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Fostering the use of sharing mobility solutions via control-oriented policy design

E. Villa * V. Breschi ** C. Ravazzi *** F. Dabbene *** M. Tanelli *

* Department of Electronics, Information and Bioengineering, Politecnico di Milano, P.za Leonardo da Vinci 32, 20133, Milano, Italy (e-mail: {name.surname}@polimi.it).
** Eindhoven University of Technology, 5600 MB Eindhoven, Netherlands (e-mail: v.breschi@tue.nl).
*** Institute of Electronics, Computer and Telecommunication Engineering, National Research Council of Italy (CNR-IEIIT), c/o Politecnico di Torino, Corso Duca Degli Abruzzi, 10129, Torino, Italy (e-mail: {name.surname}@ieiit.cnr.it)

Abstract: In the quest for reducing greenhouse gas (GHG) emissions, mobility plays a lion's role. In particular, moving from ownership to usership has profound individual implications, as vehicles are in many cultures proxy of social status and power symbols. To sustain the shift to shared mobility, we use data to extrapolate the main socio-economic drivers that guide the adoption of this model, the so-called Sharing-DNA, ultimately building a dynamical model characterizing the evolution of individual inclinations over time. This novel representation allows us to exploit optimal control tools for the design of innovative human-centric policies to foster the adoption of sharing mobility solutions. The results here presented demonstrate the potential impact of individualized closed-loop policies in promoting this crucial behavioral change.

Keywords: Human-centered systems engineering; Shared mobility; Opinion dynamics.

1. INTRODUCTION

The impact of mobility on the current environmental and energetic crisis has been largely discussed (see, e.g., Poudenx (2008); Docherty et al. (2018)). Radical changes in individual mobility choices are thus imperative to accomplish the carbon-neutrality goals imposed at the national and international level. Among others, the transition from ownership to usership is likely to play a pivotal role in a shift towards greener habits. Indeed, pre-pandemic trends of mobility choices in large cities have already shown a natural transition of citizens towards sharing services, that today involve any type of vehicle (ranging from e-scooters to cars). As an example, in Europe the number of shared-rides users reached a peak of 196 billions, sta (2022). Although these tendencies have fostered huge investments in shared mobility in general, and car sharing in particular, shared mobility has not reached its full potential yet, due to several socio-economic and psychological barriers preventing its widespread diffusion. As a matter of fact, people's inclination towards shared mobility solutions is usually determined (and limited) by individual needs and preferences, along with demographic and economic factors, see e.g., Prieto et al. (2017). Based on a Greek survey, Efthymiou et al. (2013) shows that subscriptions to sharing services are correlated to age and income, along with environmental consciousness and usage of public transports. Another picture of the sharing community is provided in Ballús-Armet et al. (2014), showing that mainly young adults, attending university, with a middle-low income use sharing services. Instead, by relying on a more extensive European survey including 7 countries, the most common mobility habits and socio-demographic profiles driving car sharing usage/non-usage are analyzed in Ramos et al. (2020), identifying five distinct clusters of mobility styles. Besides users profiling, Shaheen and Cohen (2018); Česnuitytė et al. (2022); Feigon et al. (2018) provide an overview of common practices employed by governments and private investors to support and promote the diffusion of sharing mobility. Nevertheless, none of these works shows how a deep knowledge on user characterization and motivations can be exploited to improve such fostering policies. Only Xiong et al. (2020) integrates social factors into the optimization of personalized incentives promoting sustainable trip planning in a control-oriented formulation, but they do not account for the key role that social interactions among individuals may have in the adoption process. Indeed, the adoption process is further complicated by the fact that individual profiles constantly evolve over time, because of life experiences, the impact of advertisements and social influences. In this respect, understanding and modeling the dynamical evolution of individual attitudes is key to predict and analyze social systems (see, e.g., Ravazzi et al. (2021)), setting the ground for designing optimal feedback policies to foster the massive adoption of shared mobility solutions.

