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Intervening me softly – Modeling nudging interventions to change EV user preferences

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Abstract

The charging of an increasing number of electric vehicles (EVs) leads to load peaks in the distribution grid. Controlled charging can reduce these peaks, but could also impair the mobility needs of the EV owners. Financial incentives are a frequently discussed measure to stimulate grid-friendly consumption, but they are limited in their attractiveness for the consumers. A more intuitive approach is the so-called nudging interventions, which influence the decision-making of consumers through a change in their environment.

The design of nudging interventions, such as social comparison and normative feedback, is investigated in the literature but – so far – not simulated. A translation of nudging interventions, into a modelling environment would, however, capture effects beyond a theoretical setting. We address this research gap – for the case of EV charging – by setting up an agent-based simulation that models the decision-making of and interaction between EV users.

Our model displays the effect of nudging interventions on the preferred EV battery state of charge (SoC) for each agent. Based on social networks, we model how interventions spread within the agent population. The selected interventions, social comparison, and normative feedback aim to minimize the preferred SoC. The model captures different sensitivities of agents towards the interventions, different sizes, and structures of the networks, frequency of interventions, as well as the boomerang effect.

Our results show an overall reduction of the SoC for all interventions. The strongest impact can be allocated to the normative feedback. Our findings thus indicate that nudging interventions cause agents to accept a lower SoC. Correspondingly, a larger share of the flexibility potential provided by EVs would be made accessible for controlled charging. While our model is theoretical, it can be substantiated with empirical data on consumer preferences and combined with the modelling of controlled charging on the household, grid, and electricity system levels.

Introduction

Driven by subsidies, positive user experience, and a growing product portfolio, the number of newly registered electric vehicles (EV) in Germany is rising. Currently, most EVs are charged in an uncontrolled manner. The strong growth in EVs has thus resulted in an increased demand for electricity, especially during the peak load hours in the afternoon and early evening (Kühnbach et al. 2020). This increased peak load creates a risk of congestion of local distribution grids and is a major challenge for grid operators (see Hadley and Tsvetkova 2009, Verzijlbergh et al. 2014; Ioakimidis et al. 2018).

To avoid load peaks, the charging period can be shifted within the parking period or a lower final state of charge (SoC) can be accepted. With the help of controlled charging management, this theoretically large flexibility can be exploited (see Dallinger et al. 2013). For a broad adaptation, the attractiveness for consumers needs to be increased and financial incentives, such as variable tariffs, are a frequently discussed measure to stimulate grid-friendly consumption, but their consideration in the daily routine involves high social acceptability cost in form of comfort loss, price uncertainty and monitoring effort (Da Silva and Santiago 2018; Dutta and Mitra 2017; Khan et al. 2016). A higher degree of automation and more intuitive communication of price signals can increase the attractiveness for consumers (Darby and McKenna 2012).

The latter is provided by the so-called nudging intervention. In addition to financial incentives, which address the rational part of our decision-making, nudging interventions target the automatic part based on intuition. Consumers make the majority of daily decisions based on intuition and heuristics (see Kahneman 2011; Lehner et al. 2016). Decision-making based on the automatic system saves time and awareness, but it is also prone to cognitive biases. Loss aversion, confirmation, or salience bias are frequently mentioned in the literature (see Abrahamse et al. 2006; Caraban et al. 2019). Acknowledging these cognitive biases and heuristics, nudging interventions support the consumers' decision-making by subtle changes in their choice architecture (see Thaler and Sunstein 2008).

Nudging interventions referring to social norms, such as social comparison and normative feedback, are reported as effective in the literature (see Abrahamse et al. 2006; Caraban et al. 2019), since it creates a sense of competition with peers, and prevents social disapproval. Furthermore, in situations of uncertainty and incomplete information, the behavior of other people is used as a point of reference, assuming that more information is available on their side (see Andor and Fels 2018).

