Highway Traffic Control via Smart e-Mobility – Part II: Dutch A13 Case Study

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Abstract—In this paper, we study how to alleviate highway traffic congestions by encouraging plug-in electric and hybrid vehicles to stop at charging stations around peak congestion times. Specifically, we focus on a case study and simulate the adoption of a dynamic charging price depending on the traffic congestion. We use real traffic data of the A13 highway stretch between The Hague and Rotterdam, in The Netherlands, to identify the Cell Transmission Model. Then, we apply the algorithm proposed in [1](Part I: Theory) to different scenarios, validating the theoretical results and showing the benefits of our strategy in terms of traffic congestion alleviation. Finally, we carry out a sensitivity analysis of the proposed algorithm and discuss how to optimize its performance.

I. INTRODUCTION

W E study how to alleviate highway traffic congestions by encouraging plug-in hybrid and electric vehicles to stop at charging stations around peak congestion time. In the first part of our work (Part I: Theory) [1], motivated by the rising number of Plug-in Electric Vehicles (PEVs) and inspired by the conventional ramp metering control, we have proposed a novel Active Traffic Demand Management (ATDM) strategy based on soft measures to alleviate traffic congestion during rush hours. Specifically, we have designed a pricing policy to make the charging price dynamic and dependent on the (predicted) traffic congestion level, encouraging the PEV owners to stop for charging when the congestion level is (going to be) high. To achieve this goal, we have developed a novel framework that models how the proposed policy affects the drivers' decisions as a Mixed-Integer Generalized Potential Game (MI-GPG). From a technological point of view, we have introduced the concept of "road-to-station" (r2s) and "stationto-road" (s2r) traffic flows, and shown that the selfish behavior of the drivers leads to decision strategies that are individually optimal in the sense of Nash.

In this paper (Part II: Case Study), the proposed ATDM strategy is validated in simulation on the A13 highway stretch

between The Hague and Rotterdam, in The Netherlands. More precisely, the main contribution of this paper is to show by simulation that the adoption of a dynamic charging price policy depending on the traffic congestion can alleviate highway traffic congestion by encouraging plug-in electric and hybrid vehicles to stop at one Charging Station (CS) around peak congestion time. To the best of the authors' knowledge, this is the first study that proposes the r2s and s2r technology to develop an ATDM. Furthermore, to support the reliability of our simulation results, we use real traffic data to identify the parameters of the corresponding Cell Transmission Model (CTM), which predicts the evolution of the traffic congestion [1, Sec. II]. Finally, to show the general validity of the proposed approach and to study its performance in different scenarios, we perform an extensive sensitivity analysis on the system parameters, which allows us to identify the "best" setup that maximizes the performance of the proposed strategy, based on empirical results.

Structure of the paper: In Section II, we recall the most important components of the ATDM strategy developed in the first part of this work (Part I: Theory) [1] and the associated notation. In Section III, we use real data to identify the parameters of the CTM and discuss the choice of the parameters adopted in the decision making process. The first simulation is analyzed in Section V, where the parameters reflect the current market scenario. For the most relevant decision parameters, a sensitivity analysis is carried out in Section VI. Finally, Sections VII and VIII, respectively, discuss the policies that emerge from the simulation results as the most effective and the conclusions that summarize the strengths of our approach together with promising future developments.

II. THE ATDM STRATEGY PROPOSED IN PART I

In this section, we briefly review the ATDM strategy we have proposed in the first part of this work (Part I: Theory) [1], including the problem formulation, theoretical background and notations (see Table I).

The traffic evolution is modeled via the CTM that is a simple, yet sufficiently accurate, first order model for traffic evolution on a highway [2]. We consider a highway stretch in which there are no entering or exiting ramps, divided in N cells of length L_{ℓ} where $\ell \in \mathcal{N} := \{1, \ldots, N\}$. Each cell ℓ has an entering flow of vehicles ϕ_{ℓ} and exiting one $\phi_{\ell+1}$. We assume that the PEVs leaving cell 1 can choose to stop at the unique CS, that we assume to be located between cells 1 and 2 (see [1, Fig. 1]). The flows of PEVs entering and exiting

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TABLE I: The variables and parameters (respectively in the upper and bottom part of each table) related to the CTM and the charging scheduling decision problem.

