

Optimal Renewable Energy Curtailment Minimization Control Using a Combined Electromobility and Grid Model

Mladen Čičić* Carlos Vivas** Carlos Canudas-de-Wit*
Francisco R. Rubio**

* *Univ. Grenoble Alpes, CNRS, Inria, Grenoble INP, GIPSA-lab, Grenoble, France*

** *Dept. de Ingeniería de Sistemas y Automática, Escuela Técnica Superior de Ingeniería, Universidad de Sevilla, Spain*

Abstract: We propose an integrated power and transportation system control framework, combining the power grid model with a macroscopic electromobility model including charging stations under V2G operation. In this framework, the electrical vehicles (EVs) act as energy storage, but also as an additional virtual power grid link, transporting energy from one point to another. This new holistic model is used as a basis for optimal control design seeking to minimize renewable energy curtailment, while accounting for the structural limitation of the grid and other SoC constraints necessary for the optimal operation of the EVs. The proposed control scheme is shown to eliminate approximately 50% of curtailment compared to uncoordinated EV charging.

Copyright © 2023 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Keywords: Electromobility, Energy curtailment, Optimal control, Renewable energy sources

1. INTRODUCTION

As efforts towards decarbonization of all economical sectors become a major priority, Electric Vehicles (EVs) have started to emerge as one of the main components of sustainable transportation systems worldwide. Since EVs are projected to reach around 40% of the total fleet in the EU by 2030 (Conway et al., 2021), it is clear that their integration with the power grid via the charging infrastructure poses unsolved problems that will be critical in the coming years (EU 2019).

Although the constant increase of the electrification of the transportation systems (*electromobility*) may put a strain on the power grid, due to the large charging power demands (Fernandez et al., 2010), the massive adoption of EVs has the potential to help with the introduction of renewable energy sources (RES) (Wenzel et al., 2017), by using their batteries for energy storage, thus increasing RES dispatchability. From the power system side, the grid operator can use this EV flexibility to deal with network congestion management issues, which will especially be important in a future dominated by intermittent RES. As the natural interface between the mobility and power networks, the charging stations will play an essential role in the electromobility ecosystem. Today's power electronics technology and new DC grid topologies, together with V2G-enabled EVs, allow charging stations to providing ancillary services such as frequency stabilization and congestion relief to the power grid López et al. (2013).

One critical barrier to fully exploiting the EVs' potential is the lack of tools and methods for forecasting EV flexibility

in time and space. A model combining electromobility and the power grid is required for using the EVs to minimize the RES curtailment and improve the use of the existing power transmission network. This entails forecasting when and where the EVs move, how their State of Charge (SoC) evolves, and how they interact with the charging infrastructure and the power grid. Though some approaches based on historical data do exist (Morlock et al., 2019), a model-based framework is preferable for optimal control purposes. In Henry and Ernst (2021), RES curtailment was minimized by using optimal control, which was also used for reinforcement learning of another computationally efficient control law. Nevertheless, in this work storage and charging of EVs was assumed to be situated at a single point in the power network, whereas in reality both the EVs and the charging stations are distributed in time and space, and connected to different power grid nodes. In Zhou et al. (2021), coupled traffic and power grid dynamics were considered, but the traffic flows were only described on graph level.

In this paper we propose an integrated model, combining the power grid model with a macroscopic electromobility model distributed in space, including charging stations (in Section 2). The proposed multi-class electromobility model extends the simplified CTEC model from Čičić and Canudas-de-Wit (2022) to capture richer electromobility dynamics by allowing for several different co-located SoC levels in the vehicular flow. The electromobility layer is interfaced with the power layer through the charging stations, which act as predictable time-varying energy storage. This novel holistic model is used to design optimal control minimizing RES curtailment, while accounting for the structural limitations of the grid and EV-related constraints (in Section 3). Finally, the control framework is tested in simulations (in Section 4), based on which we are able to draw some conclusions (in Section 5).

E-mail: {mladen.cicic, carlos.canudas-de-wit}@gipsa-lab.fr, {vivas, rubio}@us.es. This work has received support from the Scale-FreeBack project, funding by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement N 694209), ENGREEN group from University of Sevilla, and projects US-1381503 (FEDER, JA), PID2020-115561RB-C32 (Spanish National Research Agency) and TED2021-131604B-I00 (MCI Spain).

2. COMBINED ELECTROMOBILITY AND POWER GRID MODEL

In this section we present the combined electromobility and power grid model, starting with the new multi-class aggregated electromobility model including the charging stations, followed by the grid model, and finally connecting the two parts into a combined model. We study a scenario similar to the one used in Henry and Ernst (2021), abstracting the situation where people commute between home and work using EVs, potentially stopping on the way at a public charging station. As shown in Fig. 1, we consider a power grid with three nodes (*Home*, *Public charging station*, and *Work*, in further text denoted by \mathbf{h} , \mathbf{p} , and \mathbf{w} , respectively) also connected by roads. The two considered road links connect nodes \mathbf{h} and \mathbf{w} , with a pair of off- and on-ramps at the middle, towards node \mathbf{p} . We assume that there is RES power generation and EV charging ports at all three nodes, and that there is some time-varying load at nodes \mathbf{h} and \mathbf{w} . While the combined model is adapted to this specific setup it can accommodate other types of road and power networks as well.