A translation of these empirical insights into a modeling environment captures effects beyond the specific setting. This is practiced by a range of scholars for the case of adapting behaviour for energy savings in different contexts (e.g., Chen et al. 2012, Anderson et al. 2014, Anderson and Lee 2013, 2016, Azar and Al Ansari 2017, Azar and Menassa 2012, 2014, 2015, Abdallah et al. 2018, 2019, Bastani et al. 2016, Zarei and Maghrebi 2020, Walzberg et al. 2019, Jensen et al. 2016). The structure of the social environment is modeled in the context of behavior diffusion (Chen et al. 2012) or intervention effectiveness (Anderson et al. 2014, Anderson and Lee 2016, Azar and Al Ansari 2017). Anderson and Lee (2013) use a model to assess how a changing social network affects intervention effectiveness. The influence of social interaction and the resulting peer pressure is the focus of modeling works by Abdallah et al. (2018) and Bastani et al. (2016). Jensen et al. (2016) model how the introduction of a feedback device affects people's ventilation behavior and thus indirectly their energy consumption.

In contrast to the energy saving models, van der Kam et al. (2019) simulate charging behaviour in response to interventions without involving interactions between agents in a social network. The agents choose a charging mode with a different degree of renewable electricity usage depending on their range anxiety and environmental self-identity. Both variables change during the simulation depending on the individual charging and driving experience of the agents (van der Kam et al. 2019). The flexibility provision of EV in response to interaction-based interventions has not been a subject of modeling research yet.

By combining the insights from the charging behaviour and the social network simulation in an agent-based model about the decision-making of EV users, we address this research gap. Our method provides the basis for future analyses based on empirical data on EV users' behavior. Missing empirical data is mapped generically or based on assumptions derived from the literature[1].

Our model simulates the impact of interventions and external factors on the preferred final SoC and thus the flexibility provided to the grid by the agents over a given period. Based on the SoC, the battery share available for flexibility provision can be calculated and serve as input for techno-economical models. Thereby, a socio-economic dimension is added to the existing techno-economic modeling work. In this paper, a large number of scenario paths are constructed to test different specifications of the interventions and external factors. This involved the following steps:

1. Setting up the simulation model based on a social network
2. Testing and demonstrating the model functionalities in two sub-steps:
   a. Influence of nudging interventions and external factors on the SoC (experiment)
   b. Influence of the agent settings on the results of 2.1 (sensitivity analysis)

The modeling approach and the input data are introduced in the following methodology section. The results of the testing are presented in Section 3, discussed in Section 4, and concluded in Section 5.

Methodology

Our model depicts a large number of EV owners and their charging behaviour. The behaviour is expressed in the form of the preferred final SoC of the EV battery after the charging process. As more than 70 % of EV owners charge their vehicles only once per day (Quirós-Tortós et al. 2015), we assume that the entire daily mobility demand must be met by this one charging operation.

The agents are autonomous, independent, and interact with other agents. The preferred final SoC of an individual agent *í* changes throughout the simulation time steps , influenced by the nudging interventions and external factors. Both nudging interventions are based on social norms, one referring to the individual interaction in the social network (and the other referring to the overall behaviour in the network (normative feedback,). Unknown external factors are summarised under the term . The three partial influences are explained in the following sub-section.

As soon as all partial influences have been calculated, the total cumulated influence is calculated for each agent and its SoC is adjusted correspondingly. If there is no influence on the agent at time t, it retains its SoC from the previous period. In the presence of at least one partial influence the new SoC () at time t+1 of agent i is calculated using Equation (1).

$$SoC^f_{i,t+1} = (1 - s_i) * SoC^f_{i,t} + s_i * \frac{SI_{i,t} + NI_{i,t} + EI_{i,t}}{p_t + q_t + r_t} \quad (1)$$

1. Emperical data to complement and validate the model in a next step is collected in field experiments of theEuropean Union's Horizon 2020 project NUDGE (grant agreement no. 927012).

To which degree the agents react to the three influences depends on the sensitivity of an individual agent. The binary variables indicate whether the partial influence of social interaction, normative feedback, and external factors, respectively, is present at time t.

