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Electric Vehicle Charging Pricing Design for Agent-Based Traffic Microsimulation

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Abstract

Over the past few years, electric vehicles (EVs) have become a popular mode of individual transportation due to their significant benefits over internal combustion engine vehicles, resulting in significant growth in their penetration rate. However, the current flat electricity charging pricing and rapid diffusion of EVs may impose challenges to both transportation systems and power grids. It is well-accepted that the implementation of charging pricing schemes is a promising solution for changing and controlling EV users' charging behavior. Nevertheless, in most research studies that have examined pricing schemes, the charging logic is defined in a way that agents will charge their vehicles while performing their daily activities. This will make the application of pricing schemes unfeasible, as agents will not have the freedom to unplug their EVs whenever they want, to reduce their billing costs. Accordingly, this paper provides an agent and activity-based framework for charging pricing schemes by decoupling activity and charging start and end times. Following this, three different charging pricing schemes have been introduced, including time of use (TOU), non-linear and zonal pricing and tested on the Montreal scenario.

Keywords: Electric Vehicle; Charging Pricing; Agent-based Simulation; MATSim; Microsimulation.

1. Introduction

Fossil fuels are considered one of the main sources of energy, especially for the transport sector. The Canadian transportation sector's contribution to energy consumption is even higher than the world average, 30% compared to

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27% (*1*). However, this dependence needs to be broken due to environmental, economic, and political concerns, which can be done with the help of electric vehicles (EVs). Large penetration of EVs, however, will raise the electricity demand and generate an extra load on the existing power grids (*2; 3*), as the current power grids are not designed for these to some extent unpredictable loads. From the transportation point of view, it may create long queues at charging stations (*4; 5*), and parking problems (*6*). Here is where Demand Side Control Action (DSCA) comes in handy (*7*).

The charging pricing scheme for EVs is an example of DSCA's effort to control, shift and coordinate EV charging demand by offering flexible prices (*8*). Over the past few years, electricity pricing schemes for EVs have been extensively examined, to resolve power grid issues (*9; 10*). One of the most evaluated pricing policies is the Time of Use (TOU) scheme, in which electricity price is raised during peak hours to reduce peak load demand (*11*). However, from the transportation perspective, it does not contribute to the reduction of queues at charging stations, and it is unable to account for the charging demand's spatial variations.

In transportation, agent-based simulations have become a standard tool for policy and infrastructure planning, due to their strengths in detailed behavioral modeling, and analysis of the interconnection between agents and their physical environment (*12*). As subtypes of transportation simulations, electromobility simulations also benefit from agent-based simulation techniques. These models allow an analysis of microscopic aspects such as individual State of Charge (SOC) and charging patterns as well as global factors such as charger utilization by considering heterogeneous vehicle fleets, a variety of infrastructure types, charging behaviors, and charger accessibility of the simulated population (*13*). As an example, MATSim and its EV-Contrib frameworks have been a key element in the development of the UrbanEV, since they have been validated, widely used, and well-established in transport and infrastructure planning (*12*). Using microscopic agent-based simulations, studies have modeled different aspects of EVs either by focusing on the charging behavior or the charging location choice of EV users (*12; 14-23*).

In the current litreature, the charging logic is defined in a way that agents will charge their vehicles while performing their daily activities, such as shopping, working, etc. The charging ending time is usually based on simplified assumptions that agents will stop charging their EVs when the battery charge reaches a fixed threshold (usually 80%) (*19; 22*), or when the activity time is finished (*19; 22*). As a result of these approaches, agents would not be able to terminate their charging activities whenever they wish, to reduce their billing costs. This would force them to charge their EVs during the entire activity period, regardless of how costly this charging could be. However, developing a framework that allows agents to decouple their charging activities from their daily activities will lead to more realistic simulations of EVs, and more accurate results. To fill this gap, this paper will contribute to the current state of the art as follows: a) a new charging logic has been developed which allows agents to decouple their charging activity from their daily activity pattern in a way that agents can pause their primary activities to plug in or unplug their EVs, b) to reduce the queue at charging stations, and control the spatial variation of charging, two new pricing schemes namely non-linear, and zonal-based pricing have been developed in addition to the well-known TOU pricing. In non-linear pricing, the price of electricity is raised non-linearly according to the amount or duration of electricity usage. In the zonal-based approach, the charging prices would vary from zone to zone in such a way that prices can be set to lower values in areas with lower charging demands, and vice versa.