Starting from the data collected with an European survey Fiorello et al. (2015), the first contribution of the paper is that of modeling adoption patterns of sharing mobility

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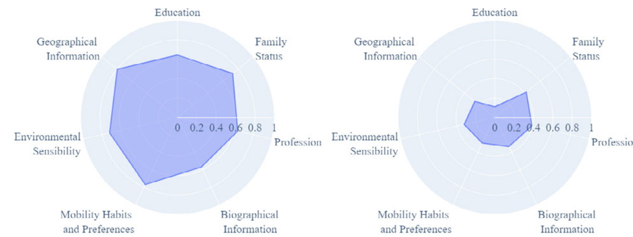
over a sample metropolitan community. Such a model lays its ground on the theory of opinion dynamics and it is build with data allowing us to integrate socio-economic insights into the model of personal inclinations, while enabling us to leverage indirect information on individual mobility patterns (differently from Breschi et al. (2022)). Within the proposed modeling framework, we show for the first time how tailored optimal control techniques can be leveraged to design policies that foster the widespread adoption of sharing mobility services, while performing their cost-benefit analysis at design time. Ultimately, our contribution shows that human-centric policies can speed up the adoption process with potential costs reductions.

The paper is organized as follows. In Section 2, we summarize the main features of the considered dataset. Then, Sections 3-4 are devoted to describe how individuals and their mutual connections are characterized from the available data, respectively. The opinion diffusion-based modeling framework is introduced in Section 5, while Section 6 presents the optimal control framework proposed in this work for policy design. Through a set of simulation results, Section 7 shows how the proposed framework and policies can be actively exploited by policy makers as actionable tools to foster the widespread adoption of shared mobility.

2. ON THE AVAILABLE DATASET

In this work, we exploit the data gathered by the 2014 Eurostat survey on transport and mobility issues Fiorello et al. (2015)) (a later survey has been conducted in 2018, but the questions have substantially changed, so unfortunately the two cannot be easily compared, and clear-cut questions on sharing predisposition was not included in the last survey). The dataset comprises the answers to a 39-questions survey, collected over statistically relevant samples of the population across the different European countries. These questions are related to the socio-economic status of the respondents, as well as to their mobility habits. For what concerns this last aspect, the questions mainly focus on the individual attitude towards innovative mobility solutions, such as sharing services and electric vehicles. The questions of the survey can be divided into 7 macro-groups, according to which features of the respondent they aim at unveiling. In particular, it is possible to distinguish between questions on: Biological information (Bio), e.g., the age; Family status (Fam), such as the income level; Geographical information (Geo), e.g., the living region; Education (Edu); Profession (Prof); Environmental awareness (Env); Mobility habits (Mob). Among all available questions, the target variable considered in this study is the answer to the query: *Would subscribe car sharing (if available).* Indeed, answers to this question allow us to have a picture of the respondents' attitude towards sharing services, at the time they were interviewed. Nonetheless, the personal inclination is likely shaped by the answers the respondent provided to the other questions in the survey. These answers thus represent the features we have at our disposal to further enrich the description of individual predisposition.

To this end, the raw answers gathered from the European survey have been pre-processed as described in Villa et al. (2022). With the aim of having a binary description of individual preferences with respect to sharing services, data



(a) Positive respondent (b) Negative respondent

Fig. 1. Sharing-DNA of two respondents. The more components are close to 1, the more the respondent is well-inclined towards sharing mobility solutions.

have initially been reduced, discarding those respondents whose target answer is *Maybe not, Maybe yes* and *Don't know.* This led to a reduction of the dataset of about 56% of its initial dimension. Although slightly different in their flavor, all positive answers towards the subscription to sharing services have further been reduced to a single label. We stress that these operations do not undermine the statistical relevance of the remaining sample of the population within each European country. In particular, the two classes resulting from these pre-processing steps respectively comprise 46% and 54% of the remaining sample, thus resulting in a balanced set of data. The remaining data have then been cleaned, properly grouped (when needed) and encoded [1] .

