# Fostering the Mass Adoption of Electric Vehicles: A Network-Based Approach

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***Abstract*—Mobility will surely be at the core of the smart cities of the future. As such, it must be planned based on novel mobility models, smart enough to answer the multifaceted needs of users, while being sustainable and energy efficient. In this evolution, electric vehicles (EVs) will be crucial, as confirmed by the fact that many governments are already actively sustaining their spread in place of common internal combustion engine (ICE) ones. Nonetheless, for their adoption to be actually widespread, one must be able to govern the mass adoption mechanisms, by designing policies that are cost-effective and successful in making the mobility transition a reality in due time. In this work, we propose a novel framework that can represent a valuable control-oriented tool to serve this ambitious goal. Our framework lays its foundation on a quantitative description of the inclination of traditional car owners toward EVs, which is retrieved by relying on data-driven insights on their mobility habits only. This information is further exploited to construct a proximity-based network, that is combined with the individual characterization into a cascade model describing the adoption dynamics. To show the potential of the introduced framework, we exploit it to assess the unforced spread of EVs starting from a set of known EV owners, and to test and quantitatively evaluate the cost and benefits of policies enacted to foster adoption.**

***Index Terms*—Electric vehicles (EVs), smart cities, social networks, spread maximization, technology adoption models.**

## I. Introduction

A LARGE part of the *Next Generation EU* program will be devoted to the so-called environmental transition, sharing the same goals of the *Clean Energy Revolution and Environmental Justice Plan* of the new US administration. One of the main objectives of both initiatives is to reach carbon-neutrality by 2050. In this challenging journey, mobility will for sure be a major player, since about 24% of total energy consumption in 2020 was used for moving people and goods along [1]. All policy makers share the belief that electric vehicles (EVs) are the platform on which such mobility transition must be built, but their adoption must reach mass levels for this change to take place. Nonetheless, to achieve mass adoption, incentive policies must be conceived and tested at design-time, so that only the most cost-effective ones are deployed. However, the sociocultural complexity of the alleged adopters and their different mobility habits make the definition of a general incentive scheme difficult to conceive [2], [3], so up to now, EV adoption has somehow lagged behind.

### A. Contribution

This article aims at providing a new framework to support the policy design step. At its core, we introduce a data-driven description of each potential adopter and we set up a multiagent network. These elements allow us to account for both the peculiarities of each agent and the social interactions that might take place among them, so that they can be actively exploited to activate the social contagion that drives mass adoption. Both the agents' description and the network construction are based on measured spatiotemporal mobility patterns, derived from real anonymized data measured on board of ICE vehicles equipped with telematic e-Boxes, that have been monitored over a 12-month period [4]. Leveraging on these data, we characterize the suitability of each agent to adopt a *fully electric vehicle* in a quantitative fashion. To do so, we detect the share of daily trips that could be seamlessly accommodated by an EV, while assuming a single overnight recharge as in [5]. Nonetheless, we extend the preliminary results in [5] by segmenting the agents into four classes, each of them denoting an increasing suitability of the agents to switching from an ICE vehicle to an EV, without altering their mobility habits. According to the rationale that adoption is guided by homophily, namely, the tendency of individuals to be maximally influenced by closest neighbors [6], agents are immersed into a network defined by geographical proximity. Once again, the inferred geographical proximity is retrieved from the anonymized data. To effectively combine the individual descriptions and the data-based network into a unique framework, we rely on state-of-the-art tools and methods of adoption dynamics, which allow for a formal description of

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opinions' formation and their spread among agents. We show that our framework can be effectively exploited to characterize the spread of EVs over the network when no incentive policy is enacted, while it can be a valuable starting point for the design of incentive and mass adoption control strategies. This last asset is preliminarily highlighted by showing that, within the proposed framework, policy design problems can be easily cast into spread maximization ones [7]. This allows policy makers to benefit from existing methods, while accounting for both the features of the social connections between agents and their personal inclinations. To provide a complete overview of the potential of the framework, we additionally propose a set of indicators that can be used to quantitatively evaluate incentive schemes to foster mass adoption of EVs and their potential environmental impact.

### B. Relations to Prior Literature

So far, the impact of social relationships to mobility habits has received little attention, especially when compared with other factors, such as working and shopping activities [8]. However, the individuals' social network is emerging as a relevant ingredient in shaping new models of travel behavior [9], with recent empirical studies confirming their strong relationship [10]. In this context lays the increased popularity of studies of opinion formation in social networks [11], which has shown to be a powerful tool for studying innovation diffusion in general [12], [13] and environmental ones in particular (see [14] and references therein). Indeed, individual behaviors are often influenced by social relations with others, and their understanding is key to predict, analyze, and control social systems [15], [16]. Driven by these results, in this work, we leverage on existing models within the realm of opinion dynamics to describe the adoption process as a dynamical system. Similar to [14] and [17], the initial predisposition of agents toward EVs is based on a rational factor, namely, the daily driving range and stop length. Nonetheless, by blending this information with insights on the technological limits of EVs, initial opinions are shaped by how effortlessly individual mobility habits can be served by the use of a fully electric vehicle. This allows us to derive a *quantitative* predisposition indicator that accounts for an essential psychological factor influencing the individual intention to adopt EVs, i.e., how much one has to change its routine to switch to a green mobility solution. A first attempt in this direction is our recent work [5] that is improved by considering a more refined classification of the agents based on their data-inferred habits and extended by exploiting the adoption model to design and assess the effectiveness of several policies. By following another stream of works, in this article, the incentive strategies are designed by solving influence maximization problems [13], so as to detect and favor the most influential nodes within the considered network [18]. Nonetheless, the influence maximization problem has been proven to be NP-hard, with exact algorithms to solve it having exponential complexity in the size of the network [13]. This has created the ground for the development of suboptimal algorithms, either based on greedy rules [19], or on classical "centrality measures," e.g., [7] and [20]. In this context, several works further propose solutions to the static maximization influence problem in social networks [21], [22]. Nonetheless, our data-based approach is the first effort in considering optimal policies and seeding of cascades, simultaneously taking into account the heterogeneity of individuals.

### C. Notation

Let $\mathbb{R}^n$ be the set of real vectors of dimension $n$ and $\mathbb{Z}_{\geq 0}$ be the set of non-negative integers. The cardinality of a set $\mathscr{S}$ is indicated as $|\mathscr{S}|$. A graph is denoted by a pair $\mathscr{G} = (\mathscr{V}, \mathscr{E})$, where $\mathscr{V}$ is the set of unitary elements of the network (or nodes), and $\mathscr{E} \subseteq \mathscr{V} \times \mathscr{V}$ is the set of edges or links representing the relationships among such entities. A path in $\mathscr{G}$ is a sequence of edges which joins a sequence of vertices. A graph $\mathscr{G}$ is said to be connected if there is a path from each vertex in the graph to every other vertex. Given a matrix $A \in \{0,1\}^{|\mathscr{V}|\times|\mathscr{V}|}$, the graph $\mathscr{G} = (\mathscr{V}, \mathscr{E})$ associated with $A$ is defined by drawing an edge $(i, j) \in \mathscr{E}$ if and only if $A_{ij} = 1$. If $A$ is symmetric, i.e., $A_{ij} = A_{ji}$ for each $i, j \in \mathscr{V}$, the *undirected* edges will be denoted as unordered pairs $\{i, j\}$, corresponding to both the directed links $(i, j)$ and $(j, i)$. Let $\mathscr{G} = (\mathscr{V}, \mathscr{E})$ be a graph, then the *in-neighborhood* of a node $i \in \mathscr{V}$ is defined as $\mathscr{N}_i = \{j \in \mathscr{V} : (j, i) \in \mathscr{E}\}$, while the *in-degree* of a node is defined as $d_i = \sum_{j\in\mathscr{V}} A_{ij}$.

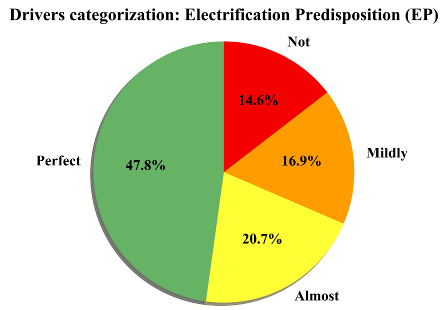
### D. Outline of this Article

The rest of this article is organized as follows. Section II illustrates the dataset and the processing steps needed to build the network and characterize the agents' classes. Section III describes the cascade model that governs the adoption mechanism, which is exploited for an open-loop analysis of the adoption dynamics in Section IV. Section V illustrates a possible formulation for incentive policies design within our framework, whose impact on the network is then analyzed in Section VI via a set of quantitative indicators. Finally, Section VII concludes this article.

