Optimal Thermal Management, Charging, and Eco-Driving of Battery Electric Vehicles

Ahad Hamednia, Nikolce Murgovski, Jonas Fredriksson, Jimmy Forsman, Mitra Pourabdollah, and Viktor Larsson

Abstract—This article addresses optimal battery thermal management, charging, and eco-driving of a battery electric vehicle (BEV) with the goal of improving its grid-to-meter energy efficiency. Thus, an optimization problem is formulated, aiming at finding the optimal trade-off between trip time and charging cost. The formulated problem is then transformed into a hybrid dynamical system, where the dynamics in driving and charging modes are modeled with different functions and with different state and control vectors. Moreover, to improve computational efficiency, we propose modeling the driving dynamics in a spatial domain, where decisions are made along the traveled distance. Charging dynamics are modeled in a temporal domain, where decisions are made along a normalized charging time. The actual charging time is modeled as a scalar variable that is optimized simultaneously with the optimal state and control trajectories, for both charging and driving modes. The performance of the proposed algorithm is assessed over a road with a hilly terrain, where two charging possibilities are considered along the driving route and the battery is soaked to the ambient before departure. According to the results, trip time including driving and charging times, is reduced by 44%, compared to a case without active heating/cooling of the battery.

Index Terms—Battery thermal management, charging, eco-driving, grid-to-meter energy efficiency, hybrid dynamical system.

I. INTRODUCTION

ELECTRIC vehicles (EVs) have recently emerged as a viable technology to fulfill the increasingly stringent legislation against greenhouse gas emissions, and to counteract the drawbacks associated with combustion engine vehicles, such as air pollution, climate change, high operating and maintenance costs, and high oil prices [1], [2]. These issues as well as recent advances in battery technology propel vehicle manufacturers towards electromobility, aiming at developing more sustainable vehicles [3], [4]. However, electromobility must confront several issues hindering the widespread use of EVs. Among them, the limited electric range of EVs is a major concern, which emphasizes the significance of reducing total energy consumption [5]. Also, lithium-ion (Li-ion) batteries, as a dominant cell chemistry in the market, are highly temperature sensitive, i.e., Li-ions have reduced performance at subzero and very high temperatures, e.g., 45 °C – 60 °C [6]. Thus, developing a suitable battery thermal management (TM) for the electric powertrain is another hindrance to ponder on.

One promising way to reduce the EVs’ total energy consumption is by improving grid-to-meter efficiency, referred to as the conversion of electrical energy drawn from the electrical grid into kinetic and potential energies required for the vehicle’s movement, and accompanied losses. To do so, a suggested way in the literature is to follow the principles of eco-driving, [7]. Eco-driving can be achieved by optimizing the velocity profile of the vehicle given the road conditions and traffic situation. In case of driving in a hilly terrain, the optimal speed has a varying behaviour, where the vehicle typically decelerates when climbing uphill, and accelerates when rolling downhill. This reduces non-recoverable energy waste at the braking pads, compared to driving with a constant speed [8]. To obtain an eco-driving velocity profile over complex road topographies, model-based optimal control strategies are employed to optimally coordinate energy use, see e.g., [9], [10], [11], [12]. Dynamic programming (DP) [13] is a widely used approach in eco-driving applications [14], [15], [16] due to its capability of solving mixed-integer, non-convex, and nonlinear optimization problems. However, main drawback of the DP method is the curse of dimensionality, i.e., computational time increases exponentially with the dimension of the optimal control problem (OCP). For high-dimensional OCPs, it is possible to reduce computational complexity by adjoining system state dynamics to the cost function and neglecting the state constraints [17], as suggested by Pontryagin’s Maximum Principle (PMP) [18], [19]. In [20] PMP is used for solving an OCP describing the driving mission with incorporated real-world considerations, e.g., speed limits and safety. A PMP-DP method is devised for optimal speed control and energy management of hybrid electric vehicles (HEVs) in [21]. Nonlinear programming (NLP) is another approach employed to investigate the eco-driving problem and trip time under various traffic situations [22]. In this context, several strategies are proposed in [23], [24], [25], [26], [27], [28], [29], aiming at improving computational efficiency. Different tasks, for e.g., gear optimization or disturbance

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Ahad Hamednia, Nikolce Murgovski, and Jonas Fredriksson are with the Department of Electrical Engineering, Chalmers University of Technology, 412 96 Gothenburg, Sweden (e-mail: ahad.hamednia@chalmers.se; nikolce.murgovski@chalmers.se; jonas.fredriksson@chalmers.se).

Jimmy Forsman, Mitra Pourabdollah, and Viktor Larsson are with the Department of Vehicle Energy and Motion Control, Volvo Car Corporation, 405 31 Gothenburg, Sweden (e-mail: jimmyforsman@gmail.com; mitrapo@gmail.com; viktor.larsson@volvocars.com).

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Another challenge impeding the deployment of EVs is the
development of a battery management system that satisfies strict
requirements on durability, performance, and safety. At high
battery temperatures, the battery performance is deteriorated due
to overexposure to heat, i.e., excessive battery temperatures can
create sparks, flames, bulge and bubbles, and lead to battery
corrosion and even explosion [31]. This raises the importance of studying battery life, as well as the energy efficiency, being especially relevant for heavy-duty vehicles, where the battery temperature is increased due to frequent use of fast charging [32], [33], [34]. At sub-zero temperatures, the electro-chemical process is severely slowed due to an increase in internal impedance of the battery cell. This leads to a drastic loss of the cell’s available power and energy [35]. Thus, it is essential to develop an adequate TM system, especially in places where temperature drops to sub-zero values for a considerable period of time in a year [36], [37], [38], [39], [40], [41]. Within the TM system, several components, e.g., heating, ventilation, and air conditioning (HVAC) and high-voltage coolant heater (HVCH), are utilised for controlling the battery pack’s temperature. As these components draw power from the battery, it is pivotal to consider the TM when optimizing the EV’s grid-to-meter energy efficiency. This increases the awareness on total demanded power of the vehicle to achieve a more energy efficient drive [42], [43]. Thus, various research efforts have been carried out on developing a TM system based on optimal control techniques. In [44] a DP algorithm is applied for the TM of an electrified vehicle parked outside at low temperatures, and unplugged from the electrical grid. The algorithm’s objective is to maximize the available energy in the battery pack prior to vehicle departure, and minimise the cell degradation stemming from low temperatures. Also, PMP is used in [45] to find an optimal compromise between battery life expectancy and energy cost. Furthermore, several TM strategies are developed within an MPC framework for achieving energy savings due to optimal cooling/heating [6], [46], [47], [48]. Moreover, the TM is addressed in [42], [43], where the vehicle speed profile is known a priori [43], or future speed prediction is included into the energy efficiency improvement OCP [42]. Although a vast portion of research has been carried out on TM systems, to the best of our knowledge, the optimal coordination of eco-driving, TM, and charging for a BEV has not been explored, especially for long driving missions where optimal trade-off has to be made between travel time, energy efficiency and charging cost and trip time.