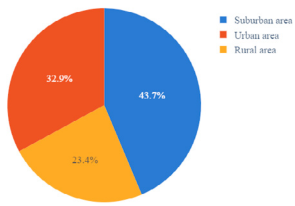
3. SHARING-DNA: A TOOL TO CHARACTERIZE INDIVIDUAL INCLINATIONS

Exploiting all available features to learn individual predispositions towards shared-rides, we have employed machine learning techniques to extract the most relevant factors influencing the target (see Villa et al. (2022) for a detailed description). By leveraging the most important features identified for each macro-category, we then devise a more exhaustive description of individual predispositions through the so-called Sharing-DNA. To construct it for the v-th respondent, we calculate the empirical likelihood

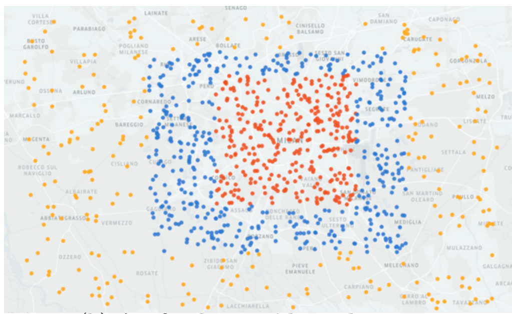
$$\ell_v^i = \frac{\#\left(\mathcal{P} \cap \mathcal{R}_j^i\right)}{\#\left(\mathcal{R}_j^i\right)} \quad \in [0,1], \tag{1}$$

of the agent being positively inclined towards sharing mobility, according to each of the $i = 1, \dots, 7$ macro-groups, with $\mathcal{P}$ denoting the set of *positive* respondents and $\mathcal{R}_j^i$ indicates the set of respondents whose i-th feature assumes the j-th value, for $j = 1, \dots, J$ (J varies depending on the considered answer). Note that, ℓ_v^i represents the empirical probability that, based on the answer provided by agent v to the feature of macro-group i, he is positively inclined towards sharing mobility. This shift towards likelihoods allows us to scale all DNA features, making its different "souls" compatible and comparable, since the available features come from very different realms (e.g., mobility habits and psychological factors). As shown by the two instances reported in Fig. 1, it is clear how this compact representation provides insights on individual inclinations, even just by visual inspection. Considering that a DNA feature close to 1 indicates that the respondent is less

[1] Encoding approached have been used, due to the pervasive presence of categorical features.



(a) Respondents' home locations



(b) Artificial agents' home locations

Fig. 2. Respondents' and artificial agents' home locations within Milan metropolitan area.

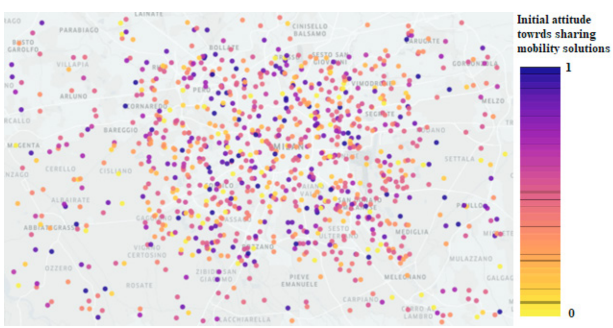


Fig. 3. DNA-based inclination towards sharing services α_v. Values of α_v close to 1 suggest that artificial agents are well inclined towards sharing mobility.

affected by (macro-group specific) barriers preventing the subscription to sharing services, it is indeed clear that the respondent with Sharing-DNA as in Fig. 1(a), is more inclined towards using shared mobility solutions than the one with the Sharing-DNA in Fig. 1(b). This conclusion is further validated by the value of the target. By still relying on the likelihoods, the information encrypted into the Sharing-DNA can be further condensed in

$$\alpha_v = \bar{\ell}_v = \frac{1}{7}\sum_{i=1}^{7} \ell_v^i, \qquad \alpha_v \in [0,1], \tag{2}$$

which provides a compact characterization of the predisposition to sharing, rooted on data but not solely guided by the target.

4. EXPLOITING MOBILITY TRAITS TO CHARACTERIZE MUTUAL INFLUENCES

Since the diffusion of technological innovations is knowingly driven by both individual inclinations, imitation mechanisms and other factors related to social contagion, see e.g., Delre et al. (2010), it is thus crucial to characterize the connections between respondents. Although providing

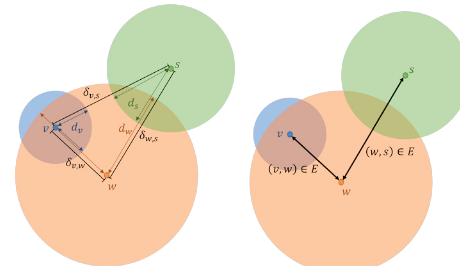


Fig. 4. Example of how the network is constructed. The shaded area surrounding each node represents its *action area* and two agents are connected only if their *action areas* overlap.