2.1 Electromobility model

We introduce a *multi-class* extension of the simplified CTEC model (Čičić and Canudas-de-Wit, 2022), consisting of the macroscopic dynamics of the EVs on the roads and the dynamics of the EVs at charging stations, coupled through ramp flows. In this work, we focus on the discretized version of the model, and the reader is referred to the cited paper for its continuous-time PDE version,

$$\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial(v(x,t)\rho(x,t))}{\partial x} = 0, \quad (1)$$

$$\frac{\partial \varepsilon(x,t)}{\partial t} + v(x,t) \frac{\partial \varepsilon(x,t)}{\partial x} = \mathcal{D}(v(x,t)), \quad (2)$$

$$\frac{\partial \eta(\varepsilon,t)}{\partial t} + \frac{\partial(c(\varepsilon,t)\eta(\varepsilon,t))}{\partial \varepsilon} = 0, \quad (3)$$

where x is the position along the road, t the time, $\rho(x,t)$ the traffic density, $v(x,t)$ the traffic speed, $\varepsilon(x,t)$ the SoC, $\mathcal{D}(v)$ the battery discharge as a function of EV speed, $\eta(\varepsilon,t)$ the distribution of EVs at a charging station according to their SoC ε , and $c(\varepsilon,t)$ the charging rate of EVs, potentially different for different ε . We extend the discretized version of the model by splitting the traffic flows into different classes which have the same behaviour while driving on the road, but may have independent SoC dynamics or behaviour at on- and off-ramps. These classes can be used to distinguish e.g. between combustion engine vehicles and EVs, or between vehicles with different routes and/or SoC, in order to avoid problems with the situation when two traffic flows with very different SoC merge.

Aggregate traffic density equations. Each road l is split into N_x^l cells of length L_x , $L_x \geq v_{\text{ff}}T$, where

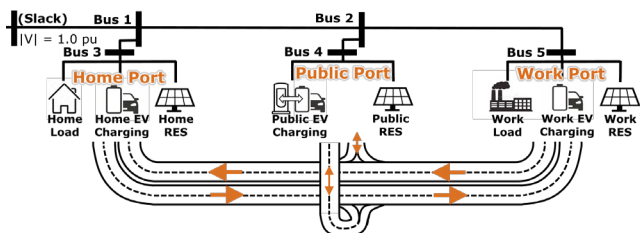


Fig. 1. Layout of the combined electromobility and power grid model used for this study.

v_{ff} is the free flow speed of the traffic, and T is the model sampling period, appropriately selected to ensure numerical stability. The aggregate macroscopic state of EV traffic on each road link l is given by the traffic density ρ_i^k and SoC ε_i^k in each cell i at each discrete time instant k . Since here we consider multiple classes of vehicles, the aggregate macroscopic SoC ε_i^k is not used, but instead we will track the SoC of each class. The update equations for the aggregate traffic density are:

$$\rho_i^{k+1} = \rho_i^k + \frac{T}{L_x} (q_{i-}^k - q_{i+}^k), \quad (4)$$

$$q_{i+}^k = \min \left\{ v_{\text{ff}} \rho_i^k, \frac{\omega(\rho_{\text{jam}} - \bar{\rho}_{i+1}^k) - r_{\text{on},i+1}^k}{1 - \beta_i^k} \right\}, \quad (5)$$

$$q_{i-}^k = q_{i-1+}^k (1 - \beta_{i-1}^k) + r_{\text{on},i}^k, \quad (6)$$

Here, q_{i-}^k denotes the traffic flow entering cell i at its upstream end, and q_{i+}^k the traffic flow exiting cell i at its downstream end. The on-ramp flow into cell i is denoted $r_{\text{on},i}^k$ and assumed to enter it at its upstream end, and the off-ramp flow from cell i is assumed to leave it at its downstream end, and denoted $r_{\text{off},i}^k = \beta_i^k q_{i+}^k$, where β_i^k is the splitting ratio of mainstream traffic flow towards the off-ramp. The traffic is assumed to follow a triangular fundamental diagram with critical density ρ_{cr} and jam density ρ_{jam} , yielding congestion wave speed $\omega = v_{\text{ff}} \frac{\rho_{\text{cr}}}{\rho_{\text{jam}} - \rho_{\text{cr}}}$, and we denote $\underline{\rho}_i^k = \min\{\rho_i^k, \rho_{\text{cr}}\}$ and $\bar{\rho}_i^k = \max\{\rho_i^k, \rho_{\text{cr}}\}$. Note that we omit stating to which road link l we are referring for better readability.

Multi-class traffic density equations. The aggregate traffic flow is split into some number of traffic classes $\xi \in \Xi$, with individual traffic densities denoted $\xi \rho_i^k$. Since here we assume that all vehicle classes have the same traffic behavior, the evolution of their traffic densities is given by

$$\xi \rho_i^{k+1} = \xi \rho_i^k + \frac{T}{L_x} (\xi q_{i-}^k - \xi q_{i+}^k), \quad (7)$$

$$\xi q_{i+}^k = \frac{\xi \rho_i^k}{\rho_i^k} q_{i+}^k, \quad (8)$$

$$\xi q_{i-}^k = \xi q_{i-1+}^k (1 - \xi \beta_{i-1}^k) + \xi r_{\text{on},i}^k, \quad (9)$$

where the ramp flows defined through $\xi \beta_{i-1}^k$ and $\xi r_{\text{on},i}^k$ are defined independently for each class ξ , with $\xi r_{\text{off},i}^k = \xi \beta_{i-1}^k \xi q_{i+}^k$. The per-class quantities relate to the aggregate quantities according to

$$\rho_i^k = \sum_{\xi \in \Xi} \xi \rho_i^k, \quad r_{\text{on},i}^k = \sum_{\xi \in \Xi} \xi r_{\text{on},i}^k, \quad \beta_i^k = \sum_{\xi \in \Xi} \frac{\xi \rho_i^k}{\rho_i^k} \xi \beta_i^k. \quad (10)$$

Once the vehicles reach the end of the road link from \mathbf{h} to \mathbf{w} or from \mathbf{w} to \mathbf{h} , all of them exit the road and enter the respective charging station, $\beta_{N_x}^k = 1$ for both road links. The splitting ratios towards the public charging stations $\xi \beta_i^k$, where $i = i_{\text{ph}}^{\text{in}}$ for the link \mathbf{h} to \mathbf{w} , and $i = i_{\text{pw}}^{\text{in}}$ for \mathbf{w} to \mathbf{h} , depend on the SoC of the approaching vehicles,

$$\xi \beta_i^k = 1 - \left(1 + e^{-\frac{\varepsilon_i^k - \varepsilon_{\text{low}}}{\gamma}} \right)^{-1}, \quad (11)$$

as a monotonically decreasing sigmoid function centered at some ε_{low} , with slope calibrated by some parameter γ . This function models the assumption that EVs are more likely to stop to charge if their SoC is low.