This paper considers a BEV over long-distance trips with a hilly terrain, where the vehicle’s electric range is not sufficient to reach the destination. This necessitates multiple intermediate (and terminal) charging options along the driving route. In addition to the battery temperature, the maximum available cell power is also dependent on the battery state of charge (SoC), i.e., as SoC increases, charging power capability decreases and discharging power capability increases. Furthermore, constraints on state variables and control inputs as well as governing dynamics describing the vehicle’s behaviour in driving and charging modes, generally differ. If not formulated with care, the optimal control problem for optimizing eco-driving, charging, and TM may suffer several computational issues. These include:

1) the time instants that belong to the charging and driving modes are not known prior to the vehicle’s mission. Thus, there is no explicit clue of using the state variables, control inputs, constraints, and governing dynamics of each mode;

2) the vehicle longitudinal dynamics are nonlinear with respect to trip time, as the aerodynamic drag has quadratic dependency to the vehicle speed. Also, the road slope can be an arbitrary nonlinear function of distance. Furthermore, the speed limits can have abrupt changes for some segments of the road. Accordingly, the speed limits may be non-smooth and non-differentiable functions of travel distance.

To overcome above-mentioned computational drawbacks and achieve optimal TM, charging, and eco-driving, we propose an optimization problem formulated as a hybrid dynamical system. Within the problem formulation, the dynamics in driving and charging modes are modeled with different state and control vectors, and with different functions. The driving dynamics are modeled in a spatial domain, i.e., decisions are made along the traveled distance. Also, charging dynamics are modeled in a temporal domain, i.e., decisions are made along a normalized charging time. The actual charging time is optimized together with the optimal state and control trajectories, for both charging and driving modes. Within the problem formulation, multiple intermediate (and terminal) charging possibilities are included along the route, to increase scalability and feasibility of the developed algorithm in expressing more realistic driving situations. Note that the developed algorithm is capable of addressing both cold and hot ambient operations. However, here we have focused on the impact of cold ambient temperatures on the energy efficiency and trip time, when the battery is soaked to ambient before departure.

Fig. 1. Schematic diagram of the studied electric powertrain, which consists of a battery, an EM, a transmission system, a thermal management system, and an on board charger. The thermal management system includes HVCH and HVAC, which are actively regulating the battery pack and cabin compartment temperatures. HVCH is used for heating and HVAC is used for cooling of the battery and cabin.
The rest of the paper is organized as follows. Section II addresses the overall vehicle model including longitudinal dynamics and multi-domain powertrain structure. Section III corresponds to the problem formulation in a temporal domain. Section IV proposes the hybrid dynamical system with the goal of alleviating computational drawbacks. In Section V simulation results are presented. Finally, Section VI concludes the paper and outlines the possible future research directions.

II. MODELING

In this section, the dynamics of a BEV are addressed. A multi-domain configuration of an electric powertrain is described, including powertrain components connecting via electrical, thermal, and mechanical paths.

A. Vehicle as a Lumped Mass System

According to Newton’s law of motion, the longitudinal dynamics of the vehicle are described by

\[ \dot{v}(t) = a_i(t) - a_{air}(v(t)) - a_o(s(t)), \]

where \( v \) is the vehicle’s speed, \( a_i \) is traction acceleration at the wheel side of the vehicle, and \( a_{air} \) and \( a_o \) are the accelerations associated with air drag (drag force normalized by vehicle mass), rolling resistance, and gravitational load, respectively, as

\[ a_{air}(v(t)) = \frac{\rho_a c_d A_t v^2(t)}{2m}, \]

\[ a_o(s(t)) = g \left( \frac{\sin(\alpha(s(t)))}{\cos(\alpha(s(t)))} + c_r \right), \]

where \( \rho_a \) is air density, \( c_d \) is aerodynamic drag coefficient, \( A_t \) is the vehicle’s frontal area, \( m \) is the vehicle’s total lumped mass, \( g \) is gravitational acceleration, \( c_r \) is rolling resistance coefficient, and \( \alpha \) is road gradient.

The vehicle’s travelled distance, \( s \), is given by integrating the vehicle speed:

\[ s(t) = \int v(t) \, dt \]

where \( t \) is trip time.

B. Multi-Domain Powertrain Structure

Fig. 1 depicts the schematic diagram of the studied electric powertrain. The powertrain consists of an electric machine (EM) as an actuator, a transmission system and a battery for energy supply or storage. Apart from the propulsion components the powertrain also consists of a thermal management system, and an on board charger (OBC). As demonstrated in Fig. 1, the electric power flow through an electrical path is bidirectional depending on operating mode of the EM. Thus, the battery receives energy from the EM in generating mode, or delivers energy to the EM in motoring mode. HVAC and HVCH are the components used for the thermal management of cabin compartment and battery pack, i.e., HVCH and HVAC are mainly used for heating and cooling, respectively. The OBC is a device that is employed for regulating the flow of electricity from the electrical grid to the battery, monitoring the charging rate and for protection purposes. Note that the OBC is assumed to be ideal in this paper.

1) Electrical Domain: The battery is modeled using an equivalent circuit shown in Fig. 2. The circuit includes a voltage source \( U_{oc} \) and an internal resistance \( R_{int} \), which are mainly influenced by SoC and battery temperature, respectively. The internal resistance is generally proportional to the inverse of battery temperature [6]. Thus, the internal resistance has been modeled as a monotonically nonlinear decreasing function of the battery temperature in this paper. Also, a slight mismatch between the internal resistance while charging and discharging has been neglected here. Open-circuit voltage is commonly a nonlinear monotonically increasing function of SoC, which is usually derived via offline experiments at different battery aging stages and ambient temperatures. The change of SoC, \( \Delta \text{soc}(t) \), is given by

\[ \Delta \text{soc}(t) = -\frac{P_b(t)}{C_b U_{oc}(\text{soc}(t))}, \]

where \( P_b \) is battery power including internal resistive losses, and \( C_b \) is maximum capacity of the battery. \( P_b \) is positive when discharging, and is negative while charging.

2) Thermal Domain: An energy balance is used to describe the battery pack’s thermal dynamics. Following the fundamental thermodynamic principle, a lumped-parameter thermal model describing the dynamical variations of the battery pack’s temperature is given by

\[ \dot{T}_b(t) = \frac{1}{c_T m_b} \left( Q_{\text{gen}}(t) + Q_{\text{act}}(P_{\text{hvch}}(t), P_{\text{hvac}}(t)) + Q_{\text{exh}}(T_b(t), T_{\text{amb}}(t), v(t)) \right), \]

where \( c_T \) is specific heat capacity of the battery pack, \( m_b \) is total battery mass, the symbol \( \cdot \) is a compact notation for a function of multiple variables, \( Q_{\text{gen}} \) is the rate of generated heat by sources that passively affect the battery temperature, \( Q_{\text{act}} \) is the heat rate due to components that can actively adjust the battery pack temperature, \( P_{\text{hvch}} \) and \( P_{\text{hvac}} \) are HVCH and HVAC powers, respectively, and \( Q_{\text{exh}} \) is the heat exchange rate among the battery pack, ambient air and/or the chassis of the vehicle.