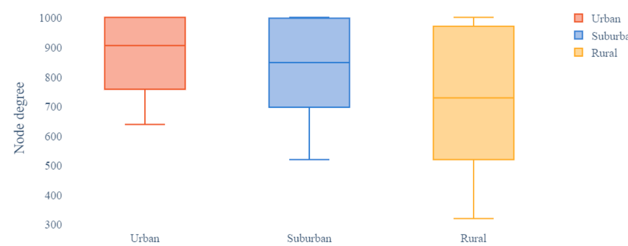


Fig. 5. Distribution of the agents' degree over urban, suburban and rural areas.

insights on the socio-economic group each respondent belongs to, the available data do not easily allow one to draw any conclusions on the actual social bonds among individuals, as only similarity-based connections might eventually be postulated. Meanwhile, the survey exploited in this work gives us information on the respondents' geographical locations and their mobility habits.

Based on these characteristics of our dataset, in this work we focus our attention on *homophily* induced by similar mobility habits. Accordingly, we classify each respondent by *Country* and, then by *Region*, thus allowing us to distinguish between several, relatively smaller geographical communities located in the different regions of each European country. For our analysis to be meaningful, we then consider only a sub-group of the ones retrieved based on the attribute *Region*, specifically focusing on the 158 respondents living in Lombardy, Italy. Since this choice reduces the dimension of the set of individuals considered to describe the diffusion of shared mobility. To overcome this issue, here we regard the 158 respondents as *sample individuals* leaving in the metropolitan city of Milan. Accordingly, we construct a prototypical, yet data-informed, population, by randomly generating 1002 agents, whose DNA and attitude towards sharing services is inherited by one of the *sample individuals*. For the prototypical population to reflect the features of the actual 158 respondents, the randomization procedure is performed by keeping an eye on maintaining the same ratio of positive/negative agents towards sharing services of the *sample population*, keeping its proportion of agents living in urban, suburban and rural areas (see Fig. 2(a)). According to this last classification, the agents are then randomly spread around the metropolitan area of Milan as shown in Fig. 2(b). Meanwhile, in our random extraction, we paid attention in having all the sample DNAs fairly represented with the artificial population, as exemplified by the rather diverse values of α_v shown in Fig. 3.

Once the artificial population is constructed, we have to characterize the mutual influences between agents. Such contagion patterns are here described via an *undirected* graph $G = (V, E)$, whose set of nodes V is constituted by the 1002 artificial agents of our prototypical population. Meanwhile, the set of edges E is here retrieved by looking at the mobility habits of each artificial agents [2]. In particular, two agents $v, w \in V$ are assumed to mutually influence one another (i.e., $(v, w) \in E$) if the following holds

$$d_v + d_w \geq \delta_{v,w}, \tag{3}$$

where $\delta_{v,w}$ [km] is the geographical distance between the location of the two agents, while d_v, d_w [km] are the maximum distance they travel in their most frequent trip. This constructive logic is schematized in Fig. 4, and it relies on the assumption that personal inclination towards sharing services is most likely influenced by individuals that frequently visit and, thus, share the same *action area*. Based on this logic, our prototypical network results in decreasing nodes' degree when moving from central to suburban and rural areas (see Fig. 5).

5. DATA-BASED IRREVERSIBLE CASCADE MODEL

We now model changes in the agents' attitude towards sharing services over relatively short time horizons (i.e., $t \in [0, T-1]$, with T finite and "small"). In constructing the model within this context, we thus rely on three structural hypotheses: (i) once a user, an agent cannot change its attitude towards shared mobility solutions; (ii) changes in the personal inclination towards shared mobility are driven by the relative popularity among agents' neighbors in G; (iii) the "level of popularity" $\rho_v(t) \in [0, 1]$ required at each time instant t for an agent to change its opinion is initially indicated by α_v in (2), namely $\rho_v(0) = 1-\alpha_v$. The first assumption is reasonable as long as shared mobility providers do not drastically modify their fleets, as they are already satisfying the needs of users and the expectations of well-disposed individuals, which would thus not likely to negatively change their attitude towards the service, at last over relatively short time spans.