		CTM cell $\ell \in \mathcal{N}$				
ϕ_ℓ	[veh/h]	flow entering the cell				
r2s	[veh/h]	flow entering the CS				
s2r	[veh/h]	flow exiting the CS				
$ ho_\ell$	[veh/km]	traffic density				
Δ_ℓ	[h]	extra travel time due to congestion				
Δ_{ℓ}	[h]	predicted future extra travel time				
		due to congestion				
L_{ℓ}	[km]	cell length				
\bar{v}_ℓ	[km/h]	free-flow velocity				
w_ℓ	[km/h]	congestion wave speed				
q_{ℓ}^{\max}	[veh/h]	maximum cell capacity				
ρ_{ℓ}^{\max}	[veh/km]	maximum jam density				
ρ_{ℓ}^{\max} T	[h]	length of the time interval				
Decision making process of agent $i \in \mathcal{I}$						
x_i	_	battery State of Charge (SoC) of PEV i				
u_i	[kWh]	energy purchased by PEV i				
δ_i	-	binary var. 1 iff PEV i is charging				
u^{PEV}	[kWh]	total energy purchased by PEVs				
p	[€/kWh]	price for 1kWh at CS				
\hat{p}	[€/kWh]	predicted future price at CS				
t_i	[h]	interval in which PEV i enters cell 2				
ϑ_i	-	rectangular function centered in t_i				
ξ	[h]	(over)estimation of the extra travel time				
+CS	6.1	due to congestion				
$\xi_i^{ ext{CS}}$	[h]	estimation of the extra travel time				
		due to PEVs exiting the CS				
x_i^{ref}	_	min. SoC of PEV i before leaving the CS				
p_{EV}	_	percentage of PEVs in the market				
lT	[h]	length of the time interval				
$T_{\rm h}$		number of intervals composing the horizon				
C_i	[kWh]	battery capacity				
η_i	[1/kWh]	scaling associated to battery efficiency				
$\frac{\alpha_i}{\bar{\delta}}$	-	interest of PEV <i>i</i> in saving money				
u^{\max}	[kWh]	number of charging spots at the CS CS max. energy providable in an interval				
$\frac{u}{\overline{u}(\underline{u})}$	[kWh]	upper(lower) bound on purchasable energy				
$d^{(\underline{u})}$	[kWh]	base energy demand in the grid				
	[€/kWh ²]	price scaling factors				
$c_1, c_2 \\ c_3$	$\left[\frac{\epsilon}{h \cdot kWh} \right]$	price scaling factor				
\overline{p}_i	[€/kWh]	fixed avg. price for 1kWh not at CS				
$\beta_0^{p_i}$	[€/kWh]	estimated price scaling factor				
	$\left[\frac{(h \cdot kWh)}{(h \cdot kWh)} \right]$	estimated price scaling factor				
131		half width of ϑ_i				
${egin{array}{c} eta_1 \ W \end{array}}$						
W	[h]	scaling used to compute in \mathcal{E}^{CS}				
	[h] [h]	scaling used to compute in ξ_i^{CS} time-varying scaling of the travel time				

the CS are r2s and s2r respectively. The relation between a cell's flow ϕ_{ℓ} and its density ρ_{ℓ} describes the traffic evolution as defined in [1, Eq.1–4].

We consider that the Highway Operator (HO) regulates the price of the electricity purchased by the PEVs at the CS. This price p is dynamic and subject to a discount that is proportional to the level of the actual (or predicted) traffic congestion:

$$\forall k \in \mathbb{N}, \ p(k) \coloneqq c_1 \ d(k) + c_2 u^{\text{PEV}}(k) - c_3 \sum_{\ell=2}^N \Delta_\ell(k), \ (1)$$

where $c_1, c_2, c_3 > 0$ and Δ_{ℓ} is the cell's extra travel time due to the traffic congestion. The PEVs exiting cell 1 face a choice, namely, whether or not it is convenient to stop at the CS given their SoC x_i , the available plugs $\overline{\delta}$ and the current/predicted traffic situation. Sharing the facility and the dependency of p in (1) on u^{PEV} make the choice of the optimal charging strategy a challenging problem that has to be solved locally by each PEV. Each driver aims at finding the best trade-off between the money saved by exploiting the electricity price discount and the extra travel time due to the stop at the CS. This is modeled via the following two-term cost function:

$$J_i \coloneqq \alpha_i J_i^{\text{price}} + (1 - \alpha_i) J_i^{\text{time}}, \qquad (2)$$

which each PEV (or agent) $i \in \mathcal{I}(k)$, with $\mathcal{I}(k)$ being the set of all the agents involved in the game, desires to minimize. The coefficient $\alpha_i \in (0,1)$ is the realization of a Gaussian random variable, with mean μ_{α} and variance σ_{α} . It represents the interest of agent *i* in saving money rather than time. The first term in (2) describes the total savings, i.e.,

$$J_i^{\text{price}}(k) \coloneqq \sum_{t \in \mathcal{T}(k)} (\hat{p}(t) - \bar{p}_i) u_i(t) , \qquad (3)$$

where $\mathcal{T}(k) \coloneqq \{k, k+1, \dots, k+T_h\}$ is the prediction horizon. The predicted price $\hat{p}(t)$ that the HO applies during $t \in \mathcal{T}(k)$ is computed by the following approximation:

$$\hat{p}(t) \coloneqq c_1 \, d(t) - \left[\beta_0(t) + \beta_1(t) \sum_{\ell=2}^N \hat{\Delta}_\ell(t)\right] \,. \tag{4}$$

To characterize the interval $t_i \in \mathcal{T}(k)$ during which agent *i* enters cell 2, we introduced in [1, Sec. III.A.3] the rectangular function ϑ_i that takes non-zero values during the *W* intervals preceding and succeeding t_i . The second term in (2) models the extra travel time that PEV *i* experiences for stopping at the CS and/or for the traffic situation, i.e.,

$$J_i^{\text{time}}(k) \coloneqq \sum_{t \in \mathcal{T}(k)} \chi(t) \big[(t-k)\upsilon + \xi(t) + \xi_i^{\text{CS}}(t) \big] \vartheta_i(t).$$
(5)

If agent *i* enters cell 2 during $t \in \mathcal{T}$, $\xi(t) + \xi_i^{\text{CS}}(t)$ describes the estimated remaining travel time to complete the transit through cells $\{2, \ldots, N\}$. The value of $\xi(t)$ is computed by exploiting the CTM as an oracle to predict the evolution of the traffic congestion (see [1, Sec. III.A.3] for further details).

