Revolutionizing Electric Vehicle Management: Spatial Computing Challenges and Opportunities

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ABSTRACT

Electric vehicles (EVs) have been identified as one of the necessary solutions to reduce the carbon footprint of transportation, a large source of greenhouse gas (GHG). As adoption of EVs and infrastructures to support them grow, formidable hurdles to achieving equitable economic growth and reliable transportation and energy system via effective management of EVs have been discovered. This opens major opportunities and challenges for spatial computing research. Equitable distribution of EV infrastructure in a broad region presents complicated spatial computing challenges with a great social impact. Spatial computing informed adoption and management of EVs will be essential to achieving the maximum carbon reduction through EVs along with a reliable transition to a renewable energy future. On the road, EV drivers may benefit from spatial computing to choose routes that take into account public fast-charging stations as well as energy needs of the route, such as speed, weather (e.g. air-conditioning, heating, and elevation changes). This paper presents open research questions of spatial computing related to EV management.

CCS CONCEPTS

• Spatial and physical reasoning; **• Power networks**; **• Transportation**; **• Renewable energy**;

KEYWORDS

Electric vehicles, Climate Change, Charger placement, Range prediction, Renewable energy, Transportation, Grid reliability

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1 INTRODUCTION

The Electric Vehicle (EV) revolution is ready for its next phase: building a deep infrastructure of public charging stations and assuring the reliability of the nation's electric grid. Along with leading global initiatives, as seen in Figure 1, the US has adopted the important objectives to combat climate change and promote equity in the positive impacts of its transition. We believe spatial computing has a vital role to play in these endeavors. Our field is uniquely positioned to manage the future of EV technology and help ensure these larger goals are met.

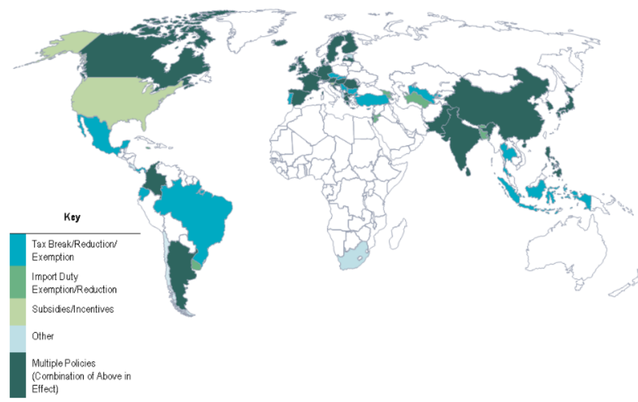

Figure 1: Countries with Fiscal Policies Encouraging EV Uptake[15]

1.1 Societal Significance and Urgency

Combating Climate Change. Climate change has become the foremost issue for the global community and transformational solutions are being considered to drastically reduce greenhouse gas (GHG) emission, a major cause of climate change. In its recent report on the longer-term strategy of the United States, the Biden administration is targeting net-zero carbon emission by 2050 ([25]). Compared to the historical trajectory of U.S. net GHG emissions from 1990 to 2019, the emission targets indicated in Figure 2 are ambitious and urgent.

Decarbonization is closely linked to electrification. Eliminating liquid or gaseous fuels, which are generally more difficult and costly to decarbonize than electricity, is a crucial step towards reducing the carbon footprint ([17]). A third of the GHG emission currently comes from transportation ([1]), making EV one of the key solutions combating climate change. U.S. Department of Transportation has made a commitment to build public network of EV charging stations (EVCS), installing 500,000 public EVCSs by 2030, to support the transition to net-zero emissions ([23]). EVs are uniquely posed to serve both as consumption and battery storage for the electric grid,

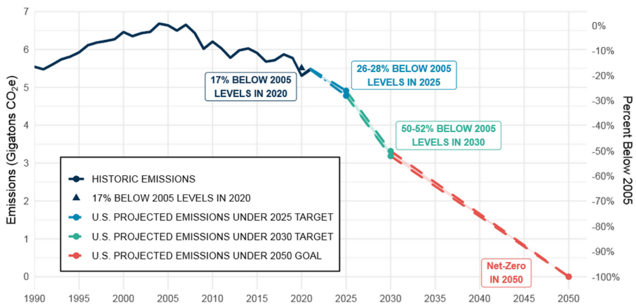

Figure 2: Biden administration's decarbonization goals, highlighting Net-Zero emission by 2050[25]

making the charge and discharge strategy of EV fleets vital to the renewable energy transition ([21]).