According to these assumptions, we model the adoption of sharing mobility as an *irreversible cascade*. Each agent $v \in V$ is thus paired with a time-varying, binary variable $z_v(t) \in \{0, 1\}$, whose value is equal to 1 if the agent is well-disposed to sharing mobility services and 0 otherwise. Let $S_0 \subset V$ be the *seed set* of the cascade model, i.e.,

$$S_0 = \{v \in V : z_v(0) = 1\}, \tag{4}$$

and here constituted by all those artificial agents paired with the answer *Yes, I'm already a client* to the question *Would you subscribe car sharing services, if available?* by our randomized creation of the prototypical population. While $z_v(t) = 1$, for all $t > 0$ when $v \in S_0$, the binary variable associated to all agents $v \notin S_0$ evolves as follows

$$z_v(t+1) = \begin{cases} 1, & \text{if } \frac{1}{|N_v|}\sum_{w \in N_v} z_w(t) \geq \rho_v(t), \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

with $N_v = \{w \in V : (v, w) \in E\}$ being the set of the agent neighbors and $|N_v|$ is its cardinality. Differently from standard irreversible cascade models Granovetter (1978), here we assume that the individual *resistance* $\rho_v(t)$ to the adoption of sharing mobility solutions can vary over time. In particular, we describe the dynamics of $\rho_v(t)$ as

$$\rho_v(t+1) = \rho_v(t) + \beta_v u_v(t), \tag{6}$$

thus accounting for external factors $u_v \in \mathbb{R}$, i.e., governmental/local policies or improvements in shared vehicles fleets. Note that the impact of these external factors is "filtered" through a coefficient $\beta_v \in [0, 1]$, which encodes the individual *receptivity* to external policies.

In this work, we consider three possible scenarios, where receptivity (i) is not linked to the DNA, and thus β_v is *randomly chosen* (RAN); (ii) depends on the agents' environmental sensibility (ENV), with β_v being equal to the empirical likelihood associated to this DNA component; (iii) depends on individual mobility habits (MOB) and, accordingly, β_v is set to the empirical likelihood associated this last element of the DNA.

6. OPTIMAL CONTROL TO FOSTER SHARED MOBILITY

The model presented in Section 5 allows us to exploit feedback strategies to design optimal (i.e., "cheap" and effective) strategies to foster a massive adoption of sharing mobility solutions within our population. Over an horizon T, such an optimal control problem can thus be cast as:

$$\underset{\{U_v\}_{v \in V}}{\text{minimize}} \sum_{v \in V} \sum_{t=0}^{T} J_v(\rho_v(t), z_v(t), u_v(t), \bar{\rho}_v(t)), \tag{7a}$$

where $U_v = \{u_v(t)\}_{t=0}^{T-1}$ is the sequence of external actions affecting the resistance of the v-th agent. The local cost $J_v = J_v(\rho_v(t), z_v(t), u_v(t), \bar{\rho}_v(t))$ corresponds to

$$J_v = Q_v(t)(\rho_v(t) - \bar{\rho}_v)^2 + R u_v^2(t) + Q_v(T)(\rho_v(T) - \bar{\rho}_v)^2, \tag{7b}$$

where $R > 0$ is a positive weight, penalizing excessive efforts on the policy maker/service provider side, $\{Q_v(t)\}_{t=0}^{T}$ are non-negative, time-varying weights defined as