The resources available at the CS are finite and must be shared among the PEVs. This creates a coupling between the agents' decisions, both in the cost (5) and in the constraints. Next, we qualitatively list the most important constraints that PEV $i \in \mathcal{I}(k)$ has to meet during the choice of the optimal feasible charging schedule. For clarity we refer the reader to the corresponding formal definitions in [1, Sec. III.B]:

- Charging only if *i* is at the CS, [1, Eq. 16],
- exit the CS if *i* stops charging, [1, Eq. 17],
- if *i* stops, it has to remain at the CS for at least 2W + 1 intervals, [1, Eq. 19],
- exit the CS only if $x_i > x_i^{\text{ref}}$, [1, Eq. 20],
- total energy purchased by the PEVs has to be lower than u^{max} , [1, Eq. 21],
- the number of PEVs simultaneously charging must be lower than $\overline{\delta}$, [1, Eq. 21].



Fig. 1: Location along the A13 highway of the 8 sensors selected for the simulations; [4] indicates how to access this info.

All the constraints are cast in an affine form via auxiliary variables and described in a compact form by means of the matrices A and b. Organizing all the decision variables associated to each PEV i in a vector z_i (and $z := \operatorname{col}((z_i)_{i \in \mathcal{I}(k)})$) allows us to cast the charging problem above as an exact MI-GPG, defined via the following set of interdependent optimization problems

$$\forall i \in \mathcal{I}(k) : \min_{z_i \in \mathcal{Z}_i(k)} J_i(z_i, \boldsymbol{z}_{-i}|k) \quad \text{s.t.} \ A\boldsymbol{z} \le b \quad (6)$$

where $Z_i(k)$ is the time-dependent set of feasible decisions of each agent *i*, [1, Eq. 24]. Algorithm 1 in [1] is based on the sequential mixed-integer best response. It ensures convergence to an ε -Mixed-Integer Nash Equilibrium (ε -MINE), since (6) is an exact potential game [1, Th. 1]. The remainder of the paper is devoted to the implementation of the ATDM strategy proposed in (Part I: Theory) [1], and to show via numerical simulations its beneficial effects on traffic alleviation. Moreover, we analyze how different configurations of the parameters in Table I affect the travel time.

III. CTM IDENTIFICATION

Let us introduce the examined case study and identify the parameters of the associated CTM starting from realworld data and following the schematic procedure depicted in Figure 2. We consider a stretch of the A13 highway in The Netherlands connecting the cities of The Hague and Rotterdam. The Dutch government embraces the policy of making traffic data accessible via the Nationaal Dataportaal Wegverkeer (NDW) [3]. In particular, the NDW-Dexter portal [4] allows us to access the sensors placed along the highway and extract the traffic data related to a particular date and time. Here, we select 8 sensors, denoted in the following by s_1, \ldots, s_8 , on the roadway that from The Hague enters Rotterdam (Figure 1). The sensors are placed approximately at $500 \,\mathrm{m}$ from each other and measure the number of vehicles and their average speed during a period of 1 minute. We consider the data of the 15/10/2019 from 07:00 to 20:00, since there is no traffic congestion during the remaining hours.

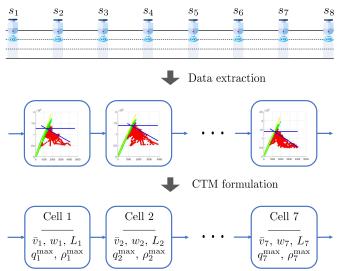


Fig. 2: Schematic structure of the procedure adopted to identify the parameters of the CTM.

Remark 1 (Minimum sample frequency): The frequency of the data samples has to be high enough to allow the CTM to evolve correctly. In fact, if for some $\ell \in \mathcal{N}$ the inequality

$$\frac{T\bar{v}_\ell}{L_\ell} < 1$$

is not satisfied, then the associated cell's density ρ_{ℓ} can take negative values. This is a consequence of the density definition in [1, Eq. 1] and the lower bound for the sampling frequency is obtained from the worst-case scenario. One can solve this issue by considering longer cells or by interpolating the data obtained from the sensors to decrease the sampling time. For the problem at hand, we show that the free flow speed is approximately 120 km/h, therefore we interpolated the data to obtain a sampling time of T = 10s, so $T\bar{v}_{\ell}/L_{\ell} \simeq 0.66 < 1.\square$ We construct a CTM composed of N = 7 cells, in which the flows ϕ_1, \ldots, ϕ_8 between cells are obtained directly from the raw data provided by the sensors, i.e., for all $j \in \{1, \ldots, 8\}$

$$\phi_j \coloneqq \frac{\text{\# veh. from } s_j}{T}$$

The the average speed of the vehicles is also measured by each sensor, thus for each cell $\ell \in \{1, ..., 7\}$ the density is

$$\rho_{\ell} \coloneqq \frac{\phi_{\ell}}{\text{avg. speed from } s_{\ell}}.$$

The relation between the flow and the density is represented for cell 1 in the *fundamental diagram* depicted in Figure 3a, where we used a threshold on the average vehicles' velocity to distinguish between the data associated with the free flow and those measured during a traffic congestion. As in [5] and more in details in [6, Sec. 3.2], we identified the parameters of each cell of the CTM by using linear regression. For a cell ℓ , the free flow speed \bar{v}_{ℓ} is the slope of the linear regression applied to the data measured during the free flow (the yellow line in Figure 3a). Similarly, the congestion wave speed w_{ℓ} is the slope of the quantile regression applied to the leftover data.

