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Research paper

Can charge scheduling incentives mitigate the impact of EVs on the power grid?

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ABSTRACT

The number of Electric Vehicles (EVs) on the roads is expected to dramatically rise within the next few years. This is poised to substantially increase the total electricity demand due to EV charging. The key question is whether today's distributions systems can handle this increased charging demand. Our central hypothesis is that coordinated charging is a must to enable wide scale deployment of EV chargers. Coordinated charging refers to scheduling, and possibly optimizing, the charging action of EVs so that charging is more focused during grid off-peak hours. Due to the importance of charging incentives, the objective of this paper is to take a step back and obtain real data that help gauge EV drivers' level of acceptance to charging scheduling incentives. Using New York City as a living lab, a case study was carried out to analyze the effectiveness of those incentives. The results of a survey, taken by 119 New Yorkers, shed light on people's response to charging incentives. For instance, 85% of the survey respondents chose to travel longer for a cheaper EVSE instead of heading to a near EVSE at a higher cost.

1. Introduction

According to the US department of energy, in 2020, the US imported about 3% of the petroleum it consumed. The transportation sector accounted for 26% of the total energy demand and 29% of greenhouse gas emissions (GHG) (NYC, 2021a). In urban regions, the problem is further exacerbated. For instance, the transportation sector is responsible for 36% of GHG in New York City (NYC). Therefore, to combat global warming, there is an imperative to replace conventional internal combustion engine vehicles with EVs. In NYC, the goal is to place 400,000 of EVs on the roads by 2030 (NYC, 2021a).

The barriers against widescale EV deployment have historically been cost and range anxiety. Recently, thanks to advances in electric machines, power electronic switching devices, and energy storage systems, the cost of EVs has fallen and the range improved (∼520 miles) (Wallace, 2021). However, lack of fast charging stations is increasingly becoming a key obstacle (NYC, 2021b). Therefore, several States have set mandates to deploy more EV charging stations in the near future.

EV charging stations represent a major load on the power grid. In some estimates, the load resulting from widescale deployment of EV charging stations may be equivalent to the current load demand (Groom and Bellon, 2021; Hafez and Bhattacharya, 2021). With the aim of mitigating the impact of EV charging on the power grid, several articles in the literature proposed charging scheduling algorithms (Han et al., 2018; Alinia et al., 2022; Tang et al., 2016).

In Luo et al. (2017), a charging coordination framework was developed based on the gradient boosting regression tree method. Scalability was not adequately evaluated. However, the results showed good coordination performance and local solar production was taken into consideration. In Hafez and Bhattacharya (2021), a game theory (Mean Field Game) method was used for charging coordination. The proposed solution is scalable to large systems and robust against single-point failures since it relies on distributed control. On the other hand, a centralized controller based on Internet of Things was proposed in Chen

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et al. (2019). This work took into consideration distributed energy resources that may be connected to the same charging infrastructure, as well as the communication infrastructure required to enable coordinated operation.

These articles, and others in the literature, often assume that an EV owner will inevitably be willing to shift their charging time. To the best of our knowledge, there has been no effort to evaluate people's response to charging incentives and this, in our review, represents a research gap in the literature that this paper is attempting to fill.

In this paper, EV drivers' response to scheduling incentives has been evaluated. Specifically, we relied on two approaches: (1) directly surveying current and potential EV drivers; and (2) simulating the impact of charging scheduling incentives, using a NYC-based case study. We focus on public charging stations and their influence and dependence on the power grid.

The main contributions of this paper are as follows:

1. A survey gauging New Yorkers' willingness to change their normal EV charging behavior in response to incentives
2. Simulation of the impact of EV charging incentives on the power grid using a New York based case study
3. Open-source codes to reproduce the results of this study and replicate the work for other regions

The rest of the paper is organized as follows. In Section 2, our hypothesis and methodology will be presented. In Section 3, the case studies will be discussed. The results and discussion will be presented in Section 4. Finally, some of the conclusions that can be derived from this study will be presented in Section 5.

2. Hypothesis and methodology

In megacities, such as NYC, EV mobility is heavily impacted by factors, such as road congestion, construction, charging prices, weather, etc. Due to its dense population, urban regions may have multiple Electric Vehicle Supply Equipment (EVSE) within close geographic proximity. In addition, the distribution grid is highly meshed. Therefore, some EVSEs, although geographically close to each other may be fed from, hence impacting, different electricity distribution feeders. While this can be viewed as a challenge, it also provides a unique opportunity for urban regions. With proper incentives, a driver can be influenced (e.g., through dynamic charging prices) to slightly shift their targeted EVSE and go charge at another one, which is located in a less energy-constrained power network.