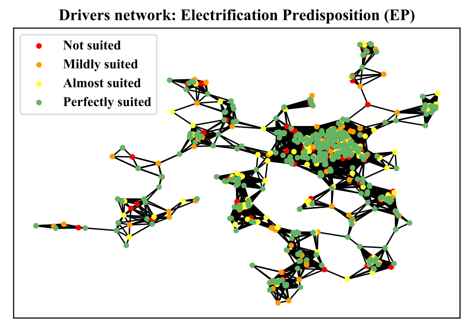
## II. Agents and Network Description Under a Data-Based Lens

To understand the intertwining relationship between social relationships and EV adoption, it is pivotal to characterize the *network* embedding connections between agents and their *mobility attitudes*. In this work, both these features are retrieved from a set of *anonymzed* data collected from 1000 ICE vehicles equipped with e-Boxes,[1] all registered within the Italian province of Parma. The dataset comprises the GPS latitudes and longitudes gathered at ignitions, shutdowns, and during trips of each vehicle over one year (from September 1, 2017 to August 31, 2018) with the respective time stamps. These raw data are aggregated to retrieve information on the distance traveled daily by each agent and the duration of the stops between trips, ultimately allowing us to have insights on their real mobility patterns.

[1]The considered vehicles are a statistically significant sample extracted from a much larger dataset, with the aim of easing the presentation of the proposed approach.




(a)




(b)

Fig. 1. Agents' classification based on their EP index: Shares of each class and distribution of categorized agents over the proximity-based network. (a) Percentage of agents belonging to each macro-level cluster. (b) Influence network with class-dependent labeling of the nodes.

## A. Data-Based Proximity-Based Network

The influence network between agents is formalized by means of an *undirected graph* $\mathscr{G} = (\mathscr{V}, \mathscr{E})$, where each node $v \in \mathscr{V}$ of the graph represents one of the travelers. Since the available data are *anonymized* and, thus, we have no actual information on the social relationship between agents, the edges $\mathscr{E}$ of the graph cannot be selected as effortlessly. By relying on the inferred mobility patterns to specify how agents influence each others, we build $\mathscr{G}$ based on the *geographical proximity* of their *bases* $\{b_v\}_{v \in \mathscr{V}}$, the features of which are retrieved by averaging individual GPS coordinates associated with at least 50% of the overnight stops with a duration greater than or equal to 7 [h]. Accordingly, an edge is added to $\mathscr{G}$ when the following holds $(v, w) \in \mathscr{E} \iff d(b_v, b_w) \leq D$, where $d(b_v, b_w)$ is the geodesic distance between the bases of the $v$th and $w$th agents, and $D = 3$ [km] denotes the maximum distance between base positions for two agents to be seen as *neighbors*. The value of $D$ is dictated by the average size of a neighborhood in the city of Parma[2]. This design choice is driven by the inkling that agents are likely to form a "bond" whenever they are *close* enough to habitually interact with each others, for a fairly long time. In turn, a prolonged interaction favors shifts of the agents' attitude toward EVs when the number of their close neighbors already owning an electric vehicle increases. Based on these principles, the 1000 vehicles initially considered are pruned to discard agents whose bases are either 1) outside the city of Parma or 2) not uniquely defined. During this cleaning phase, 6% of the initial agents are dropped, leading to a network that comprises 940 nodes out of the starting 1000.

Despite the pruning phase, the resulting proximity-driven network is still characterized by subcommunities that are barely connected among each others, as expected due to the extent of the Parma province. The presence of these *isolated* groups is likely to hinder the diffusion of new mobility habits over the whole network, especially when most members of a community are resistant to EV adoption. We thus detect the *largest connected component* in the adjacency matrix $A$ associated with $\mathscr{G}$, and retain the latter only for our subsequent analysis. The resulting data-based influence network $\mathscr{G} = (\mathscr{V}, \mathscr{E})$ [see Fig. 1(b)] is constituted by $|\mathscr{V}| = 728$ nodes. Note that several agents are concentrated in an area corresponding to the city of Parma and its close surrounding belt, while the others are spread over the province. This result shows that we are still able to consider a geographically meaningful suburban community, despite the reduction in the number of agents. It is worth stressing that several agents are still poorly connected, i.e., they have strictly less than 50 neighbors, and thus, they might hamper the diffusion of EVs, especially if they are particularly resistant to this new technology. Further details on the network and the associated degree distribution can be found in [23].

[2]The average area of a neighborhood in the city of Parma is about 19 km$^2$.

## B. Capturing Agents Attitude: A Data-Based Classification

As for the proximity-based network described in Section II-A, the attitude of each agent toward EVs can only be inferred from real mobility patterns. To blend this data-based information with the features of the considered technology, we rely on the intuition that agents are more likely to buy an electric vehicle if their mobility habits somehow comply with the main limitations of EVs. To this end, here we focus on their battery autonomy range and recharge time. Accordingly, we follow the same rationale of [4], by categorizing the daily trips of each agent based on their feasibility with respect to the technological limits of EVs.

For each agent $v \in \mathscr{V}$, we consider the set $\mathscr{A}_v$ of *active days*, namely the ones in which the vehicle is actually used, and we determine the associated kilometers traveled. By considering a rather conservative autonomy range for an EV of about 300 km, we exploit the data-based mobility patterns to determine which active days can be *critical* for a potential EV owner, as the daily trips exceed this technological limits. Nonetheless, a critical day might not hamper the final adoption of an EV if the daily trips feature at least one stop, that is long enough to be potentially compatible with an EV recharge. As the minimum charging time (at a fast charging point) of a battery to regain sufficient driving range amounts at approximately 30 min, we thus search for the subset $\mathscr{E}\ell_v \subseteq \mathscr{C}_v$ of *eligible days*, namely critical days with at least one stop longer than this lower thresholds. This categorization allows us to find a data-based *proxy* for the adaptability of agents' mobility habits to a prompt transition to an EV. Indeed, the higher the number of critical and noneligible days, the more agents have to change their daily routine to satisfy the constraints imposed by electric vehicles. This insight is translated into the *critical ratio* $CR_v \in [0,1]$, a compact indicator that quantifies how much the habits of the $v$th agent have to be modified for a smooth transition to an EV. The critical ratio is defined as

$$CR_v = \frac{|\mathscr{C}_v| - |\mathscr{E}\ell_v|}{|\mathscr{A}_v|}, \quad v \in \mathscr{V} \tag{1}$$

so as to be closer to 0 whenever an agent is suited for an immediate shift to an EV according to the previous classification. Because of the features of their mobility patters, the considered agents are all characterized by relatively small critical ratios. This provides narrow margins for an actual discrimination between the considered agents, which might negatively affect our analysis. To overcome this problem, we first normalize the agents' critical ratios as

$$\tilde{CR}_v = \frac{(CR_v - \min_{v\in\mathscr{V}}(CR_v))}{(\max_{v\in\mathscr{V}}(CR_v) - \min_{v\in\mathscr{V}}(CR_v))}, \quad \tilde{CR}_v \in [0,1] \tag{2}$$

and, then, we exploit the information embedded in $\{\tilde{CR}_v\}_{v\in\mathscr{V}}$ to build the final *electrification potential* (EP) index, which is given by

$$\mathrm{EP}_v = 1 - \tanh \boldsymbol{\varepsilon}(\tilde{CR}_v), \ \mathrm{EP}_v \in [0,1]. \tag{3}$$

This definition, along with the choice of $\boldsymbol{\varepsilon} = 10$, allows us to emphasize differences between the suitability of agents to EVs. We stress that $\boldsymbol{\varepsilon}$ is a tunable parameter, that can be adapted according to the features of the considered scenarios.

By relying on the continuous EP indexes [see (3)], EV adoption is analyzed by clustering agents into four macro-level groups, based on the "similarity" of their electrification potential. This choice allows us to account for a rather detailed picture of the individual attitudes toward EVs, while still limiting the number of classes. Because of the nonlinear nature of the mapping exploited in constructing the EP index, the agents are classified as follows:

1) $\mathrm{EP}_v < 0.67$: the $v$th agent is *not suited* for EV adoption;
2) $\mathrm{EP}_v \in [0.67, 0.83)$: the agent is *mildly suited* for EV adoption;
3) $\mathrm{EP}_v \in [0.83, 1)$: the agent is *almost suited* for EV adoption;
4) $\mathrm{EP}_v = 1$: the agent is *perfectly suited* for EV adoption.

This uneven splitting allows us to consider a framework in which only the agents with full electrification potential can effortlessly adopt an EV, while emphasizing the natural unwillingness of agents with lower EPs to change their mobility habits. The shares of each class for the considered set of agents is reported in the Fig. 1, along with the agents' location within the proximity-based influence network. As shown in Fig. 1(a), perfectly suited agents represent a rather large portion of the overall agents and they are quite scattered across the network [see Fig. 1(b)]. Therefore, they are allegedly able to influence those agents more reluctant to buy an EV. It is worth commenting that all the classes are significantly represented, in spite of the predominant number of perfectly suited agents. We stress that the proposed classification solely relies on information that can be deduced from individual mobility patterns. Indeed, the data used in this work are anonymized, and thus, we have no insights on the actual predispositions of each agent toward EVs nor we have information on the presence of EV owners within our set of agents. If additional information was available, it could have been easily embedded into the proposed framework, and exploited to refine the tuning of $\boldsymbol{\varepsilon}$ in (3) and to validate and improve the splitting in discrete classes.