2. Methodology

2.1. General Framework for the Micro-Simulation

In this study, an existing simulation platform, called MATSim (Multi-Agent Transport Simulation) is used. MATSim is an agent-based, activity-based, and open-source transport simulation implemented in JAVA (*24*). The logic behind the MATSim is to optimize individual agents' choices such as route, departure time, activity location or duration, and the mode for a given plan, utilizing co-evolutionary techniques and microsimulation (*25*). A MATSim run contains a configurable number of iterations, represented by the loop shown in Fig. 1.

Every agent is loaded in MATSim with its initial activity plan. These activity plans contain precise information on the activity chains, each activity's location, and duration, opening and closing times, as well as the trips between activities, including trips' mode and route. The initial daily plan of trips and activities is executed by mobility simulation (mobsim). The utility function is used to calculate the score for each plan based on the simulation results.

From iteration to iteration, a configurable share of agents is allowed to change some of their daily decisions such as routes, working hours, travel modes, departure times, locations visited, etc., by adapting the previous one to search for a plan with a higher utility. This step is called replanning. After a certain number of iterations, the average population score stabilizes, meaning the plans score no longer improves. This is interpreted as a situation, which is close to User Equilibrium (EU). Every agent's plan at equilibrium is supposed to approximate their actual behavior in the real world, so at this point, results can be analyzed. Additional information on the framework itself and existing scientific applications can be found in (*24*).

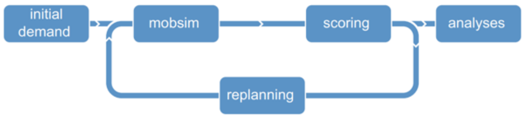

Fig. 1. Co-evolutionary algorithm of MATSim

2.2. EV's Framework in MATSim

MATSim has a modular design, meaning that it is structured with a core of classes that are providing all basic functionalities and with plug-in extensions that provide additional functionalities. MATSim has an extension that allows modeling EVs called EV-Contrib. A special vehicle type that consumes electric energy based on an energy consumption model is introduced and charging stations are coded with a defined power level that charges EVs based on a non-linear charging model. In the default MATSim EV logic, charging events are introduced as separate, additional activities in agents' daily plans, which can be triggered based on a certain SOC threshold level or charging behavior. This means that charging events cannot be integrated with other primary activities in agents' daily plans. Although this modeling approach can be justifiable for long-distance trips, in which EVs typically stop for the mere purpose of recharging (*26*), this is in contrast to the behavior expected in urban EV scenarios. However, two recent efforts have developed charging behavior for urban EV scenarios in which charging events have been integrated with primary activities (*12; 27*).

In the urban EV framework, EV users estimate their consumption for all their EV trips between activities (legs) upfront. In other words, while improving their plan set in the replanning step, before starting the plan, agents go through their chosen plan to simulate discharging of their EVs. As soon as they find at which leg the SOC drops below the critical level, activities before this leg are considered for charging. A set of criteria such as activity type and duration are used to select the activity from these candidate activities for charging the EV. Priority is given to the nearest activity to the critical leg unless the activity does not meet the predefined criteria. In the case that agents have enough SOC to come back to their first activity location (mostly home) at the end of their daily plans, and they have a home charger, agents will charge their EVs at home, regardless of their available SOC.

2.3. Modeling Approach

In the existing urban EV framework, EVs are assumed to be charged throughout the entire activity time or until the time that the battery is fully charged (or when the battery charge reaches a fixed value, usually 80%), regardless of the pricing. This means that one cannot model the effect of pricing schemes with that approach. In the model we are proposing here, the charging behavior logic has been developed in a way that agents can pause their primary activities to plug in or unplug their EVs. Fig. 2. shows the flowchart of the proposed charging modeling approach.

2.4. Accounting for Activity and Charging Time Decoupling

Here's an example of how the new replanning approach works. We assume a critical SOC (when the EV needs to be charged) of 30% and a primary SOC of 75%. The initial daily plan of an agent follows the following pattern: Home, Work, Leisure, Shopping, and finally returning Home. This plan is outlined before the simulation, and the SOC is emulated in each leg. Thus, the available SOC reached 25% at the start of the shopping activity, which is less than the critical SOC. It is now necessary to find an activity suitable to plug in the EV before this leg, and leisure would therefore be an appropriate choice (assuming it meets the criteria).