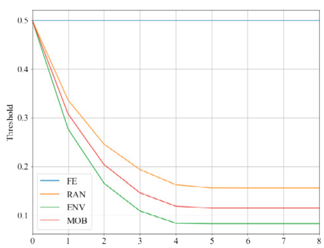
$$Q_v(t) = Q(1 - z_v(t)), \quad t \in [0, T-1], \tag{7c}$$

thus penalizing the tracking error between $\rho_v(t)$ and the reference $\bar{\rho}_v$ with $Q \geq 0$ if and only if the v-th agents is not yet well-disposed to sharing mobility services at time t. This choice allows us to account for the evolution of the binary variable $z_v(t)$, i.e., the individual attitude towards sharing mobility. Since the weights in (7c) can only be computed by having a preview of the individual inclination $z_v(t)$, over $t = [0, T-1]$, we exploit the model in (5) to make predictions on the binary variables $\{z_v(t)\}_{v \in V}$ over the considered horizon, that are updated at each time instant according to the current individual attitudes. Despite the reference $\bar{\rho}_v$ can be potentially set to zero, for the optimal policy $\{u_v(t)\}_{t=0}^{T-1}$ to target a complete annihilation of the individual resistance, such a goal is excessive and it could lead to a potential waste of resources. Instead, for an individual to become an adopter, it is sufficient that its resistance $\rho_v(t)$ becomes sufficiently small, to be at least overcome by the initial number of the neighbor adopters of the v-th agent. According to this logic (see (5)), the target for each agent is set to

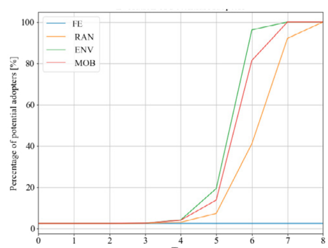
[2] Once again, these features are inherited from the sample agents, through the random generation of the prototypical population.

Table 1. Policies *vs* receptivity: cost C, average cost per step $\bar{C}_t$, relative dimension of the adopters' set $s(t)$ at step $t = 6$ and $t = 10$.

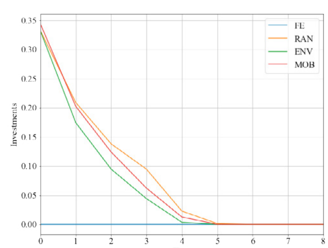
$\{\beta_v\}_{v\in V}$	weights	C	$\bar{C}_t$	$s(6)$	$s(10)$
RAN	RH_1	799	88	0.44	1
	RH_2	873	97	0.96	1
	RH_3	713	79	0.05	0.99
ENV	RH_1	649	72	0.95	1
	RH_2	668	74	1	1
	RH_3	629	69	0.09	1
MOB	RH_1	746	82	0.80	1
	RH_2	795	88	1	1
	RH_3	702	78	0.08	1



(a) Average evolution of resistance thresholds



(b) Percentage of potential adopters over time



(c) Average evolution of the personalized actions

Fig. 6. FE *vs* RH_1 for the three receptivity scenarios RAN, ENV and MOB.

$$\bar{\rho}_v = \frac{1}{|N_v|} \sum_{w \in N_v} z_w(0), \quad \forall v \in V. \tag{8}$$

Among possible alternatives, in this work we parameterize the policies/strategies enacted by policy makers or sharing service providers on the v-th agent as follows:

$$u_v(t) = K_v(t)(\rho_v(t) - \rho_v), \tag{9}$$

with $K_v(t) \in \mathbb{R}$ being the gain characteristic for agent-tailored strategies. Combined with the loss in (7b), this characterization of the policies allows us to retrieve a closed-form expression for the optimal action $u_v^\star(t)$ to be performed on each of the agents, with $v \in V$, to foster sharing mobility usage and its widespread diffusion. In particular, by exploiting Bellman's equations (see Bertsekas (2012)), the gain $K_v(t)$ can be updated backwards as

$$P_v(t) = Q_v(t) + P_v(t+1) - \frac{(\beta_v P_v(t+1))^2}{R + P_v(t+1)\beta_v^2}, \tag{10a}$$

$$K_v(t) = -\frac{\beta_v P_v(t+1)}{R + P_v(t+1)\beta_v^2}, \tag{10b}$$

starting from the final value $P_v(T)$.

7. SIMULATION RESULTS AND DISCUSSION

Through a set of different simulations, we now explore the potential of the proposed setup as tool to foster the adoption of sharing mobility services. We stress that the presented results are not intended to provide realistic forecasts, but they are instrumental to discuss the potential of the proposed framework and policy design strategy.