As a constraint, the mobility needs of the agent must be met at every time step. We do not only consider the technical mobility needs respecting the EV consumption , but also a range anxiety of 10% of the total battery capacity , which describes the driver's concern about not reaching the destination due to technical limitations (see Nilsson 2011). This implies that at the end of each day, after mobility needs have been met, at least 10% of the battery capacity must be retained (see Franke et al. 2016). This results in the technical constraint given by Equation (2) for the model regarding the SoC of the battery for agent I at any point in time:

$$SoC_{i,t}^{f} \geq \frac{MN_i * {C_i}/{100}}{BS_i} * 100 + 10, \qquad \forall t, i \tag{2}$$

At the beginning of the simulation, the agents and their characteristics are created, followed by the social network. Before the start of the model, all agents are assigned to the social network. At each time step, the resulting behavioural influence of social interaction, normative feedback, and external influence factors is calculated, provided that these are scheduled for the respective time step. Then, the total influence (positive or negative) of the previously calculated influencing factors is calculated, resulting potentially in an adjusted charging behaviour (i.e., an adjusted preferred SoC). The order of activation of the agents is random, but has no effect on the modelling results since the calculation of the influence is based on the values of the previous period. The model run ends as soon as the exogenously predefined number of time steps is reached.

MODELLING OF INTERVENTIONS AND EXTERNAL FACTORS

Intervention 1: Social Interaction

The change in behaviour in the model caused by social interaction is adapted from the modelling of Zarei and Maghrebi (2020), which is based on the ISC model of Duggins (2014). The influence at time t on agent i resulting from the social interaction is calculated as shown in Equation (3),

$$SI_{i,t} = \frac{\sum_{j=1}^{m}(w_{ij} * SoC_{j,t}^{f})}{\sum_{j=1}^{m} w_{ij}}, \qquad \forall t, i \tag{3}$$

Therein, w_{ij} describes the weighting factor that indicates the strength of the relationship between agents i and j. The number of social interactions is represented by m.

In the model, agents interact only with the agents in their social network and behavioural adjustment occurs only once interaction has occurred with all agents in the social network.

Two assumptions are made for the weighting factors. First, similar social contacts (for example, a similar circle of friends) lead to an increased influence of the interactions on the behaviour of the individuals involved (see Friedkin 2001, Zarei and Maghrebi 2020). Second, a similar behaviour of the individuals also increases the influence on behaviour (see Deffuant et al. 2002, Duggins 2014).

Following the ISC model, the consideration of the two assumptions leads to Equation (4) for calculating the weighting factors.

$$w_{ij} = c_{ij} * \left(1 - \frac{|\, SoC_{i,t}^{f} - SoC_{j,t}^{f} \,|}{50}\right), \qquad \forall t, i \tag{4}$$

The number of identical social contacts is given by c_{ij}.

Intervention 2: Normative Feedback

The calculation of the influence of normative feedback is based on Friedkin (2001). One difference is that, in contrast to the weighted influence of Friedkin (2001), our model assumes equal influences of the behaviour of the different agents. This follows from the assumption that the normative feedback is electronic, anonymized feedback (e.g., via charging app).

Furthermore, two additional assumptions are made. First, the sampling frame of the data from the feedback is the entirety of all agents. Second, there is the option of a boomerang effect, which leads to an opposite of the aimed behaviour (Schultz et al. 2007). If the boomerang effect is deactivated, the model sends feedback only to agents whose final SoC is not lower than the average of all agents.

The influence of normative feedback $NI_{i,t}$ at time t on agent i is formalized with Equation (5).

$$NI_{i,t} = \frac{1}{n} * \sum_{j=1}^{n} SoC_{j,t}^{f}, \qquad \forall t, i \tag{5}$$

$SoC_{j,t}^{f}$ is defined analogously to the previous calculations, and n represents the total number of agents.

To account for the fact that feedback is not read or is read inattentively, an equally distributed probability between five and fifty percent is introduced, following Anderson and Lee (2013) that the feedback is read and the behaviour is adjusted.