Multi-class SoC equations. The macroscopic SoC of each class is denoted $\xi_{\varepsilon_i^k}$, and its evolution is defined by

$$\xi_{\rho_i^{k+1}} \xi_{\varepsilon_i^{k+1}} = \xi_{\rho_i^k} \left(\xi_{\varepsilon_i^k} + \xi_{d_i^k} T \right) + \frac{T}{L_{\varepsilon}} \left(\xi_{\phi_{i-}^k} - \xi_{\phi_{i+}^k} \right), \quad (12)$$

$$\xi_{\phi_{i-}^k} = \left(\xi_{q_{i-}^k} - \xi_{r_{on,i}^k} \right) \left(\xi_{\varepsilon_{i-1}^k} + \xi_{d_{i-1}^k} T \right) + \xi_{r_{on,i}^k} \xi_{\varepsilon_{on,i}^k}, \quad (13)$$

$$\xi_{\phi_{i+}^k} = \xi_{q_{i+}^k} \left(\xi_{\varepsilon_i^k} + \xi_{d_i^k} T \right). \quad (14)$$

where the battery discharge rate $\xi_{d_i^k}$ is given by

$$\xi_{d_i^k} = \mathcal{D}_{\xi} \left(v_i^k \right), \quad v_i^k = \frac{q_{i+}^k}{\rho_i^k}, \quad (15)$$

depending on the traffic speed v_i^k , according to discharge functions \mathcal{D}_{ξ} defined for each class.

Charging stations equations. Finally, the electromobility model is completed by the charging station dynamics. For each charging station ζ , we split the SoC space into N_{ε} bins of length L_{ε} , $N_{\varepsilon} L_{\varepsilon} = 1$. Each bin $j = 1, \dots, N_{\varepsilon}$ corresponds to a range of SoC $[(j-1)L_{\varepsilon}, jL_{\varepsilon}]$, and we describe the state of the charging station through the number of vehicles in each bin $\zeta_{\eta_j^k}$.

Different classes of vehicles at a single physical charging station can be represented by using multiple virtual charging stations ζ to represent charging of each vehicle class ξ . We allow the rate of charging $\zeta_{c_j^k}$ for each charging station ζ and for each SoC level j , to vary in time within some range $|\zeta_{c_j^k}| \leq C$, with $L_{\varepsilon} \geq CT$ required for numeric stability. The charging station state update is given by

$$\zeta_{\eta_j^{k+1}} = \zeta_{\eta_j^k} + \frac{T}{L_{\varepsilon}} \left(\zeta_{c_{j-1}^k} \zeta_{\eta_{j-1}^k} - |\zeta_{c_j^k}| \zeta_{\eta_j^k} - \zeta_{c_{j+1}^k} \zeta_{\eta_{j+1}^k} \right) \dots \quad (16)$$

$$\dots + T \left(\zeta_{\mu_{in,j}^k} - \zeta_{\mu_{out,j}^k} \right),$$

where $\zeta_{c_j^k} = \max\{0, \zeta_{c_j^k}\}$, and $\zeta_{c_j^k} = \min\{0, \zeta_{c_j^k}\}$, and $\zeta_{\mu_{in,j}^k}$ and $\zeta_{\mu_{out,j}^k}$ represent the flows of vehicles entering and exiting the charging station, respectively.

The flows between the road and the charging station ζ are

$$r_{on,i_{\zeta}^{out}}^k = \sum_{j=1}^{N_{\varepsilon}} \zeta_{\mu_{out,j}^k}, \quad r_{on,i_{\zeta}^{out}}^k \varepsilon_{on,i_{\zeta}^{out}}^k = \sum_{j=1}^{N_{\varepsilon}} \zeta_{\mu_{out,j}^k} (j-1) L_{\varepsilon}, \quad (17)$$

$$r_{off,i_{\zeta}^{in}}^k = \sum_{j=1}^{N_{\varepsilon}} \zeta_{\mu_{in,j}^k}, \quad r_{off,i_{\zeta}^{in}}^k \varepsilon_{i_{\zeta}^{in}}^k = \sum_{j=1}^{N_{\varepsilon}} \zeta_{\mu_{in,j}^k} (j-1) L_{\varepsilon}, \quad (18)$$

where i_{ζ}^{in} and i_{ζ}^{out} are the cells where the off- and on-ramp connecting the road to the charging station ζ are, respectively, ensuring both the vehicles and the energy are conserved. In this work, we assume that multiple classes of vehicles can enter a single charging station ζ ,

$$\zeta_{\mu_{in,j}^k} = \sum_{\xi \in \Xi} \zeta_{\xi} \mu_{in,j}^k, \quad (19)$$

and that all vehicles exiting the charging station are of the same class ξ_{ζ}^{out} , therefore $r_{on,i_{\zeta}^{out}}^k = r_{on,i_{\zeta}^{out}}^k$ with $\xi = \xi_{\zeta}^{out}$, and $r_{on,i_{\zeta}^{out}}^k = 0$ for $\xi \neq \xi_{\zeta}^{out}$. The flows entering and exiting the charging stations are further determined by