We assume that EVSEs will be collectively represented by a local virtual aggregator. There will be coordination between the EVSE aggregator and the distribution grid. We presented a detailed example of this form of coordination in Mohamed (2019a). This coordination can potentially take multiple forms, e.g., demand response. When the grid is faced with a challenging condition (e.g., a constrained feeder/branch), it will incentivize EV owners to charge at other EVSEs that are fed by less constrained power networks.

Our central thesis is that EV owners will change their targeted EVSE in response to incentives as long as the distance towards the new EVSE and the incentive itself are reasonable. The definition of "reasonable" is to be tackled in this work. The key research questions include what a proper incentive can be, what EV owners care more about, and to what extent can incentives mitigate charging impact on the power grid? Our implementation approach to tackle the research questions includes a survey of current and potential EV owners and simulation of a realistic case study.

3. Survey

We developed a survey that was answered by 119 takers, both in-person and hybrid formats. About two thirds of the survey takers currently own EVs. The survey covered different neighborhoods in New York City. The purpose of this survey was to gauge people's response to the following parameters: charging cost, distance to the charging station, charging time, crowdedness of the charging station and impact on the power grid. The survey questions were the follows.

1. Do you own an electric vehicle?

Response: Among 119 people, 67.23% of them have EVs, while 32.77% do not have EV. Later for questions 2, 3, 4, 5, 8, and 9, we will distinguish the responses for both groups.

2. What factors/parameters would you consider for selecting a charging station to go to?

Response: It was found that people currently owning EVs care more about distance, followed by cost to the charging station, charging time, and crowdedness of the charging station. Similar trends can also be seen among non-EV owners, as shown in Fig. 1a and b, respectively. However, current EV owners seem more aware and cautious of the effect of EV charging on the power grid. This is evident by 58.75% current EV owners who selected the effect on the power grid as a deciding factor, as compared with 23.08% for non-EV owners.

3. If your car is near a charging station with high charging cost, and there is another charging station which is 6–7 blocks far from you with cheaper charging cost, which one will you choose to charge your car? (Nearer/Farther)

Response: For the third question, almost 15% of the people chose the nearer charging station and around 85% chose the far charging station. The majority of respondents seem to prioritize monetary savings. There was a negligible difference observed between responses of EV owners versus non-EV owners (i.e., 15.38% and 84.62%, respectively).

4. Following up to the previous question, what if the farther EVSE is in a power constrained area (may cause problems to the power grid), which one will you choose to go? (Nearer/Farther)

Response: For the fourth question, the majority of survey respondents chose the nearer charging station, to decrease the impact on the power grid. Some differences between the responses of EV owners and non-EV owners were observed. While 86.25% of current EV owners changed their preference to the nearer station, only 67.57% of non-EV owners did. This aligns with the observation related to question 2 that current EV owners seem to generally be more aware of the impact of EV charging on the power grid.

5. If the far charging station is cheaper but located in a crowded area, which one will you go to? (Nearer/Farther)

Response: most current EV owners prioritized cost over crowdedness (82.50% vs. 17.50%). On the other hand, non-EV owners, there was a less significant difference between the two choices, with 42.11% choosing the far EVSE (cheaper) and 57.89% choosing the near EVSE.

6. If you are at equal distance from two charging stations, one of them is fast and expensive, the other one is slow and cheap, which of them will you choose to go to? (Fast and expensive/Slow and cheap/It does not make any difference)

Response: the majority of survey takers preferred the faster charging station even though it is more expensive. This was the case for both EV owners and non-EV owners, as shown in Fig. 2a and b, respectively. Non-EV owners seem more acceptable to slow charging (33%) as compared with current EV owners (10%).

