}} = 1 \), at which the propulsion power is purely provided by the ICE. The slopes of straight lines that fit the \((E_e, E_f)\) data of these two segments are identified as the negative values of \( S_{d,\text{efc}} \) and \( S_{c,\text{efc}} \). It will now be shown that the EFC definition inherently drives the optimal EFC solutions (of an EMS) to be strictly CS as in (35).

As the hybrid mode is enabled only during an emergency when \( P_{PL} < 0 \), it is reasonable to assume that \( P_{SS} = P_{PL} \), \( \forall t \in \Psi \). As such, the fuel consumption at the end of the driving mission, in light of (10), (11), and (12), is expressed as

\[
m_f = q_f \int_0^T s dt + a_f \int_\Phi P_{PL} dt - a_f \int_\Phi P_{SS} dt + N_v m_p \tag{37}
\]

where \( N_v \) is the number of engine restarts during the mission and \( a_f \int_\Phi P_{PL} dt \) is fixed for a given driving cycle and independent of the EM control. The fuel energy for a given driving cycle is \( E_f = qHV m_f \). In terms of the electrical energy \( E_e \), when \( u_{\text{efc}} \geq 1 \), it means that \( E_e \) is never used for propulsion, that is, \( \Phi_{d} = \emptyset \), \( \Phi = \Phi_{s} \), and when \( u_{\text{efc}} < 1 \), it is clear that \( \Phi_{s} = \emptyset \), \( \Phi = \Phi_{d} \). Therefore, \( E_e \) can be rewritten as

\[
E_e = \left\{ \begin{array}{ll}
\int_\Phi \frac{P_{SS} V_{oc}}{\eta_{dc}} dt + E_{e,\psi}, & \text{if } u_{\text{efc}} < 1 \\
\int_\Phi \frac{P_{SS} V_{oc}}{\eta_{dc}} dt & \text{if } u_{\text{efc}} \geq 1
\end{array} \right.
\]

where \( E_{e,\psi} = \Delta \psi SOC Q_{\text{max}} V_{oc} \) only depends on \( P_{PL} \), considers two arbitrary values of \( u_{\text{efc}} \geq 1 \) within the admissible set \([1, 1 + \Delta u_{\text{efc}}]\). It is obvious that \( N_v \) and \( s \) are invariant between the two scenarios. Then, the slope corresponding to \( S_{d,\text{efc}} \) is evaluated by

\[
S_{d,\text{efc}} = -\frac{\Delta E_f}{\Delta E_e} = \frac{qHV \alpha_f \int_{\Phi} (P_{SS,1} - P_{SS,2}) dt}{\eta_{dc} \int_{\Phi} \frac{P_{SS} V_{oc}}{\eta_{dc}} dt - \int_{\Phi} (P_{SS,1} - P_{SS,2}) dt} = \frac{qHV \alpha_f \int_{\Phi} ((i_{b,1} - i_{b,2})(V_{oc} - R_b(i_{b,1} + i_{b,2}))) dt}{V_{oc} \int_{\Phi} \frac{P_{SS} V_{oc}}{\eta_{dc}} dt - \int_{\Phi} ((i_{b,1} - i_{b,2}) dt)}
\]

where subscripts 1 and 2 indicate the two scenarios driven by the two distinct \( u_{\text{efc}} \) values. Since \( V_{oc} - R_b(i_{b,1} + i_{b,2}) \geq V_{oc}, \forall t \in \Phi_{s} \), it is obtained that

\[
S_{d,\text{efc}} > \frac{1}{\eta_{dc}} qHV \alpha_f. \tag{38}
\]

Similarly, \( S_{c,\text{efc}} \) is evaluated as follows, with respect to two arbitrary values of \( u_{\text{efc}} < 1 \) within the admissible set \([1 - \Delta u_{\text{efc}}, 1]\):

\[
S_{c,\text{efc}} = \frac{qHV \alpha_f \int_{\Phi} (i_{b,3} - i_{b,4})(V_{oc} - R_b(i_{b,3} + i_{b,4}))) dt}{V_{oc} \int_{\Phi} \frac{P_{SS} V_{oc}}{\eta_{dc}} dt - \int_{\Phi} (i_{b,3} - i_{b,4}) dt}
\]

which implies

\[
S_{c,\text{efc}} < \frac{1}{\eta_{dc}} qHV \alpha_f. \tag{39}
\]