External influences

The agents may be subject to external influences that go beyond the scope of the interventions defined in the model, and thus can only be represented generically. For this purpose, a random influence variable is defined that can change the agents' behaviour every time step.

With a probability of five percent, each agent changes its charging behaviour every time step by a random value between -10 and +10 percent of the value of the previous period (own assumptions, adapted from Anderson and Lee (2013) and Anderson and Lee (2016)). As with the other mechanisms, the actual change in behaviour is subject to the sensitivity of the agent. The case of isolated external influence at time t on agent i is illustrated in Equation (6).

$$EI_{i,t} = (1 + x_i) * SoC_{i,t}^{f}, \qquad \forall t, i \tag{6}$$

Complementing the quantities defined in the previous subsections, represents a random number between -0.1 and +0.1.

INITIALIZATION & INPUT DATA

The model starts with the instantiation of the agents. The number of agents within the model is defined by the model user. The initialization of the agents is done sequentially. First, the technical framework of the EV is defined for the agent. This consists of the usable battery capacity (in kWh) and consumption (in kWh/100km). We assumed three different battery size categories: large (75.7 kWh), medium (47.4 kWh), and small (26.3 kWh) (assumptions based on Gnann and Speth 2021).

For the consumption, current manufacturer data and test results are chosen as a reference point. The exact consumption of the vehicles, depending on the driving behaviour, is mapped by a uniform distribution in the interval between 16 and 25 kWh/100km. Additionally, each agent has a daily mobility demand (in km/d). These data are taken from the Mobility Panel Germany (see Gnann and Speth 2021). From the three previous variables (battery size, consumption, mobility demand), the required number of kilowatt-hours per day is calculated, assuming that each agent charges his vehicle once a day. This, in turn, results in a minimum SoC that is required to meet mobility needs.

The initial SoC is assigned to the agent. This is based on the distribution of the SoC of EVs after charging, published in the study by Quirós-Tortós et al. (2015), taking into account the minimum capacity needed to meet daily mobility needs, which was previously defined.

Following the initialization of all agents, the social network is created. This can be a small-world, random, regular, or scale-free network. The network type is the same for all agents within a model run. The value of the sensitivity for the agents ranges from zero to one and follows the distribution obtained in Azar and Al Ansari (2017).

EXPERIMENT SCENARIOS & SENSITIVITY ANALYSIS

The influence of nudging interventions and external factors on the SoC is tested in five different scenarios. As a reference scenario, all influences are activated and compared to scenarios with one or no activated intervention. The external influences are activated for all scenarios. The boomerang effect as a part of the normative feedback is deactivated for the four principal scenarios. It is examined in an additional scenario through a reference run with a boomerang effect.

In a pre-run with 400 simulation steps in the reference scenario, the convergences in the model are assessed. This indicates an ideal number of simulation steps in the experiment. The results are illustrated in Figure 1. From the left graph, it can be seen that an equilibrium state for the SoC is reached after approximately 200 time steps. The upper bound of the behavioural adjustment is just under -12 percent compared to the simulation start. Also, the number of agents at the limit of behaviour change (right graph) shows convergence. While the ones that have reached their upper limit show an equilibrium state after about 50 simulation steps, the ones at the lower limit show this after about 200 time steps. The slight fluctuations in the subsequent time steps until the end of the simulation occur since a few agents deviate from their limit every time step due to external influences.

To obtain meaningful results for the various scenarios, 100 simulation runs were performed for each scenario. The network selected for the scenarios consists of 100 agents. A limit of behaviour adjustments for every simulation step is set at 18 percent. To make the simulation runs comparable to each other, the same initial value for randomization (seed) is chosen for each simulation run. This ensures that each simulation run is based on the same population of agents with the same attributes. The model inputs for the experiment as well as the different scenarios can be found in Tables 1 and 2.