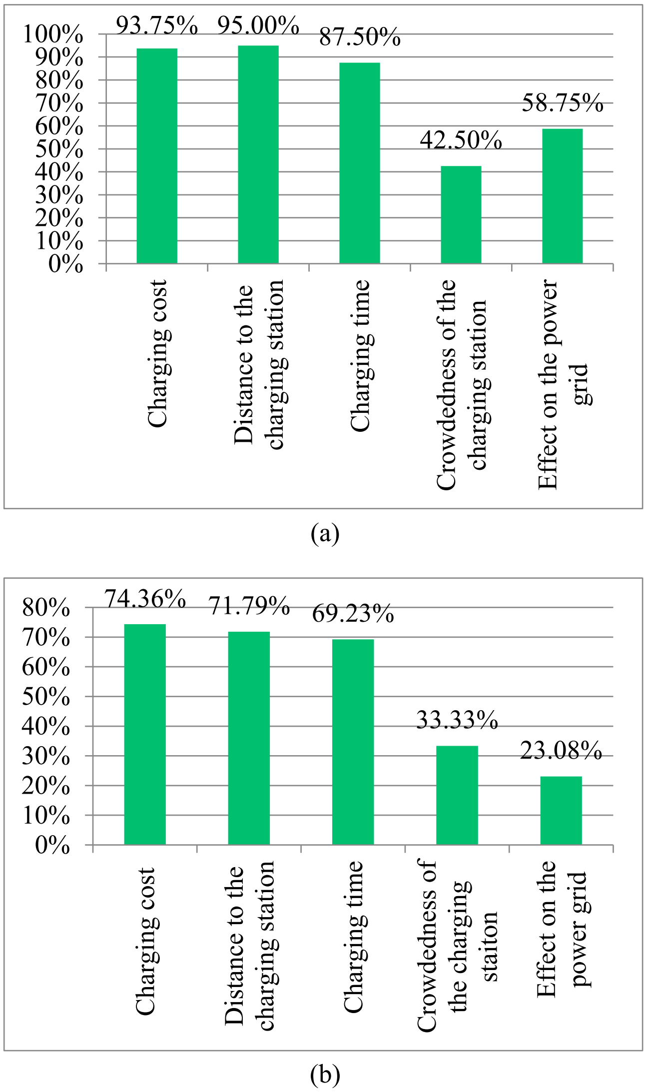


Fig. 1. A summary of responses on question 2: (a) EV owners; and (b) non-EV owners.