Turning to the steps required for the calculation of \( m_{\text{efc}} \) and by applying (8) to (37), it holds that

\[
m_f = q_f \int_0^T s dt + a_f \int_\Phi P_{PL} dt - a_f \int_\Phi \eta_{\text{sign}(P_{pl})} \frac{P_{PL}}{P_{pl}} dt + N_v m_p \tag{40}
\]
where the term \( \alpha_f \int \eta d \Phi \, P_b \, dt \) can be expanded by using the definitions of \( \Phi_d \) and \( \Phi_c \), as follows:

\[
\alpha_f \int \eta d \Phi \, P_b \, dt = \alpha_f \left( \int \eta d \Phi \, P_b \, dt + \int \frac{1}{\eta d \Phi} \, P_b \, dt \right). \tag{41}
\]

In relation to the charging and discharging intervals, let us define

\[
V_{b,d} \triangleq V_{oc} - R_b \, i_b \leq V_{oc} \quad \forall t \in \Phi_d
\]

\[
V_{b,c} \triangleq V_{oc} - R_b \, i_b > V_{oc} \quad \forall t \in \Phi_c. \tag{42}
\]

Then, (41) can be expressed as

\[
\alpha_f \left( \int \eta d \Phi \, P_b \, dt + \int \frac{1}{\eta d \Phi} \, P_b \, dt \right) = -Q \max \alpha_f \left( \eta d \int \frac{dSOC}{dt} \, dt + \frac{1}{\eta d} \int \frac{dSOC}{dt} \, dt \right) \tag{43}
\]

where \( i_b = -Q \max (dSOC/dt) \) is applied. Due to the mean value theorem, there exist two time instants \( t_d \in \Phi_d \) and \( t_c \in \Phi_c \) such that

\[
\int \frac{dSOC}{dt} \, dt = V_{b,d}(t_d) \int \frac{dSOC}{dt} \, dt = V_{b,c}(t_c) \int \frac{dSOC}{dt} \, dt = -V_{b,c}(t_c) \Delta \phi_c \, SOC. \tag{44}
\]

By substituting (40) in (36) and applying (43) and (44), it is immediate to obtain the explicit expression of \( m_{efc} \) as follows:

\[
m_{efc} = \begin{cases} 
\frac{m_{f0} - \left( \eta d c, V_{b,d}(t_d) \Delta \phi_c \, SOC + \frac{1}{\eta d c} V_{b,c}(t_c) \Delta \phi_c \, SOC \right)}{Q_{\max} V_{oc} Q_{\max} \eta d c} \Delta \SOC \geq 0, \\
\frac{m_{f0} - \left( \eta d c, V_{b,d}(t_d) \Delta \phi_c \, SOC + \frac{1}{\eta d c} V_{b,c}(t_c) \Delta \phi_c \, SOC \right)}{Q_{\max} V_{oc} Q_{\max} \eta d c} \Delta \SOC < 0.
\end{cases} \tag{45}
\]

where \( m_{f0} = q \, \int_0^T \! s \, dt + N_s \, m_p + \alpha_f \int \eta d \Phi \, P_L \, dt \), and the piecewise function (45) is continuous at \( \Delta SOC = 0 \).

