POLITECNICO
MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Executive Summary of the Thesis

Control-enabled policy design for fostering sustainable and just mobility habits

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'Automazione

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Academic year: 2021-2022

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1. Introduction

The widespread adoption of new technologies related to the ecological and environmental transition is crucial in the context of the current climate emergency. However, as the acceptance of new technologies is heavily influenced by the traits of the individuals who will be using them, understanding how adoption occurs is not trivial. An important element of the environmental transition involves the mobility sector as it is responsible for nearly 25% of Europe's greenhouse gas emissions [5]. Due to the difficulty of overcoming cultural and mindset barriers to foster the adoption of sustainable mobility solutions, public incentives are crucial. Nevertheless, a wide and complete knowledge of individual characteristics affecting personal adoption propensity must be pondered to design successful government policies. Besides, it is important to highlight that as the introduction of new technology has strong and ethical impacts, thus it is essential to consider fairness and social justice directly in the designing of policy schemes. This should be done in order to mitigate biases that may result in special treatment for specific groups or individuals.

1.1. Contributions

This work aims to propose a novel framework to design policies to promote the adoption of Car-sharing services. The framework exploits a data-driven tool that defines individual inclination to the adoption of sharing mobility services (the Sharing-DNA) and a multi-agent network. In this way both data-driven individual characteristics and social interactions are taken into account. The agents' features and the network are built based on the data retrieved from the *EU survey on issues related to transport and mobility* [2], a survey that aimed at collecting data on the mobility habits of European citizens, together with their socio-economic characteristics. Using the irreversible cascade model to describe the diffusion of the new technology through social contagion, we exploit an LQR formulation to design policies aimed at minimizing a specific cost function combing boosting effects with cost saving. Specifically, three possible formulations of the LQR problem are analyzed and compared. Finally, this work tries to innovatively integrate the concept of fairness in the problem formulation by adding an additional component in the LQR formulation. This allows us to evaluate social impact of the designed policies at design time and not just in retrospect after service deployment as canonically done in the literature.

2. State of the art and background

To start we have to cover the theoretical background for the work, including an overview of the literature on Car-sharing adoption and attitudes and an introduction to opinion dynamics and the Linear Quadratic Regulator.

2.1. What affects the demand for car-sharing services

Low awareness of their use, concerns about the high cost of the service and the lack of consistency in building charging infrastructure are the most common barriers preventing the adoption of sharing services [5]. Income is another significant determinant, with those in the low-mid income class being more likely to join car-sharing programmes as well as people with higher education levels [1].

2.2. Deterministic Irriversivle Cascade Model

To model the adoption spread dynamics within a network of users we will exploit state-of-the-art tools from the theory of opinion dynamics. In fact, this field of study focuses on how beliefs and views evolve and spread over time within a population. The specific method on which we rely is the deterministic irreversible cascade model. The latter operates in a network defined as an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ are nodes of the graph that represent the N agents and $\mathcal{E}$ are the edges that establish the mutual influence among them. Each individual is characterized by a state variable evolving over time. The state variables can assume binary values, i.e. $x_v(t) \in (0, 1)$, indicating whether at time $t \in \mathbb{N}_0$ the v_{th} agent is an adopter ($x_v(t) = 1$) or not ($x_v(t) = 0$). In this model when an agent becomes an adopter remains so until the end of the horizon. The evolution of each agent's state is described by the following equation:

$$x_v(t+1) = \begin{cases} 1, & \text{if } x_v(t) = 1 \text{ or} \\ & \frac{1}{|\mathcal{N}_v|}\sum_{w \in \mathcal{N}_v} x_w(t) \geq \alpha_v \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $\mathcal{N}_v$ is the neighbour of the $v - th$ agent and α_v a thresholds characterizing every agent. Hence, the adoption is driven by the relative popularity of the technology among the neighbours of each person.

2.3. Linear Quadratic Regulator

To design the optimal incentive policy and apply it in closed-loop, the tool used in this work is the control algorithm of the Linear Quadratic Regulator. This control technique optimizes the performance of a given dynamic system computing a feedback control law that minimizes a quadratic cost function at each time step. The latter in discrete time is expressed as:

$$J = \sum_{t=0}^{T-1} \left(Q(x(t) - \bar{x})^2 + Ru(t)^2\right) dt + Q(x(T) - \bar{x})^2 \tag{2}$$

where the first and the third term, multiplied by their weight Q, are respectively the error between the current state of the system $x(t)$ and the desired state $\bar{x}$ and between the terminal state $x(T)$ and the target $\bar{x}$. The second term, multiplied by its weight R, accounts for the control input $u(t)$.