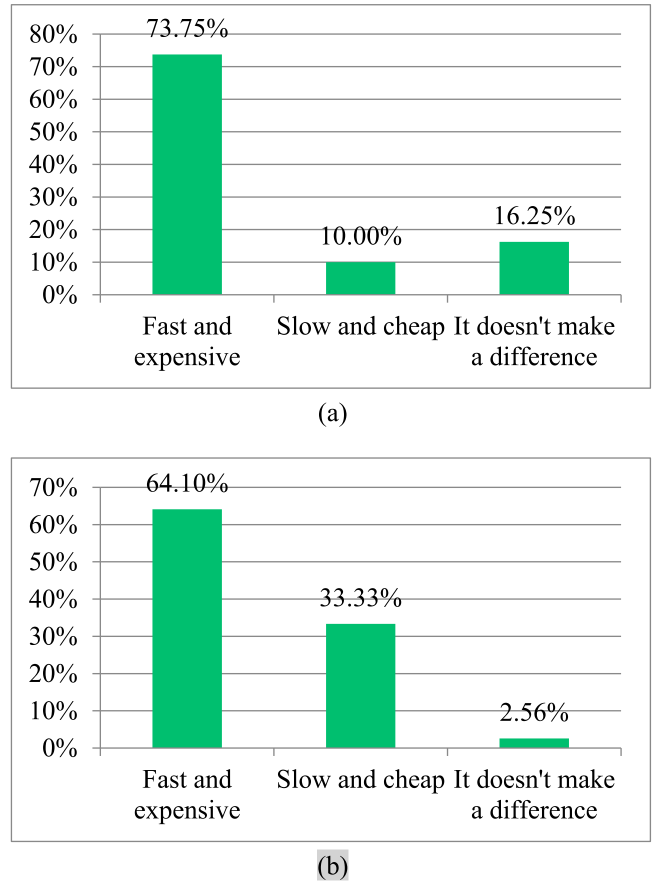


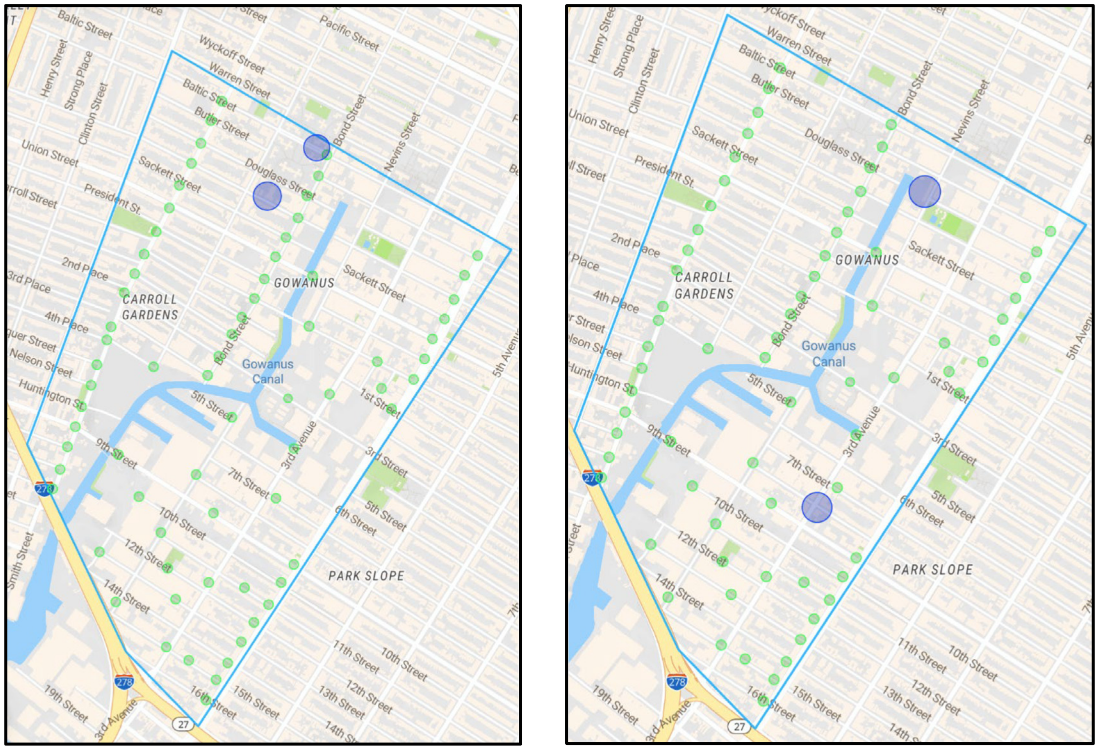
Fig. 2. A summary of responses on question 6: (a) EV owners; and (b) non-EV owners.

4. Simulations: Influence graph

With the increasing numbers of EVs on the roads, the power grid and the traffic network are becoming more interdependent than ever. The EV charging demand affects the flow of power, and hence must be taken into consideration while operating and planning the power grid. With proper incentives, stemming from grid impacts of EV charging, EV owners may opt to travel a longer distance to charge at a cheaper charging station. The survey results presented earlier in this paper support this conclusion. One can view this two-way dependency as an opportunity to optimize both networks. In other words, using proper incentives, the power grid can discourage EVs from charging at EVSEs that exist in energy constraints portions of the power grid. This can be done by raising the price of charging at those EVSEs. Similarly, EVs can be diverted from roads with congested traffic by raising the price of charging within those roads. This multi-objective optimization problem requires coordination between the distribution power grid operator and the transportation operator. A detailed example of this coordination was presented by the author in Mohamed (2019a).

In this section, we simulate the impact of charging incentives on EV drivers' decisions using a case study at Gowanus, Brooklyn, New York City. We assume that this area has two charging stations and 70 EVs. The EVs start at random origins and normally head to their destination EVSE based on a shortest path problem. This represents the base case. We assume that one of the EVSEs is in an energy constrained region (Mohamed, 2019a). We then evaluate to what extent incentives will be able to reduce the number of EVs arriving to charge at that EVSE and choosing to go to the EVSE which exists in a more relaxed energy network. We also show how traffic flow will be affected due to this arrangement.

For visualization we will rely on influence graphs (Mohamed, 2019b). Modeling the Gowanus area as a complex network would normally entail translating the streets into nodes and street junctions into links. In influence graphs, on the other hand, the links do not represent the topological connection between the nodes (i.e., the streets) but the probability that the sink node fails following failure of the source node, while the nodes are the streets. Failure here refers to street congestion/closure. We will simulate a base case when EVs are departing their origins and arriving their targeted destinations. Then, many cases will be simulated when roadblocks are placed in the network. EVs that were originally supposed to flow through those blocked streets on their shortest path would now need to use an alternative route. The added traffic on the new links, which got affected by this rerouting, is attributed to link failure. Hence, running a large enough set of simulations with random roadblocks and diverse origins and destination, one can develop an understanding on how likely it is that failure of any link will impact other links in the network. The Gowanus area under study is depicted in Fig. 3. We looked into two scenarios with varying distance between the two EVSEs.



(a) (b)

Fig. 3. Map of Gowanus area (OpenStreetMap tile style): (a) Coordinate set A; and (b) Coordinate set B.