The passive generated heat includes:

1) irreversible ohmic Joule heat induced by the battery internal resistive losses; and
2) heat \( Q_{\text{ed}} \) generated by electric drivetrain (ED) power losses, including the excess heat from power electronic devices and EM. For a given pair of vehicle speed and traction acceleration; the
passive generated heat rate can be written as
\[ Q_{\text{pass}}(t) = R_b(T_b(t)) \frac{P_b^2(t)}{T_{b,\text{dc}}^2(soc(t))} + Q_{\text{cd}}(v(t), a_i(t)). \] (7)

Note that the heat losses can generally originate from two types of conductive and convective heat transfers. In this paper, the uneven conductive distribution of the battery pack temperature associated with the diffusion is overlooked to avoid increasing complexity of the thermal model. Thus, the core and crust battery pack temperatures are assumed to be identical.

The active heat rate
\[ Q_{\text{act}}(P_{\text{hvch}}(t), P_{\text{hvac}}(t)) = \eta_{\text{hvch}}P_{\text{hvch}}(t) - \eta_{\text{hvac}}P_{\text{hvac}}(t) \] (8)

corresponds to the power conversion of the HVCH and HVAC systems, respectively, with the battery pack’s heating with efficiency of \( \eta_{\text{hvch}} \) and its cooling with efficiency of \( \eta_{\text{hvac}} \). Note that cabin temperature is not treated as a dynamic state, but rather as a disturbance, irrespective if there is a cooling or heating need for the cabin.

The convective heat exchange rate between the battery pack and ambient air is modeled as
\[ Q_{\text{exh}}(T_b(t), t) = \gamma(v(t))(T_{\text{amb}}(t) - T_b(t)), \] (9)

where \( T_{\text{amb}} \) is ambient temperature, and \( \gamma \) is a speed dependent function representing parasitic heat transfer between the battery and the ambient air, i.e., if the battery temperature is higher than the ambient temperature, heat is conveyed from the battery to the ambient air.

3) Mechanical Domain: The EM when operated in motoring mode, provides propulsive power, which is delivered via the transmission system to the wheels through a mechanical path, see Fig. 1. To do so, the EM torque and rotational speed are translated by the transmission system to traction acceleration and vehicle speed, respectively. Speed dependent bounds on EM torque are translated as limits on traction acceleration via
\[ a_i(t) \in [a_{\text{min}}(v(t)), a_{\text{max}}(v(t))]. \] (10)

III. PROBLEM STATEMENT

Consider a BEV driving in a hilly terrain, as in Fig. 3. The trip starts from point A with a cold initial battery temperature and a fully-charged battery, where the ambient temperature is also low during the vehicle’s trip. As the vehicle continues its drive, the battery depletes and its temperature may increase due to the passive and/or active heating sources. The vehicle’s travelled distance is greater than its range and intermediate (and terminal charging) possibilities have to be considered along the driving route.

A. Bounds on Vehicle Speed, Battery Power and Grid Power

Using available information about the road and traffic situation, the vehicle speed limits are defined as
\[ v(t) \in \begin{cases} \left[t_{\text{in}}(s(t)), t_{\text{out}}(s(t))\right], & t \in T_{\text{drv}} \\ \{0\}, & t \in T_{\text{chg}} \end{cases} \] (11)

where \( 0 < v_{\text{min}} \leq v_{\text{max}} \), \( T_{\text{drv}} \) and \( T_{\text{chg}} \) denote the sets of driving and charging time instants, respectively, \( i \in I = \{1, 2, \ldots, N_{\text{chg}}\} \) is charger index, and \( N_{\text{chg}} \) is total number of charging stations along the route.

The speed limits include legal and dynamic speed limits that resemble realistic driving situations. New modern technologies, e.g., e-horizon systems, can provide the information about legal and dynamic speed limits and the road slope [49]. The dynamic speed limits are enforced due to presence of e.g., intersections, ramps, junctions and traffic lights. The legal speed limits may have abrupt changes for different segments of the driving road, where such variations can lead to computational issues that are discussed later in this section and in Section IV. Note that the vehicle speed is equal to zero when the vehicle stops at the charging station.

For a given pair of battery temperature and SoC, the battery power limits corresponding to driving and charging modes for \( i \in I \) are given by
\[ P_b(t) \in \begin{cases} \left[P_{\text{min}}(\text{soc}(t), T_b(t))\right], & t \in T_{\text{drv}} \\ \left[P_{\text{max}}(\text{soc}(t), T_b(t)), 0\right], & t \in T_{\text{chg}} \end{cases} \] (12)

where \( P_{\text{max}} > 0 \) and \( P_{\text{min}} < 0 \) are the battery discharge and charge power limits, respectively. It can be deduced from (12) that the battery power during driving can also be negative due to
regenerative braking, referred to as a mechanism that transforms the vehicle’s kinetic energy into electrical energy to be stored in the battery. Note that the charging power limit may differ in driving and charging modes. Here, we assume that the same bound is applied, for simplicity, and without loss of generality.

Normalized absolute values of the battery discharge and charge power limits versus battery temperature and SoC are illustrated in Fig. 4(a) and (b), respectively. These figures are derived from a vehicle original equipment manufacturer (OEM) data to form a representative but generic data set describing the battery power for a given pair of the battery temperature and SoC. As shown in Fig. 4(a), the battery discharge power limit is proportional to the battery temperature and SoC level, also, the charge power limit is proportional to the battery temperature and inverse of SoC level, according to Fig. 4(b). For the studied battery, the desirable SoC range for the discharge and charge power limits are about 25%–100% and 0%–60%, respectively. Also, the battery temperature window for attaining high power availability is about 25°C–45°C, when both charging and discharging. Thus, for a cold battery it is generally favourable to perform battery pre-conditioning, referred to as heating up a cold battery prior to charging in order to charge the battery with a high power, thereby reducing the charging time.

The power $P_{\text{grid}}^i(t)$ provided by the $i$th charger is limited by

$$P_{\text{grid}}^i(t) \in \begin{cases} \{0\}, & t \in T_{\text{drv}}^i, \\ \left[0, P_{\text{grid}}^{i,\max}\right], & t \in T_{\text{chg}}^i \end{cases}$$

where $P_{\text{grid}}^{i,\max}$ is rated power of the $i$th charger. It is here assumed that grid charging power is not supplied to the vehicle during the driving mode, although the method presented later can directly be applied to the vehicles driving on an electric road, e.g., when charging lanes are installed on the road [50].

### B. Objective Function

In order to achieve an optimal compromise between trip time and charging cost, an optimization problem is formulated with the performance function $J$, as

$$J(\cdot) = \sum_{i=1}^{N_{\text{chg}}} \left( \int_{t \in T_{\text{chg}}} c_e^i P_{\text{grid}}^i(t) dt + c_T^i \max \left(0, t_{\text{chg}}^i - t_{\text{occ}}^i \right) \right) + \int_{t \in T} c_{t,\text{trip}} dt,$$

where the charging cost can be expressed as energy and/or time, depending on the pricing plan of each charging station. Thus, $J$ includes:

- Electrical energy supplied to the vehicle by chargers, as
  $$\sum_{i=1}^{N_{\text{chg}}} \int_{t \in T_{\text{chg}}} c_e^i P_{\text{grid}}^i(t) dt,$$

where $c_e$ is currency per-kilowatt-hour charging electrical energy cost.