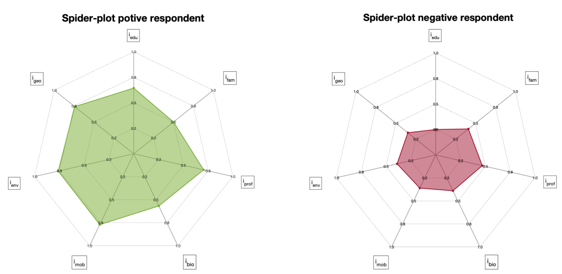
3. Dataset and network

3.1. Dataset

The *EU survey on issues related to transport and mobility* [2] aimed at collecting data on mobility habits as well as opinions on various policy issues related to transportation, and additional info related to the socio-economic status of the respondents. The survey involved 28 European countries and collected information from a sample of 1000 individuals in each country. Attributes can be categorised into seven main groups including biological information (Bio), family status (Fam), geographic information (Geo), education (Edu), profession (Prof), environmental sensitivity (Env), and mobility habits (Mob). Among these questions, the one saying *Would subscribe car sharing (if available)* is here considered as the "target" question, namely an indicator of the actual individual inclinations towards Car-sharing.

3.2. Sharing-DNA

After reducing and cleaning the data by discarding the uncertain answers to the target question, these are used to retrieve the Sharing-DNA, i.e. quantitative and compact representation of the personal propensity to use a sharing service. To do so, first, a classifier is built in order to identify which socio-economic factors are most strongly associated with people's likelihood of using shared mobility services. Using machine learning algorithms, we select the set of features that optimize the classification outcome. To do so, an algorithm that quantifies the impact of each feature on the model's performance, i.e. the Permutation Importance Algorithm, is used. To the subset of selected features are attributed seven indices i_{mob}, i_{geo}, i_{env}, i_{edu}, i_{prof}, i_{bio} and i_{fam} found as the likelihood of being an adopter and of presenting a specific value for each of the seven features. They indicate the propensity of the user to buy an electric or hybrid electric vehicle (i_{mob}), the individual's country of origin (i_{geo}), how much the environmental issues worry the user (i_{env}), the level of education of the individual (i_{edu}), the user's employment (i_{prof}), the age of the individual (i_{bio}) and the user's level of income (i_{fam}). Finally, the Sharing-DNA is defined as the vector of these indices and can be outlined through spider-plots where vertices represent the value of the seven indices (closer to 1 for higher propensity, 0 otherwise). Thus the area is linked to the individual inclination towards the adoption of shared mobility services (see Fig.1).



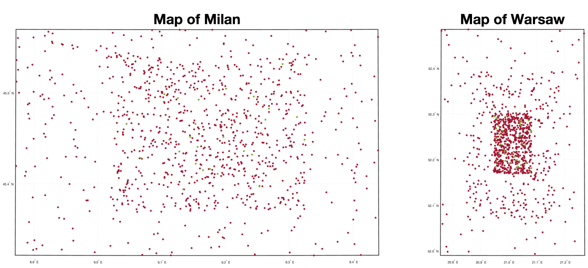
(a) (b)

Figure 1: Spider plots for reference individuals: positively (1a) and negatively inclined (1b)

Finally, we can further compress the info contained in the Sharing-DNA by computing the Sharing index i_{sha}, calculated by as the normalized average of the Sharing-DNA components.