## III. Cascade Model for EV Adoption

The influence network and the agents' attitudes toward EVs inferred from their real mobility patterns are now used to characterize the EV adoption mechanism over $\mathscr{G}$. To this end, we rest on the following assumptions.

***Assumption 1:*** Agents already owning an electric vehicle do not modify their inclination. Whenever an agent becomes an adopter, its attitude toward EVs cannot further change. □

***Assumption 2:*** Each agent is endowed with a class-dependent, constant threshold $\alpha_v \in [0,1]$, $v \in \mathscr{V}$, dictating the share of adopter neighbors it needs to switch to an EV. □

Since the average period of ownership of a private car in Italy is about ten years, Assumption 1 seems quite reasonable whenever EV adoption is analyzed within that time range. Instead, Assumption 2 is introduced to exploit the data-based categorization in Section II-B to characterize the adoption process. Specifically, we focus on a *setup* in which the agents' thresholds $\{\alpha_v\}_{v\in\mathscr{V}}$ are drawn from the following uniform distributions at random:

1) $\alpha_v \sim \mathscr{U}_{[0.55,0.95]}$ if the agent is *not suited* for an EV;
2) $\alpha_v \sim \mathscr{U}_{[0.15,0.55]}$ if the agent is *mildly suited* for an EV;
3) $\alpha_v \sim \mathscr{U}_{[0.001,0.15]}$ if the agent is *almost suited* for an EV;
4) $\alpha_v \sim \mathscr{U}_{[0,0.001]}$ if the agent is *perfectly suited* for an EV.

According to Assumption 2, this choice is dictated by the intuition that agents with mobility patterns that are somehow compliant with the technological limits of electric vehicles are likely to need less neighbor adopters to be persuaded to switch to an EV. Note that in the considered scenario even agents belonging to the same class are equipped with different thresholds, so as to ground the diffusion process on the data-based description of individual inclinations.

Based on our assumptions, the EV adoption process can be effectively described through a *deterministic irreversible cascade model* on our influence network [20]. To this end, let $x_v(t) \in \{0,1\}$ be a Boolean time-varying variable, that indicates the attitude[3] of the $v$th agent toward EVs at time $t \in \mathbb{N}$. Denote with $S_0 = \{v \in \mathscr{V} : x_v(t_0) = 1\}$ the set of initial adopters at the beginning of the analysis, i.e., for $t = t_0 = 0$. In this work, we model the evolution of the agents' opinion according to the following logic:

$$x_v(t+1) = \begin{cases} 1, & \text{if } x_v(t) = 1 \textbf{ or } \frac{|\mathscr{N}_v^\star|}{|\mathscr{N}_v|} \geq \alpha_v \\ 0, & \text{otherwise} \end{cases} \qquad v \in \mathscr{V} \tag{4a}$$

where $\mathscr{N}_v$ is the set of in-neighbors nodes of the $v$th agent and $\mathscr{N}_v^\star(t) \subseteq \mathscr{N}_v$ denotes the subset of neighbor adopters. We stress

[3] At time $t$, the $v$th agent has switched to an EV if $x_v(t) = 1$.

that $x_v(t)$ can be seen as the state of the $v$th agent, whose evolution is regulated by both its individual inclination, embedded in the thresholds $\alpha_v$, and its position within the network. As such, the cascade model can be seen as a foundational state-space description of the adoption process, for which incentive policies can be designed by exploiting both feedback control and spread maximization approaches.

At each time step[4] $t$, the set $S_t = \{v \in \mathscr{V} : x_v(t-1) = 0 \text{ and } x_v(t) = 1\}$ of agents that have switched to an EV thus satisfies the following relationship:

$$S_t = \left\{ v \in \mathscr{V} \setminus (\cup_{\tau=0}^{t-1} S_\tau) : \frac{|S_t^\star \cap \mathscr{N}_v|}{|\mathscr{N}_v|} \geq \alpha_v \right\}, \quad t \geq 1 \quad (4b)$$

where $S_t^\star := \cup_{\tau=0}^{t} S_\tau$ is the set comprising all EV-adopters up to time $t$. In this light, EV adoption is thus regulated by the relative popularity of this mobility solution among neighbors. Because of the characteristics of the considered adoption model, the dimension of the set $S_t^\star$ increases monotonically over time, and the overall opinion dynamics converges to a final adopter set $\bar{S}^\star$. According to [12], the latter can be characterized based on the features of the influence network $\mathscr{G}$, the seed set $S_0$ and the thresholds $\{\alpha_v\}_{v\in\mathscr{V}}$ making use of the concept of cohesive sets, that are defined as follows.

***Definition 1:*** [Cohesive set]: A set $\Omega \subseteq \mathscr{V}$ is said *cohesive* if for all $\omega \in \Omega$ it holds that $\frac{|\Omega \cap \mathscr{N}_\omega|}{|\mathscr{N}_\omega|} > 1 - \alpha_\omega$.

Accordingly, a set $\Omega$ is cohesive if for each element $\omega \in \Omega$ the ratio of neighbors not belonging to $\Omega$ is strictly smaller than threshold $\alpha_\omega$. Based on Definition 1, $\bar{S}^\star$ can be formalized according to the following theorem.

***Theorem 1 (Lemma 2 [12]):*** Given a network with seed set $S_0 \subset \mathscr{V}$, let $\Omega \subset \mathscr{V} \setminus S_0$ be the cohesive set with maximal cardinality. Then, the set of final adopters is given by $\overline{S}^\star = \mathscr{V} \setminus \Omega$.■

This theoretical result endorses the convergence of our adoption model over an infinite horizon, but provides a characterization of the final adopter set that is rather demanding to be computed in practice. Indeed, retrieving the maximal cohesive set contained in the complement of $S_0$ is computationally expensive, as shown in [22]. Nonetheless, the difficulties that one have to face in retrieving $\bar{S}^\star$ do not constitute a limitation to our analysis, since our goal is to study the spread of adoption over a finite time horizon. This implies that the final adopter set might not be reached and, thus, its explicit computation is not required. We stress that looking at a limited time span is reasonable when studying the EV adoption process, as over long horizons the agents' mindset can change due to advances of the EV technology not accounted for in our model.

As clearly indicated by Theorem 1, the actual diffusion of EVs over the considered community is tightly bond to the set of initial adopters $S_0$. Therefore, their characterization is crucial to have a complete model for the EV adoption process. To construct the seed set, we rely once again on the real mobility patterns extracted from data and, in particular, on the classification introduced in Section II-B. Based on this categorization, perfectly suited agents are the ideal candidates to constitute $S_0$, since their mobility habits would allow them to immediately switch to EVs smoothly. Meanwhile, only about 7% of the overall vehicles registered in Italy are actually electric. Consistently with this trend, not all perfectly suited agents might already own an EV and, thus, $S_0$ is constructed by uniformly drawing (at random) a subset of the agents belonging to this macro-level group. Once again, it is worth commenting that our choices are based on the fact that no information is available on actual EV owners within our dataset. Nonetheless, if this information was available, it could have been directly exploited to construct the seed set $S_0$.

[4]The time step size should be chosen based on the expected time required for an individual to have an actual shift in its inclination. To this end, one should account for time required for both technological advances and neighbors' behaviors to have an influence on individual opinions.

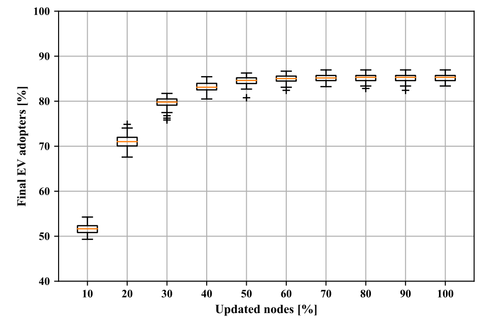



Fig. 2. Percentage of EV adopters after five years versus agents changing their attitude at each step, with $|S_0| = 30\%$ of perfectly suited agents (median and first and third interquartile range).