By using (16), (45) can be rearranged into (46), as shown at the bottom of the next page. As it can be seen, (46) is a piecewise bilinear function of \( V_{b,d}(t_d) \), \( V_{b,c}(t_c) \), \( \Delta \phi_c \, SOC \), \( \Delta \phi_d \, SOC \), \( s \), and \( N_s \), which are all influenced by the EM strategy through \( PSS \). On the other hand, the last two terms of each part in (46) are independent of the EM and only depend on \( P_L \), and therefore, are constants for a given \( P_L \) profile. As a consequence, \( \Delta \phi_d \, SOC \) occurs only once a pair of boundary conditions of SOC (SOC(0), SOC(T)) is given (that determine \( \Delta SOC \)). The \( PSS \) profile that meets the the desired \( \Delta \phi_d \, SOC \) is not unique, and it is possible to find some \( PSS \) profile that sets \( V_{b,d} \) and \( V_{b,c} \) independently of each other to some desirable profiles, and as a result, \( \Delta \phi_c \, SOC \), \( \Delta \phi_d \, SOC \), \( s \), and \( N_s \) (that are determined by \( V_{b,d} \) and \( V_{b,c} \)) can be independently assigned to desired values. By considering the inequality conditions (38) and (39), as well as (42) and that \( \eta d c \leq 1 \), it can be inferred that

\[
S_{d,efc} - \eta d c \alpha_f q H V V_{b,d}(t_d) \frac{V_{oc}}{V_{oc}} > 0 \tag{47}
\]

\[
S_{c,efc} - \eta d c \alpha_f q H V V_{b,c}(t_c) \frac{V_{oc}}{V_{oc}} < 0. \tag{48}
\]

By referring to the \( \Delta SOC \geq 0 \) case in (46), it can be easily inferred that \( m_{efc} \) is minimized when \( \Delta \phi_d \, SOC \) is minimized since (47) is true. By further taking into account (16), it can be concluded that \( \Delta SOC = 0 \) is necessary when \( m_{efc} \) is minimum. Similarly, when \( \Delta SOC < 0 \) in (46), \( m_{efc} \) is minimized when \( \Delta \phi_c \, SOC \) is maximized since (48) is true. Therefore, by referring to (16), the necessary condition to minimize \( m_{efc} \) in this case is also \( \Delta SOC = 0 \) (due to the continuity of (46) at \( \Delta SOC = 0 \)). Hence, the strictly CS condition (35) is a necessary condition overall for EFC minimization.

IV. NUMERICAL RESULTS

The EM control strategies considered and developed in this work are tested by simulations in which the vehicle follows predefined driving cycles. The WLTP corresponds to the latest test procedure adopted by industry and it is therefore utilized in the present work. As shown in Fig. 10, the WLTP profile is a single driving cycle with four stages, defined by their average speed: low (WL-L), medium (WL-M), high (WL-H), and extra high (WL-E). Each of the stages can be considered on their own as independent driving cycles. In addition to the WLTP, an experimental speed profile (shown in Fig. 11) is also adopted for performance and robustness assessment purposes. These time history data, which are recorded by a newly built data acquisition device [39], exhibit realistic driving behavior on a rural road. Compared to standard test cycles, this experimental speed pattern contains particular features that better reflect real-world driving, such as the influences of legal speed limits and road grades, and the driving style of the human driver who is inclined to apply higher values of acceleration and deceleration than in the WLTP.

The proposed HPTS is individually applied to the four segments of the WLTP speed profile, and the solutions are benchmarked against DP [40] and XOS [23] in the context of both linear FCM (4) and experimental (quasi-linear) FCM (dotted line in the right of Fig. 3) for robustness verification purposes. It is noteworthy that ECMS, which is one of the popular EM control strategies in the literature, breaks down for the problem addressed in this article and therefore not used for comparison. The reason is briefly explained as follows. ECMS finds the optimal power split to minimize an EFC, defined as

\[
\dot{m}_{eq} = \begin{cases} 
\dot{m}(PSS) + S_d q H V PSS, & PSS \geq 0, \\
\dot{m}(PSS) + S_c q H V PSS, & PSS < 0.
\end{cases} \tag{49}
\]