3.3. User' interaction network

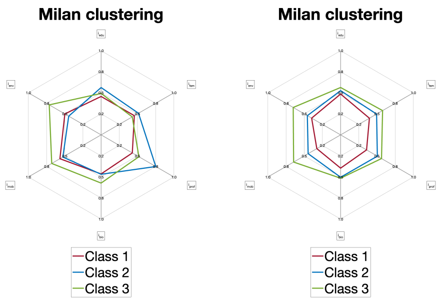
Based on the processed survey data we are going to build two multi-agent networks. We focus on two areas (Milan and Warsaw) and starting from the available sample of respondents living in these regions, for both networks we extract a set of approximately 1000 individuals in order to simplify the numerical analyses. In this procedure, we ensure that the statistical composition of the population is preserved, namely the proportion of individuals living in central, suburban or peripherical areas is maintained as well as the proportion of the adopters/non-adopters. Each agent in the network is characterized by an individual resistance with respect to shared mobility α_v defined as $\alpha_v = 1 - i_{sha,v}$. Accordingly, the information on the location of residence reported in the survey it is possible to randomly associate each individual with a geographical position in an urban/suburban or peripheral region. Moreover, we decided to connect agents in the network based on geographical proximity considering the users being the most influenced by those near them, hence their representative examples. Specifically exploiting information on personal mobility habits, it is possible to identify the geographic region mostly frequented by each agent and thus connect two agents if they move in similar areas, namely their influence regions overlap. The two retrieved networks present (see Fig. 2) have respectively 1005 and 1002 nodes, they are almost fully connected and the early adopters are 2.59% and 3.59% of their total nodes.



(a) (b)

Figure 2: Milan and Warsaw network.

To better focus the policy design, it is interesting to group individuals in sets with a clusterization. The results are reported in the spider-plots in Fig.3 where vertices represent the average value of a certain index with respect to all users belonging to the same class. From these results, we can clearly see that Warsaw (Fig.3b), contrary to Milan (Fig.3a), presents more clearly separate clusters.



(a) (b)

Figure 3: Milan and Warsaw clusters.

This outcome allows us to finally identify the low (Class 1), the medium (Class 2), and the high (Class 3) propensity groups.

4. Network evolution

Now that we have built the networks, we can test their evolution, i.e. the spreading of the adoption of Car-sharing services with or without external intervention.

4.1. Free evolution

The first scenario that we test is the one of the free-evolution of the adoption, i.e. without external incentives. To do so we have to consider the model described by Eq. 1 and an initial set of adopters, i.e. the users v that in the initial time t=0 have the state $x_v(0) = 1$. Considering a time horizon of T=10 steps where each step corresponds to 3 months, in this scenario, the two networks don't evolve. This is due to the fact that the early adopters in the two networks are not enough to trigger the spread of adoption.

4.2. Policy design: Scenario A

To boost the adoption throughout the networks, we want now to design incentive policy schemes. To this end, we have to consider the model in Eq. 1, but now with time-varying thresholds. In this way, we can treat the thresholds as directly modifiable by external incentives. Accordingly, the impact of a policy is taken into account by considering threshold dynamics as follows:

$$\alpha_v(t+1) = \alpha_v(t) + B_v u_v(t),\ t = 0, ..., T,\ v \in \mathcal{V}, \tag{3}$$

where $B_v \in \mathbb{R}$ quantifies how much the $v-th$ agent is willing to accept the policy, thus indicating the impact level of the policy $u_v \in \mathbb{R}$ directed to the $v-th$ user. Moreover, to find the optimal policy u_v, we consider an LQR problem that minimizes the Eq. 2 where the tracking objective is the difference between the Sharing index $i_{sha,v}(t)$ and its target $\bar{i}_{sha,v}$, i.e. $1-\bar{\alpha}_v$ where $\bar{\alpha}_v$ is the average of early adopters between the neighbours of each user at time t=0. The weights Q and R are here considered to be Q=10 and R=1. For what concerns B_v, the value is selected according to the cluster to which the user belongs by dividing the interval [0,1] in three ranges and then randomly extracting the value B_v in the lower range if the v_t user is in Class 1, in the middle range if the v_t user is in Class 2 or in the highest range if the v_t user is in Class 3. The retrieved policy schemes make the network evolve and reach full adoption at time t=6, i.e. after 18 months from the start of the simulation. As the network evolves the Sharing indices of the users increase boosted by the incentives, but for Milan, as can be evaluated by the poorly separated clusters (see Fig.3a), the users are all very similarly inclined towards sharing mobility, and even if the initial Sharing index values of users of different clusters are slightly separate, they end up being all indifferently very high. On the other hand in Warsaw, the values of the sharing index of users in class 1 (Fig.3b) are smaller in values from the initial to the final step of the time. The resources allocated are higher for Warsaw than for Milan (see Table 1). In particular, the inputs given to the Class 1 users of Warsaw are higher than all of the other classes of both Warsaw and Milan.