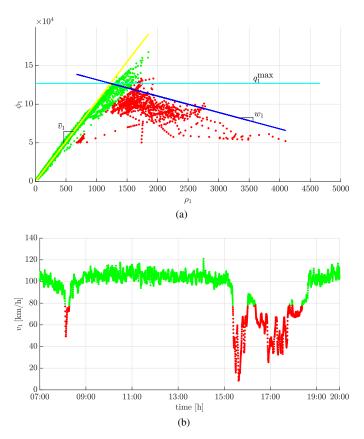


Fig. 3: (a) The fundamental diagram of cell 1 obtained from the data of s_1 . The data points are green if the cell is in a free-flow condition and red otherwise. (b) Average vehicles speed in cell 1 during the day (the color legend is as in (a)).

The result of the regression is illustrated via the blue line in Figure 3a, and the density at which it intersects the horizontal axis represents the (theoretical) cell's maximum density ρ_{ℓ}^{max} . Finally, the intersection of the two regression lines (i.e., the blue and the yellow) defines the maximum cell capacity q_{ℓ}^{max} . Therefore, by applying these steps, sketched in Figure 2 for all the cells, we identify the parameters that, together with ϕ_1 and ϕ_8 , fully describe the CTM. Their final values are reported in Table II and the code used is available at [7].

IV. DECISION PROCESS' PARAMETERS SELECTION

In this section, we focus on the parameters describing the decision making process (or game) in which the PEVs are involved during every time interval (see Table I for the description of each parameter). The chosen values are reported in Table III and characterize what we call the *base case* in the remaining of the paper. Now, we list the motivations behind the choice of the values of the most significant parameters in the game.

- *p*_{EV}: the current market share of PEVs in the Netherlands is around 2%. However, PEVs are expected to constitute more than 7% of total vehicles in the market by 2030 [8]. For this reason, we choose *p*_{EV} = 5%.
- *l*: it is natural to consider the interval during which each player does not vary its strategy (namely if/when and for

how long to stop at the CS) longer than T. Then, we choose lT = 100s.

- $T_{\rm h}$: in [9] a group of commuters traveling via the A12 in the Netherlands participated in a test, whose results indicate that 60% of the involved commuters could start their work within 30 min later than usual. Therefore, we considered $T_{\rm h} = 15$, implying that the maximum time PEVs can spend at the CS (i.e., the length of the prediction horizon) is equal to 25 min.
- δ : in The Netherlands, the government is putting a lot of effort in increasing the number of available charging points, doubling it between 2015 and 2019 [10]. Thus, we choose $\overline{\delta} = 100$ to model the foreseeable increment in charging spots.
- C_i : the battery capacity of each PEV is randomly chosen from a pool of the most common PEV models. Specifically, $C_i \in [12, 100]$, where 12 kWh represents the capacity of a Mitsubishi Outlander and 100 kWh the one of a Tesla Model S.
- α_i : for the realization of this Gaussian variable we choose mean and variance equal to $\mu_{\alpha} = 0.05$ and $\sigma_{\alpha} = 0.03$, respectively. This choice reflects the assumption that agents are more keen to save time rather than money. The small variance mimics an homogeneous interest among the PEVs owners. The case of a more heterogeneous population is analyzed in Section VI.
- \bar{u} : the charging spots are able to fast charge the PEVs and the maximum energy that can be delivered by each spot in an hour is 150 kWh. Thus, during a single time interval we have $\bar{u} = 150 \cdot lT = 4.16$ kWh.
- u^{\max} : the CS is assumed to be able to deliver the maximum power to all the charging spots simultaneously.
- *p
 _i*: this energy price is chosen equal to 0.205 €/kWh and represents the average between the price for fast charging (see [11], [12]) and the one for charging at home (see [13]).
- d: the base demand profile of the grid is obtained from [14] and scaled to match the average demand of a regional grid in the Netherlands, so $d(k) \in [3.94, 4.16]$ MWh.
- c_1, c_2, c_3 : these values must be chosen simultaneously to make the average value of p(t) equal to \bar{p}_i and normalize the three components in the price. Furthermore, c_3 is particularly important, since it defines the discount due to the traffic congestion. We introduce here what we refer to as *incentive* in the remainder of the paper. We say that we apply an incentive of y% if the term in the price function directly associated to the traffic congestion makes p decrease of y% during the intervals of peak traffic congestion.
- χ : this normalizing factor takes different values along the prediction horizon. Specifically, $\chi(t) = 1/(W+1)$ for the first W + 1 time intervals in $\mathcal{T}(k)$ and $\chi(t) = 1/(2W+1)$ for the others. This is due to the definition of and constraints on ϑ_i (see [1] for more details).

Finally, let us suppose that the percentage of the PEV users that are traveling with an insufficient SoC is very low, since we focus on drivers commuting during the rush hours so

TABLE II: The variables and parameters (respectively in the upper and bottom part of each table) related to the CTM and the charging scheduling decision problem.

Para	ameters	Identified values of the CTM						
l	_	1	2	3	4	5	6	7
L_{ℓ}	[km]	0.39	0.41	0.365	0.365	0.365	0.5	0.5
T	[s]	10	10	10	10	10	10	10
\bar{v}_{ℓ}	[km/h]	103.15	109.34	111.67	112.77	113.07	114.12	114.18
w_ℓ	[km/h]	21.23	26.19	19.91	26.13	27.73	26.62	31.11
q_{ℓ}^{\max}	[veh/h]	$1.26 \cdot 10^{5}$	$1.38\cdot 10^5$	$1.28\cdot 10^5$	$1.40\cdot 10^5$	$1.40\cdot 10^5$	$1.38 \cdot 10^{5}$	$1.40\cdot 10^5$
$ ho_\ell^{ m max}$	[veh/km]	$7.2 \cdot 10^3$	$6.56\cdot 10^3$	$7.58\cdot 10^3$	$6.62\cdot 10^3$	$6.29\cdot 10^3$	$6.41\cdot 10^3$	$5.73\cdot 10^3$

TABLE III: The values of the parameters in the decision making process for the base case.