Reliable and Equitable Transportation Infrastructure. The drastic growth of EVs necessitates widely deployed and publicly accessible EVCSs. For example, residential charger access may not be available in multi-unit houses, and routes for heavy-duty EV trucks should be supported by public EVCSs. Studies have indicated that charging infrastructure costs represents a significant increase in the total cost of ownership (TCO) for zero-emission tractor-trailer trucks, some studies showing a increase over $110,000 per tractor-trailer by 2025 ([14]). Society's dependency on reliable transportation has only increased in the recent times, evident in the consequences of the disruption of supply chains witnessed during Covid-19 pandemics as an example. Building and managing the EV charging infrastructure to ensure the reliability and equity across all communities would be an essential requirement towards a net-zero emission future.

1.2 Position

To accomplish net-zero carbon emission as well as maintain infrastructural security, we envision the use of innovative spatial techniques that integrate the physics model of individual EVs with the locations and availability of EVCSs, road network conditions, and energy infrastructure data.

To realize the full potential of EVs, significant spatial computing challenges need to be met. Modeling charge status and optimizing EV operation would require capturing stochastic input variables in real-time, such as demand and generation status of the local electric grid, electro-thermal characteristics of each EV, and availability of EVCSs. Realizing this vision in the real-world requires processing EV measurement data on a large geographic scale at a close to real-time basis, a colossal challenge of spatial big data science and engineering.

As EV fleets and their infrastructure rapidly evolve across regions, setting up a closed-loop process to monitor the regional state of EV ecology and forecast the impacts of different development scenarios in a timely manner is a vital task. Prognostics of the evolution of EVs from statistical patterns in different regions will be a rich spatial computing challenge.

2 OBJECTIVES AND OPEN QUESTIONS

We identified four research objectives with outstanding spatial computing tasks. For each research area, we discuss existing techniques, identify research gaps and envision new opportunities. Table 1 presents some example open questions per each objective discussed in the following section.

Table 1: Open questions to prepare for the revolution of EVs

Objective	Open Questions
Equitable Access to EV Resources	• How do we measure spatial equality of EV adoption (e.g. accessibility to EVCS, environmental benefits, cost of driving)? • How do we encourage equitable distribution of EV infrastructures?
Realistic Routing Services for EVs and Optimal Site Selection for EVCSs	• What unique features of EVs does the routing service need to consider for reliable operation of EVs (e.g. weather, elevation of roads)? • How do we place EVCSs for optimal reduction of emission and reliability of infrastructure?
Network-aware Charge/Discharge Scheduling for EVs	• How do we integrate currently disjoint energy and transportation networks? • How do we model and operate EVs as dispatchable energy storage?
EV Spatio-temporal Big Data Engineering for Prognostics and Reliability	• What statistical features of EV driving big data provide most significant prognostics for large-scale EV management? • Where and which kind of renewable energy should administrative or industry plan to invest in to minimize the carbon footprint of EVs with the least disruption to the existing infrastructure?