- The time based cost for occupying the charging spot, as
  $$\sum_{i=1}^{N_{\text{chg}}} c_{t,\text{occ}}^i \max \left(0, t_{\text{chg}}^i - t_{\text{occ}}^i \right),$$

where $c_{t,\text{occ}}$ is currency per-minute cost due to occupying the charger for longer time than $t_{\text{occ}} \geq 0$, and $t_{\text{chg}}$ is a scalar variable representing charging time.

- A penalty on total trip time, as
  $$\int_{t \in T} c_{t,\text{trip}} dt,$$

where $c_{t,\text{trip}}$ is the penalty factor and $T = \bigcup_{i \in I} T_{\text{chg}}^i \cup T_{\text{drv}}$. Note that the trip time includes the charging time; thus, charging time may need to be paid twice, due to a longer trip and/or occupying the charger.

### C. Optimization Problem With Respect to Trip Time

For $i \in I$, the optimization problem can now be summarised, as

$$\min_{P_{\text{dis}}^i, P_{\text{brk}}^i, P_{\text{grid}}^i, t_{\text{chg}}^i} J(\cdot)$$

**(18a)**
subject to: (11)–(13) and
\[
\dot{T}_b(t) = \frac{1}{c_p m_b} (Q^\text{gen}(t) + Q^\text{act}(P^\text{b}(v(t)), P^\text{vac}(v(t))) + Q^\text{exh}(T_b(t), T^\text{amb}(t), v(t))), \quad t \in T
\]
(18b)
\[
\dot{\text{soc}}(t) = \frac{P_b(t)}{C_b V^\text{soc}(\text{soc}(t))}, \quad t \in T
\]
(18c)
\[
\dot{s}(t) = v(t), \quad t \in T^\text{drv}
\]
(18d)
\[
\dot{v}(t) = a_1(t) - a_\text{aux}(v(t)) - a_\alpha(s(t)), \quad t \in T^\text{drv}
\]
(18e)
\[
P^\text{grid}(t) + P^\text{b}(t) = R(T_b(t)) \frac{P^2_b(t)}{U^2_b(\text{soc}(t))} + P^\text{prop}(v(t), a_\alpha(t)) + P^\text{hvac}(t) + P^\text{hvhc}(t) + P^\text{aux}(t), \quad t \in T
\]
(18f)
\[
s(t) = s^\text{chg}, \quad t \in T^\text{chg}
\]
(18g)
\[
T_b(t) \in [T^\text{min}_b(t), T^\text{max}_b(t)], \quad t \in T
\]
(18h)
\[
\text{soc}(t) \in [\text{soc}^\text{min}(t), \text{soc}^\text{max}(t)], \quad t \in T
\]
(18i)
\[
P^\text{hvhc}(t) \in [0, P^\text{max}_\text{hvhc} - P^\text{min}_\text{hvhc}(t)], \quad t \in T
\]
(18j)
\[
P^\text{hvac}(t) \in [0, P^\text{max}_\text{hvac}], \quad t \in T
\]
(18k)
\[
a_\alpha(t) \in [a^\text{min}(v(t)), a^\text{max}(v(t))], \quad t \in T^\text{drv}
\]
(18l)
\[
t^\text{chg} \in [0, t^\text{max}_\text{chg}]
\]
(18m)
\[
T_b(0) = T^\text{bo}, \quad \text{soc}(0) = \text{soc}_0, \quad s(0) = s_0, \quad v(0) = v_0
\]
(18n)
\[
T_b(t_i) \geq T^\text{bf}, \quad \text{soc}(t_i) \geq \text{soc}_i, \quad s(t_i) = s_t
\]
(18o)

where $T^\text{bo}$ and $T^\text{bf}$ are initial and final battery temperatures, respectively, $\text{soc}_0$ and $\text{soc}_i$ are initial and final SoC values, respectively, $s_0$ and $s_t$ are initial and final travel distances, respectively, $v_0$ is initial vehicle speed, $P^\text{prop}$ is propulsion power including the internal losses of the powertrain for a given pair of vehicle speed and traction acceleration, $P^\text{aux}$ is given auxiliary load demand, $T^\text{min}_b$ and $T^\text{max}_b$ are the bounds on battery temperature, $\text{soc}^\text{min}$ and $\text{soc}^\text{max}$ are SoC limits, $P^\text{max}_\text{hvhc}$ and $P^\text{max}_\text{hvac}$ are the maximum deliverable HVCH and HVAC power values, respectively, $s^\text{chg}$ is the charging position that is known prior to starting the vehicle’s driving mission, $t^\text{chg}$ is the maximum allowed charging time, and $P^\text{c}_\text{hvhc}$ is the HVCH power demand for heating the cabin compartment. Note that the $P^\text{c}_\text{hvhc}$ is assumed to be a function of the known ambient temperature.

The full problem (18), including the formulations of both driving and charging modes with respect to $t$ is difficult to solve due to the following reasons:

- The sets including charging mode and driving mode time instants, $T^\text{chg}$ and $T^\text{drv}$, respectively, are unknown prior to the optimization. Thus, imposing the right dynamics/values/bounds in (18) may require introducing integer variables, which would make the problem intractable.
- The vehicle longitudinal dynamics (1) are nonlinear with respect to $t$, as the aerodynamic drag is quadratically dependent on vehicle speed in (2), the road gradient can be any arbitrary nonlinear function of $t$ in (3), and the speed limits (11) may also be non-smooth functions of $s$, i.e., the speed limits can generally change abruptly for different positions are given. Subsequently, driving and charging distance instances are known prior to optimization.
- Charging mode: Despite fixed position of the vehicle at the charging station, battery temperature and SoC will change during charging. Thus, the battery temperature and SoC dynamics cannot be described with respect to $s$ for the charging mode. Instead, the decisions are planned with respect to a variable $\tau^i \in [0, 1]$, defined, as

\[
\tau^i = \frac{t}{t^\text{chg}}, \quad t \in T^\text{chg}, \quad i \in I.
\]

Thus, the aerodynamic drag (2) becomes a linear function of unit mass kinetic energy. Note that the decision making in the spatial coordinate is promising, since the charging positions are given. Subsequently, the decisions are planned with respect to $\tau^i$ as

\[
E(s) = \frac{v^2(s)}{2}.
\]
Following this selection of independent variables, problem (18) is transformed into a hybrid dynamical system, see Fig. 5. Note that state variables, control inputs and governing dynamics describing each mode may differ with those from the other mode, which will be explained later in this Section. By repeating the combination of driving and charging modes, it is possible to investigate multiple charging scenarios along the vehicle’s trip. Hereafter, the variables with subscripts or superscripts ‘drv’ or ‘chg,’ are the previously introduced variables that now belong specifically to the driving mode or charging mode, respectively.