Base case: Game parameters						
x_i^{ref}	_	[0.25, 0.35]				
$p_{\rm EV}$	_	5%				
lT	[h]	0.0278				
$T_{\rm h}$	_	15				
C_i	[kWh]	$\{12, \cdots, 93.4, 100\}$				
η_i	[l/kWh]	[0.85, 0.99]				
$\frac{\eta_i}{\delta}$		100				
α_i	_	(0, 1)				
u^{\max}	[kWh]	416.6				
$\overline{u}(\underline{u})$	kWh	4.16				
d	[MWh]	[3.94, 4.16]				
c_1, c_2	[€/kWh ²]	$5.07 \cdot 10^{-5}$				
c_3	[€/(h · kWh)]	0.33				
\overline{p}_i	[€/kWh]	0.205				
β_0	[€/kWh]	0				
β_1	[€/(h · kWh)]	0.3315				
W		3				
γ	[s]	1.79				
X	[h]	$\{0.143, 0.25\}$				
v	_	1				

that the optimization problem is always feasible. From a theoretical point of view, one can prevent feasibility problems by increasing the length of the prediction horizon T_h or by translating the hard constraint on the minimum SoC into a soft one. In a real scenario, this would not be an issue, since these users will simply extend their staying at the CS.

V. NUMERICAL RESULTS

In this section, we present and discuss the simulation results for the base case introduced in the previous section (see Table III), focusing on the benefit of the ATDM strategy in terms of the average total travel time for all the drivers.

A. Performance index

The goal of the proposed policy is to alleviate traffic congestion during the rush hours for *all* the drivers on the highway, not only for the PEV owners. To quantify the benefit (and performance) of the proposed policy, we first define the quantity $\Delta_0 := \sum_{\ell=1}^N \Delta_{0,\ell}$, which denotes the sum of the extra travel times $\Delta_{0,\ell}$ of the drivers in the absence of the CS. Furthermore, we define $\Delta := \sum_{\ell=1}^N \Delta_\ell$ as the extra travel time in the presence of the CS and supposing that PEVs subscribe the proposed policy. We then introduce the following performance index:

$$\pi(\Delta_0, \Delta) \coloneqq \frac{\sum_{k \in \mathbb{N}} \Delta_0(k) - \Delta(k)}{\sum_{k \in \mathbb{N}} \Delta_0(k)} \cdot 100.$$
(7)

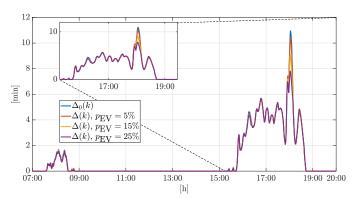


Fig. 4: Comparison of the extra travel time due to the congestion in the presence (Δ) and absence (Δ_0) of the CS, respectively. The simulations are carried out for different values of p_{EV} .

The larger π , the greater the benefit emerging from the behavior of PEV owners. The index (7) is a good yardstick to evaluate the performance of the policy over the whole day and whether or not its adoption achieves the desired traffic congestion alleviation.

B. Simulation base case

We are now ready to discuss the effects of the ATDM strategy proposed in (Part I: Theory) [1]. Figure 4 highlights that there are two time intervals during which a traffic congestion occurs and they are centered around 08:00 and 18:00, respectively, and reflect the real data in Figure 3b, where the velocity drops exactly in those time intervals. The traffic jam in the morning lasts fro almost one hour while the one in the afternoon for three hours, with a particularly high peak (in terms of travel time) at 18:00. Remarkably, despite the percentage of PEVs on the highway is modest, our algorithm manages to decrease the afternoon peak of more than 5.4% in terms of Δ . If there is no congestion all the cells are traveled by a vehicle in 1.62 min. During peak traffic congestion this time becomes 12.54 min, the proposed ATDM strategy reduces it to 12.06 min. The overall achievement in terms of travel time is $\pi = 1.05$. In Figure 5, we highlight the difference between the travel time with vs without our ATDM strategy. The ATDM manages to decrease the peaks and redistribute the vehicles in the "valleys", i.e., the parts in which the curve takes lower values with respect to the closest peaks. This emerging behavior matches the expectation: in fact, it relates to the "valley filling" phenomenon, well known in the electricity

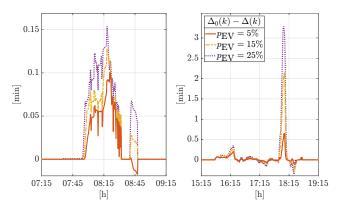


Fig. 5: Comparison of the difference $\Delta_0 - \Delta$ computed with different values of p_{EV} . The two figures show the detail related to the morning and afternoon congestion, respectively.