2.1 Equitable Access to EV Resources

Figure 3 shows the distribution of public EVCSs in the U.S., as of 2021, on top of interstate highways. At a glance, wide distribution of EVCSs can be observed in the east and west coast, while a sizeable gap appears towards the middle of the country. The uneven accessibility to EV infrastructures is a trend that holds true not only on a national level but also on a state level ([14], [12]). The U.S. government has already taken some early steps towards addressing this issue, such as proposing a federal regulation to limit the distance between EVCSs to be no more than 50 miles apart ([9]), although the interpretation and implementation of such regulation is largely undetermined. Current literature related to optimal distribution of EVCSs rarely, if ever, includes equal access as part of its objectives while highly emphasizing meeting the existing demand ([27],[10]). This can aggravate the inequality of EV resource distribution by favoring locations that can afford a large fleet of EVs, if equal access to EV resources is not proactively pursued. The spatial computing community may play a key role in defining the spatial equity of EV accessibility as well as deriving an effective method to distribute EV resources.

2.2 Routing Services for EVs and Optimal Site Selection for EVCSs

Spatial Modeling of EV Rides. Modeling physical behaviors of an EV on the road relative to the location and road conditions of its potential routes is necessary for reliable routing service for EVs. Many studies have identified the unique constraints of the EVs

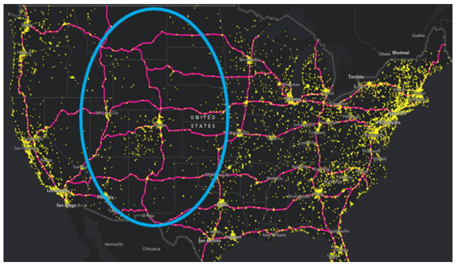

Figure 3: Public EVCSs nationwide, as of February 2022, identified by ESRI [5]. Yellow dots show locations of EVCS and fuchsia lines indicate major highways. Region with prominent gaps between EVCSs is circled in blue.

related to their energy consumption and battery lifetime in relation to driving conditions ([6],[13]). For instance, in hotter days, due to battery overheating, the driving range of EVs will decrease as much as half during a normal driving condition. Vehicles relying solely on electric power also pose other weather related dangers to the drivers, such as losing heat during an extremely cold condition ([16]). Discovering spatio-temporal patterns of the behavior of EVs under various environmental factors is a critical juncture to ensure a sense of reliability for the EV drivers.

Route selection platforms, such as Uber or Google Map, have started to adopt some of the constraints unique to EVs, such as available EVCSs within the chosen route. However, more sophisticated representation of EVs' characteristics need to be captured in this algorithm in order to make the selected route feasible. Weather conditions ([2]) or light vs heavy duty vehicle model ([7], [8]) are examples of factors that have high correlation with EV's trip range but are currently being omitted in the major route selection platforms.

One-size-fit-all approach in modeling EV also results in an inaccurate spatial characterization of EV's GHG emission. For example, in Figure 4, shows GHG emissions (life cycle gCO_2 eq/mile) (Y-axis) and total monthly cost (vehicle, fuel, maintenance) (X-axis) for many electric (yellow dots), hybrid (light and dark pink dots), diesel (gray dots) and gasoline (black dots) vehicles for the US states of California (left half) and Minnesota (right half). The thicker spread of yellow box on the right, corresponding to the range of carbon intensity of EV models in Minnesota, is prominent and caused by spatial variability between the two regions, such as fuel mix of electric generation and gasoline price.

This is a major opportunity for the spatial computing community to enhance navigation apps for recommending routes that lower emissions rather than travel distance or travel time. In general Physics models and vehicle big data may help compare the expected greenhouse gas emissions of alternative routes and share that with the audience. Recently, in October 2021, Google Maps started putting a leaf symbol next to routes which are likely to have lower emissions. However, they use a generic vehicle to compare route choices and future research can improve the emissions estimates by using more accurate vehicle parameters (e.g., weight, shape, engine-type) and electricity generation sources, which can impact the emissions of a particular EV model across locations as illustrated in Figure 4.