A. Driving Mode: Dynamics and Performance Function

Governing dynamics during driving mode include the vehicle’s longitudinal dynamics, and the dynamical variations of battery temperature and SoC. To group the state variables and control inputs belonging to driving mode, it is possible to introduce state and control vectors, respectively $x_{\text{drv}}$ and $u_{\text{drv}}$, with respect to $s$, as

$$x_{\text{drv}}(s) = \begin{bmatrix} E(s) \\ \text{soc}^{\text{drv}}(s) \\ T_b^{\text{drv}}(s) \end{bmatrix}, \quad u_{\text{drv}}(s) = \begin{bmatrix} P_{b,\text{drv}}(s) \\ P_{\text{hvc}}(s) \\ \alpha_i(s) \end{bmatrix}.$$  

Accordingly, the relation between the time and space derivatives is given as

$$\frac{dx_{\text{drv}}(t)}{dt} = v(s)\frac{dx_{\text{drv}}(s)}{ds}, \quad t \in T_{\text{drv}}, s \in S_{\text{drv}},$$  

where $S_{\text{drv}}$ is a set including driving distance instances.

Following (21), the longitudinal dynamics (1) are now described in the space coordinate $s$, as

$$\frac{dE(s)}{ds} = a_i(s) - c_a E(s) - a_c(s),$$  

where $\frac{dv}{dt} = v \frac{dx}{ds}$ represents longitudinal acceleration in $s$ domain, and the coefficient $c_a = \rho_c c_A s_i/m$ contains the air drag related factors.

Using the relations (19) and (21), the dynamical change of battery SoC with respect to $s$ is given by

$$\frac{d\text{soc}^{\text{drv}}(s)}{ds} = -\frac{P_{b,\text{drv}}(s)}{C_{b}U_{oc}(\text{soc}^{\text{drv}}(s))}\sqrt{2E(s)}.$$  

Similarly, the position dependent dynamical change of the battery pack temperature is given by

$$\frac{dT_b^{\text{drv}}(s)}{ds} = \frac{1}{c_p m_b \sqrt{2E(s)}} \left( Q_{\text{pass}}(s) + Q_{\text{act}}(P_{b,\text{hvc}}^{\text{drv}}(s), P_{b,\text{drv}}^{\text{drv}}(s)) \right) + Q_{\text{exh}}(T_b^{\text{drv}}(s), T_{\text{amb}}(s), v(s)).$$  

The power balance (18f) can also be summarized throughout the driving mode, as

$$P_{b,\text{drv}}^{\text{drv}}(s) = R(T_b^{\text{drv}}(s))\left(\frac{P_{b,\text{hvc}}^{\text{drv}}(s)}{U_{oc}^{\text{soc}^{\text{drv}}(s)}} + 2P_{\text{prop}}^{\text{prop}}(v(s), a_i(s)) \right) + P_{b,\text{hvc}}^{\text{drv}}(s) + P_{\text{hvc}}^{\text{drv}}(s) + P_{\text{aux}}^{\text{drv}}(s).$$

The governing dynamics during driving mode can be summarized as

$$\frac{dx_{\text{drv}}(s)}{ds} = f_{\text{drv}}(x_{\text{drv}}(s), u_{\text{drv}}(s), s),$$

where $f_{\text{drv}}$ is a vector function including nonlinear scalar functions illustrating each state variable’s dynamical change, according to (22)–(24). We also define a vector $x_{\text{drv}}^{\text{ts}}$, as

$$x_{\text{drv}}^{\text{ts}}(s) = \begin{bmatrix} \text{soc}^{\text{drv}}(s) \\ T_b^{\text{drv}}(s) \end{bmatrix},$$

which will be used later for describing the transition between the modes.

The performance function during driving mode includes the penalty on trip time, as

$$J_{\text{drv}}(\cdot) = \int_{s \in S_{\text{drv}}} \frac{c_{\text{trip}}}{\sqrt{2E(s)}} \, ds,$$  

which is directly obtained from the trip time to travel distance transformation, i.e., $c_{\text{trip}}, \text{d}t = c_{\text{trip}}/\sqrt{2E(s)} \, s$. The set $S_{\text{drv}}$ includes the driving distance instances.

B. Charging Mode: Dynamics and Performance Function

The governing dynamics during charging mode corresponds to the dynamical changes of battery temperature and SoC. The state variables and control inputs of charging mode for $i \in I$ are stacked, respectively, in vectors $x_{\text{chg}}^i$ and $u_{\text{chg}}^i$, as

$$x_{\text{chg}}^i(t) = \begin{bmatrix} \text{soc}^{\text{chg}}_i(t) \\ T_b^{\text{chg}}_i(t) \end{bmatrix}, \quad u_{\text{chg}}^i(t) = \begin{bmatrix} P_{b,hvc}^{\text{chg}}(t) \\ P_{b,\text{hvc}}^{\text{chg}}(t) \\ P_{\text{grid}}(t) \end{bmatrix}, \quad i \in I.$$

Also, the charging time associated with each charging station is considered as a scalar variable, which is optimized simultaneously with the optimal state and control trajectories of both driving and charging modes. According to (5) and (20), the relation between the time derivative and the derivative with respect to $t^i$ for $i \in I, t \in \tau^i$, is

$$\frac{dx_{\text{chg}}^i(t)}{dt} = \frac{1}{t_{\text{chg}}^i} \frac{dx_{\text{chg}}^i(t)}{dr^i}, \quad t \in \tau_{\text{chg}}, s(t) = s_{\text{chg}}.$$

Following (27), the dynamical variation of battery SoC with respect to $t^i$ for $i \in I$ is given by

$$\frac{d\text{soc}^{\text{chg}}_i(t^i)}{dt^i} = -\frac{t_{\text{chg}}^i}{C_{b}U_{oc}(\text{soc}^{\text{chg}}_i(t^i))}.$$  

Similarly, the $t^i$ dependent dynamical change of the battery pack temperature for $i \in I$ is given by

$$\frac{dT_{b}^{\text{chg}}(t^i)}{dt^i} = \frac{t_{\text{chg}}^i}{c_p m_b} \left( Q_{\text{pass}}(t^i) + Q_{\text{act}}(P_{b,hvc}^{\text{chg}}(t^i), P_{b,\text{hvc}}^{\text{chg}}(t^i)) \right) + Q_{\text{exh}}(T_{b}^{\text{chg}}(t^i), T_{\text{amb}}(t^i)),$$  

using (5) and (20).
For $i \in I$, the power balance (18f) during the charging modes is

\[
P^i_{\text{grid}}(\tau^i) + P^i_{\text{b,chg}}(\tau^i) = R(T^i_{\text{b,chg}}(\tau^i)) \left( \frac{P^i_{\text{b,chg}}(\tau^i)^2}{U^i_{\text{ SOC}}(\text{SOC}_{\text{chg}}(\tau^i))} \right) + P^i_{\text{hvac}}(\tau^i) + P^i_{\text{aux}}(\tau^i).
\]

(30)

Note that propulsion power is equal to zero during charging in (30). Also, the power demand for heating the cabin compartment during charging is assumed to be zero in (30), without loss of generality in the formulated problem later in IV-C. Such assumption is reasonable for the case when the driver/passengers stay outside the vehicle during charging.

The governing dynamics during charging mode for $i \in I$ can be summarized as

\[
\frac{dx^i_{\text{chg}}(\tau^i)}{dt^i} = f_{\text{chg}}(x^i_{\text{chg}}(\tau^i), u^i_{\text{chg}}(\tau^i), t^i_{\text{chg}}, \tau^i),
\]

where $f_{\text{chg}}$ is a vector function including nonlinear scalar functions describing each state variable’s dynamical variation, according to (28) and (29).