## IV. Data-Based Analysis of EV Adoption

EV adoption is initially studied by looking at the *free evolution* of the EV-adoption model presented in Section III. For the sake of discussion, we simulate the cascade model for $T = 9$ steps of six months each, so as to analyze EV adoption over a time span of five years. The chosen time intervals allow us to consider a rather realistic scenario, in which an individual does not change its inclination toward a mobility solution often in time. Instead, our choice of simulation time span is made by accounting for the time generally needed to achieve actual advancements of the EV technology and getting them into production. All simulations are carried out by considering 100 realizations of the thresholds $\{\alpha_v\}_{v\in\mathscr{V}}$ and of the set $S_0$ of initial adopters, so as to comprehensively study how their choices can impact the adoption process. To further bridge the gap between the theoretical cascade model and the actual dynamics governing EV adoption, we assess how the number of new adopters at each time step influences the wide-spread diffusion of this new technology. Indeed, in reality, agents that are thinking of replacing their vehicle are likely to rethink their inclination toward EVs, while the others might not even consider a change of mindset on the subject. The results in Fig. 2 show that the size of $S_0$ becomes less relevant on the average number of final adopters, whenever the opinion of enough agents is updated at each time step. Meanwhile, it still governs its variance over the 100 threshold realizations. This behavior can be explained by acknowledging that, with fewer agents adapting their opinion at each time step, a node is more likely to be *isolated*. In this case, agents segregation is due to the limited reactivity of their neighbors, rather than their position

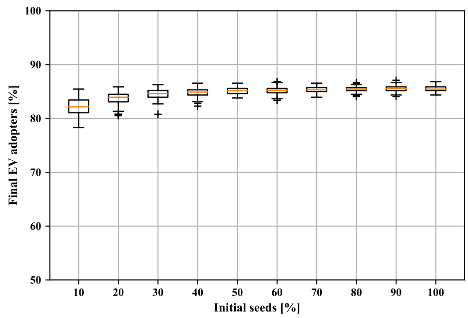



Fig. 3. Percentage of EV adopters after five years versus percentage of perfectly suited agents considered as seeds. Updated at a time: 50% of nonadopters (median and first and third interquartile range).

within the network. This conclusion is supported by the results reported in Fig. 3. Indeed, they further highlight that the effect of the dimension of $S_0$ on the percentage of final adopters is almost negligible, when at least 50% of agents can change their attitude at a time. Therefore, the presence of less reactive agents seems to prevent the spread of EVs more than a limited seed set. To provide a complete picture of the EV-adoption process, we finally consider a specific instance of the seed set and the agents' thresholds. To this end, we focus on the scenario in which around 14.3% of the agents[5] are assumed to own an EV at time $t = 0$. This choice of $S_0$ allows us to consider a case in which EVs spread over the network even when no incentive policy is enacted, if enough agents actually reconsider their opinion at each time step (see Figs. 2 and 3). As such, we impose that 50% of the agents that have yet not switched to an electric vehicle can change their inclination toward this mobility solution at each step. The actual spread of EVs in this specific scenario is depicted on the network in Fig. 4, showing that electric vehicles are widely adopted within the considered community despite the limited size of $S_0$. It is worth commenting that we do not observe changes in the number of adopters if considering longer horizons and at least 50% of the non-adopters are allowed to change their opinion at each time step[6].

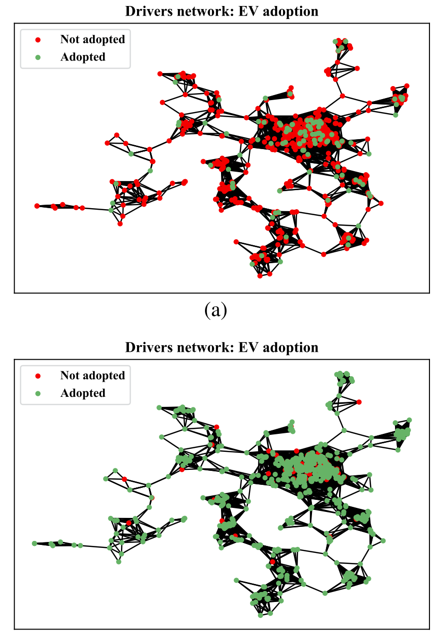
## V. Efficient Spread Maximization Policies

We now show how incentive policies can be designed to foster EV adoption by relying on our framework. To attain this goal, we focus on finding optimal strategies to boost the spread of EVs that leverage on the influence mechanism in the social network. Specifically, we search for the set of optimal agents maximizing the adoption when becoming EV owners, while accounting for how costly changing their opinion is based on their personal inclination. The policies are thus enacted by resetting the thresholds of the selected agents to zero. They are then assessed by looking at the free evolution of the cascade model with the new policy-shaped thresholds.

Let $\boldsymbol{\kappa}_v \in \{0,1,2,3\}$ denote the class of each agent $v \in \mathscr{V}$, with $\boldsymbol{\kappa}_v = 0$ associated with perfectly suited agents and $\boldsymbol{\kappa}_v = 3$

[5]This corresponds to 30% of perfectly suited agents, drawn at random.

[6]This behavior is theoretically supported by the results shown in [24], where the convergence time is linked to the degree of clustering of the network.




(a)

(b)

Fig. 4. EV adoption over the influence network. The color associated to each node is dictated by the Boolean variable $x_v(t)$ at time $t$. (a) $t = 0$. (b) $t = 9$.

TABLE I
Class-Dependent Cost to Influence a Node

| | Class $\boldsymbol{\kappa}$ | | | |
|---|---|---|---|---|
| | 0 | 1 | 2 | 3 |
| $c_{\boldsymbol{\kappa}}$ | $5{\cdot}10^{-4}$ | $7.55{\cdot}10^{-2}$ | 0.35 | 0.75 |

linked to not suited ones. Let $\mathscr{V}_{\boldsymbol{\kappa}}$ be the set of agents belonging to class $\boldsymbol{\kappa}$, *i.e.*, $\mathscr{V}_{\boldsymbol{\kappa}} = \{v \in \mathscr{V} : \boldsymbol{\kappa}_v = \boldsymbol{\kappa}\}$, for $\boldsymbol{\kappa} \in \{0,1,2,3\}$. We denote the cost to influence a node in class $\boldsymbol{\kappa} \in \{0,1,2,3\}$ as $c_{\boldsymbol{\kappa}} \in \mathbb{R}$, which is here determined based on the logic exploited to generate the nodes' thresholds in Section III. Specifically, $\{c_{\boldsymbol{\kappa}}\}_{\boldsymbol{\kappa}\in\{0,1,2,3\}}$ is quantified as the average of the interval within which the thresholds characterizing the $\boldsymbol{\kappa}$th class are generated, resulting in the class-dependent costs reported in Table I. Although these costs do not directly translate into monetary ones, they allow us to explicitly link the effort to influence an agent with the percentage of neighbor adopters required for it to change attitude toward EVs. Therefore, they provide a realistic quantification of the effort needed to enact the polices, by facilitating the adaptation of the agents' habits to the features of this mobility solution.

Based on this quantification of the costs, we formalize the policy design problem as a combinatorial influence maximization problem with a fixed budget. Initially, we impose a fixed budget on each class. This, in turn, translates into a fixed number $m_{\boldsymbol{\kappa}}$ of nodes to influence in each class $\boldsymbol{\kappa} \in \{0,1,2,3\}$. Within this scenario, the influence maximization problem can be formalized as follows.

***Problem 1 (Spread maximization with class budget):*** Find the sets $\Gamma^{\boldsymbol{\kappa}} \in \bigcup_{\boldsymbol{\kappa}} \mathscr{V}_{\boldsymbol{\kappa}} \setminus S_0$ such that $|\Gamma^{\boldsymbol{\kappa}}| \leq m_{\boldsymbol{\kappa}}$ and the expected number of final adopters

$$f(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}}) = \mathbb{E}[S^{\star}(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}})] \quad (5)$$

is maximal. □

This problem is known to be challenging and computationally expensive, given its combinatorial nature. In fact, an exhaustive search would require the policy maker to test $\prod_{\kappa\in\{0,1,2,3\}} \binom{|\mathscr{V}_{\kappa}|}{m_{\kappa}}$ potential seeds and evaluate the size of the final adopters to determine the most influential nodes.

As a second instance we impose an overall budget, by formally considering the following optimization problem.

***Problem 2 (Spread maximization with global budget):*** Let $\chi > 0$, find the sets $\Gamma^{\kappa} \in \bigcup_{\kappa} \mathscr{V}_{\kappa} \setminus S_0$ such that

$$\max f(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}}) \quad s.t. \quad \sum_{\kappa} c_{\kappa}|\Gamma^{\kappa}| \leq \chi. \quad (6)$$

□

Also in this case an exhaustive search would require to test a number of configurations that scales exponentially in the size of the network.

***Remark 1 (About the hardness of Problems 1–2):*** The considered problems inherit the NP-hardness proven in [13] for the problem of selecting the $k$ most influential nodes in a single-class setting. Indeed, both incentive design problems require the computation of the expected number of final adopters [see (5) and (6)], but in our scenario, a closed form expression for the cost function $f$ does not exist. In turn, the final set of adopters can be formally defined according to Theorem 1, but it would be computationally hard to find it for our arbitrary network. ■

## A. Handling the Complexity of the Policy Design Problems

To overcome the complexity that would arise when searching for an exact solution of Problems 1 and 2, we propose to 1) approximate the function $f$ using Monte Carlo samples, and to 2) resort to a common approach in the literature [25]. In this last case, the constrained influence maximization problems are solved for one target at a time in a greedy manner, i.e., choosing at each iteration a target that gives the largest marginal increase in the spread of EVs. For a set $\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}}$, to approximate the cost function we simulate the cascade process for $N_R$ realizations of the agents' thresholds, under the assumption that all non-adopters can change their opinion at each time step. Note that, based on the results attained in Section IV, this entails that the cascade process is simulated up to convergence, as defined in Theorem 1. Given the set $\overline{S}^{\star}_r(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}})$ of final adopters obtained for the $r$th simulation, with $r \in \{1,\ldots,N_R\}$, the approximated cost function is

$$\widehat{f}_{N_R}\left(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}}\right) = \frac{1}{N_R}\sum_{r=1}^{N_R} \overline{S}^{\star}_r(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}}) \quad (7)$$

for which the following theorem holds.