where the two constants \( S_d \) and \( S_c \) are equivalence factors that translate the energy discharged/charged by the SS into a corresponding amount of fuel consumed/stored. Due to the linear/quasi-linear FCM for a series HEV, (49) becomes a linear/quasi-linear combination of \( PSS \) and \( PSS \) with individual
gradients depending on $\alpha_f$, $q_{HV}$, $S_f$, and $S_c$. Hence, the ECMS simply operates $P_{PS}$ always at its maximum or always at its minimum throughout a mission, irrespective of the power demand, and with the choice of (always) maximum or minimum $P_{PS}$ depending on the sign of the gradients, unless SOC limits are reached. For a fair comparison and also to satisfy the necessary condition of fuel consumption optimality, the same SOC CS boundary condition $SOC(0) = SOC(T) = 0.65$ is imposed for all methods. The penalty fuel coefficient for engine restarts is set to $K$ = 0.8 in the first instance, while an investigation of its influence on the comparative results is also carried out.

Given a driving cycle, the proposed HPTS is applied by tuning the design parameters $P_{PS,th}$, $\mathbf{P}_{PS,th}$, and $\Delta P_{PS}$ while also aiming to satisfy the CS condition as mentioned. Thus, the tuning process involves finding the combination of the three parameters, among all combinations that lead to CS operation, which minimizes the fuel consumption; the EFC is now equal to the fuel consumption due to the CS condition. Fig. 12 presents an example of the tuning graph for the WL-M cycle with the linear FCM model (4). The surface in Fig. 12 denotes the control solutions satisfying $\Delta SOC = 0$, and the optimal solution in terms of fuel consumption is identified approximately at $P_{PS,th} = 18.5$ kW, $P_{PS,th} = 6.5$ kW, and $\Delta P_{PS} = 9.5$ kW.

Fig. 13 presents the power profiles and the associated engine ON/OFF states determined by these control methods when the WL-M cycle is simulated. Compared to the XOS, both DP and the HPTS can reduce the engine restarts by manipulating the operation of the PS and SS. In particular, when the ICE is activated in cases of DP and HPTS, the powertrain is operated in the hybrid mode, in which the battery is charged by the ICE at a constant SS power, and therefore, additional engine breaks are allowed to prevent the engine status from being changed too frequently, as can be found in the control solution of XOS (e.g., around 50 and 250 s in Fig. 13). Further comparing the solutions of HPTS and DP, the HPTS is more sluggish in its response to a PS power request (a phase delay can be observed in Fig. 13 by comparing their PS profiles) due to the impact of the hysteresis switching mechanism. Moreover, the PS operating power of HPTS is higher than DP, which also yields more battery charge during $s = 1$ and further reduced ICE ON/OFF transitions. As a consequence, the battery SOC of HPTS has more noticeable variations than the profiles generated by the other two methods, as shown in Fig. 14. For
example, the battery in the case of HPTS is charged intensively from 180 to 220 s, thereby allowing the ICE to be switched off for the next 50 s. Although the SOC in the case of XOS performs closely to the DP solution, it will be shown later that the fuel economy of XOS is significantly impaired by the unnecessary ICE switches (which incurs additional fuel usage). The fuel consumption of all the methods is compared in Table II.

The solutions of the HPTS are much closer to the results of DP compared to the XOS for all cases. Approximately, there is 0.48%–6.06% more fuel usage by HPTS than the DP for WLTP cycles, and the gap decreases from WL-L to WL-E.

This can be understood that more fuel saving is expected by an optimally controlled SSS during urban driving rather than driving on the motorway, where the SSS is rarely engaged. In the context of the real-world experimental driving cycle that involves mixed traffic conditions, the HPTS solution is only 3.49% behind the DP and can save about 5.4% more fuel compared to the XOS. The results verify the capability of HPTS in dealing with general driving scenarios.