Fig. 4 presents a flowchart summarizing the process of obtaining the influence graphs. All the codes that the authors developed are released as open source (Smart Grid, 2022). It can be observed from the flowchart that a traffic routing problem needs to be solved recursively under various cases and scenarios. To achieve this, we used the Here routing API (here, 2022). To incorporate energy related incentives into Here routing, the routing cost function is modified by an energy factor, as in (1). This energy factor is to come from the distribution power grid operator based on optimal power flow analysis (locational marginal price of energy) as described in (Mohamed, 2019a,b).

$$C_T = \wp_\tau\left(\tau\left(V_n, CS_m\right)\right) + \wp_{En}\left(E_c\left(V_n, CS_m\right)\right) + \frac{NCS_m}{2}\left[\wp_{dist}\left(dist\left(V_n, CS_m\right)\right) + \wp_\tau\left(\tau\left(V_n, CS_m\right)\right)\right] \quad (1)$$

where

$C_{\mathbb{T}}$:	total cost from vehicle V_n to charging station CS_m
NCS_m	number of vehicles currently visiting charging station CS_m
$\wp_{dist}$	distance factor
$\wp_\tau$	duration factor
$\wp_{En}$	energy factor
$dist\ (V_n, CS_m)$	distance between vehicle V_n and charging station CS_m in meters
$\tau\ (V_n, CS_m)$	travel duration of the route between vehicle V_n and charging station CS_m, including real time traffic, in seconds
$E_c\ (V_n, CS_m)$	factor reflecting the charging price at the destination station and estimated energy consumed along the route between vehicle V_n and charging station CS_m given a vehicle speed consumption model in kilowatt hours

The code starts with defining the coordinates of charging stations (two different sets), followed by defining coordinates for the origins of the vehicles. The Gowanus map is then imported and visualized. The cost function is then developed. The Here API is called by the code to solve the routing problem, implement roadblocks, parts of the visualization, distance, duration, and energy. Each vehicle was assigned the route with the least cost, given all the possible roadblocks. However, prior to creating routes with roadblocks, a base case was created with no roadblocks for reference. The roadblocks in Here API were defined as bounding boxes of areas you wish to avoid. We defined them using their upper left point and lower right point. To ensure proper distribution of roadblocks in each run, a dictionary was created to store all the roadblocks that have been used in a previous run. A value of 0 indicates that a roadblock has not been placed in that street. If the value is −1, a roadblock does not exist. Otherwise, it will count the number of times that the roadblock was used.

After all runs, the influence graph is calculated as a probability matrix by, (1) counting the number of runs where a block in a given street, led a vehicle to take another street (this will be the count); (2) counting the number of times blockage of that street repeated in the runs (this will be the denominator); and (3) calculating the matrix as the ratio.

5. Results and discussion

5.1. Influence graphs

Figs. 5 and 6 present the influence graphs for Coordinate Sets A and B, respectively. The graph shows for each potentially blocked street (x-axis: Link with possible roadblock) what the probability is (z-axis: Probability) that the EV will reroute to other links (y-axis: Alternative link). It can be observed that Coordinate Set A results in a more clustered scatter plot as compared with Coordinate Set B, since the two EVSEs are in closer geographic