***Theorem 2:*** For any arbitrary instance of $\mathscr{G} = (\mathscr{V}, \mathscr{E})$, the set function $\widehat{f}_{N_R}(\Gamma)$ defined in (7) is monotone and submodular. ■

**Algorithm 1:** Greedy Algorithm for Problem 1.

**Require:** $\mathscr{G} = (\mathscr{V}, \mathscr{E})$ graph, seed set $S_0$, partition $\{\mathscr{V}_{\kappa}\}_{\kappa\in\{0,\ldots,3\}}$ budget constraints $\{m_{\kappa}\}_{\kappa\in\{0,\ldots,3\}}$
**Initialization:**
 $\Gamma^{\kappa}_0 = \emptyset$, $\Lambda = \emptyset$, $n_{\kappa} = 0, \forall\kappa \in \{0,1,2,3\}$
**for** $\ell \in \{1,\ldots,\sum_{\kappa} m_{\kappa}\}$ **do**
 $\hat{v} = \arg\max_{v\in\mathscr{V}\setminus\Lambda}\{\Delta(v|\Gamma^{\kappa}_{i-1})\}$
 **for** $\kappa \in \{0,1,2,3\}$ **do**
  **if** $\hat{v} \in \mathscr{V}_{\kappa}$ **then**
   $\hat{\kappa} = \kappa$
  **end if**
 **end for**
 **if** $n_{\hat{\kappa}} < m_{\hat{\kappa}}$ **then**
  $\Gamma^{\kappa}_i = \Gamma^{\kappa}_{i-1} \cup \{\hat{v}\}$
  $n_{\hat{\kappa}} = n_{\hat{\kappa}} + 1$
 **else**
  $\Lambda = \Lambda \cup \{\hat{v}\}$
 **end if**
**end for**
**return** $\Gamma^{\kappa}_{\sum_{\kappa} m_{\kappa}}$, $f(\Gamma^{\kappa}_{\sum_{\kappa} m_{\kappa}})$

***Proof:*** For an arbitrary instance $r \in \{1,\ldots,N_R\}$ of the cascading model in (4a), the resulting set of final adopters $\overline{S}^{\star}_r(\Gamma^{\kappa})$ is submodular. This claim can be straightforwardly proven by applying the results in [19], or it can be alternatively obtained by adapting the proof devised in [13]. Being a sum of submodular functions, the function $\widehat{f}_{N_R}(\Gamma)$ is thus submodular. ■

Note that, as $N_R \to \infty$, the function $\widehat{f}_{N_R}(\{\Gamma^{\kappa}\}_{\kappa\in\{0,1,2,3\}})$ converges uniformly because of the law of large numbers. In this ideal scenario, the computational complexity of evaluating the cost function becomes proportional to the number of simulations and the time required for the convergence of the dynamics, i.e., $O(N_R \cdot T)$.

We review the procedure in Algorithm 1. Starting from the empty set $\Gamma_0 = \emptyset$, at each iteration $i$ a new element $\hat{\nu} \in \mathscr{V} \setminus \Gamma^{\kappa}_{i-1}$, maximizing the discrete derivative $\Delta(v|\Gamma^{\kappa}_{i-1})$ and not violating the constraint on the class budget, is added to the seed set, with $\Delta(v|\Gamma^{\kappa}_{i-1})$ given by

$$\Gamma^{\kappa}_i = \Gamma^{\kappa}_{i-1} \cup \arg\max_v \Delta(v|\Gamma^{\kappa}_{i-1}).$$

and $\Delta(v|\Gamma) = \widehat{f}_{N_R}(\Gamma \cup \{v\}) - \widehat{f}_{N_R}(\Gamma)$. In Algorithm 2, a similar procedure is exploited, but the maximum search is not constrained to each class. Instead, the influence maximization set is searched on the entire set of nodes, with new agents added to $\Gamma$ until the saturation of the constraint. Note that, both strategies exploit the predictive power of the cascade model proposed in Section III, here used to test and greedy select the set of influential nodes, while guaranteeing constraint satisfaction. The greedy search of influential nodes needed to design the incentive strategies is carried out in both cases by choosing one node at a time, reducing significantly the computational complexity of the proposed solution with respect to exact ones. Indeed, this strategy allows us to perform a finite number of evaluations of the cost function $\widehat{f}_{N_R}$ only.

**Algorithm 2:** Greedy Algorithm for Problem 2.

**Require:** $\mathscr{G} = (\mathscr{V}, \mathscr{E})$ graph, seed set $S_0$, partition $\{\mathscr{V}_{\boldsymbol{\kappa}}\}_{\boldsymbol{\kappa} \in \{0,\dots,3\}}$ budget constraint $\chi > 0$
**Initialization:**
$\Gamma_0^{\boldsymbol{\kappa}} = \emptyset, m_{\boldsymbol{\kappa}} = 0, \quad \forall \boldsymbol{\kappa} \in \{0,1,2,3\}$
**while** $\sum_{\boldsymbol{\kappa}} c_{\boldsymbol{\kappa}} m_{\boldsymbol{\kappa}} < \chi$ **do**
$(\hat{v}, \hat{\boldsymbol{\kappa}}) = \arg\max_{v \in \mathscr{V}} \{\Delta(v|\Gamma_{i-1}^{\boldsymbol{\kappa}}).\}$
$\Gamma_i^{\boldsymbol{\kappa}} = \Gamma_{i-1}^{\boldsymbol{\kappa}} \cup \{\hat{v}\}$
$m_{\boldsymbol{\kappa}} = m_{\boldsymbol{\kappa}} + 1$
**end while**
**return** $\Gamma^{\boldsymbol{\kappa}}$, $f(\Gamma^{\boldsymbol{\kappa}})$

By combining known results in the optimization of submodular functions with the law of large numbers and the Chebyshev bounds, also for Algorithm 2 we can provide a probabilistic bound on the quality of the greedy solution with respect to the optimum of Problem 2 [25].

***Corollary 1:*** Let $\Gamma^{\boldsymbol{\kappa}}$ be the output of Algorithm 2. Then, for all small $\varepsilon \geq 0$, it holds

$$\mathbb{P}\left(\widehat{f}_{N_R}^{\star} \geq (1 - 1/\mathrm{e})\,(f^{\star} - \epsilon)\right) \geq 1 - \frac{\eta}{N_R \epsilon^2}$$

with $\widehat{f}_{N_R}^{\star}$ and $f^{\star}$ being the optimal costs obtained by running Algorithm 2 and by solving Problem 1 respectively, and $\eta$ a finite constant. ∎

## VI. Policy Evaluation

We now test and compare different incentive strategies obtained by running Algorithms 1 and 2 and considering different design scenarios. In all cases, we focus on the setup devised in Section IV, where the seed set is selected uniformly at random among the perfectly suited agents and the individuals are classified based on their electrification potential index. In particular, we fix the seed set $S_0$ as the one exploited to obtain the results shown in Fig. 4. The agents' thresholds are chosen according to their class, as explained in Section III. In our tests, Algorithms 1 and 2 are both run by considering $N_R = 20$ random instances of the thresholds. The spread maximizing sets $\{\Gamma^{\boldsymbol{\kappa}}\}_{\boldsymbol{\kappa} \in \{0,1,2,3\}}$ are then retrieved by averaging over the resulting marginal increase in the number of adopters. The "investment" policies dictated by the results of the two algorithms in the different scenarios are deployed once, at the beginning of the horizon, and then their effectiveness is evaluated by letting the cascade model evolve based on the new initial conditions. Note that we could also have enacted the policies for one time step only, then running again the two algorithms based on the evolution of the model in a *receding horizon* fashion. This operation is allowed, thanks to the dynamical nature of the proposed framework, but it would be computationally demanding and it might be quite unrealistic with respect to how actual incentive policies are enacted at a governmental level. We stress that the available dataset does not allow us to validate the designed strategies on a data basis, since we have no actual information on existing EV owners, individual inclinations nor their changes over five years.[7] We thus focus on simulating their effect on the proposed model and on providing a quantitative evaluation ground, that can be exploited to assess the benefits of different strategies. Once designed, each policy is evaluated by deploying it and looking at its effect on a *single realization* of the thresholds introduced in Section III. Specifically, to assess the overall boost in EV adoption resulting from their application, we look at the percentage $\tilde{S}_T$ [%] of final adopters over the horizon of $T = 9$ steps already considered in Section IV, namely

$$\tilde{S}_T := \frac{|S_T|}{|\mathscr{V}|} \times 100, \ [\%] \tag{8a}$$

with $S_T$ being the set of final adopters [see (4b)] and $|S_T|$ dictating their number. Along with the benefits induced by each policy, we look at its cost $C$, given by $C := \sum_{\boldsymbol{\kappa}} m_{\boldsymbol{\kappa}} c_{\boldsymbol{\kappa}}$, which is lower than or equal to the upper bound $\chi$ in (6) if Algorithm 2 is used. To combine these indexes, we further evaluate the *cost/benefit tradeoff* of each policy, $CB$, which is defined as the ratio