Site Selection of EVCSs. The availability of ride condition data and road network data will significantly alter site selection of EVCS network ([28], [24]). Current studies related to the subject tend to lack a holistic representation of EV fleets. Studies often focus on optimizing the problem based on a small subset of spatial variability, such as some hypothetical characteristics of a vehicle (e.g. battery lifetime, traveled distance) or historical cost and congestion information of the electric grid ([22], [11]). As some real-world data for the existing EV models became available, spatial computing research has already begun to incorporate their operating data in site selection algorithms and test feasibility of optimal scenarios ([8], [24]). However, vehicle and energy data to capture the spatial and physics-related variability of EVs are constantly growing. The continuing and rapid growth of EV fleets presents a rich area of research for the SigSpatial community to discover the dynamics between spatial variability of EVs and EVCS development and enhance the driving experience of the EV adopters while minimizing the societal cost.

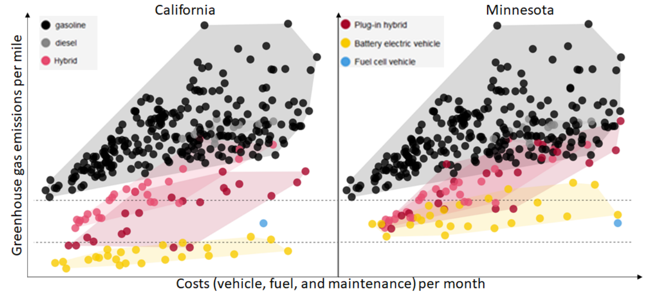

Figure 4: Carbon intensity vs lifetime cost of personal EVs by vehicle model. Left graph shows the carbon intensity and cost of EVs in California while the right side shows that of Minnesota. Yellow dots indicate EV models while black and gray dots indicate combustion engines. Same 125 models are represented on both graphs. A smaller gap between the gray shade and yellow shade indicate EV models operating in the state are emitting GHG almost as much as combustion engine models. Dotted lines, from top to bottom, indicate emission goals of 2030 and 2040. [20]

2.3 Network-aware Charge/Discharge Scheduling for EVs

Scheduling charging and discharging states of a large-scale EV fleet poses a formidable yet exciting challenges for the SigSpatial community. For the electric grid management, managing EV's charging hours to match hours and locations at which electricity demand is low while securing idle EVs with residual charge as battery storage during peak demands of electricity is a crucial objective([11], [19]). Preliminary studies have already shown that integration of EVs to the electric grid without consideration of the charging strategy may reduce carbon emission minimally or even worsen the net emission because of the investment cost of new technologies and increased usage of electricity ([18], [4]). EVs' participation in the energy market will have a direct impact on overall electric system and current research has cautioned that, without near-real-time monitoring and meticulous planning, a large moving fleet of EVs may lead to volatility and instability of the electric grid ([3], [28]). Spatial computing techniques, such as spatial temporal graphs and spatial big data querying, will make a significant impact on the solution of this problem.

2.4 EV Spatio-temporal Big Data Engineering

Computationally, EV measurement data sets have spatio-temporal graph semantics, where EVCSs can be modeled as vertices and electric connections between the stations are represented as edges ([26]). Because of the scale required to incorporate spatio-temporal data of quasi-real-time granularity, cloud computing platforms will play an essential role to scale up data analytics for handling the huge volume of EV data. Although graph representation databases are gaining popularity (e.g. Neo4j, Arangodb), their applications to represent spatial computing environment have been limited and the volume of temporal data generally remains as a challenge for any graph structure. Hence, spatial temporal graph-aware computational infrastructure is needed to improve the computational solubility of EV data analytics, leveraging the graph-like nature of its data. The ability to abstract graphs of different time slices to properly represent system-level temporal patterns along side the vehicle-level behaviors will be critical.

3 CONCLUSION

In this paper, we introduced a vision of managing EVs that takes full advantage of the innovation of clean transportation and the opportunity of EVs as a vital part of society's transition to a renewable energy future. The goal of net-zero emissions, improved public health, and reliable energy transition all rely on spatial computing informed management of EV fleet and the infrastructures it depends on. The SigSpatial community is poised to make a lasting contribution to society by taking on these challenges and doing the research that needs to bring forth the EV revolution.

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