$$\zeta_{\xi} \mu_{in,j}^k = \begin{cases} \left(j - \frac{\xi_{\varepsilon_{i_{\zeta}^{in}}^k}}{L_{\varepsilon}} \right) \xi_{r_{off,i_{\zeta}^{in}}^k}, & j-1 \leq \frac{\xi_{\varepsilon_{i_{\zeta}^{in}}^k}}{L_{\varepsilon}} < j, \xi \in \Xi_{\zeta}^{in}, \\ \left(\frac{\xi_{\varepsilon_{i_{\zeta}^{in}}^k}}{L_{\varepsilon}} - j + 2 \right) \xi_{r_{off,i_{\zeta}^{in}}^k}, & j-2 \leq \frac{\xi_{\varepsilon_{i_{\zeta}^{in}}^k}}{L_{\varepsilon}} < j-1, \xi \in \Xi_{\zeta}^{in}, \\ 0, & \text{otherwise,} \end{cases} \quad (20)$$

$$\zeta_{\mu_{out,j}^k} \in \left[0, \left(\frac{1}{T} - \frac{|\zeta_{c_j^k}|}{L_{\varepsilon}} \right) \zeta_{\eta_j^k} + \frac{\zeta_{c_{j-1}^k}}{L_{\varepsilon}} \zeta_{\eta_{j-1}^k} - \frac{\zeta_{c_{j+1}^k}}{L_{\varepsilon}} \zeta_{\eta_{j+1}^k} \right], \quad (21)$$

where Ξ_{ζ}^{in} denotes the set of vehicle classes that enter charging station ζ , and the exiting flow $\zeta_{\mu_{out,j}^k}$ depends on the particular behavioural logic of each charging station. We assume that each traffic class ξ enters at most one charging station ζ from each cell i , but it may enter multiple charging stations in case off-ramps leading to them are in different cells $i_{\zeta_1}^{in} \neq i_{\zeta_2}^{in}$.

Charging stations control variables. Charging stations are of particular importance because they serve as the interface between the electromobility layer and the power grid, and can be used as actuators to improve the situation in the wider power system. At each time step k , the power system operator gets from each charging station ζ the range of power that they can consume or generate, denoted by \bar{U}_{ζ}^k and \underline{U}_{ζ}^k , respectively. Based on these limits, the operator can choose the normalized current power flow to (or from) each charging station ζ , denoted $u_{\zeta}^k \in [-1, 1]$.

Here we adopt the convention that if $u_{\zeta}^k > 0$, the charging station is a net power consumer from the perspective of the grid, and is using the grid power to charge the EVs. Otherwise, if $u_{\zeta}^k < 0$, the charging station is a net power provider to the grid, and is using the energy stored in the batteries of some EVs to provide V2G services. The actual charging station powers, denoted U_{ζ}^k , represent the control input to the electromobility system, and are given by

$$U_{\zeta}^k = \begin{cases} u_{\zeta}^k \bar{U}_{\zeta}^k, & u_{\zeta}^k \geq 0, \\ u_{\zeta}^k \underline{U}_{\zeta}^k, & u_{\zeta}^k < 0, \end{cases} \quad (22)$$

therefore we have $\underline{U}_{\zeta}^k \leq U_{\zeta}^k \leq \bar{U}_{\zeta}^k$. This charging station power relates to its EV charging rates as

$$U_{\zeta}^k = \sum_{j=1}^{N_{\varepsilon}} \zeta_{c_j^k} \zeta_{\eta_j^k} B \quad (23)$$

where B is the EV battery average capacity. In order to best utilize the available power, we employ a hierarchical charging scheme, where vehicles with lower SoC have a higher charging priority. We split the vehicles into three groups according to their SoC: low SoC EVs, with $0 \leq \varepsilon < \varepsilon_{low}$, medium SoC EVs, with $\varepsilon_{low} \leq \varepsilon \leq \varepsilon_{high}$, and high SoC EVs, with $\varepsilon_{high} < \varepsilon \leq 1$. In case there is not enough power to charge the low SoC EVs, or if the grid operators requests power to be provided to the grid, we utilize the energy stored in batteries of EVs with higher SoC to satisfy the power demands.

Given the boundaries between these groups of EVs ε_{low} and ε_{high} , we define j_{low} as the highest $j \in \{1, \dots, N_{\varepsilon}\}$ for which $\varepsilon_j < \varepsilon_{low}$ and j_{high} as the lowest for which $\varepsilon_j > \varepsilon_{high}$. The number of EVs in each group is then

$$\zeta_{\eta_{low}^k} = \sum_{j=1}^{j_{low}} \zeta_{\eta_j^k}, \quad \zeta_{\eta_{med}^k} = \sum_{j=j_{low}+1}^{j_{high}-1} \zeta_{\eta_j^k}, \quad \zeta_{\eta_{high}^k} = \sum_{j=j_{high}}^{N_{\varepsilon}} \zeta_{\eta_j^k}. \quad (24)$$

For each charging station we define the maximum charging rate $\bar{C}_{\zeta} \geq 0$ and maximum discharging rate $\underline{C}_{\zeta} \leq 0$ per EV, yielding $\underline{C}_{\zeta} \leq \zeta_{c_j^k} \leq \bar{C}_{\zeta}$, respecting $|\bar{C}_{\zeta}| \leq C$ and $|\underline{C}_{\zeta}| \leq C$. We assign a different charging rate to each group of EVs, denoted $\zeta_{c_{low}^k}$, $\zeta_{c_{med}^k}$, and $\zeta_{c_{high}^k}$, and given by

$$\zeta_{C_j^k} = \begin{cases} \zeta_{C_{low}^k}, & j = 1, \dots, j_{low}, \\ \zeta_{C_{med}^k}, & j = j_{low} + 1, \dots, j_{high} - 1, \\ \zeta_{C_{high}^k}, & j = j_{high}, \dots, N_\varepsilon. \end{cases} \quad (25)$$