$$CB := \frac{C}{\tilde{S}_T}.$$

This concise indicator captures the cost required to drive a 1% increment in the final adopters, thus indirectly allowing one to assess whether a policy repays itself (i.e., when $CB < 1$, since the cost is lower than the attained increment) or not. In addition to these indicators, we further evaluate the overall expected environmental impact of the considered policies by looking at the resulting percentage reduction in $CO_2$ emissions (R-$CO_2$), which is computed as

$$\text{R-CO}_2 = 100 \times \frac{|\text{CO}_{2,T} - \text{CO}_{2,0}|}{\text{CO}_{2,0}}, \ [\%] \tag{9}$$

with $\text{CO}_{2,t} = \beta \sum_{v \notin S_t} Y_v$ being the amount of $\text{CO}_{2,t}$ emissions at time $t$, $Y_v$ [km] denoting the yearly kilometers traveled by the $v$th agent and $\beta = 18.32$ [kg of $CO_2$/100 km] being a constant linking these two quantities. Note that, since the data are anonymized, all agents that are not EV adopters are assumed to own a mid-sized ICE vehicle.

The effectiveness of the policies is not assessed at a global level only, but we also consider the percentage of final adopters within each of the four classes introduced in Section II-B, i.e.,

$$\tilde{S}_T^{\boldsymbol{\kappa}} = \frac{|S_T^{\boldsymbol{\kappa}}|}{|\mathscr{V}_{\boldsymbol{\kappa}}|} \times 100, \ [\%] \tag{10a}$$

where $S_T = \{v \in S_T : \boldsymbol{\kappa}_v = \boldsymbol{\kappa}\}$, and $|S_T^{\boldsymbol{\kappa}}|$ indicates the number of final adopters belonging to class $\boldsymbol{\kappa}$, with $\boldsymbol{\kappa} \in \{0,1,2,3\}$. As for the overall performance, we evaluate the class-dependent cost $C^{\boldsymbol{\kappa}}$, which is given by $C^{\boldsymbol{\kappa}} := m_{\boldsymbol{\kappa}} c_{\boldsymbol{\kappa}}$. The value of $C^{\boldsymbol{\kappa}}$ is dictated by the upper bound characterizing Problem 1 when Algorithm 1 is run, while not being fixed a priori when Algorithm 2 is used. We can thus retrieve the cost/benefit tradeoff $CB^{\boldsymbol{\kappa}}$ for each class, namely, $CB^{\boldsymbol{\kappa}} := \frac{C^{\boldsymbol{\kappa}}}{\tilde{S}_T^{\boldsymbol{\kappa}}}$. As for the performance and cost related indexes, we also look at the environmental

[7] The data cover one year only and they are anonymized.

impact that the strategies can have on each group of agents, by considering the class-based counterpart of (9), i.e.,

$$\text{R-CO}_2^{\boldsymbol{\kappa}} = 100 \times \frac{|\text{CO}_{2,T}^{\boldsymbol{\kappa}} - \text{CO}_{2,0}^{\boldsymbol{\kappa}}|}{\text{CO}_{2,0}^{\boldsymbol{\kappa}}}, \ [\%] \tag{10b}$$

where $\text{CO}_{2,t}^{\boldsymbol{\kappa}}$ indicates the emissions due to members of the $\boldsymbol{\kappa}$th class at time $t$.

We stress that these indexes are exploited for validation purposes only, while they do not shape the costs reported in Table I nor they influence the imposed budget constraints.

By providing both a macro-level and a more granular evaluation of the polices, we can identify the clusters that mainly benefit from their introduction. Concurrently, we can retrieve guidelines on the classes the policies have to focus on to reduce costs and lead to a consistent spread of EVs across the network.

***1) Algorithm 1:*** Problem 1 is solved by looking at different scenarios, characterized by alternative choices for the class budget. The latter is here dictated by $m_{\boldsymbol{\kappa}} = \boldsymbol{\gamma}_{\boldsymbol{\kappa}}|\mathscr{V}_{\boldsymbol{\kappa}}|$, where $\boldsymbol{\gamma}_{\boldsymbol{\kappa}} \in [0,1]$ indicates the percentage of agents belonging to each class on which the policy can be enacted. Clearly, the parameters $\{\boldsymbol{\gamma}_{\boldsymbol{\kappa}}\}_{\boldsymbol{\kappa}\in\{0,1,2,3\}}$ allow us to shape the incentive policy, and thus, its ultimate cost. In this work, we have focused on the scenarios listed as follows:

1) Scenario 1: $\boldsymbol{\gamma}_{\boldsymbol{\kappa}} = 0.2 \ \forall \boldsymbol{\kappa} \in \{0,1,2,3\}$. According to this choice, the class budgets correspond to $m_0 = 70$, $m_1 = 30$, $m_2 = 25$ and $m_3 = 21$, so that the policy is characterized by an overall budget of $\sum_{\boldsymbol{\kappa}} m_{\boldsymbol{\kappa}} = 146$. Since the class of perfectly suited agents is preponderant over the others, this incentive strategy favors this cluster over the ones comprising agents that are less willing to buy an EV.
2) Scenario 2: $\gamma_0 = 0.3$, $\gamma_1 = 0.25$, $\gamma_2 = 0.2$, $\gamma_3 = 0.15$. The policy obtained with these parameters result in the class budgets $m_0 = 104$, $m_1 = 38$, $m_2 = 25$, and $m_3 = 16$, and a corresponding overall budget of $\sum_{\boldsymbol{\kappa}} m_{\boldsymbol{\kappa}} = 183$. As *not suited* agents ($\boldsymbol{\kappa} = 3$) are the most costly to be influenced, this policy is likely to result in the least cost among the incentive strategies considered here to tackle Problem 1. Meanwhile, although cost-efficient, it tends to leave out those agents that are more averse to switching to an EV.
3) Scenario 3: $\gamma_0 = 0.15$, $\gamma_1 = 0.2$, $\gamma_2 = 0.25$, $\gamma_3 = 0.3$. In this case, the class budgets are $m_0 = 52$, $m_1 = 30$, $m_2 = 31$, and $m_3 = 32$, while the overall budget is given by $\sum_{\boldsymbol{\kappa}} m_{\boldsymbol{\kappa}} = 145$. Clearly, the resulting policy is directed toward the classes of agents whose driving habits are mildly and not suited. Despite the overall budget is almost equal to that of the first scenarios, this strategy will be more costly due to the higher number of unwilling agents on which the policy is enacted.

The results shown in Table II clearly indicate that all policies favor the spread of EVs across the influence network. Nonetheless, the strategy obtained within the third scenario outperforms the others in terms of final adopters, and thus, of environmental impact, while concurrently being much more costly. The similarity between the cost/benefit tradeoff indexes

TABLE II
ALGORITHM 1: FREE ($c_{\boldsymbol{\kappa}} = 0$, $\boldsymbol{\kappa} \in \{0,1,2,3\}$) VERSUS POLICY-DRIVEN EVOLUTION

| | | | Scenario | | |
|---|---|---|---|---|---|
| | | Free | 1 | 2 | 3 |
| Final adopters | $\lvert S_T \rvert$ | 86 % | 94.6% | 94.1% | 96.6% |
| Cost | $C$ | - | 26.80 | 23.67 | 37.14 |
| Cost/benefit | $CB$ | - | 0.28 | 0.25 | 0.38 |
| $CO_2$ reduction | R-$CO_2$ | 80.4% | 91.0% | 89.9% | 94.2% |

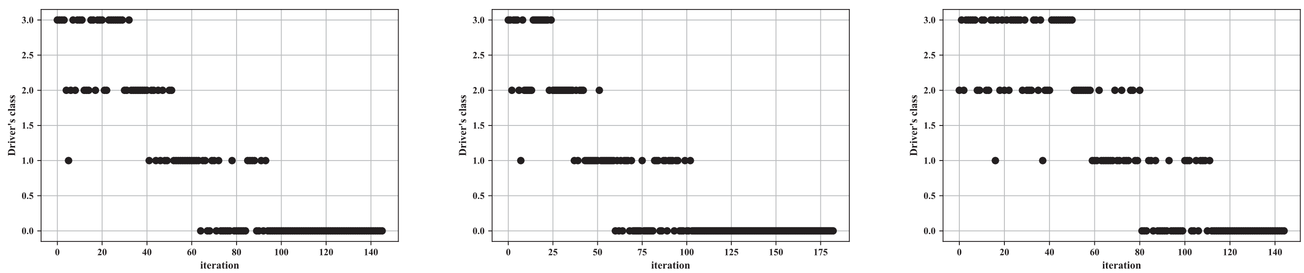
$|S_T|$ is the percentage of final adopters, $C$ is the cost of the policy, $CB$ is the associated cost/benefit index, and R-$CO_2$ is the resulting reduction in carbon emissions.