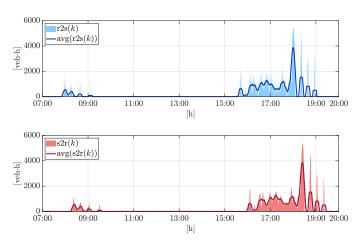


Fig. 6: The flows entering and exiting the CS, i.e., r2s and s2r respectively. The shaded area represents the actual flow, while the solid line a moving average with a window of 10 min.

market, where the energy price depends on the energy demand, see [15], [16]. The redistribution of the vehicles creates a global reduction of the travel time. This effect of the ATDM on the PEVs is confirmed by the flows shown in Figure 6, where r2s increases before the two peaks of Δ , while s2r peaks immediately after the reduction of Δ after the rush hours.

The dynamic energy price p designed by the HO is reported in Figure 7. It shows a slow variation due to the base energy demand d and a fast one associated with the traffic congestion on the highway stretch. Interestingly, these two quantities act in opposite directions since the major traffic congestions happen during the rush hours, which are notoriously those during which the demand of energy is at its highest. The parameters c_1, c_2 and c_3 are chosen such that the incentive provided is the 25%, i.e., the maximum discount is equal to $0.05 \notin/kWh$ with respect to the average price $\bar{p}_i = 0.205 \notin/kWh$. Finally, in Figures 8 and 9, we illustrate the number of PEVs simultaneously connected to the grid, i.e., $\sum_{\bar{k} < k} \sum_{i \in \mathcal{I}(\bar{k})} \delta_i(\bar{k})$, and the amount of energy purchased u^{PEV} . These two quantities are closely related and for this reason their profiles are almost identical. In both cases,

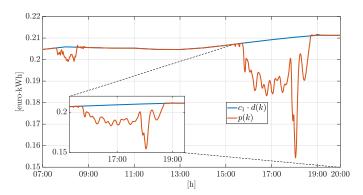


Fig. 7: The energy price p adopted by the CS and the base demand d scaled by the factor c_1 .

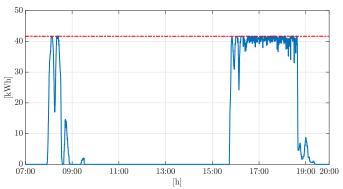


Fig. 8: The total energy purchased by the PEVs, u^{PEV} . The red dashed line denotes u^{max} .

the strategies implemented satisfy the upper bound constraints. As expected, during the period of high traffic congestion all the charging spots at the CS are busy. This highlights a key difference between longer and shorter traffic congestion; in the latter, there are only brief periods during which no charging spot is available, i.e., $\sum_{\bar{k} < k} \sum_{i \in \mathcal{I}(\bar{k})} \delta_i(\bar{k}) = \bar{\delta}$. Therefore, if a PEV decides to enter the CS, then it is almost sure to connect immediately. On the other hand, a traffic congestion that lasts for a substantial amount of time creates a queue of PEVs at the CS waiting for charging. This idle waiting time creates an extra cost for the PEVs stopping. Moreover, this phenomenon generates detrimental effects in the concurrence of high traffic congestion peaks surrounded by an overall elevated traffic congestion level. In fact, if we consider PEVs exiting cell 1 at 18:10, then it should be beneficial for them to stop and charge for a short period, waiting for the traffic congestion to disappear. Unfortunately, all the charging spots are occupied, so the PEV cannot stop, hence contributing to increase the traffic congestion. In fact, Figure 6 shows that in concurrence with the highest congestion peak, the r2s flow decreases.

This first example highlighted the overall benefit of adopting a dynamic energy price to enforce an ATDM. The most important macroscopic effect is the redistribution of the vehicles that creates a valley filling like phenomenon in the travel time.

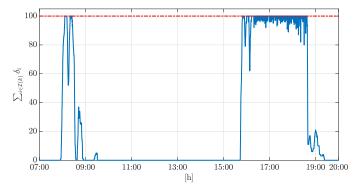


Fig. 9: The number of busy charging spots at the CS. The red dashed line is set equal to $\bar{\delta} = 100$, the capacity of the CS.

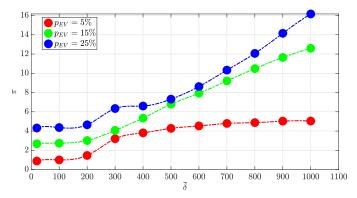


Fig. 10: Effect of the increment δ on the performance index π in (7). The simulations are carried out for different values of p_{EV} .

VI. SENSITIVITY ANALYSIS

Next, we investigate the effects that a single parameter has on Δ . They are difficult to extrapolate directly from the base case due to the complexity of the decision making process and the multitude of variables involved. In this section, we propose a sensitivity analysis that focuses on the most compelling features of the proposed ATDM. Specifically, we start from the parameter configuration in Table III and vary one parameter (or at most two) to highlight how it affects the travel time. Note that the values used for this variation may deviate from what one can reasonably expect in a real-world scenario, e.g. a CS with $\overline{\delta} = 1000$, but they are meant to investigate the performance in extreme configurations or approximations of possible future configurations, e.g. one CS that approximates the charging capacity of two or more nearby CSs.