4.3. Policy design: Scenario B

In Scenario B, we consider Eq. 2 with the tracking error being the difference between $i_{sha,v}(t)$ and its target $\bar{i}_{sha,v}$ while the policy acts on those features that are changeable, i.e. i_{env}, i_{mob}, i_{fam} . B_v, Q, R are chosen as in the previous scenario, but in this case, since the policy acts on the vector $i_{DNA,v}(t)$, the B_v is a vector itself. In order for the network to evolve in this case, since we act on only three out of seven features, we decided to make the changeable features weight more on the final output of the Sharing index in accordance with the Permutation Importance algorithm discussed in Section 3.2. The policy schemes obtained in this way make the Warsaw network reach the full adoption on t=6 while for Milan only at t=9. The reason why this difference occurs can be found in the different index i_{geo} that characterizes the two cities: for Milan, this value is 0.6653 while for Warsaw, it is a little bigger, i.e. 0.7418 and since the policy only acts on the three changeable features of the DNA, the Milan's values of the i_{sha} are inevitably smaller than those of Warsaw. From the evolution of the Sharing index over time we notice that Sharing indices of the Class 1 users increase but remain in any case distinctly lower than those of the other classes, nevertheless, the individuals in the network quickly become adopters. On the contrary, the Sharing index of users in Milan has to reach a high value in order for the corresponding node to become an adopter. In fact, as can be seen in Table 1, the final average value of Milan's i_{sha} is higher than that of Warsaw's. Therefore we can say that in Warsaw the adoption of people less inclined to Car-sharing is driven particularly by the relative popularity of the technology, while in Milan it is mainly powered by the increase of the personal i_{sha}.

4.4. Policy design: Scenario C

The Scenario C considers the Eq. 2 with the tracking error being the difference between $i_{DNA,v}(t)$ and its target $\bar{i}_{DNA,v}$ while the policy act again on the $i_{DNA,v}(t)$. The target value $\bar{i}_{DNA,v}$ is the vector with elements all equal to $\bar{i}_{sha,v}$. The policy schemes retrieved make the network evolve and reach full adoption at time t=6 for Warsaw and at t=7 for Milan. The way that the Sharing index evolves over time is very similar to that of the previous Scenario as well as the allocation of the input (see Table 1).

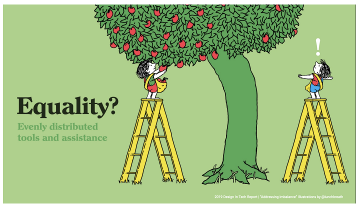
Table 1: Scenario A vs. Scenario B vs. Scenario C

	A		B		C	
	M	**W**	**M**	**W**	**M**	**W**
er_T	0.0083	0.0164	0.0600	0.0506	0.0117	0.0144
$i_{s,T}$	0.9304	0.9489	0.9159	0.9151	0.9558	0.9510
u_{tot}	0.7471	0.8729	1.3385	1.6676	1.5618	1.8735
t_{100}	6	6	9	6	7	6

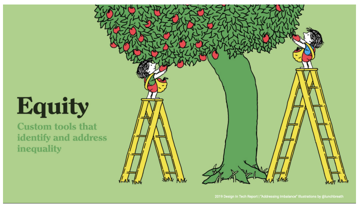
er_T is the mean final tracking error, $i_{s,T}$ is the mean final Sharing index, u_{tot} is the total average allocated input and t_{100} is the time needed to the 100% adoption

4.5. Policy design: fair LQR

We now want to include a concept of fairness in the formulation of the LQR problem in order to avoid getting an unfair resource allocation. In order to do so we have to first formalize the concept of fairness, a not-so-trivial task. In the majority of cases, fairness is defined as the equal consideration of all people, however, in this case, we consider the concept of equity (see Fig. 4).