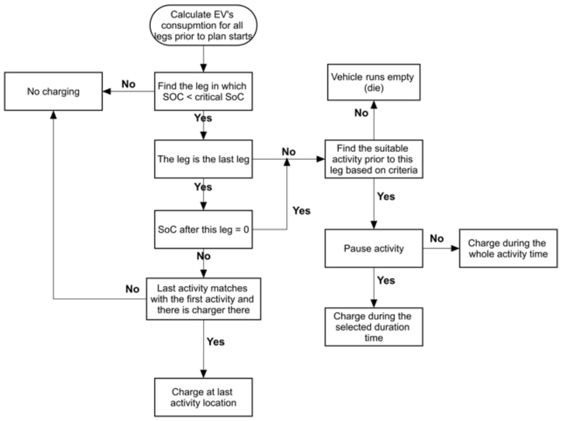

Fig. 2. Modelling approach flowchart

In this case, a configurable share of agents will be able to pause their primary activities, the leisure activity. All other agents will charge their EVs according to the exsisting UrbanEV charging behavior. There are two options available for activity pause. Agents would be able to charge their EVs either at the beginning or at the end of the leisure activity. Among those who pause their activities, a configurable share will charge their EVs at the beginning and the rest at the end. Whenever agents charge their EVs at the beginning, they will drive directly to the charging station with their EVs and then walk to their primary activity. Once the charging time is over, agents will walk to the charging station, unplug their EVs, and drive to the location of their primary activity, e.g., leisure (Fig. 3., left).

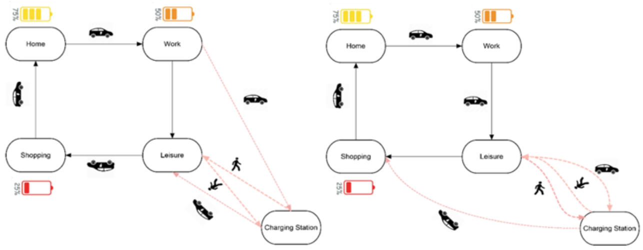

Fig. 3. New Urban EV charging behavior logic, left) Charging at the beginning of the activity, right) Charging at the end of the activity

In the case that agents charge their EVs at the end of the activity, they will directly head to the leisure activity and then will pause their activity to take their EVs to the charging station. Once the primary activity is finished, agents will walk to charging stations to unplug their EVs and will directly head to the next activity in their plan, in this case, shopping (Fig. 3., right). In either case, when a vehicle arrives at a charging station, it is plugged in and charged in accordance with its charging profile, as well as the charging capacity of the station. Ideally, the distance from the charging station to the activity should be as short as possible so that the total travel time, including the deviation from the original plan to the charger station, is as minimum as possible.

2.5. Accounting for the Charging Duration Time

In either case (charging at the beginning or the end of an activity), the time that agents need to pause their activities to plug in or unplug their EVs is calculated based on the charging duration. In our model, the charging duration is calculated using Equations 1, 2, and 3:

$$C_c = \min\left\{ (C_r \times S.F),\ C_{cap} \right\} \tag{1}$$

$$C_r = \sum_{i=c}^{last} C_{r,\,i} \tag{2}$$

$$C_t \sim \mathcal{N}(\,Cc, COV \times Cc) \tag{3}$$

Where for each person *i*, the C_c, is the amount of energy that agents' vehicles should be charged for, based on the remaining activity or battery capacity. C_r is the required amount of charge that agents need to reach their remaining activities, which is calculated by the sum of the energy needed that each of the remaining trips to be performed, multiplied by a safety factor S.F. C_{cap} is the amount of charge that the battery requires to be fully charged.

We let the agents charge a random amount of charge based on a normal distribution with mean C_c, and variance COV^*C_c, used to model randomness in agents' choices in the charging amount. The time necessary to transfer C_t amount of energy to agents' EVs based on the charging power of charging stations is the charging duration t_t. Based on this calculated time, if charging occurs at the beginning of an activity, agents will take a pause at (activity start time + t_t), and if the charging occurs at the end of an activity, agents will pause (activity end time - t_t). The safety factor is being applied to make sure that agents will be able to finish their daily plans without running out of battery, in case of any unpredictable events like traffic congestion. This factor can also model the agents' risk-taking tendency (For a high risk-aversion behavior, the S.F can be set to a higher value).