The exception is charging at home, $\zeta = \mathbf{h}$, where we assume that all vehicles charge at the same rate,

$$\mathbf{h}_{C_j^k} = \min \left\{ \frac{P_{\mathbf{h}}^k}{\mathbf{h}\eta_{low}^k + \mathbf{h}\eta_{med}^k + \mathbf{h}\eta_{high}^k}, \bar{C}_{\mathbf{h}} \right\}. \quad (26)$$

Given the current provided or demanded power U_ζ^k , these charging rates are given by

$$\zeta_{C_{low}^k} = \min \left\{ \frac{\zeta_{\mathcal{P}_{low}^k}}{\zeta_{\eta_{low}^k}}, \bar{C}_\zeta \right\}, \quad (27)$$

$$\zeta_{C_{med}^k} = \begin{cases} \bar{C}_\zeta, & \zeta_{\eta_{low}^k} \bar{C}_\zeta > \zeta_{\mathcal{P}_{low}^k}, \\ \min \left\{ \frac{\zeta_{\mathcal{P}_{med}^k}}{\zeta_{\eta_{med}^k}}, \bar{C}_\zeta \right\}, & \zeta_{\eta_{low}^k} \bar{C}_\zeta \leq \zeta_{\mathcal{P}_{low}^k}, \end{cases} \quad (28)$$

$$\zeta_{C_{high}^k} = \begin{cases} \bar{C}_\zeta, & \zeta_{\eta_{med}^k} \bar{C}_\zeta > \zeta_{\mathcal{P}_{med}^k}, \\ \min \left\{ \frac{\zeta_{\mathcal{P}_{high}^k}}{\zeta_{\eta_{med}^k}}, \bar{C}_\zeta \right\}, & \zeta_{\eta_{med}^k} \bar{C}_\zeta \leq \zeta_{\mathcal{P}_{med}^k}, \end{cases} \quad (29)$$

where we define maximum available charging power to each group of vehicles, $\zeta_{\mathcal{P}_{low}^k}$, $\zeta_{\mathcal{P}_{med}^k}$, and $\zeta_{\mathcal{P}_{high}^k}$, as

$$\zeta_{\mathcal{P}_{low}^k} = U_\zeta^k - (\zeta_{\eta_{med}^k} + \zeta_{\eta_{high}^k}) \bar{C}_\zeta, \quad (30)$$

$$\zeta_{\mathcal{P}_{med}^k} = U_\zeta^k - \zeta_{\eta_{low}^k} \bar{C}_\zeta - \zeta_{\eta_{high}^k} \bar{C}_\zeta, \quad (31)$$

$$\zeta_{\mathcal{P}_{high}^k} = U_\zeta^k - (\zeta_{\eta_{low}^k} + \zeta_{\eta_{med}^k}) \bar{C}_\zeta. \quad (32)$$

This charging scheme results in a range of charging station ζ power consumption or production $[\underline{U}_\zeta^k, \bar{U}_\zeta^k]$, given by

$$\bar{U}_\zeta^k = (\zeta_{\eta_{low}^k} + \zeta_{\eta_{med}^k} + \zeta_{\eta_{high}^k}) \bar{C}_\zeta B, \quad (33)$$

$$\underline{U}_\zeta^k = \max\{0, (\zeta_{\eta_{low}^k} \bar{C}_\zeta + (\zeta_{\eta_{med}^k} + \zeta_{\eta_{high}^k}) \bar{C}_\zeta) B\}. \quad (34)$$

Finally, we define the flows of EVs exiting each charging stations by their scheduled departure demand $\zeta_{\hat{\mu}_{out}^k}$,

$$\zeta_{\mu_{out,j}^k} = \begin{cases} \min \left\{ \zeta_{\hat{\mu}_{out}^k}, \left(\frac{1}{T} - \frac{|\zeta_{C_j^k}|}{K_\varepsilon} \right) \zeta_{\eta_j^k} \right\}, & j = j_\zeta^k, \\ 0, & j \neq j_\zeta^k. \end{cases} \quad (35)$$

For $\zeta = \mathbf{h}$ and $\zeta = \mathbf{w}$, $\zeta_{\hat{\mu}_{out}^k}$ is given externally, to represent EVs commuting from home around $t = 6$ h, and from work to home around $t = 16$ h. For $\zeta = \mathbf{p}$, we assume that the EVs stay at the charging station for 1 h, so the departure demand will depend on the flow entering the charging station in the past. At each sampling time, we randomly select the SoC of the departing EVs for each charging station j_ζ^k , with probabilities of each SoC level proportional to the number of vehicles currently at charging station ζ .

2.2 Power Grid Model

This section describes the dynamics of the AC power grid that interacts with the electromobility layer. For notation clarity, in this section, parameters and variables of the power grid model are denoted by tilde.

A balanced three-phase power network can be represented in phasor form as an equivalent single-phase representation, where only one of the phases is taken into account. Also, for mathematical convenience, the power system will be analyzed using the per-unit (p.u.) notation, in which all

electrical quantities are normalized with respect to a set of base quantities.

The distribution grid is modelled as a set of nodes $\tilde{\mathcal{N}}$ linked by a set of directed edges $\tilde{\mathcal{E}}$ that represent the transmission lines. Each edge $\tilde{e}_{ij} \in \tilde{\mathcal{E}}$ links buses i and j and can contain transmission lines, power transformers and/or phase shifters. Here the conventional π transmission line model is employed where each branch can be defined by five parameters: a series resistance \tilde{r}_{ij} , a series reactance \tilde{x}_{ij} , a charging susceptance \tilde{b}_{ij} , a tap ratio magnitude $\tilde{\tau}_{ij}$ and phase shift $\tilde{\theta}_{ij}$. These magnitudes allows to define the link series admittance $\tilde{y}_{ij} = 1/(\tilde{r}_{ij} + \sqrt{-1}\tilde{x}_{ij})$ and shunt admittance $\tilde{y}_{ij}^{sh} = \sqrt{-1}\frac{\tilde{b}_{ij}}{2}$ as well as the complex tap ratio of transformers, $\tilde{t}_{ij} = \tilde{\tau}_{ij}e^{\sqrt{-1}\tilde{\theta}_{ij}}$.