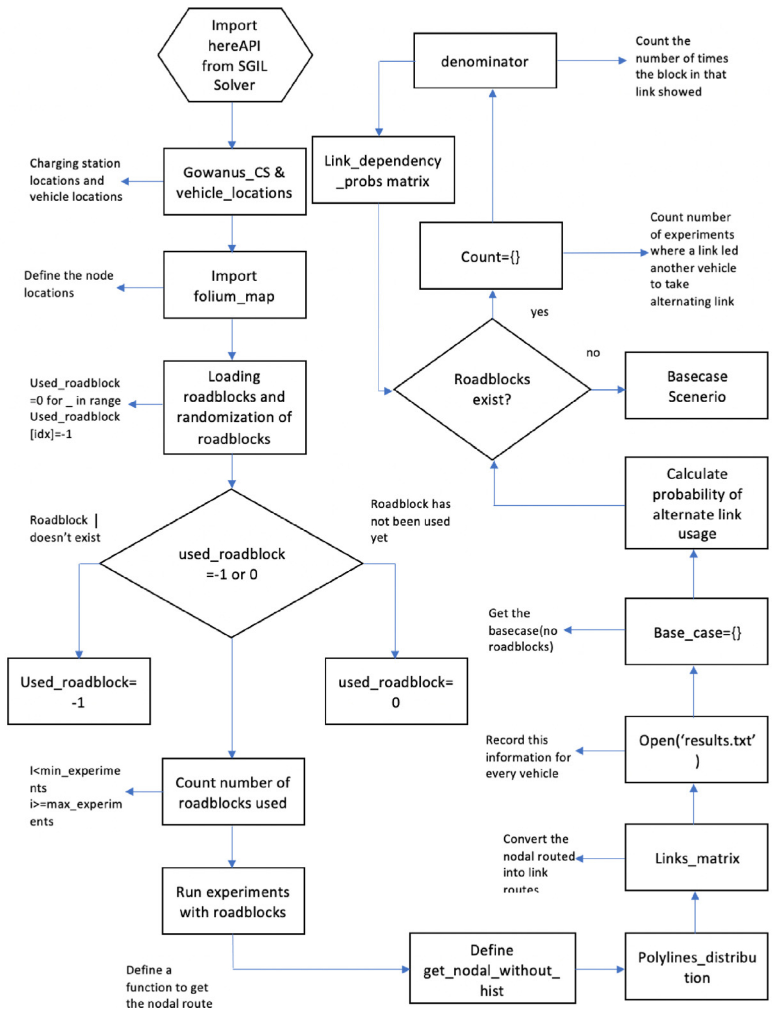


Fig. 4. Flowchart of the methodology to develop influence graphs.

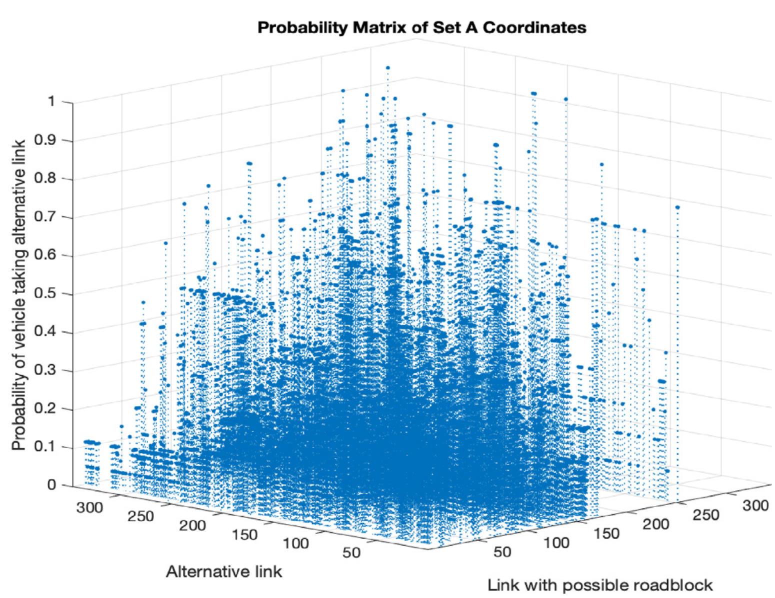


Fig. 5. Influence graph with coordinates set A.

proximity. With Coordinate Set B, the graph is more dispersed since more available possible routes exist.

Figs. 7 and 8 depict influence graphs for Coordinate Sets A and B, when cost of charging is incorporated into the routing

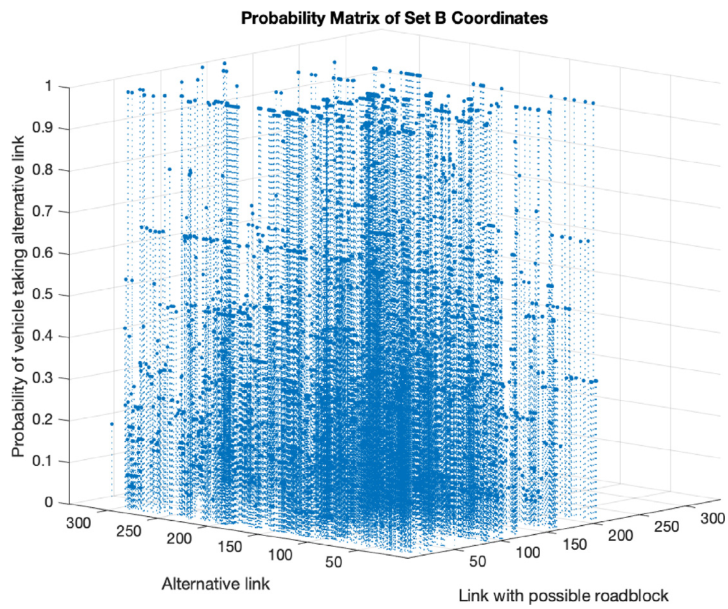


Fig. 6. Influence graph with coordinates set B.