2.6. Scoring Modifications

The utility of a plan in MATSim is measured by summing up the activity utilities and the travel (dis)utilities for the activities and trips in that plan, as presented in Equation 4 (*24*),

$$U_T = \sum_{i=1}^{A} U_{act,\,i} + \sum_{i=1}^{Tr} U_{travel,\,i} \tag{4}$$

Where A is the number of total activities and Tr is the total number of trips in the plan. $U_{act,i}$ and $U_{travel,i}$ are the utility of activity and trip respectively. $U_{act,i}$ is calculated by considering the type and duration of performing the activity, and the disutility of undesired events related to the performing of the activity (waiting for a shop to open, arriving late at work, etc.). $U_{travel,i}$, however, is calculated by considering a mode-specific constant, travel time between activity locations, fares, the travel distance between activity locations, transfers (for public transit trips), etc. When it comes to travel distance, the dis(utility) of a given trip for each agent, in its basic form, is calculated by Equation 5 (*24*):

$$U_d = \left(\,\beta_d + \beta_m \cdot \gamma_m\right)\,\cdot\, d \tag{5}$$

Where β_d is the distance's marginal utility, β_m is the marginal utility of money, and γ_m is the mode-specific monetary distance rate, and *d* is the traveled distance between two successive activity locations. The marginal utility of distance accounts for the money that agents must pay for the unit distance of travel while traveling with each mode of transportation, such as gasoline price for internal combustion engine vehicles (ICEVs). The marginal utility of distance should be modified for EVs as they do not consume gasoline. In this study, the scoring function is changed in such a way that it can separate EVs and ICVs, (mode-specific). Afterward, the distance-based disutility will be applied for ICEVs, while the electricity price will be applied for EV charging. Therefore, Equation 5, would be in the form of Equation 6 for EVs.

$$U_d = \beta_d . d \tag{6}$$

2.7. Pricing Schemes

When the new framework is ready, different pricing policies can be applied and analyzed. As mentioned earlier, in this study, in addition to TOU pricing, two new pricing schemes have been introduced as follows: i) Time of Use (TOU) pricing: According to this scheme, electricity prices will be raised during peak hours compared to off-peak hours. Electricity operators will be able to manage peak-hour electricity supply constraints with this scheme. The assumption is that this scheme will be able to reduce the electricity peak usage demand. ii) Nonlinear pricing: In this scheme, the electricity price can be raised during different time steps, e.g., 0 to 30 minutes, 31 to 60 minutes, and higher than 60 minutes. As a result of this scheme, electricity operators will be able to manage queues at charging stations. With the implementation of this policy, it is anticipated that more EVs will be served at charging stations, while fewer EVs will be waiting in queues. iii) Zonal-based pricing: In this scheme, charging pricing is spatially defined, which means that the study area can be divided into different zones with different electricity price multipliers. As a result of this scheme, electricity operators will be able to manage spatial constraints in electricity supply. Following the implementation of this policy, electricity usage is expected to be dispersed between lower-priced zones.

EVs' charging pricing framework has been proposed and implemented for EV users by introducing a charging pricing vector profile. Pricing vectors are introduced as Equation 7,

$$p(t) = \left[p_1\ p_2\ p_3\right] \tag{7}$$

where for 24 different times of day, t, the pricing vectors are various to reflect the TOU scheme for each charger (id), as the price for different charger types is different. The vector values reflect three different values for three predefined time steps to account for the non-linear pricing scheme. For zonal pricing, the study area can be divided into n zones, while their centroid coordinates are identified. Afterward, the closest path between the chargers' location and the centroid of each zone is calculated to find the closest zone centroid to each charger, to assign each charger to a proper zone. For each zone, a pricing multiplier will be applied to pricing vectors to reflect the zonal pricing scheme. In this study, for the TOU pricing scheme, the peak hour charging price is 100% higher than the off-peak hour price. The morning peak hours and evening peak hours are considered as (7- 9), and (14-18), respectively. For the non-linear pricing scheme, the electricity prices are 50% and 100% higher in the second and third 30-minute time steps compared to the first step, respectively. Finally, for zonal pricing, six different zones are considered.

3. Results

Four simulation scenarios were run: base, TOU, non-linear, and zonal until equilibrium was reached. The results of TOU and non-linear pricing schemes have been compared with a base scenario, in which there is no price applied to chargers, while the zonal pricing scheme's results have been compared to the TOU scheme.