highlights that it is worth investing slightly more to convince unwilling agents to switch to an EV, so as to boost the adoption over the network and favor a reduction in carbon emissions. Note also that, in the third scenario, the number of *mildly suited* ($\boldsymbol{\kappa} = 2$) agents on whom the policy is enacted increases, along with that of *not suited* agents. This suggests that giving incentives to these two groups of hesitant agents leads to policies that repay themselves the most, with the set of most influential agents in the network likely belonging to these two clusters. This conclusion is supported by results in Fig. 5 , showing the label associated to the node selected at each iteration of Algorithm 1. It is clear that, independently of the considered scenario, mildly and not suited agents are the first to be selected, with other classes considered once the budget of these two groups is saturated. By looking at the number of in-neighbors of the agents selected within each scenario (see Fig. 6 ), it is also clear that the third one allows us to select nodes with higher degree, once again corroborating our intuition. The conclusions on the costs and benefits of each strategy drawn when looking at the macroscopic indicators are further confirmed by the class-dependent indexes reported in Table III . Indeed, it can be seen that the third scenario results in a consistent increase in the number of adopters within each class, with relatively similar cost/benefit tradeoff indexes. This resemblance is particularly evident when comparing the first and third scenarios, thus highlighting the possible benefits of not selecting a *flat* policy[8] as the one considered in the first case. The same conclusion can be drawn with respect to the environmental impact of the different strategies.

***2) Algorithm 2:*** When considering Problem 2, a maximum cost $\chi$ is introduced rather than a class budget to shape the policy. Alternative strategies are thus originated by varying the upper-bound in (6), here obtained as a fraction $\delta \in [0,1]$ of the cost required to enact the policy on all agents not belonging to the seed set as $\chi = \delta \sum_{\boldsymbol{\kappa}} \sum_{v\in\mathscr{V}_{\boldsymbol{\kappa}}\setminus S_0} c_{\boldsymbol{\kappa}}$.

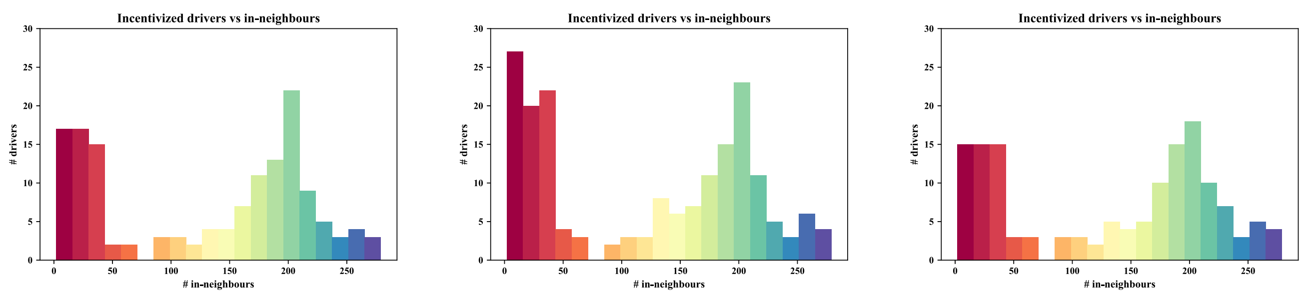
Problem 2 is addressed by considering three different scenarios, characterized by an increasing overall budget with $\delta = \{0.2, 0.5, 0.7\}$. The resulting upper constraints are reported in Table IV, along with the percentages of final adopters, the costs and the cost/benefit tradeoff indexes of the policies retrieved within each scenario. Clearly, the final cost of each policy increases with $\delta$, and full adoption of EVs happens only in the last two scenarios. Note that the actual cost of each strategy is

[8] A policy is here considered as *flat* if the same percentage of agents is selected within each class.




(a) (b) (c)

Fig. 5. Algorithm 1: Selected nodes' class $\boldsymbol{\kappa}$ versus iterations. In the initial runs, the classes of *not* and *mildly suited* agents are the first to be filled. (a) Scenario 1. (b) Scenario 2. (c) Scenario 3.




(a) (b) (c)

Fig. 6. Algorithm 1: Number of in-neighbors versus selected nodes. A clear pattern exists with respect to the number of in-neighbors. (a) Scenario 1. (b) Scenario 2. (c) Scenario 3.

TABLE III
ALGORITHM 1: CLASS-BASED PERFORMANCE: FREE VERSUS POLICY-DRIVEN EVOLUTION

| $\kappa$ | Free | | | | Scenario 1 | | | | Scenario 2 | | | | Scenario 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ |
| 0 | 99.7% | - | - | 99.6% | 100% | 0.04 | $4 \cdot 10^{-4}$ | 100% | 100% | 0.05 | $5 \cdot 10^{-4}$ | 100% | 100% | 0.03 | $3 \cdot 10^{-4}$ | 100% |
| 1 | 92.7% | - | - | 91.5% | 100% | 2.3 | $2 \cdot 10^{-2}$ | 100% | 100% | 2.9 | $3 \cdot 10^{-2}$ | 100% | 100% | 2.3 | $2 \cdot 10^{-2}$ | 100% |
| 2 | 73.2% | - | - | 74.4% | 96.7% | 8.8 | $9 \cdot 10^{-2}$ | 98.4% | 97.6% | 8.8 | $9 \cdot 10^{-2}$ | 100% | 100% | 10.9 | 0.11 | 100% |
| 3 | 46.2% | - | - | 40.7% | 67.0% | 15.8 | 0.2 | 57.7% | 62.3% | 12.0 | 0.2 | 55.1% | 76.4% | 24.00 | 0.3 | 67.3% |

$\tilde{S}_T^{\boldsymbol{\kappa}}$ Denotes the in-class percentage of final adopters, $C^{\boldsymbol{\kappa}}$ is the cost of the policy linked to the $k$th class, $CB^{\boldsymbol{\kappa}}$ is the associated cost/benefit Index, and R-$CO_2^{\boldsymbol{\kappa}}$ assess the class-dependent carbon emissions.

TABLE IV
ALGORITHM 2: FREE ($c_{\boldsymbol{\kappa}} = 0$, $\boldsymbol{\kappa} \in \{0, 1, 2, 3\}$) VERSUS POLICY-DRIVEN EVOLUTION

| | | Free | Scenario $\delta = 0.2$ | $\delta = 0.5$ | $\delta = 0.7$ |
|---|---|---|---|---|---|
| Final adopters | $\lvert S_T \rvert$ | 86 % | 93% | 100% | 100% |
| Cost | $C$ | - | 26.65 | 66.9 | 93.55 |
| Global budget | $\chi$ | - | 26.82 | 67.06 | 93.89 |
| Cost/benefit | $CB$ | - | 0.29 | 0.67 | 0.94 |
| $CO_2$ reduction | R-$CO_2$ | 81.5% | 88.7% | 100% | 100% |

$\lvert S_T \rvert$ is the percentage of final adopters, $C$ is the cost of the policy, $CB$ is the associated cost/benefit Index, and R-$CO_2$ the resulting reduction in carbon emissions.

always quite close to the considered upper-bound, indicating that Algorithm 2 allows us to devise a policy that fully exploits the available resources. Despite the spread of EVs across the whole network, it is clear that the costliest strategies lead to policies that have less pay back, as the cost/benefit tradeoff shows. In particular, the rather conspicuous investments required to enact the third strategy are quite close to not repaying themselves, providing policy makers an interesting insight on the effect that different budget upper-bounds can have on EV adoption. On the environmental impact side, clearly the more one invests, the more people will shift to an EV, thus leading to a full reduction of carbon emissions.

By looking at the single policies more closely through the information provided in Fig. 7, it is clear that the upper-bound is reached after rather few iterations when $\delta = 0.2$ (43 agents are selected, against the 159 and 353 considered for $\delta = 0.5$ and $\delta = 0.7$, respectively), as all the agents on which the policy is enacted are fairly unwilling to change their driving habits to switch to an EV. Despite the limited number of selected seeds with the policy obtained for $\delta = 0.2$, it is clear that most of them is characterized by a relatively high in-degree, as shown in Fig. 8. The distributions of the number of in-neighbors reported therein further highlight that the higher is the available budget, the greater is the number of agents selected by Algorithm 2 with a relatively low in-degree. As of the indicators, this result suggests that an excessively high budget might not be exploited

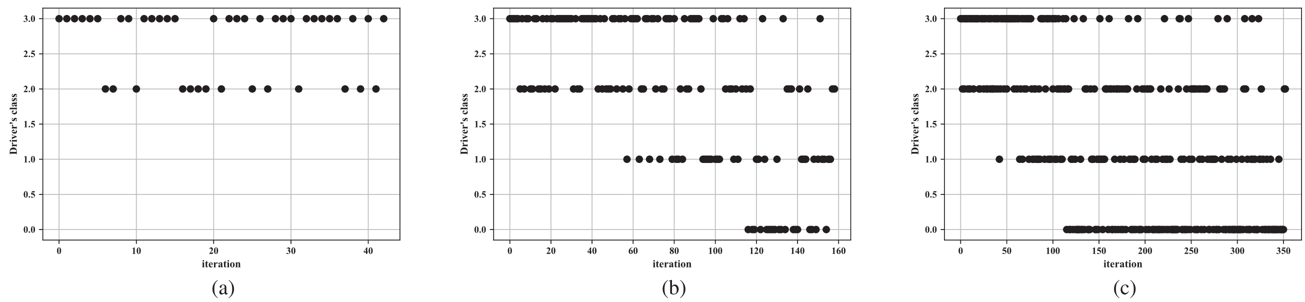



Fig. 7. Algorithm 2: Selected nodes' class $\boldsymbol{\kappa}$ versus iterations. The higher the budget, the more agents are drawn from $\boldsymbol{\kappa} = \{0, 1\}$ at early stages. (a) Scenario 1: $\delta = 0.2$. (b) Scenario 2: $\delta = 0.5$. (c) Scenario 3: $\delta = 0.7$.