7.1 *Simulations setup*

In our simulations, we analyze the effect of optimal policies over an horizon of $T = 10$ steps, corresponding to a time span of 6 months, that we deem being sufficiently short for the irreversible cascade model to be used. Overall, we analyze the impact of three alternative optimal strategies: (i) a *balanced* policy (RH_1) obtained setting $Q = R = 1$ and, thus, imposing no priority between fostering the use of sharing services and containing the effort required to enact a policy; (ii) a *fostering-oriented* policy (RH_2) characterized by $Q = 2$ and $R = 1$, slightly prioritizing the diffusion of sharing services over cost containment; a *cost-efficient* policy (RH_3), designed by setting $Q = 0.5$ and $R = 1$ and, thus, promoting a containment of costs. These policies are compared with the *free evolution* (FE) of the irreversible cascade model, which is attained when $u_v(t) = 0$, for all $t \in [0, T-1]$ and $v \in V$.

Coming to policy personalization, we analyze the differences brought in the final number of adopters when considering the three possible receptivity scenarios introduced in Section 5 with respect to the value of $\{\beta_v\}_{v\in V}$. Note that, when the receptivity is linked to the environmental sensitivity (ENV), the input we design can be linked to investments directed to boost people consciousness on the environmental impact of a shift from ownership to usership (e.g., through advertising campaigns). On the other hand, when β_v is dictated by mobility habits (MOB), the optimal input can represent strategies to better suit the users' needs with the shared fleet (e.g., performing investments to diversify or augmenting it).

To quantitatively evaluate the considered scenarios, we consider a set of indicators, that allow us to perform a cost-benefit trade-off of the tested policies. Specifically, let $S(t)$ be the dimension of the set of adopters at time t, i.e.,

$$S(t) = |\{v \in V : z_v(t) = 1\}|, \quad t \in [0, T-1]. \tag{11}$$

Our first indicator is the relative dimension $s(t)$ of the adopters' set at each time instant, namely

$$s(t) = \frac{S(t)}{|V|}, \quad t \in [0, T-1], \tag{12}$$

where $|V| = 1002$ is the dimension of the considered artificial population. Moreover, we consider the total "cost" of a policy C and its average "cost" per step, defined as

$$C = \sum_{t=0}^{T-1} \sum_{v \in V} u_v(t), \quad \bar{C}_t = \frac{1}{T} \sum_{t=0}^{T-1} \sum_{v \in V} u_v(t). \tag{13}$$

7.2 *Discussion*

For each policy and receptivity scenarios, the values of the performances metrics presented above are reported in Table 1. As expected, due to the chosen weights, the policy RH_2 results in a quicker increase in the dimension of the adopter set, at the price of an increase in both the total and step-wise "investments" with respect to those required by RH_3. Still not unexpectedly, the lower resource usage resulting from RH_3, is paired with a slower boost in the number of agents that change their attitude towards sharing mobility services. The balanced strategy RH_1 places itself between the previous two when looking at the dimension of the seed set over time, while requiring a more consistent investment. Note that these conclusions are valid independently of the considered receptivity scenario, since they are only related to the relative weights of the cost terms in (7b).

By focusing on RH_1 only, we now show how the previous results translate into the evolution of the average individual resistance and personalized "incentives", along with that of the percentage of adopters, over time. As shown in Fig. 6(a), all closed-loop policies result in a decrease of the average agents' resistance over time, with it fading faster in the ENV scenario, namely when each β_v is dictated by the individual environmental sensitivity. This last result thus indicates that (at least in our prototypical scenario) actions undertaken to foster adoption across environmental-friendly individuals are preferable to a random resource allocation (RAN) and to incentive strategies dictated by mobility habits (MOB). At the same time, the decrease of agents' resistance (independent from the receptivity scenario) concurrently translates in a faster widespread diffusion of sharing mobility services throughout the population (see Fig. 6(b)), especially when compared to the free evolution. Indeed, due to the limited number of initial adopters in the network and their low connectivity, sharing mobility services do not diffuse over the population without proper interventions (FE scenario). Instead, when policies are enacted, they lead to a decrease in individual resistance, which progressively makes social contagion more effective in promoting the acceptance of sharing mobility solutions, up to a point where the adoption process is solely driven by mutual influences (i.e., after $t = 6$). Indeed, the policy-induced diffusion requires agent-tailored actions $u_v(t)$, which nonetheless fade over time (see Fig. 6(c)) and become zero when shared mobility solutions have spread over the whole population, thus avoiding unnecessary costs.