Power Network equations. For a network with $\tilde{N}_b = |\tilde{\mathcal{N}}|$ buses, and after applying Kirchhoff's current law at each bus $i \in \tilde{\mathcal{N}}$, the constant impedance elements of the model are incorporated into a complex $\tilde{N}_b \times \tilde{N}_b$ bus admittance matrix \tilde{Y} , systematically defined in the standard way, that relates the complex nodal current injections, \tilde{I} to the complex node voltages, \tilde{V} , as $\tilde{I} = \tilde{Y}\tilde{V}$.

Power flow solution. The standard power (load) flow problem involves solving for the set of voltages and flows in a network corresponding to a specified pattern of load and generation. The definition of grid admittance matrix \tilde{Y} allows to define the nodal equation in an equivalent form in terms of power injections and voltage level at buses as

$$\tilde{S}_i^{\text{bus}} = \tilde{V}_i \tilde{I}_i^* = \tilde{V}_i (\tilde{Y}_i \tilde{V})^* = \tilde{V}_i \tilde{Y}_i^* \tilde{V}^*, \quad \forall i \in \tilde{\mathcal{N}}, \quad (36)$$

where $\tilde{S}_i^{\text{bus}} = \tilde{P}_i^{\text{bus}} + \sqrt{-1}\tilde{Q}_i^{\text{bus}}$ is the complex power phasor accounting for active (\tilde{P}_i^{bus}) and reactive (\tilde{Q}_i^{bus}) powers injected at bus i , and \tilde{Y}_i denotes the i -th row of the admittance matrix \tilde{Y} .

Equation (36) is a set of \tilde{N}_b complex-valued equations, that can be posed as $2\tilde{N}_b$ quadratic real valued equations with $2\tilde{N}_b$ real unknowns. By convention, a single generator bus is typically chosen as a reference bus to serve the roles of both a voltage angle reference and a real power slack. Unknowns for the problem will thus be active and reactive power at the slack bus together with complex voltage at the remaining $\tilde{N}_b - 1$ buses. These equations are solved at every iteration step providing equilibrium power and voltage at every bus.

2.3 Combined model

We denote the encapsulated full state of the mobility model at time k as E^k ,

$$E^k = \left(\xi_{\rho_{l,i}^k} | l \in \{\mathbf{hw}, \mathbf{wh}\}, i = \{1, \dots, N_x\}, \xi \in \{\mathbf{h/w}, \mathbf{p}\}, \dots, \xi_{\varepsilon_{l,i}^k} | l \in \{\mathbf{hw}, \mathbf{wh}\}, i = 1, \dots, N_x, \xi \in \{\mathbf{h/w}, \mathbf{p}\}, \dots, \zeta_{\eta_j^k} | j \in \{1, \dots, N_\varepsilon\}, \zeta \in \{\mathbf{h}, \mathbf{w}, \mathbf{p}, \mathbf{hw}, \mathbf{wh}\} \right), \quad (37)$$

capturing the traffic density $\xi_{\rho_{l,i}^k}$ and SoC $\xi_{\varepsilon_{l,i}^k}$ for all classes ξ and all cells i on both road links l , and the numbers of charging vehicles $\zeta_{\eta_j^k}$ at each SoC level j at each charging station ζ . The vehicles are split into classes based on whether they enter the road from $\mathbf{h/w}$, or from \mathbf{p} . Physical charging station \mathbf{p} is modelled by two virtual charging stations \mathbf{pwm} and \mathbf{phw} , connected to either link.

The electromobility state is updated according to (7), (12), and (16), as defined in Section 2.1, and we write jointly

$$E^{k+1} = \mathcal{M}(E^k, U^k), \quad (38)$$

where U^k is the collection of U_ζ^k to all physical charging stations, $\zeta \in \{\mathbf{h}, \mathbf{w}, \mathbf{p}\}$, yielding charging rates (25) that directly determine the evolution of $\zeta \eta_j^k$ through (16).

Power grid equations at discrete time step k is given by a static mapping, and can be expressed compactly as

$$\tilde{F}^k = \tilde{\mathcal{F}}(U^k, \tilde{\Lambda}^k, \tilde{V}^k), \quad (39)$$

$$\tilde{P}_c^k = \tilde{\mathcal{C}}(\tilde{F}^k, \tilde{V}^k), \quad (40)$$

$$\tilde{P}_r^k = \tilde{\mathcal{R}}(E^k), \quad (41)$$

where \tilde{F}^k are the power flows at time k as a function of the EV power injected/retrieved U^k , loads $\tilde{\Lambda}^k$, and RES distributed generation \tilde{V}^k . RES curtailment is given by \tilde{P}_c^k , and mobility power reserves by \tilde{P}_r^k . Except for power flows \tilde{F}^k , all other variables in (39)–(41) are collection of variables related to different ports $\zeta \in \{\mathbf{h}, \mathbf{w}, \mathbf{p}\}$.

3. OPTIMAL CONTROL DESIGN

3.1 Power system optimization

The proposed optimization problem focuses on active network management (ANM) policies to reduce generation curtailments by providing near future scheduling of the optimal power flow policy to/from EVs plugged at the charging poles of the system (\mathbf{h} , \mathbf{w} , and \mathbf{p}).

The optimization problem is formulated based on a prediction model and operated in a receding horizon manner using the latest system information. In this approach, load injections and generation profiles of RES are non-controllable variables. Only the active power (and reactive, within operational limits) of EV demand is assumed to be manageable. The objective function, constraints, and optimization algorithm will be presented next.