The influence of the agent settings, in particular the network type, the network size, and the limit of behaviour change are examined in a sensitivity analysis. For the sensitivity analysis, we test whether the variation in settings leads to statistically significant differences in the manifestation of the SoC. Since the prerequisites for an analysis of variance are not met, a distribution-free, non-parametric procedure is chosen, in particular, the Kruskal-Wallis test followed by Dunn's test as a post-doc test and the Mann-Whitney U test for testing two groups.

Results

RESULTS OF THE EXPERIMENT

Our results show that for all scenarios we examined, i.e., for all combinations of the two interventions (social intervention & normative feedback) the final SoC of all agents decreased. The average final SoC changes vary between slight and major improvements (see Figure 2) but always remain considerably below the limit of behaviour adjustments. The average final SoC reduction for the scenario "All" – combing the three influences – is -6.76 % compared to the initial SoC. The presence of only external influences without interventions results in a slight average improvement of -1.64 %. This is due to the agents who received a preferred SoC of 100 % in the initial distribution and, thus, can only reduce their SoC.

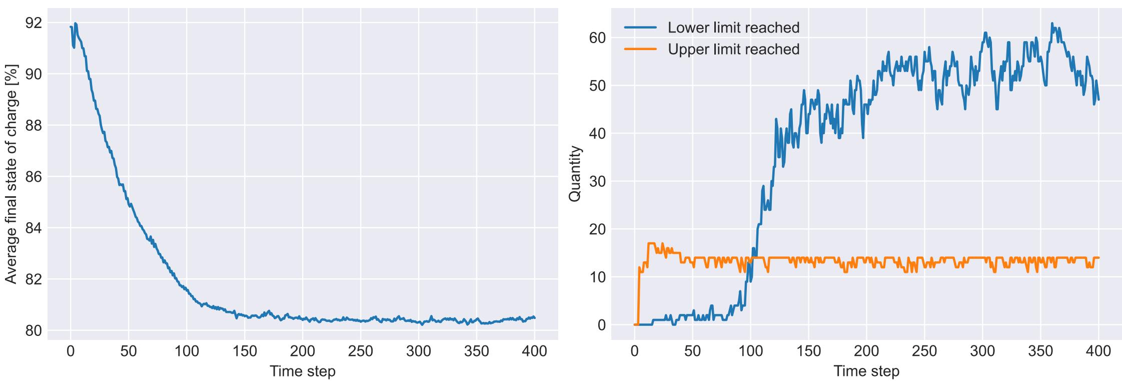

Figure 1. Long-term development odthf average SoC of all agents (left) & number of agents at the limit of behaviour change (right).

Table 1. Agent settings and parameterization and corresponding values.

Parameter	Value
Number of agents	100
Number of simulation runs	100
Average size of social contacts	12
Limit behaviour adjustment	18%
Simulation steps	52
Social network type	small-world

Table 2. Scenarios and corresponding scenario parameters.

Scenario	Intervention / Influences	Frequency	Boomerang (for NI)
All (EXO + SI + NI)	All	default	off
EXO + SI	Social interaction + external influences	default	-
EXO	External influences	default	-
EXO + NI	Normative feedback + external influences	default	off