(a)



(b)

Figure 4: Equality vs. equity. From Design in Tech Report 2019 [3]

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Equity takes into account the fact that each person's circumstances are unique and provides the precise resources and opportunities required to achieve equality [4]. Based on this, we formalise this concept with the minimization of the difference between each person's distance from the respective target and the mean of the others' distances from their target, as follows:

$$\min \sum_{p \in P} \left[(x_p - \bar{x}_p) - \frac{1}{N} \sum_{b \in P,\ with\ b \neq p} (x_b - \bar{x}_b) \right], \quad (4)$$

where x_p is the state of the $p-th$ person of a group P of N people and $\bar{x}_p$ is its target. The equity factor outlines as in Eq. 4 can now be added in the formulation of Scenario C by considering the additional element in such a way that it has the form of a tracking error objective where the actual state is the tracking error and the target is the mean of the other tracking errors at time t. The fair policy scheme is designed with Q = 10, R = 1 and different tunings of the weight of the equity factor W, i.e W=1 and W=10. To fully analyze how the concept of fairness influences the adoption process it is best to work with clearly separated clusters, hence with the Warsaw network. The evolution of the W=1 and the W=10 case are very different from each other, for the first one the full adoption is reached at t=8, while in the second case, the spreading only starts at t=9. Taking under consideration also the outcomes of Scenario C, we noted that, besides the fact that the evolution gets slower, as the weight W gets higher, the users' value of the Sharing index and the altered features approaches each other more over time. Moreover, with the increase of W also the resources allocated to the Class 1 users rise. That being said, now we want to find a way to quantitatively assess the fairness level of policy schemes present. To do that, we define the equity index $\mathcal{I}_e \in [0,1]$ as follows:

$$E(t) = \frac{1}{N}\sum_{v\in V}\left|\left|e_v(t) - \frac{1}{N}\sum_{w\in V} e_w(t)\right|\right|_2 \quad (5a)$$

$$\mathcal{I}_e(t) = e^{-E(t)} \quad (5b)$$

with Eq. (5a) be the average deviation of the tracking errors with respect to their mean. The evolution of the Index of equity (Eq. (5b)) of Scenario C, fair LQR with W=1 and fair LQR with W=10 is figured in Fig. 5 and in accordance with the analysis carried out in this section, we can see that the higher the value of W, the closer the Index of equity gets to its maximum possible values, i.e equal to 1.

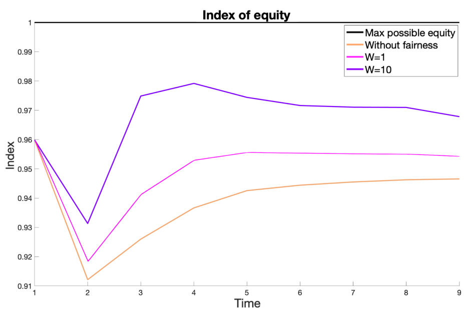

Figure 5: Index of equity, Scenario C vs W=1 vs W=10

5. Concluding remarks

In this work, we introduced a network-based framework to analyze the adoption process of Car-sharing services and to design policies that will help to boost the widespread of this technology. The framework offers a basis for formulating policies targeted at boosting the number of individuals who choose to use sharing mobility by exploiting data-driven studies on the factors that impact the adoption. After proposing different control formulations that differ in how the policy schemes act, we have seen that what influences the adoption is the composition of the network and the characteristics of the user that belongs to it. We have then provided a preliminary attempt to explicitly account for fairness in the design process. To this end, we have formulated a fair LQR that takes individual performance into consideration while fostering equity among a group of agents. By means of the comparison of the results obtained with non-fair and fair control problems, we have highlighted how fairness affects both individual performance and the general allocation of the control resources available. In general, it can be said that stronger agents in the group suffer from a little loss in tracking performance, however, the group as a whole exhibits a more balanced behaviour at the end of the timeframe taken into consideration.
Nevertheless, the research conducted has a significant limitation. In fact, in the process of policy design, we have considered unlimited resources. Therefore, future work needs to examine the effect of the limitation of resources in relation to the concept of fairness in such a way that the developed policies are more robust and realistic. To do this, we aim at exploiting the MPC framework fo policy design.

References

[1] D. Efthymiou, C. Antoniou, and P. Waddell. Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport Policy*, 29:64–73, 2013.

[2] D. Fiorello and L. Zani. Publications office of the european union. *EU Survey on issues related to transport and mobility*, 2015.

[3] J. Maeda. Design in tech report 2019, 2019.

[4] Milken Institute School of Public Health. Equity vs. equality: What's the difference?, 2020.

[5] A. Ortega Hortelano, A. Tsakalidis, A.and Haq, K. Gkoumas, M. Stepniak, F. Marques Dos Santos, M. Grosso, and F. Pekar. Research and innovation in car sharing in europe. 2022.