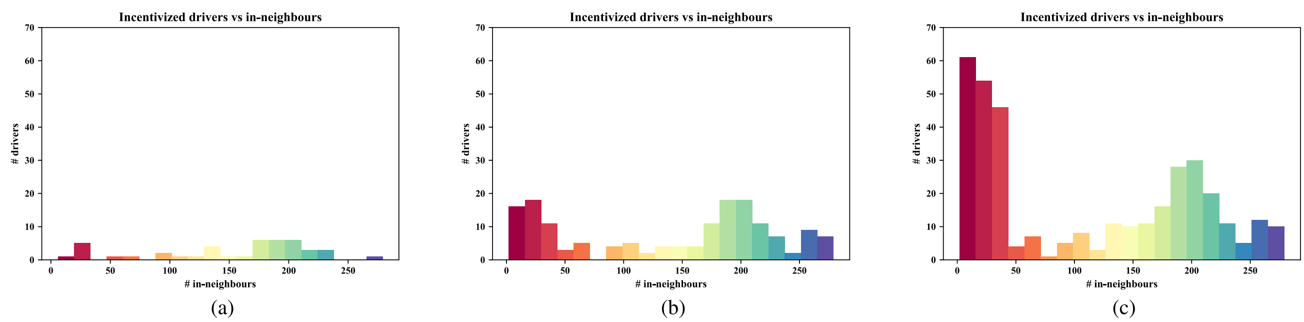



Fig. 8. Algorithm 2: Number of in-neighbors versus selected nodes. Clearly, the higher $\delta$, the more the policy is enacted on poorly connected agents. (a) Scenario 1: $\delta = 0.2$. (b) Scenario 2: $\delta = 0.5$. (c) Scenario 3: $\delta = 0.7$.

TABLE V
ALGORITHM 2: CLASS-BASED PERFORMANCE: FREE VERSUS POLICY-DRIVEN EVOLUTION

| $\kappa$ | Free | | | | Scenario $\delta = 0.2$ | | | | $\delta = 0.5$ | | | | $\delta = 0.7$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ | $\tilde{S}_T^{\kappa}$ | $C^{\kappa}$ | $CB^{\kappa}$ | R-$CO_2^{\kappa}$ |
| 0 | 99.7% | - | - | 99.6% | 100% | 0 | 0 | 100% | 100% | $1 \cdot 10^{-2}$ | $1 \cdot 10^{-4}$ | 100% | 100% | $6 \cdot 10^{-2}$ | $6 \cdot 10^{-4}$ | 100% |
| 1 | 92.7% | - | - | 91.5% | 94% | 0 | 0 | 92.6% | 100% | 2.3 | 0.02 | 100% | 100% | 5.6 | 0.06 | 100% |
| 2 | 73.2% | - | - | 74.4% | 88.6% | 4.9 | 0.06 | 87.4% | 100.0% | 15.1 | 0.2 | 100% | 100.0% | 29.4 | 0.3 | 100% |
| 3 | 46.2% | - | - | 40.7% | 73.6% | 21.8 | 0.3 | 63.5% | 100.0% | 49.5 | 0.5 | 100% | 100% | 58.5 | 0.6 | 100% |

$\tilde{S}_T^{\kappa}$ denotes the in-class percentage of final adopters, $C^{\kappa}$ is the cost of the policy linked to the $k$th Class, $CB^{\kappa}$ is the associated cost/benefit Index, and R-$CO_2^{\kappa}$ assess the class-dependent carbon emissions.

at its best, with less costly policies resulting in a similar diffusion of EVs across the network. Such an effect, in turn, provides a valuable inkling to policy makers, that can consider potential savings while still obtaining satisfactory outcomes.

The interpretation of the macro-level indexes is supported by the class-dependent results shown in Table V. They clearly show a boost in EV acceptance over all classes within all considered scenarios, with all perfectly suited adopters becoming actual EV owners even when $\delta = 0.2$. Once again, it is clear that the price of reaching full adoption is increasingly high, becoming rather consistent when looking at the more unwilling classes ($\boldsymbol{\kappa} = 3$ and $\boldsymbol{\kappa} = 4$). Concurrently, the increased cost of the policy corresponds to an improvement in the environmental impact of the latter.

*3) Policy Comparison:* To fully assess the different policies previously discussed, it is crucial to compare the results obtained solving Problems 1 and 2. It is worth commenting that only a comparison of the policies with class budgets and the ones obtained for $\delta = \{0.2, 0.5\}$ is actually fair, due to the relevant discrepancy in the size of $\tilde{\boldsymbol{\Gamma}} = \bigcup_{\boldsymbol{\kappa}} \boldsymbol{\Gamma}^{\boldsymbol{\kappa}}$ characterizing the case $\delta = 0.7$.

It is clear that imposing bounds on the classes allows one to obtain polices that are more focused on the micro-level features of the network and the agents. In turn, this translates into lower costs and a better cost/benefit tradeoff with respect to the results obtained imposing upper-bounds on the overall budget. Nonetheless, full adoption is only reached when the strategies returned by Algorithm 2 are applied. When the latter is carried out with $\delta = 0.2$, the overall indicators are quite close to those obtained with the flat policy considered in the first scenario explored with Algorithm 1, despite the reduced number of selected agents. By comparing the class-dependent indexes in Tables III and V, it is clear that the limited number of agents selected when $\delta = 0.2$ allows us to visibly boost EV adoption over the ones belonging to the class $\boldsymbol{\kappa} = 3$. Meanwhile, it leads to a rather small reduction in the number of adopters in the other clusters. This result indicates that not acting on the most relevant class from a numerical standpoint can be effective, provided that enough members of the most influential clusters are selected. Notably, both algorithms tend to select mildly and not suited agents at early stages (see Figs. 5 and 7), thus, confirming the overall trend that these classes are the most important to enact the adoption cascade over the network. As for the relationship between the effectiveness of the policies and the in-degree of the agents who are given incentives, the pattern visible in Fig. 6 does not characterize the distributions in Fig. 8. Moreover, only the distribution characterizing the scenario with $\delta = 0.5$ resembles the in-degree distributions reported in Fig. 6. When considering the results obtained for $\delta = 0.7$, it is clear that the imposition of a class budget allow one to avoid the selection of a consistent number of poorly connected agents, which instead characterizes the case in which rather loose bounds on the overall budget are considered.

## VII. Conclusion

This work presented a network-based framework, that lays the foundations for the data-based analysis of EV adoption processes and for the design of policies devoted to their mass spread. By relying on real mobility patterns, we have shown how to translate data-based information into quantitative indexes, that allow to evaluate the initial agent predisposition to the considered technological change. With the available data, we have also framed the agents within a social network model built on geographical proximity. These two main building blocks of our framework represent the starting point for a simulation analysis of EV adoption over the data-based network, and for the design of incentive policies. The results shown in this work demonstrate how the proposed framework can be effectively exploited to understand how EV ownership can spread across a network of influence, based solely on the connection between agents and their individual characteristics. By enacting a set of preliminary policies, that change these last features, we have also highlighted that data-based policies can be very cost-effective. Our analysis have demonstrated the significant potential of the proposed framework as a tool to aid in the design of effective incentive policies, both from a cost-oriented perspective and with respect to their environmental and social impact.

The presented framework is rather general, allowing to perform analysis and to design policies by blending quantitative and qualitative features of the agents and encompassing alternative (i.e., not only proximity-based) representations of their social connections, as long as they are properly framed. In this light, future work will be devoted to extend the agents' characterization to encompass additional profiling measures: technological, economic, and social, so as to account that mobility as a whole should be developed by considering all these aspects. As we are aware that a certain mobility choice is likely to be determined by the conditioning exerted by people close to us (friends, relatives, etc.), the definition of a model that can correlate mobility patterns with social relationships in the ego-networks of individuals will also be the object of our future studies. Thanks to the flexibility of the proposed framework, this will be done by relying on the data-based approach presented in the article, via other datasets comprising both social and proximity information. On the policy design side, the dynamical and control-oriented nature of the proposed model will allow us to consider alternative incentive strategies, relying also on feedback schemes.

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