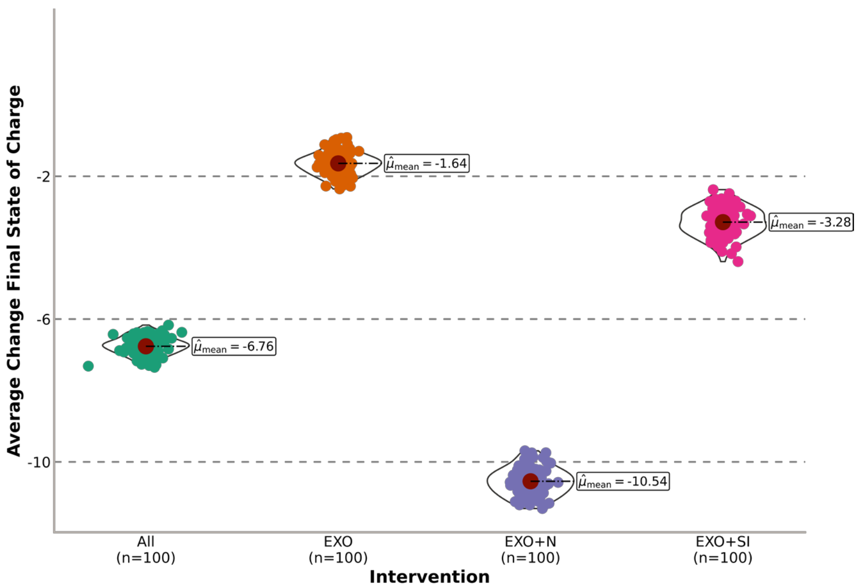

Figure 2. Average change of the SoC by scenario (All = all interventions included; EXO = external influences only; EXO+N = external influences & normative feedback; EXO + SI = external influences & social intervention) calculated based on the average of all agents for the difference of simulation start and end.

In the case of social interaction, the agents can align their behaviour to agents with a higher but also a lower SoC. Therefore, the adjustment caused by an interaction with other agents (EXO+SI) results in a comparably medium SoC reduction of -3.28 %. In contrast, the scenario EXO+NI only allows an adjustment to the normative feedback with a lower SoC and results in an average SoC reduction of -10.54 %. Since boomerang effects are not allowed, only agents above the network's mean SoC value receive feedback.

ANALYSIS OF BOOMERANG EFFECTS

To assess the boomerang effect, a fifth model run based on the scenario "All" is conducted with an activated boomerang effect (see Figure 3).

Agents are illustrated by a dot. The length of the violins represents the agents' dispersion, the width shows the concentration. This means that normative feedback is also sent to agents below the norm. By this, an incentive to deteriorate the SoC (i.e., increasing it) can appear. The results, however, show only

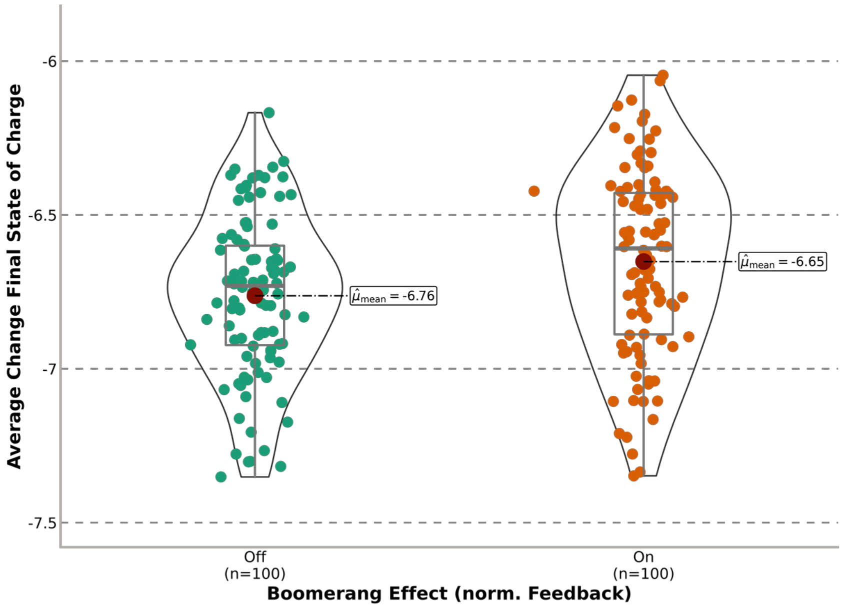

Figure 3. Impact of boomerang effects on the average SoC for the scenario"All".