A. Number of available charging spots

Intuitively, a larger number of charging spots δ mitigates the effects of prolonged traffic congestion; in fact, the PEVs take more time to saturate the available spots at the CS, and, as a consequence, the congestion alleviation during the rush hours can be more effective. The variation of π with respect to the increment of charging spots is presented in Figure 10 for different PEV shares, i.e., $p_{\rm EV}$. The curve profile for $p_{\rm EV} = 5\%$ shows two plateaus, one for small values of $\bar{\delta}$ and the other for values greater than 400. The transit between the two happens

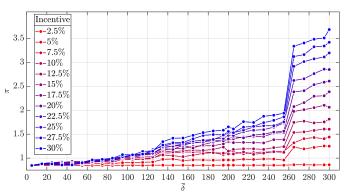


Fig. 11: The performance π as a function of the number of charging spots, i.e., $\overline{\delta}$, computed for different incentives.

between $\bar{\delta} = 200$ and $\bar{\delta} = 300$. It represents the setting in which an investment to increase the number of charging spots is the most profitable in terms of performance. In fact, going from $\bar{\delta} = 100$ to $\bar{\delta} = 300$ triples the value of π , which rises from 1.05 to 3.19.

Assuming a higher number of PEVs on the highway does not avoid the initial plateau, but, surprisingly, it prevents the occurrence of an analogous plateau for greater values of $\overline{\delta}$. This implies that investing in more charging spots creates a high return in terms of performance, after a certain "critical" value, i.e., the value of $\overline{\delta}$ after which the initial plateau ends. Interestingly, even if $p_{\rm EV}$ varies, the critical value of $\overline{\delta}$ remains between 200 and 300. In Figures 4 and 5, we note that the beneficial effect of an increment of the PEVs number. In fact, the more PEVs subscribe the higher the traffic alleviation is. Figure 5, clearly shows the valley filling effect, namely a higher peak reduction implies a subsequent increment of travel time during the less-congested period.

B. Charging spots and incentive

Starting from the parameters in Table III, we analyze the performance obtained by varying simultaneously the number of available charging spots, i.e., $\overline{\delta}$, and the incentive on the energy price. Figure 11 depicts the different curves resulting by increasing the number of available charging spots, i.e., $\bar{\delta} \in [5, 295]$, when the incentive ranges between 2.5% and 30%. An increment in the number of plugs generates, in general, an higher performance increment compared to a greater incentive. Surprisingly, the value of $\overline{\delta}$ at which the initial plateau of performance stops is not affected by the incentive. In fact, the consequent steep increment in π settles between $\bar{\delta} = 255$ and 265; this can be considered the critical value for this configuration. On the other hand, an increment in the incentive creates a smaller effect on the performance yet it is more predictable especially if the number of plugs is high. This result suggests that an investment in increasing δ leads to a high return only if the additional charging spots allow to surpass the critical level. If this is not possible, then increasing the incentive is a more profitable strategy.

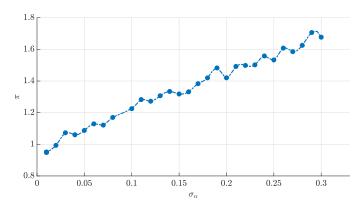


Fig. 12: Performance π as a function of σ_{α} , the heterogeneity in drivers interests.

C. Heterogeneous population of PEVs

In the simulations performed for the base case in Section V-B, we have considered a fairly homogeneous population of PEV owners, i.e., drivers that value similarly their interest of saving time or money. The probability distribution, from which all the α_i are drawn, has variance $\sigma_{\alpha} = 0.03$. Next, we consider a collection of heterogeneous PEVs, in which some are more interested in maintaining the travel time at its minimum and others in saving money. In Figure 12, we show the performance increment attained by assuming a population of agents with increasingly diverse interests (all the other parameters are set as in Table III). Interestingly, the value of π increases from 0.95, when $\sigma_{\alpha} = 0.01$, all the way to 1.71, if $\sigma_{\alpha} = 0.29$. The trend of the increment is almost linear and does not seem to slow down for higher values of σ_{α} . From [9], it seems reasonable to assume that the commuters involved in the decision making process form a heterogeneous set; nevertheless, the fact that we focus only on PEV owners may reduce this variability. The value of α that describes the best a real-world scenario is for these reasons an open problem that requires further investigation. The increment in the performance can be explained by looking at Figure 9. In fact, a more heterogeneous population leads to fewer PEVs stopping at the CS during the long afternoon congestion peak. This alleviates the problem of overcrowding the CS where all the charging spots are generally busy during the largest traffic congestion peaks.

D. Incentive

Based on our numerical study, we have chosen the incentive used in the base case heuristically. In this subsection, we study the effect of different incentives if $p_{\rm EV}$ varies. In Figure 13, we report the performance π computed for all the combinations of the incentive [10, 55] and $p_{\rm EV} \in \{5, 10, 15, 20\}$. If $p_{\rm EV} = 5\%$ the value of π is almost constant with fluctuations of ± 0.1 . In the other cases, an interesting trend arises: the optimal incentive that maximizes the performance is not the highest one. In fact, if $p_{\rm EV} = 10\%$ the optimal incentive is 15% while for $p_{\rm EV} = 15\%$ and $p_{\rm EV} = 20\%$ it is 35%. This relates to the phenomena described at the end of Section V-B. Inflating the incentive makes the number of PEVs willing to

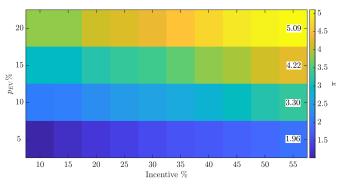


Fig. 13: The performance π in (7) for different combinations of p_{EV} and percentage of incentive. We explicitly reported the value of π only for the best performer of each row.