The performance function associated with charging mode for $i \in I$ is the compromise among charging energy cost, charging time and charger occupying time cost, as

\[
J_{\text{chg}}(\cdot) = \sum_{i=1}^{N_{\text{chg}}} \left( t^i_{\text{chg}} \int_0^{t^i_{\text{chg}}} \left( c_{\text{t,chg}} + c^i_{\text{e,chg}} P^i_{\text{grid}}(\tau^i) \right) d\tau^i 
+ c^i_{\text{occ}} \max \left( 0, t^i_{\text{chg}} - t^i_{\text{occ}} \right) \right) .
\]

(31)

C. Hybrid Dynamical System Formulation

The hybrid dynamical system’s formulation for $i \in I$, can now be summarized as

\[
\min_{u^{\text{drv}}(s), u^{\text{chg}}(\tau^i), t^{i}_{\text{chg}}} J_{\text{drv}}(\cdot) + J_{\text{chg}}(\cdot)
\]

for $\tau^i \in [0, 1]$ subject to:

\[
\frac{dx^{\text{drv}}(s)}{ds} = f_{\text{drv}}(x^{\text{drv}}(s), u^{\text{drv}}(s), s), \quad s \in S_{\text{drv}}
\]

(32b)

\[
\frac{dx^{i}_{\text{chg}}(\tau^i)}{d\tau^i} = f_{\text{chg}}(x^i_{\text{chg}}(\tau^i), u^i_{\text{chg}}(\tau^i), \tau^i), \quad s \in s^i_{\text{chg}}
\]

(32c)

\[
g_{\text{drv}}(x^{\text{drv}}(s), u^{\text{drv}}(s), s) \leq 0, \quad s \in S_{\text{drv}}
\]

(32d)

\[
g_{\text{chg}}(x^i_{\text{chg}}(\tau^i), u^i_{\text{chg}}(\tau^i), \tau^i) \leq 0, \quad s \in s^i_{\text{chg}}
\]

(32e)

\[
x^{i}_{\text{drv}}(s) \in X^{i}_{\text{drv}}(s), \quad u^{i}_{\text{drv}}(s) \in U^{i}_{\text{drv}}(s), \quad s \in S_{\text{drv}}
\]

(32f)

\[
x^{i}_{\text{chg}}(\tau^i) \in X^{i}_{\text{chg}}(\tau^i), \quad u^{i}_{\text{chg}}(\tau^i) \in U^{i}_{\text{chg}}(\tau^i), \quad s \in s^i_{\text{chg}}
\]

(32g)

\[
t^{i}_{\text{chg}} \in [0, t^{i}_{\text{chg}}]
\]

(32h)

\[
x^{i}_{\text{chg}}(0) = x^{i}_{\text{chg}}(s^i_{\text{chg}})
\]

(32i)

\[
x^{i}_{\text{drv}}(s^i_{\text{chg}}) = x^{i}_{\text{chg}}(1)
\]

(32j)

\[
x^{\text{drv}}(s_0) \in X^{\text{drv}}, \quad x^{\text{drv}}(s_1) \in X^{\text{drv}}
\]

(32k)

where $t^{i}_{\text{chg}}$ is treated as a design parameter, $s^i_{\text{chg}}$ is an instance where the vehicle is leaving the charging station, $t^{i}_{\text{chg}}_{\text{max}}$ is maximum allowed charging time, $g_{\text{drv}}$ and $g_{\text{chg}}$ denote the system general constraints, respectively during driving and charging modes, including the bounds on battery power and traction acceleration, as

\[
g_{\text{drv}}(\cdot) = \left\{ \begin{array}{l}
P^\text{min}_{\text{b,chg}}(\text{SOC}_{\text{drv}}(s), T^\text{drv}_{\text{b}}(s)) - P^\text{drv}_{\text{b}}(s), \\
\bar{P}^\text{drv}_{\text{b}}(s) - P^\text{max}_{\text{b,chg}}(\text{SOC}_{\text{drv}}(s), T^\text{drv}_{\text{b}}(s)), \end{array} \right. \]

(33a)

\[
g_{\text{chg}}(\cdot) = \left\{ \begin{array}{l}
P^\text{min}_{\text{b,chg}}(\text{SOC}_{\text{chg}}(\tau^i), T^\text{chg}_{\text{b}}(\tau^i)) - P^\text{chg}_{\text{b}}(\tau^i), \\
\bar{P}^\text{chg}_{\text{b}}(\tau^i) - P^\text{max}_{\text{b,chg}}(\text{SOC}_{\text{chg}}(\tau^i), T^\text{chg}_{\text{b}}(\tau^i)), \end{array} \right. \]

(33b)

Also, $X_{\text{drv}}$ and $X_{\text{chg}}$ denote the feasible sets of state variables, and $U_{\text{drv}}$ and $U_{\text{chg}}$ represent the feasible sets of control inputs for each mode. Furthermore, $X_{\text{drv}}^{i_0}$ and $X_{\text{chg}}^{i_0}$ denoted allowed initial states at $s_0$, and target states at $s_T$, respectively. The constraints (32i) and (32j) denote the transition between the modes. Thus, the battery temperature and SoC at the arrival of charging station must be equal to the corresponding variables when charging begins. Similarly, the battery temperature and SoC when charging is just finished must be equal to the corresponding variables when the vehicle resumes its drive.

V. RESULTS

In this section, we evaluate the performance of the proposed algorithm via simulation. The simulation setup is given in Section V-A.

A. Simulation Setup

The simulations are performed for a BEV over a 440 km long road with a hilly terrain. The BEV starts its mission with 80% SoC and cold battery, where ambient temperature is also low during the vehicle’s entire mission, i.e., $T_{\text{amb}}(s) = -10 \degree \text{C}, s \in [s_0, s_T]$. Followed by the constant ambient temperature, the HVCH power demand for heating the cabin compartment during the vehicle’s driving mode is also a fixed value. As the driving distance is greater than the vehicle’s electric range, one intermediate charging station is visited at $s = 240 \text{ km}$, and a terminal charging station is also considered at the end of the route. The terminal battery SoC is set to be the same percentage as the initial SoC, i.e., 80%. Also, the rated grid power provided by the chargers as well as the rated battery charging power are 150 kW. Note that the time based cost for occupying the charging spot is not considered in the studied scenario, i.e., $c_{\text{occ}} = 0$. The vehicle and simulation parameters are provided in Table I.