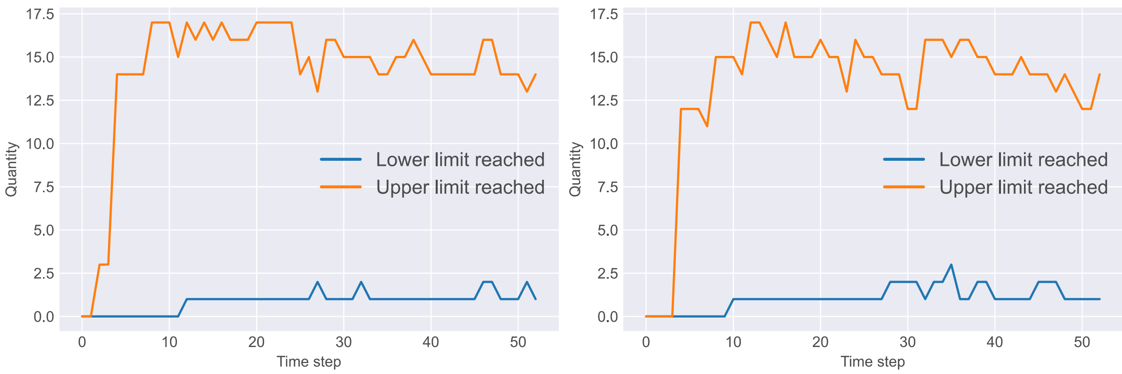

Figure 4. Comparison of agents at the limit of behaviour change for a model run with (left) and without (right) boomerang effect for the scenario "All".

insignificantly increased SoC values due to the limit of behaviour adjustment. Those agents who have an incentive to increase their SoC due to the normative feedback in the boomerang effect scenario, for the most part, already reach their upper maximum of behavioural adaptation in the "All" scenario through the previous intervention, the social interaction with agents with higher preferred SoC. Figure 4 shows the behavioural adjustment with and without the possibility of boomerang effects. It can be seen that the curves for both scenarios are similar and the number of agents who have reached their upper limit reaches its maximum relatively early (before time step 20).

RESULTS OF THE SENSITIVITY ANALYSIS

The influence of the agent settings, in particular the network type, the network size, and the limit of behaviour change, on the results are examined in a sensitivity analysis based on the scenario "All". The Dunn test yields statistically significant differences in median values only for a random network, which is associated with a 0.3 % smaller change in the preferred SoC compared to the small-world network. A regular network leads to almost identical results like the small-world network, owing to the low probability to create the random connection. For the scale-free network, significant influence can be found only found for a p-value of 10 %. A large standard deviation is recognised. Despite the varying degrees of deviations and partly significant influence, the overall influence of network types is considered as limited.

The network size is ranged between 4 and 22 contacts (in increments of 2). The results show that as the average number of social contacts increases, the average change in SoC achieved decreases. Since the influence of few agents with low initial SoC is higher the smaller the network size is, the smallest network yields the best results. The larger the social network, the smaller the influence of the outliers, and the results are correspondingly lower. Starting with a network size of 18, a threshold of about 6.61 is reached.

The behavioural adjustment limit is ranged between 5 and 50 % (in increments of 5 %). A great influence on the modelling is demonstrated. With a low limit, the improvement potential of a large number of agents with a high initial final charge level is low, and the average change is correspondingly low (2.64 with a 5 % limit). With a limit of 15 %, the achieved result is highest and even slightly higher than in the reference scenario. If the limit is increased further, the average improvement in the final load level falls successively; at a limit of 50 %, only an average change of 0.58 is achieved. The higher the limit, the more the agents with a low initial SoC increase their SoC and thus negate the SoC reduction of the agents with a high initial SoC in the overall analysis. Moreover, a high limit in the early time steps of the simulation strongly increases the average of the preferred final SoC due to the social interaction, leading to low influences on the agents in the subsequent periods.

Discussion and limitations

In this paper, we propose a simulation model that creates a large social network from which social contacts are derived for the individual agents. Within this network, the agents interact with each other and influence each other according to predefined rules of behaviour. Through normative feedback and social interaction, which both convey social norm, and external factors, the behaviour of the agents is influenced. In our EV case, a behavioural improvement is expressed by a SoC reduction, as this would increase the flexibility potential of the respective EV for controlled charging.