3.2 Optimal control formulation

We can now formulate ANM taking electromobility into account as a receding horizon optimal control problem

$$\text{minimize}_{\tilde{u}_\zeta^k} J(\tilde{k}, \tilde{u}_\zeta^k)$$

subject to Mobility and grid dynamics (38)–(41),

Grid operational constraints,

$$|\tilde{S}_{ij}| \leq \bar{S}_{ij}, \quad \tilde{e}_{ij} \in \tilde{\mathcal{E}}, \quad (42)$$

$$\tilde{V}_i \leq \tilde{V}_i \leq \bar{V}_i, \quad i \in \tilde{\mathcal{N}} - \tilde{\mathcal{N}}_{\text{slack}}, \quad (43)$$

Reactive to active power ratio limitations.

The optimization problem is articulated as constrained minimization of the cost function

$$J(\tilde{k}, \tilde{u}_\zeta^k) = \sum_{h=1}^H \sum_{\zeta \in \{\mathbf{h}, \mathbf{p}, \mathbf{w}\}} \left(w_c \tilde{P}_{c,\zeta}(t_{\tilde{k}+h} | t_{\tilde{k}}) - w_r \tilde{P}_{r,\zeta}(t_{\tilde{k}+h} | t_{\tilde{k}}) \right) \quad (44)$$

where $\tilde{P}_{c,\zeta}(t_{\tilde{k}+h} | t_{\tilde{k}})$ represent the curtailed power at time $t_{\tilde{k}+h}$ inferred from the information available at time $t_{\tilde{k}}$, at port ζ . Similarly $\tilde{P}_{r,\zeta}(t_{\tilde{k}+h} | t_{\tilde{k}})$ accounts for the mobility reserve power available at time $t_{\tilde{k}+h}$. Constants w_c and w_r weigh the different optimization terms. The optimization problem is subject to constraints on the maximum apparent power $|\tilde{S}_{ij}|$ (42), power line voltage \tilde{V}_i deviation at

buses (43), and limitations on the amount of reactive to active power ratios the distributed generation can manage.

Note that in order to ease the numeric burden, we solve this problem at a time scale different than that of the electromobility model. We take the optimization sampling period \tilde{T} as a multiple of electromobility sampling periods T , and denote the optimization time step \tilde{k} . The resulting control \tilde{u}_ζ^k is then applied to the electromobility model over a number of time steps,

$$u_\zeta^k = \tilde{u}_\zeta^{\lfloor \frac{kT}{\tilde{T}} \rfloor + 1}, \quad (45)$$

where $\lfloor \cdot \rfloor$ denotes rounding down.

The first part of the cost function accounts for the energy lost due to curtailment imposed by the ANM algorithm to satisfy grid constraints for a predicted sequence of control actions $\tilde{u}_\zeta(t_{k+h} | t_k)$, $\zeta \in \{\mathbf{h}, \mathbf{p}, \mathbf{w}\}$, $h = 1, \dots, N_u$. The control actions correspond to the normalized active power that the controller schedules to be retrieved or injected (V2G) at port ζ , and N_u is the control horizon considered. In this scheme, as is usually employed in the classic formulation of predictive control, for $N_u > 1$ only the first control action of the sequence computed is applied. The control action terms $\tilde{u}_\zeta(t_{k+h} | t_k) \in [-1, 1]$ are considered in a normalized fashion, allowing to accommodate the constraints on the time-varying mobility reserve powers in a more convenient form. The second term is designed to maximize the mobility reserve storage available within the prediction horizon, which is taken for simplicity as a proxy of the overall SoC of the EV fleet.

4. SIMULATION RESULTS

Finally, we assess the behaviour of the proposed ANM EV charging scheme by comparing two simulation scenarios. The first one corresponds to uncoordinated charging where a fixed percentage of EVs at each charging station ζ (70% for $\zeta = \mathbf{h}$, and 40% for $\zeta = \mathbf{w}$ and $\zeta = \mathbf{p}$) is charging at constant maximum rate \bar{C}_ζ . The second scenario corresponds to a scheduled charging operation as proposed in this work using a receding horizon control scheme that balances curtailment losses in relation to average EV reserves. Note that in both cases vehicles decide whether or not they enter the public charging station depending on their SoC, according to (11).

Both scenarios have been simulated on the test layout described in Fig.1 where the power network is simplified to three representative ports that lump loads, distributed generation and EV operation for aggregated domestic, work and public EV charging stations. In order to illustrate the state of the electromobility model, we show the state of charging stations over time in Figure 2 for one simulation run. As expected, all EVs start at home, then travel to work, and finally return home, with some of them stopping at the public charging station along the way. Simulations were performed assuming a grid configuration with balanced capacities on the three ports in the order of 30 MW. Power lines capacities were assigned to naturally induce RES curtailment at specific times of the day with high RES production and lower loads. Domestic and work loads, together with RES production have been simulated taking averaged typical profiles for every category. From the mobility side, a baseline of 3334 EVs with an average battery capacity of 60 kWh were considered, and their SoC was initialized in the $\varepsilon \in [0.5, 1]$ range.

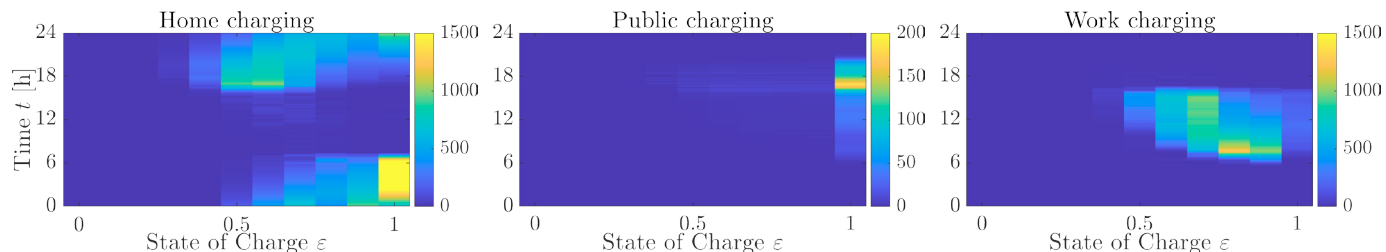


Fig. 2. Distribution of EVs according to their SoC at each charging station over time in the coordinated charging case. Brighter colours indicate more EVs at that SoC. Note the different color scale in case of public charging station.