The performance of the HPTS is further examined by employing the experimental FCM shown in Fig. 3. Similar to the linear FCM case, the optimal selection of the design parameters is identified by a global tuning process. As shown in Fig. 15, the optimal parameter selection for the nonlinear FCM is \( P_{PS,th} = 18.75 \text{ kW}, \) \( P_{PS,th} = 8.5 \text{ kW}, \) and \( \Delta P_{PS} = 15.0 \text{ kW}. \) The power and engine switching profiles of the three control methods are shown in Fig. 16. As it can be seen, the HPTS is able to emulate the power profiles solved by DP, while XOS remains at the same operation, as shown in Fig. 13. The engine switching profiles further confirm the findings; it is notable that once again, both DP and HPTS reduce significantly the engine ON/OFF events compared to the XOS. The SOC profiles reported in Fig. 17 show that, in this case, the HPTS can produce a profile closer to the DP solution compared to the XOS. To provide further evidence of the resemblance between DP and the HPTS, the control solutions of the three methods for the experimental driving cycle are also shown in Fig. 18. As it can be seen, both the DP and HPTS have similar power profiles, while the XOS entails much more engine switching operations, which incur additional fuel usage.

The fuel consumption results of all the methods in the case of experimental FCM are presented in Table III. By comparing the results with the previous solutions solved for the linear
CHEN et al. : OPTIMAL EM OF SERIES HYBRID ELECTRIC VEHICLES WITH ENGINE START-STOP SYSTEM 673

Fig. 16. Power profiles and engine switching profile when WL-M is simulated with the nonlinear experimental FCM and CS condition $\Delta$SOC = 0. (a) DP. (b) XOS. (c) HPTS. (d) Engine state $s(t)$.

Fig. 17. Battery SOC profiles when WL-M is simulated with the nonlinear experimental FCM. CS condition $\Delta$SOC = 0 is achieved in all cases.

FCM model in Table II, it can be observed that the optimality (percentage fuel increase) of the XOS degrades considerably, while the HPTS is more robust against the model nonlinearity, with the optimality decreased by only 0.4%–1.4% for each cycle compared to the linear case. It is noteworthy that for the experimental driving cycle, the fuel increase for the HPTS is only 0.04% compared to its counterpart with the linear FCM, and furthermore, the HPTS achieves an astonishing 10% less fuel consumption compared to the XOS.

To gain more insight into the effect of the penalty fuel for the engine reactivation, a further investigation is carried out to compare the solutions of the three control methods using different penalty fuel coefficient $K$. For $K \in [0, 2]$, the total fuel consumption of the three methods for the experimental FCM is shown in Fig. 19. As it can be noticed, the HPTS is found to outperform the XOS for all studied $K$ with up to 16.44% improvement in terms of fuel consumption. Moreover, the fuel usage is linearly dependent on the penalty fuel coefficient $K$ for all the three control cases, and the differences between each solution of the tested methods decrease as $K$ decreases, which is expected with the further improvement of the SSS efficiency. When $K = 0$, the HPTS highly resembles the global optimal solution delivered by DP, with only 0.4% fuel increment, whereas the XOS lags the HPTS by another 0.5%.

| TABLE III | FUEL CONSUMPTION [g] WITH THE NONLINEAR EXPERIMENTAL FCM AND PERCENTAGE FUEL INCREASE COMPARED TO DP SOLUTIONS |
|-----------|-------------------------------------------------|---------------------------------|--------------------------|
|           | DP                                              | XOS                            | HPTS                     |
| WL-L      | 55.0                                            | 68.1 (23.8%)                   | 59.0 (7.27%)             |
| WL-M      | 99.7                                            | 113 (13.3%)                    | 105.8 (6.12%)            |
| WL-H      | 174.8                                           | 192.1 (9.90%)                  | 181.0 (3.55%)            |
| WL-E      | 307.1                                           | 312.3 (1.69%)                  | 309.8 (0.88%)            |
| Experimental | 249.4                                          | 286.1 (14.72%)                | 259.9 (4.21%)            |