We tested and demonstrated the functionality of the model with different configurations of the interventions, external factors, and – in a sensitivity analysis – of the agent settings. The results show that the altered information provision by nudging interventions leads to a significant reduction of the average preferred SoC of the agents, by a maximum of 10.5 %.

Both modeled interventions correspond to different information provisions in real life. Since social interactions spread information on favourable and unfavourable behaviour in an uncontrolled manner, it stimulates behavioural changes in both directions. In this sense, the social interaction is implemented in the model in a way that it can reduce and increase the SoC based on the network of the individual agent. In contrast, the normative feedback represents a selective form of information provision, which only takes into account favourable behaviour and considers the entire network instead of the individual contacts. It is designed to only incite a reduction of the preferred SoC. Comparing the uncontrolled form of information provision (social interaction) to the selective one (normative feedback), the latter demonstrates higher effectiveness by 7.26 % points.

The combination of both interventions leads to a medium effect, which is influenced by the limits of behaviour adjustment. The agents with low initial SoC already reach their upper adaptation limit through social interaction in the early time steps of the simulation and cannot be further influenced. A sensitive parameter, such as the limit of behaviour adjustments, requires more substantiation with empirical data.

The lack of empirical data for controlled charging, such as pointed out by van der Kam et al. (2019), implies further limitations of the study. For the case of controlled charging, there is little known about the frequency of intervals and the number of social contracts of one agent that are necessary to provoke a behavioural adaptation. Insights from the literature, such as a higher frequency of real-time feedback (e.g., presented in Zangheri 2019) could be implemented in the model displaying the fundamental mechanisms of behavioural adaptation after receiving information from the social network.

As a simplification, a homogeneous network with the same network structure and settings for every agent is assumed and implemented. Different network structures and sensitivities, such as those recognized in reality, might alter the results. For instance, Anderson et al. (2014) and our sensitivity analysis indicate a greater result spread if the existing agents of the small-world network, who are only knowing their immediate surroundings are mixed with agents of a random or scale-free network, who are strongly influenced by their hierarchical social structure (e.g., supervisor at work, social media influencer). Increased sensitivity due to an altered attitude (e.g., high environmental awareness) or more effective interventions are also expected to increase the adaptation (van der Kam et al. 2019). Capturing such heterogeneity is subject of further research.

For a predictive or replicative future validation, a combination of methods is needed to ensure the conceptual, internal, and structural validity and robustness of the model. Both aspects are beyond the scope of this paper but are planned after the collection of empirical data in the European Union's Horizon 2020 project NUDGE (grant agreement no. 927012). In its field experiments, behavioural adaptations of EV users are monitored as a response to nudging interventions, including normative feedback and social comparisons. The profiling of participants, such as demonstrated in a pre-study by Van Hove et al. 2021, reveals their heterogeneity. The accumulating intervention design allows testing the limits of behavioural adaptations.

Overall, our methodological work demonstrates how the charging behaviour of individuals and its change in response to interventions can be captured in a model. By validating and complementing it with empirical data from field experiments, it will be further developed w.r.t. its limitations.

Conclusions

Financial incentives only address the consumers' decision-making to some extent. Alternative incentive schemes, such as nudging interventions, are explored by empirical research, but little by modeling, which captures the effects beyond the specific setting. We address this research gap – for the case of EV charging – by setting up an agent-based simulation that simulates the decision-making of and interaction between EV users. In the course of modeling, the influences of social interaction, normative feedback, and external factors on the preferred SoC of a population of agents are investigated. The explicit mapping of the influence of nudging interventions on the SoC makes it possible to complement techno-economic controlled charging models for EVs and thus to quantify the flexibility potential of EVs taking into account the socio-economical dimension.

Credit author statement

J. Burkhardt: Conceptualization, Methodology, Software, Formal Analysis, Visualization, Data Curation, Writing – Original Draft, Review & Editing. S. Pelka: Writing – Orignal Draft, Review & Editing, Supervision. M. Kühnbach: Writing – Review & Editing, Supervision.

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