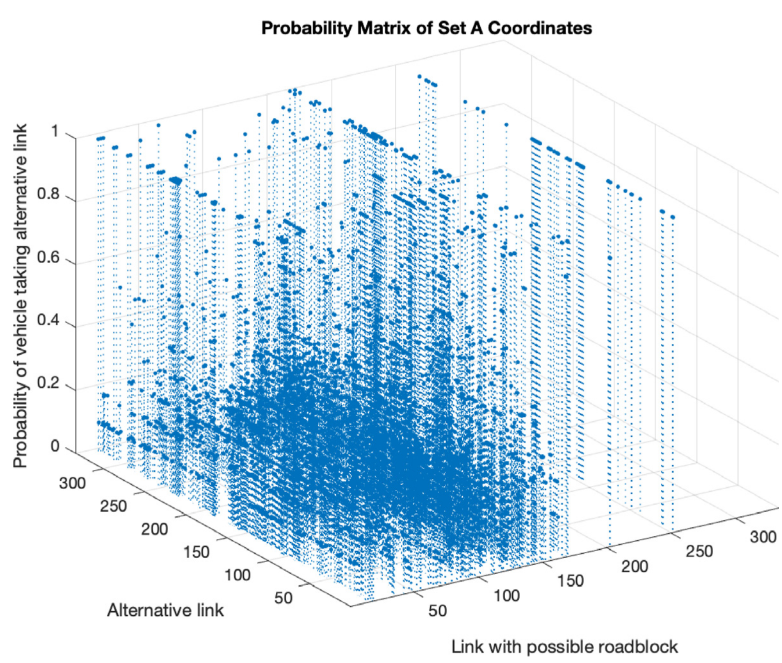


Fig. 7. Influence graph with coordinates set A with charging cost included.

problem. As can be seen from the probability matrix, there is a substantial change in the results. With one of the two EVSEs set to be more expensive than the other, Figs. 7 and 8 start to exhibit more clustering around specific regions on the 3-d plot. These regions correspond to routes that lead to the cheaper EVSE. This shows indicates that some drivers will change their initially targeted EVSE to another EVSE based on cost (incorporated into the routing problem as described earlier).

5.2. Tracing individual EV behavior

Influence graphs holistically show the effect of incentives on the system. In this subsection, we trace the trip of an individual randomly selected EV. This EV changed its destination EVSE based on charging incentive. The EVSE that is not in an energy constrained area is labeled with 0 while the other EVSE, which is in an energy constrained area, is labeled with 1. The Origin of

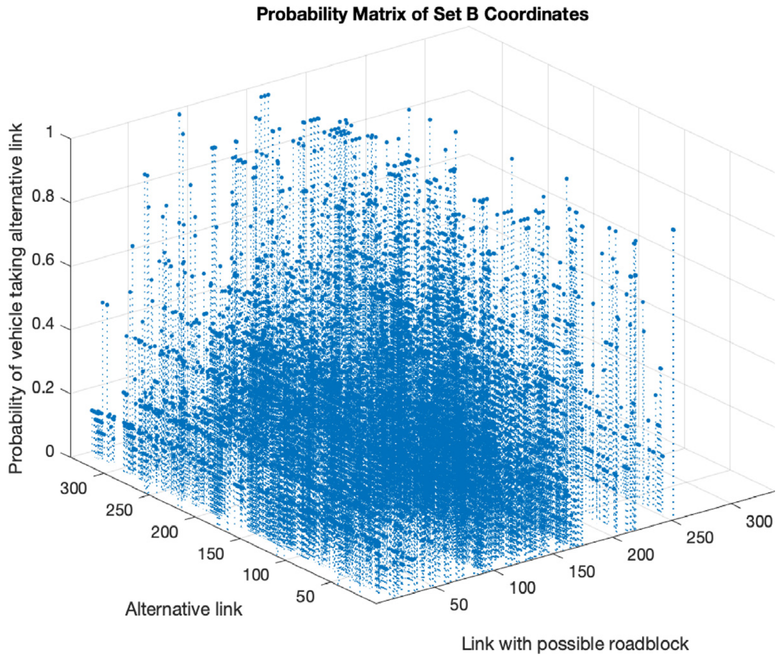


Fig. 8. Influence graph with coordinates set B with charging cost included.

Table 1
Results for sample EV without energy charging incentive vs. with incentive.

Run		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
No Incentive	EVSE	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0
Incentive		0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0		

the vehicle is at {40.68154, −73.994016} coordinates, i.e., union street at smith street. Table 1 summarizes the route in both cases. It can be seen that in many cases the EV changed its initial destination EVSE, which is closer geographically, in response to the energy-related incentive. A closer look is also depicted in Fig. 9.

6. Conclusion

This paper evaluated the effectiveness of cost incentives as a means to mitigate the impact of EV charging on the power grid. A literature survey was conducted and taken by 119 New Yorkers. The survey showed that EV charging price can be an effective way to influence drivers' decisions and mobility, with 85% of respondents choosing to travel longer for a cheaper EVSE instead of heading to a near EVSE at a higher cost. The survey also showed current EV owners care more about the impact of EV charging on the power grid as compared with non-EV owners, with about 59% of respondents indicating impact on the power grid as a decisive factor when selecting an EVSE as compared with about 23% for non-EV owners. This assumes that information about grid status is provided to EV owners while making the decision. Interdependence between the power grid and the transportation network was demonstrated using a case study focused on the Gowanus area, Brooklyn. The case study demonstrated the use of energy-related incentives, embedded into the standard routing problem, assuming coordination between the power grid operator and the transportation network operator. The case study showed how some EVs were diverted from an EVSE that is located in an energy constrained area of the power grid and rerouted to another one.