8. CONCLUSIONS AND FUTURE WORKS

Starting from a set of EU survey data, this paper presented a control-oriented framework for the simulation, analysis, and optimal design of adoption trends with respect to sharing mobility solutions. Our simulation results highlight that costs can be reduced and its effectiveness boosted by designing targeted polices, by accounting for social features characterizing individual predisposition and considering the effect of social contagion. Future work will be devoted to introduce a stochastic component in the cascade model for a more realistic representation of the adoption phenomenon, and to analyze formal properties of the defined optimal policy design strategy.

REFERENCES

(2022). Shared mobility - europe. *Statista Report*.

Ballús-Armet, I., Shaheen, S.A., Clonts, K., and Weinzimmer, D. (2014). Peer-to-peer carsharing: Exploring public perception and market characteristics in the san francisco bay area, california. *Transportation Research Record*, 2416(1), 27–36.

Bertsekas, D. (2012). *Dynamic programming and optimal control: Volume I*, volume 1. Athena scientific.

Breschi, V., Ravazzi, C., Strada, S., Dabbene, F., and Tanelli, M. (2022). Fostering the mass adoption of electric vehicles: a network-based approach. *IEEE Transactions on Control of Network Systems*.

Česnuitytė, V., Klimczuk, A., Miguel, C., and Avram, G. (2022). *The sharing economy in Europe: Developments, practices, and contradictions*. Springer Nature.

Delre, S.A., Jager, W., Bijmolt, T.H.A., and Janssen, M.A. (2010). Will it spread or not? the effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, 27(2), 267–282.

Docherty, I., Marsden, G., and Anable, J. (2018). The governance of smart mobility. *Transportation Research Part A: Policy and Practice*, 115, 114–125. Smart urban mobility.

Efthymiou, D., Antoniou, C., and Waddell, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport policy*, 29, 64–73.

Feigon, S., Frisbie, T., Halls, C., and Murphy, C. (2018). Shared use mobility: European experience and lessons learned.

Fiorello, D., Zani, L., Christidis, P., and Navajas Cawood, E. (2015). Eu survey on issues related to transport and mobility. Other LF-NA-27334-EN-N, Luxembourg (Luxembourg).

Granovetter, M. (1978). Threshold models of collective behavior. *The American Journal of Sociology*, 83(6), 1420–1443.

Poudenx, P. (2008). The effect of transportation policies on energy consumption and greenhouse gas emission from urban passenger transportation. *Transportation Research Part A: Policy and Practice*, 42(6), 901–909.

Prieto, M., Baltas, G., and Stan, V. (2017). Car sharing adoption intention in urban areas: What are the key sociodemographic drivers? *Transportation Research Part A: Policy and Practice*, 101, 218–227.

Ramos, É.M.S., Bergstad, C.J., Chicco, A., and Diana, M. (2020). Mobility styles and car sharing use in europe: Attitudes, behaviours, motives and sustainability. *European Transport Research Review*, 12(1), 1–12.

Ravazzi, C., Dabbene, F., Lagoa, C., and Proskurnikov, A.V. (2021). Learning hidden influences in large-scale dynamical social networks: A data-driven sparsity-based approach, in memory of roberto tempo. *IEEE Control Systems Magazine*, 41(5), 61–103.

Shaheen, S. and Cohen, A. (2018). Shared mobility policy briefs: Definitions, impacts, and recommendations.

Villa, E., Preti, G., Riva, M., Breschi, V., and Tanelli, M. (2022). Sharing-DNA: a data-driven tool to map the attitude towards sharing services across Europe. In *2022 IEEE International Smart Cities Conference (ISC2)*, 1–7.

Xiong, C., Shahabi, M., Zhao, J., Yin, Y., Zhou, X., and Zhang, L. (2020). An integrated and personalized traveler information and incentive scheme for energy efficient mobility systems. *Transportation Research Part C: Emerging Technologies*, 113, 57–73.