The NLP (32) is discretized using the Runge-Kutta 4th order method [51], with a distance sampling interval of 2 km. Subsequently, the discretized problem is solved in Matlab with the solver IPOPT, using the open source nonlinear optimization tool CasADi [52]. IPOPT is an open-source tool used for solving large-scale NLPs, by implementing an interior-point algorithm for continuous, nonlinear, nonconvex, constrained optimization problems [53]. The optimization was run on a laptop PC with 6600 K CPU at 2.81 GHz and 16 GB RAM, where the solving time is less than a minute.
TABLE I  
VEHICLE AND SIMULATION PARAMETERS

| Parameter                                      | Value |
|-----------------------------------------------|-------|
| Gravitational acceleration                   | $g = 9.81 \text{ m/s}^2$ |
| Air density                                   | $\rho_a = 1.29 \text{ kg/m}^3$ |
| Vehicle frontal area                          | $A_f = 1.36 \text{ m}^2$ |
| Rolling resistance coefficient                | $c_r = 0.013$ |
| Total vehicle mass                            | $m = 2200 \text{ kg}$ |
| Aerodynamic drag coefficient                  | $c_d = 0.6$ |
| Maximum battery capacity                      | $C_p = 200 \text{ Ah}$ |
| Specific heat capacity and battery mass product | $s_p m_b = 375 \text{ kJ/(K)}$ |
| Route length                                  | 480 km |
| Distance sampling interval                    | 2 km |
| Number of charging along the route            | $N_{ch} = 2$ |
| Electrical energy cost while charging         | $c_e = 5\text{ SEK/kWh}$ |
| EM max power                                  | 350 kW |
| Max. battery power (discharging)              | $P_{b,max} = 350 \text{ kW}$ |
| Min. battery power (charging)                 | $P_{b,min} = -150 \text{ kW}$ |
| Charger rated power                           | $P_{grid} = 150 \text{ kW}$ |
| Auxiliary load                                | $P_{aux} = 0.5 \text{ kW}$ |
| HVCH power for heating cabin                  | $P_{heating} = 1.5 \text{ kW}$ |
| HVCH power to heat rate efficiency            | $\eta_{HVCH} = 87\%$ |
| HVAC power to heat rate efficiency            | $\eta_{HVAC} = 87\%$ |
| Initial battery temperature                   | $T_{b,ini} = -10^\circ \text{C}$ |
| Ambient temperature                           | $T_{amb} = -10^\circ \text{C}$ |
| Initial battery state of charge               | $soc_{ini} = 80\%$ |
| Terminal battery state of charge              | $soc_{term} = 80\%$ |
| Minimum speed limit                           | $v_{min} = 65 \text{ km/h}$ |
| Maximum speed limit                           | $v_{max} = 110 \text{ km/h}$ |

Fig. 6. Pareto frontier describing the trade-off between total charging energy cost versus trip time.

### B. Energy Efficiency Versus Time

To investigate the trade-off between total charging energy cost versus trip time, the Pareto frontier is derived, as shown in Fig. 6, where the total charging cost includes the electrical energy cost during the intermediate and terminal charging modes. Also, the trip time covers both the driving and charging times. The driving time variations can be characterised as changing the vehicle’s average speed. The demonstrated Pareto frontier provides a wide range of choices for various types of car users to customise their trip. In Fig. 6, point A denotes the vehicle’s most energy efficient trip, where $c_{t,trip} = 0$. The trip time can be increased further by letting $c_{t,trip}$ be negative, where this leads to an increase in the energy cost. Thus, there is a low average speed $v_{avg}$ threshold, here about $v_{avg} \approx 70 \text{ km/h}$, below which the increased time of accumulating auxiliary loads prevails the benefit of reduced air drag. Point B in Fig. 6 corresponds to the trade-off between trip time and energy, where $v_{avg} = 100 \text{ km/h}$.

In the remainder of the paper, we will only consider the vehicle’s operation in point B. In this point, Case 1, i.e., with active heating/cooling, is compared to Case 2, i.e., without active heating/cooling, to evaluate the impact of battery pre-conditioning on the charging time and energy cost. Battery pre-conditioning is characterized as bringing the battery temperature to (or closer to) its desired range, where discharging/charging power availability is increased considerably.

### C. Case 1: Time Efficient Trip With Active Heating/Cooling

Here, the results are categorized into the optimal trajectories versus travelled distance, and versus charging time during the intermediate and terminal charging events. Total charging cost and trip time are given in Table II.

#### 1) Optimal Trajectories Versus Travelled Distance: Optimal vehicle speed profile together with the speed limits and road topography are depicted in Fig. 7(a), where the zero speed values at travel distances $s = 240 \text{ km}$ and $s = 440 \text{ km}$ indicates the vehicle stops at the charging stations. The battery depletes gradually as the vehicle continues its drive, where at the arrival of the charging stations at $s = 240 \text{ km}$ and $s = 440 \text{ km}$, the SoC levels are about $20\%$ and $15\%$, respectively as demonstrated in Fig. 7(b). The battery temperature increases primarily due to only the passive heat generation resources, i.e., Joule heat and ED losses, from $s = 0 \text{ km}$ to $s = 205 \text{ km}$, according to Fig. 7(c). Later, the HVCH, jointly with the passive heat resources, further raise the battery temperature (from $s = 205 \text{ km}$ to $s = 240 \text{ km}$, and from $s = 435 \text{ km}$ to $s = 440 \text{ km}$). Such battery temperature increase by the HVCH demonstrates the battery pre-conditioning. As shown in Fig. 4(b), the charging battery power availability is high for low SoC and high battery temperature region. This leads to a reduced charging time, but higher charging cost instead. Note that the decreasing battery temperature from $s = 240 \text{ km}$ to $s = 435 \text{ km}$ is due to an increased heat transfer to the ambient air, as the temperature difference between the battery pack and ambient air is large for this distance segment. In the intermediate and terminal charging stations, the battery is charged to $63\%$ and $80\%$ SoC levels, respectively. The propulsion power, battery discharge power and its limit are shown in Fig. 7(e). The battery discharge power limit has a step increase at $s = 240 \text{ km}$ due to the steep rise in SoC and battery temperature region due to charging.

#### 2) Intermediate Charging: During the intermediate charging, in addition to the SoC level increase, the battery temperature also rises steadily, as shown in Fig. 8(a) and (b). The SoC level throughout the intermediate charging is always in a range with high charging power availability. Also, HVCH stays on for about

| Case | Trip Time (Total Chg. Time) [min] | Chg. Cost (SEK) |
|------|----------------------------------|---------------|
| Case 1 | 294 (37) | 453 |
| Case 2 | 323 (66) | 444 |
Fig. 7. Case 1; optimal trajectories versus travelled distance. The step changes in battery temperature and SoC at $s = 240$ km and $s = 440$ km in (a) and (b), denote the increase in the corresponding variables during charging mode. (a) Road topography together with vehicle speed profile and speed limits. (b) Battery state of charge trajectory together with its bounds. (c) Battery temperature trajectory together with its upper bound and ambient temperature. (d) Trajectories of HVCH and HV AC power for battery heating. (e) Trajectory of optimal battery power together with its limits (normalized with the maximum battery discharge power).

2.5 min from the beginning of charging, in order to further raise the battery temperature above 20°C. This allows charging with high power and for a short time period, which is about 15 min here. Fig. 8(d) illustrates a 3D plot including grid power as well as the absolute values of battery charging power and its limit versus SoC and battery temperature values. The difference between the grid power and battery power is due to the Joule heat losses and the HVCH power demand for heating the battery pack.