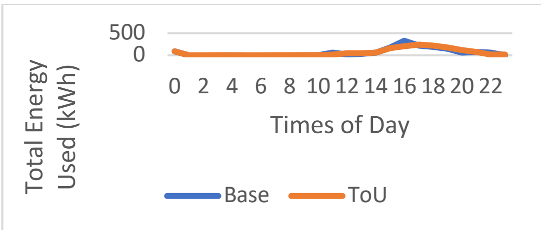

Fig. 4. Total Energy Used by EVs During Different Time Periods

The first analysis compares the TOU scheme to the base scenario. Fig. 4., shows the total energy consumed by EVs over the various periods. As can be seen, for the TOU scheme, the peak electricity demand during the evening peak period (14 to 18), when the electricity price is 100% higher, has been significantly reduced and shifted towards the off-peak hours (19 to 21). Moreover, the maximum peak consumption in the base scenario (approximately 330 kWh), has been reduced to 242 kWh in the TOU scheme. This indicates that the TOU scheme has effectively reduced peak consumption. This finding is in line with most of the studies considered the TOU scheme such as (*28*). During the morning peak hours, electricity usage is not at a level that can be interpreted. The SOC of EVs at the beginning of the day is likely higher than the critical SOC to enable agents to charge their EVs, as based on our study, all EV users are assumed to have a home charger, and they will charge their EVs upon returning home after completing their daily activities. The next analysis compares the non-linear scheme to the base scenario. Fig. 5.

depicts the total number of EVs that have been charged, and the total number of EVs that have been queued at charging stations. Queueing happens when the agents arrive at charging stations, while all the plugs are already occupied by other agents. As can be seen, the total number of plugged EVs in non-linear schemes has increased, while the total number of EVs queued at charging stations is declined. This means that more agents have charged their EVs, but for shorter periods (as much as they need rather than a full charge), thus more charging plugs are available for other users.

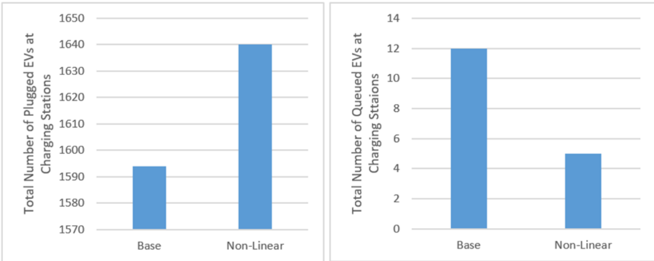

Fig. 5. Total Number of Plugged EVs at public Charging Stations (home chargers are excluded) and Total Number of Queued EVs at public Charging Stations

The results of the zonal pricing scheme are compared to the TOU scheme, as previously mentioned. For assigning the zonal pricing multipliers, the number of EVs which are plugged in for charging in each of the six zones in the TOU scenario was counted. Accordingly, the charging prices in the three zones (zones 1, 5, and 6) with the highest number of plugins were increased by 50%, while the electricity prices in the remaining three zones were diminished by 50%. Fig. 6. shows the number of plugins for each of the six zones under both zonal and TOU pricing schemes. As expected, the number of plugins in zones 5 and 6 in the zonal scheme has been reduced compared to the TOU scheme, while the number of plugins in zones 2, 3, and 4 has been increased. Zone 1 is the only exception, where the number of plugins has risen contrary to expectation. As zone 1 is the only zone located on the other side of the St. Lawrence River, a river passing from the middle of the Montreal, most EV owners would likely find it inconvenient in terms of travel time and cost to travel to the other side of the river to charge their vehicles.

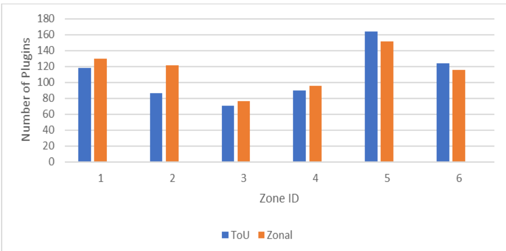

Fig. 6. Number of plugins in each zone under ToU and Zonal pricing schemes

4. Conclusion

As a part of this paper, the development of a simulation tool is described that will allow us to account for EV charging pricing schemes and evaluate the efficacy of different charging schemes. A key motivation for this project is the need to overcome the challenges associated with the rapid proliferation of EVs in urban transportation and power grid systems. This necessitates the need for models with a high level of detail to evaluate different EV charging pricing schemes. The proposed methodology is based on an existing open-source, dynamic, activity, and agent-based microsimulation framework, called MATSim. This paper describes an implementation focusing on two of the most important aspects of EVs: charging behavior and charging pricing schemes. EV users are known to be impacted by these two factors, and a model that aims to predict what EV users are under various charging pricing schemes needs to consider these factors. The model presented has been tested in the Montreal scenario and shown to be able to give plausible results in terms of overall EV usage and concerning the applied pricing schemes. The results demonstrated that the ability of EV users to pause their primary activities to perform plug-in/out activities works well in improving charging pricing schemes application, a fact that has been overlooked in previous research. Furthermore, all three charging pricing schemes presented in this study, were effective in shaping and controlling EV charging behavior and achieving the anticipated goals.

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