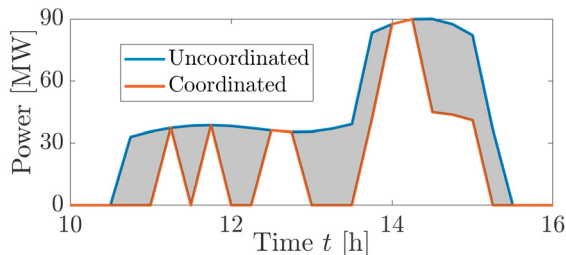


Fig. 3. Curtailment cut for the two charging scenarios.

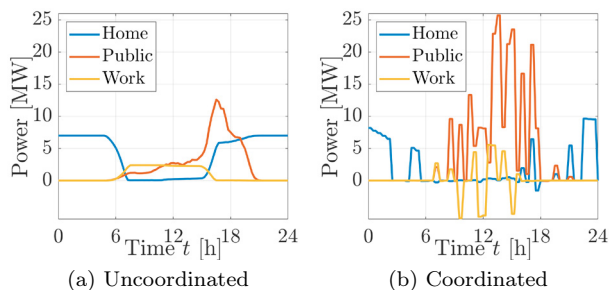


Fig. 4. Charging station power for the two scenarios.

Due to the daily cyclic nature of power loads, RES production and mobility patterns, simulations for a period of 24h were considered representative of the system. For the computation of the coordinated charging schedule, we used a prediction horizon of $HT = 5$ h, and a control horizon of $N_u \tilde{T} = 30$ min. To speed up computations, simulations were performed with different sample times, with $T = 1$ min for the electromobility model, 5 min for the power grid model and $\tilde{T} = 30$ min as sample time for the receding horizon control.

As a primary objective of the optimization problem proposed, the performance index in (44) has been balanced to maximize the use of RES (reduce curtailment losses), while preserving a reasonable average state of charge of the EVs. Figure 3 plots the compared curtailment induced by the uncoordinated and coordinated schemes, the shaded area corresponding to curtailment energy saving by the later approach. More precisely, in this particular simulation, the uncoordinated charging scenario induces 249.7 MWh losses in curtailment, while the coordinated approach provides 124.1 MWh, a significant reduction of 50.3%.

Figure 4 shows the evolution of the power used by EVs. For the uncoordinated charging scenario, the power used for charging is directly proportional to the number of EVs currently present at the charging station. Coordinated charging allows for a more nuanced use of power depending on the power grid load and RES production profile. In this case EVs end the day with somewhat lower SoC, which will be rectified through overnight charging at home.

5. CONCLUSIONS

In this work, we present a control framework combining electromobility and the power grid. Using an extended multi-class electromobility model, we are able to capture the SoC dynamics of EVs on their daily commute. The electromobility layer is interfaced with the power grid through charging stations, providing us with a way to store energy and control the power flows. We use this framework to design a receding horizon control law for active network management, in order to reduce RES production curtailment, which is shown in simulation to significantly improve the situation.

The models and results presented herein could serve as a basis for a number of future research directions. Though the network studied here was adopted for simplicity, the presented control approach should be extended to a more general case and more complex networks, both in terms of roads and power lines. In this work, we did not utilize the ratio of EVs that enter the public charging station as a control input, but this behavior could be influenced by e.g. introducing dynamic pricing of charging, which opens an entirely new area of control problems.

REFERENCES

- Čičić, M. and Canudas-de-Wit, C. (2022). Coupled macroscopic modelling of electric vehicle traffic and energy flows for electromobility control. In *CDC 2022-61st IEEE Conference on Decision and Control*.
- Conway, G., Joshi, A., Leach, F., García, A., and Senecal, P.K. (2021). A review of current and future powertrain technologies and trends in 2020. *Transportation Engineering*, 5, 100080.
- European Commission and Directorate-General for Energy (2019). *Effect of electromobility on the power system and the integration of RES : study S13*. Publications Office. doi:doi/10.2833/12919.
- Fernandez, L.P., San Román, T.G., Cossent, R., Domingo, C.M., and Frias, P. (2010). Assessment of the impact of plug-in electric vehicles on distribution networks. *IEEE transactions on power systems*, 26(1), 206–213.
- Henry, R. and Ernst, D. (2021). Gym-ANM: Reinforcement learning environments for active network management tasks in electricity distribution systems. *Energy and AI*, 5, 100092.
- López, M., Martín, S., Aguado, J., and de la Torre, S. (2013). V2g strategies for congestion management in microgrids with high penetration of electric vehicles. *Electric Power Systems Research*, 104, 28 – 34. doi:10.1016/j.epsr.2013.06.005.
- Morlock, F., Rolle, B., Bauer, M., and Sawodny, O. (2019). Forecasts of electric vehicle energy consumption based on characteristic speed profiles and real-time traffic data. *IEEE Transactions on Vehicular Technology*, 69(2), 1404–1418.
- Wenzel, G., Negrete-Pincetic, M., Olivares, D.E., MacDonald, J., and Callaway, D.S. (2017). Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. *IEEE Transactions on Smart Grid*, 9(5), 5141–5151.
- Zhou, Z., Zhang, X., Guo, Q., and Sun, H. (2021). Analyzing power and dynamic traffic flows in coupled power and transportation networks. *Renewable and Sustainable Energy Reviews*, 135, 110083.