3) Terminal Charging: The battery SoC and temperature during terminal charging at $s = 440$ km, have similar behaviours as they had during the intermediate charging. In the beginning of charging, initial battery SoC and temperature, respectively, are about 15\% and 17°C. HVCH stays on for about a minute from the beginning of charging, and the battery temperature rises up to about 20°C accordingly. Fig. 9(d) shows a 3D plot including grid power together with the absolute values of battery charging power and its limit for a given combination of SoC and battery temperature. As expected, the charging power availability drops for high SoC values. The charging time is about 22 min.
D. Case 2: Time Efficient Trip Without Active Heating/Cooling

Similar to Section V-C, the simulation results are summarized into the distance based and time based trajectories. Here, the HVCH and HVAC are not used, respectively for the battery heating and cooling throughout the vehicle’s entire trip.

1) Optimal Trajectories Versus Travelled Distance: Optimal vehicle speed profile as well as the speed limits and road topography are depicted in Fig. 10(a). The battery depletion profile, shown in Fig. 10(b), follows a similar trend as the one in Case 1, since in both cases in addition to the identical simulation parameters and the driving behaviour are similar, i.e., $v_{avg} = 100$ km/h. The SoC levels at the arrival of the charging stations at $s = 240$ km and $s = 440$ km, are respectively about 17\% and 15\%, as depicted in Fig. 10(c). The battery temperature increase is simply due to Joule heat and ED losses, according to Fig. 10(c), where at the arrival of the intermediate and terminal charging stations, the battery temperature is 0 \(^\circ\)C and 5 \(^\circ\)C, respectively. These battery temperature values are lower compared to Case 1, as no active heating is applied in Case 2. In the intermediate and terminal charging stations, the battery is charged to about 60\% and 80\% SoC levels, respectively. The propulsion power together with the battery discharge power and its limit are shown in Fig. 10(d), where the limit is generally lower compared to the one in Case 1, due to the battery’s operation in the lower temperature region.

2) Intermediate and Terminal Charging: During both intermediate and terminal charging periods, the battery temperature
and SoC increase monotonically, as demonstrated in Fig. 11(a) and (b), and Fig. 12(a) and (b), respectively. Also, the grid power together with the absolute values of battery charging power and its limit versus battery temperature and SoC, are shown in Figs. 11(c) and 12(c), respectively for the intermediate and terminal charging modes. The charging power availability for Case 2 is lower compared to Case 1, which leads to a higher charging time. According to the results reported in Table II, total charging time for Case 2 is 66 min, which is increased by 44\% compared to the Case 1 with optimal battery pre-conditioning. Instead, the charging cost is simply reduced by 2\%.

VI. DISCUSSION, CONCLUSION, AND FUTURE WORK

In this paper, optimal TM, charging, and eco-driving problems are jointly solved for a BEV over a long-distance trip. To do so, an optimization problem in the form of a hybrid dynamical system is formulated, in which the objective function includes total trip time (including driving and charging times) and charging cost. The propose an algorithm that is capable of addressing both cold and hot ambient operations, as in the TM system the components for both heating and cooling of the battery/cabin are incorporated. However, in this paper we have focused on cold ambient operation, as the limited battery power affects the optimal solution in terms of energy efficiency and charging time. The vehicle’s drivability in terms of maximum acceleration capability is another factor that is limited in the cold ambient operation. To enhance the drivability, the battery can be pre-heated before the vehicle’s departure, using the electrical grid power, as this may reduce the Joule heat losses throughout the trip and the need for pre-conditioning before fast charging. However, the disadvantage is the leakage of thermal energy to the ambient. Furthermore, it is often assumed in literature that the departure time is known when pre-heating is performed before departure. This will not always be the case, as not all car users plan far ahead. In general, pre-heating before departure may be more beneficial only if it yields skipping the charging occasion along the route, by less need for battery pre-conditioning and lower Joule heat losses.

The performance of the proposed algorithm is evaluated for a vehicle driving on a route, along which two charging possibilities are considered. To study the trade-off between trip time and charging energy cost, the Pareto frontier is derived for different driving scenarios of the vehicle. According to the results, trip time is reduced by 44\%, in case the optimal battery pre-conditioning is applied to the vehicle. Low charging time, high charging power availability, and the preservation of the vehicle’s potential range are the knock-on effects of the battery pre-conditioning.

The proposed algorithm for eco-driving and TM of BEVs can also be extended in several ways, such as:

1) A heat pump can be incorporated in the TM system to include heating/cooling the battery. In case of the battery cooling, the excess heat from the battery can be transferred to the cabin compartment and/or ambient air. Also, heat pumps are able to transfer the heat from ambient air to the cabin.
2) It is possible to optimally select the charging stops, in a way to achieve optimality in time, energy, or their trade-off.

3) An online-implementable algorithm can be developed based on the current algorithm that is capable of reacting to potential disturbances, considering model-plant mismatches, and anticipating future events.

4) Performance of the control actions provided by the developed algorithm can be verified, using a more detailed thermal model.

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Ahad Hamednia received the B.Sc. degree in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2012, and the M.Sc. degree in control engineering and industrial automation from Tarbiat Modares University, Tehran, Iran, in 2016, and the Ph.D. degree with the Mechatronics Group, Department of Electrical Engineering, Chalmers University of Technology, Göteborg, Sweden, in 2021. He is currently with the Department of Vehicle Energy and Motion Control, Volvo Car Corporation, Gothenburg, Sweden. His main research interests include modeling, simulation, and optimal control of electrified vehicles.

Nikolce Murgovski received the M.Sc. degree in software engineering from University West, Trollhättan, Sweden, in 2007, the M.Sc. degree in applied physics and the Ph.D. degree in systems and control from the Chalmers University of Technology, Gothenburg, Sweden, in 2007 and 2012, respectively. He is currently an Associate Professor with the Department of Electrical Engineering, Chalmers University of Technology. His research interests include optimization and optimal control in the automotive area.

Jonas Fredriksson received the M.Sc. degree in computer science engineering from the Luleå University of Technology, Luleå, Sweden, in 1997, and the Ph.D. degree in automatic control from the Chalmers University of Technology, Sweden, in 2002. He is currently a Professor in mechatronics with the Department of Electrical Engineering, Chalmers University of Technology. His research interests include modeling, control and simulation, and in automotive applications.

Jimmy Forsman received the M.Sc. degree in engineering physics from Umeå University, Umeå, Sweden, in 2018. He is currently with the Department of Vehicle Energy and Motion Control, Volvo Car Corporation, Gothenburg, Sweden. His main research interests include modeling, simulation and control of electrified vehicles.

Mitra Pourabdollah received the M.Sc. degree in systems, control, and robotics from the Royal Institute of Technology, Stockholm, Sweden, in 2009, and the Ph.D. degree in automatic control from the Chalmers University of Technology, Gothenburg, Sweden, in 2015. She is currently with Volvo Car Corporation, Gothenburg, Sweden. Her research interests include application of optimization and control in automotive and traffic area.

Viktor Larsson received the M.Sc. degree in space engineering from Luleå University of Technology, Luleå, Sweden, in 2008, and Ph.D. degree in automatic control from the Chalmers University of Technology, Gothenburg, Sweden, in 2014. He is currently with the Department of Vehicle Energy and Motion Control, Volvo Car Corporation, Gothenburg, Sweden. His main research interests include modeling control and simulation of electrified vehicles.