Fig. 18. Power profiles and engine switching profile when the experimental driving cycle is simulated with the nonlinear experimental FCM and CS condition $\Delta$SOC = 0. (a) DP. (b) XOS. (c) HPTS. (d) Engine state $s(t)$.
The global tuning (by repetitive simulation for a batch of parameter combinations) of HPTS and the running time of DP required for the solutions reported in Table III are further compared in Table IV. The evaluation of both methods is performed in MATLAB and Simulink environment on an Intel i5 2.9 GHz CPU with 8 GB of memory. As it can be seen, the proposed HPTS is more computationally efficient than DP, while the benefit is expected to become more significant for a more complex powertrain model as the computational burden of DP increases exponentially with the number of system states (eventually, DP becomes unusable even for moderately complex models). It is not difficult to see that the tuning effort depends on the size of the power interval of searching, which is usually identified empirically. With the tuning results obtained for more tested cycles, more accurate searching intervals can be identified when a new driving cycle is investigated based on the nature of the cycle (e.g., urban, rural, or motorway driving), and therefore, the tuning effort can be further reduced. Moreover, HPTS acts entirely on the three tunable control parameters, as opposed to classic optimal control (DP) that acts on a state input. This is another salient feature that allows the globally tuned HPTS parameters for series HEVs with the engine SSS, the HPTS. The principal mechanisms of the HPTS are developed with inspiration from the closed-form solutions of the optimal energy source power split derived in this article. In particular, the mathematical analysis is carried out for two model cases: 1) without SSS and 2) with the lossless SSS where the fuel usage for engine restarts is ignored, thus yielding two fundamental optimization solutions that can be represented by simple control rules.

The HPTS further extends these rules with consideration of a more realistic SSS model that incorporates penalty fuel for engine restarts. The HPTS essentially combines two operational modes: battery-only mode and hybrid/engine-only mode, with the latter mode depending on a tuneable power offset. The two modes are separated by a hysterisis switching algorithm parameterized by a pair of thresholds. As such, a minimum duration is ensured for each mode, which naturally prevents fast engine ON/OFF switching that is detrimental to fuel usage. The two thresholds and the offset are regulated based on the information of different HEV model (or real vehicle) parameters and driving cycles by a systematic tuning process, targeting CS operation that is proven in this article to be optimal in the context of the EFC.

DP simulation results verify the analytic solutions obtained for the two simple vehicle models. As such, the globally optimal solutions for these models can be simply produced without referring to DP, which usually involves heavy computation effort. The control performance of the HPTS is evaluated and benchmarked against DP and a recently proposed rule-based method, the XOS, in simulations with a realistic SSS that involves a fuel penalty for engine switch on. It is demonstrated that the proposed HPTS outperforms the XOS for all studied driving cycles, especially for the profiles that emulate urban driving. Moreover, the simple nature of the HPTS also makes it a potential benchmarking strategy for high-fidelity vehicle models, where DP is no longer applicable. Future work involves extending HPTS to incorporate driving speed prediction, which could allow the HPTS to be implemented in real time.

V. CONCLUSION

This article proposes a novel rule-based EM control strategy for series HEVs with the engine SSS, the HPTS. The principal mechanisms of the HPTS are developed with inspiration from the closed-form solutions of the optimal energy source power split derived in this article. In particular, the mathematical analysis is carried out for two model cases: 1) without SSS and 2) with the lossless SSS where the fuel usage for engine restarts is ignored, thus yielding two fundamental optimization solutions that can be represented by simple control rules.

The HPTS further extends these rules with consideration of a more realistic SSS model that incorporates penalty fuel for engine restarts. The HPTS essentially combines two operational modes: battery-only mode and hybrid/engine-only mode, with the latter mode depending on a tuneable power offset. The two modes are separated by a hysterisis switching algorithm parameterized by a pair of thresholds. As such, a minimum duration is ensured for each mode, which naturally prevents fast engine ON/OFF switching that is detrimental to fuel usage. The two thresholds and the offset are regulated based on the information of different HEV model (or real vehicle) parameters and driving cycles by a systematic tuning process, targeting CS operation that is proven in this article to be optimal in the context of the EFC.

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![Fig. 19. Fuel consumption cost with varied penalty fuel coefficient $K$ using the nonlinear experimental PFC and CS condition $\Delta$SOC = 0 when WL-M is simulated.](image)