CRediT authorship contribution statement

Ahmed Ali A. Mohamed: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft, Writing – review & editing. **Stephanie Lojano:** Conceptualization, Visualization. **Carlos Maldonado:** Conceptualization, Visualization. **Tamer Ibrahim:** Software, Supervision, Validation. **Hebatallah E. Mostafa:** Formal analysis, Visualization, Writing – original draft. **Razib Sarkar:** Formal analysis, Visualization, Writing – original draft. **Tafadar Soujad:** Formal analysis, Writing – review & editing. **Hegazy Rezk:** Data curation, Funding acquisition, Investigation, Project administration. **Mujahed AlDhaifallah:** Data curation, Funding acquisition, Investigation, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ahmed Mohamed reports financial support was provided by Interdisciplinary Research Center for Renewable Energy and Power Systems at King Fahd University of Petroleum & Minerals (KFUPM) under Project INRE2221.

Data availability

We have included a GitHub link to all data and codes. We are making them available.

Acknowledgments

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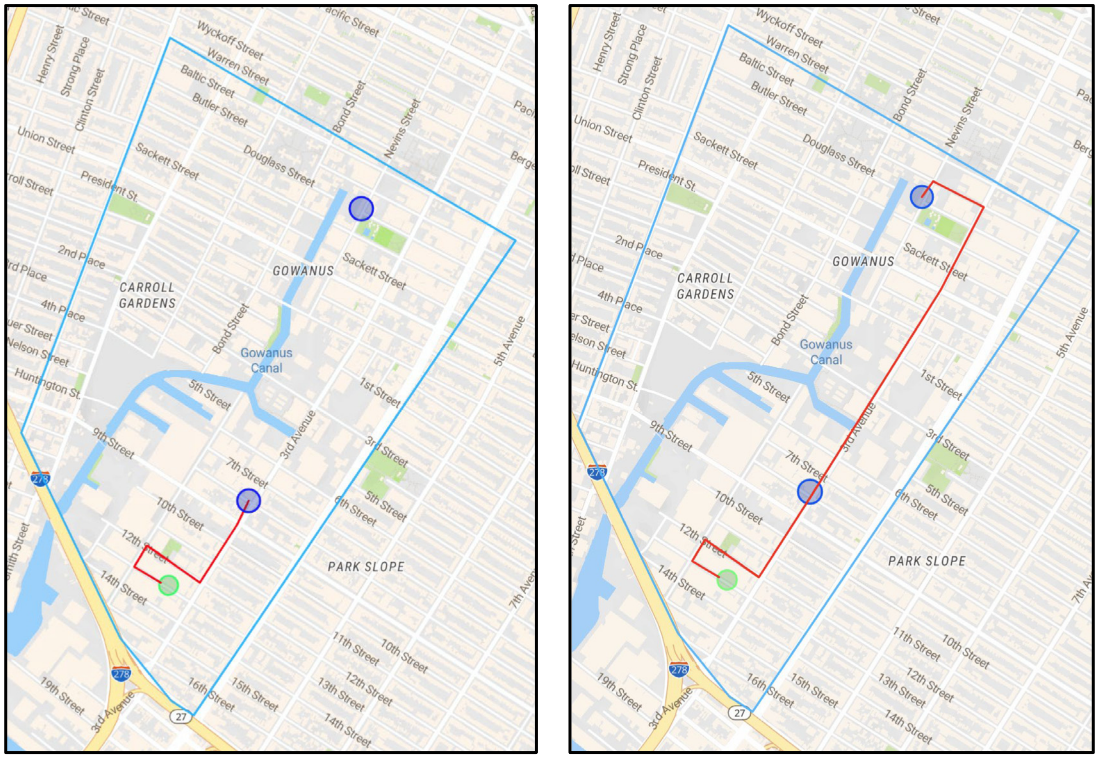

Fig. 9. OpenStreetMap tile style of Gowanus with coordinate set B depicting the route of a vehicle: (a) in the case of no charging station cost/incentive; and (b) in the case of charging cost/incentive.

Supplementary materials

The source codes of the software developed in this work can be downloaded at: https://github.com/TamerSobhy/EV-Charging-Scheduling.

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