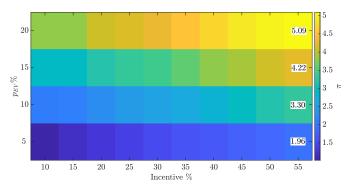


Fig. 14: The performance π in (7) for different combinations of p_{EV} and percentage of incentive. The incentive takes the nominal value during the morning peak and 1/5 of it during the afternoon peak. We explicitly reported the value of π only for the best performer of each row.

stop grow. This has a beneficial effect on the morning peak, but a detrimental one on the afternoon rush hour, since it exacerbates the problem of the overly crowded CS and the lack of available charging spots. To mitigate this issue, we propose in the next simulation a discount that varies over time and, in particular, takes a higher value during the morning traffic congestion peak and a lower value during the afternoon one. Specifically, if we say we apply an incentive of u%, then it means that we apply a y% incentive from 7:00 to 16:00, and 0.2 y% for the remainder of the day. Implementing this smarter type of incentive leads to striking results. In Figure 14, for $p_{\rm EV} = 5\%$ the travel time significantly decreases with the increment of the incentive, i.e., π goes from 1.27 (see Figure 13) to 1.96. This trend holds also for higher values of $p_{\rm EV}$, increasing the overall maximum performance π from 4.3 to 5.09. This suggests that the problem of over incentivizing the PEVs to stop during the afternoon should be solvable with incentives decreased for the afternoon peak only. Finally, the fact that the maximum value of π always coincides with the maximum incentive suggests that there is still room for improving the performance by increasing the incentive even further. Nevertheless, one should be careful in implementing a very large incentive, because it might be overly costly for the HO that has to take care of the economical burden associated with the energy price discount.

VII. POLICY RECOMMENDATION

Let us now extrapolate the key messages based on the numerical analysis and results of the previous sections, and then elaborate on possible policies that can improve the performance of the ATDM.

As illustrated in the previous section, tuning the parameters involved in the decision making process translates into infrastructural or sociological actions. The former are related to tangible features of the infrastructure, e.g., the number of available charging spots δ or the maximum power that fast charging can deliver \bar{u} ; the latter instead are intrinsically linked to the behaviors and decisions of the drivers, e.g., the interests of each agent α_i or the incentive applied to steer the drivers' behavior. As expected, the infrastructural improvements create greater outcomes in terms of performance, as shown in Figure 11 where the performance improvement by increasing the number of available charging spots overcomes that due to a higher monetary discount. This type of interventions is expensive and produces inelastic changes with respect to the demand. As an illustrative example, let us focus on $\overline{\delta}$: increasing it leads to a CS that has a low percentage of charging spots occupied throughout most of the day, and thus the return of the investment is limited. This economic point of view and the existence of a critical value of δ (see Section VI-A) suggest that the HO should carefully decide whether it is convenient to invest in this direction. Infrastructural actions should be rare and performed when a substantial leap forward can be achieved, while small incremental improvement should be avoided.

Enforcing a change in the drivers' behavior is not as straightforward as changing some physical features. Nevertheless, our formal analysis and modeling of the decision making process help us to infer some possible policies to achieve an improvement in the traffic congestion alleviation. The energy price discount generates remarkable performance, if it is designed by the HO based on the severity of the traffic congestions, see Figures 13 and 14. This policy does not require massive investment to be implemented and it is elastic with respect to the current traffic situation. Thus, from an economic perspective, a dynamic energy price currently seems the safest and the most remunerative option for the HO. The growing trend of incentivizing smart working and flexible working hours has a beneficial effect on the proposed policy for ATDM. In fact, it will increase the variety of interests among the PEV owners and consequently the performance should also increase, see Figure 12. Moreover, flexible schedules may shift the overall interest of the drivers towards saving money rather than time. This variation will allow the HO to attain the same performance even with lower incentives.

To summarize, the theoretical framework developed and the numerical simulations carried out in this work have convinced us that a solid policy to maximize the efficacy of the ATDM over time should be composed of *short term* and *long term* actions following two broad guidelines:

• Short term: a dynamic energy price should be implemented where the incentive varies with respect to the intensity and (estimated) duration of the traffic congestion.

• Long term: consider a major infrastructural investment to increase the CS capabilities, e.g., increase the number of charging spots, and consequently achieve a performance boost. In the A13 case study analyzed in this paper, the long term actions should be introduced, in addition to the short term ones, when the HO can increase the charging plugs above 100. This ensures a substantial improvement in performance that motivates the monetary investment.

VIII. CONCLUSION AND OUTLOOK

The ATDM strategy proposed in (Part I: Theory) [1] has been validated by simulation in a highly congested highway stretch, achieving a reduction of the peak traffic congestion of about 5.4% in terms of travel time. This result is achieved with the current value of PEV market shares that is around the 5%. This method creates a redistribution of the vehicles throughout the day, achieving a travel time that is on average 1% lower for all the vehicles (not only PEVs) traveling on the highway. The foreseeable increment of the PEVs and the strengthening of the charging infrastructure, together with the increasing popularity of flexible working schedules, will enhance the benefits of applying the proposed policy, making it even more effective over the upcoming years. This paper is a self-contained analysis that discovers interesting results. Nevertheless, it can act as a stepping stone to develop further research based on a similar concept. Perhaps, the most valuable extension can be a field study in which this approach is validated with humans in the loop. The framework of potential games well suits the introduction of partially rational agents (see for instance [17], [18]) that may introduce new algorithmic dynamics in the framework. In the literature, other ATDM strategies have been proposed, e.g. [19]. It can be of great value to carry out a comprehensive study that analyzes if and how well they work in combination to improve the traffic congestion alleviation.

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