EV Charging Station Location Optimization with Hotspot Visualization

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1 INTRODUCTION

Governments across the globe are promoting Electric Vehicles (EVs) as a green alternative to fossil-fuel vehicles (FFVs). EVs will constitute about 24% of all vehicles by the year 2030 [B]. It is projected that 50% of new vehicle sales by 2030 will be that of electric vehicles [B] and the EV charging station market is also projected to be around $217.5 billion [C].

However, there are several challenges to the wider adoption of EVs. Many surveys and studies point to range anxiety, infrastructure, initial cost of adoption being the primary reasons[11] and also coupled with the fact that EV charging stations cannot be built into the existing conventional gas stations because of large recharging times for EVs (can cause congestion in the station)[10]. These existing problems in the world of EV charging stations form the basis for our project. Increasing the number of charging stations in areas with the largest demand-supply will alleviate both range anxiety and infrastructure concerns. In this project, we aim to build an interactive dashboard showcasing the network flow map of national highways' traffic volumes and identifying regions and roads that require additional EV charging stations. Further, we suggest optimal locations for new EV charging stations with an objective to minimize the demand-supply gap.

2 PROBLEM DEFINITION

In this project, we aim to build an interactive dashboard showcasing the network flow map of national highways' traffic volumes and identifying regions and roads that require additional EV charging stations. Further, we suggest optimal locations for new EV charging stations with an objective to minimize the demand-supply gap.

3 SURVEY

Current research into optimizing the locations of EV stations is focused on small urban clusters, like cities or counties, and does not scale well outside the regions considered. Range anxiety is most prominent when users consider longer travel distances, which often include national highways in their routes [16].
Most solutions are also simulation-based [20], wherein simulations are carried out for EV users' behavior [21], vehicle, and grid power output, etc. An objective function is then solved for these parameters but these models have not been applied to real data explicitly. Other factors like traffic flow and hot-spot locations inside a city are also used in some research [7, 16].
Visualizations are rarely built on any of the aforementioned solutions. Traffic flow visualization do exist but they are majorly employed in rerouting, network optimization and supply chain optimization but not in the context of new locations for fuelling stations [17, 19].
Overall, the drawbacks of existing approaches are:

(1) Usually small scale and focused on factors specific to that region [4, 16]
(2) Rarely considers intercity and longer travel distances which is a major drawback for EVs in the current market [5, 7]
(3) Lack dynamic/interactive visualizations or user interface utilizing the models and data [17, 19]

4 PROPOSED METHOD

As per the proposal, we plan to implement a scalable solution based on traffic flows of USA national highways that can be utilized not only to identify new Electric Vehicle charging station locations but also a comprehensive visual representation of the existing charging stations across the whole country.

4.1 Data Cleaning and Acquisition

There are 4 primary datasets related to EVs we used to solve this problem.

- Traffic Volume across USA roads
- EV Charging Station Locations & Characteristics
- EV Sales across regions
- EV Power Usage and Range

The datasets that we have taken into consideration are real-world datasets sourced from public databases and collected via APIs and web scraping.
The EV charging stations data is obtained from NREL (National Laboratory of the U.S. Department of Energy) downloaded using their provided APIs. This data is updated continuously and includes biodiesel, compressed

natural gas, ethanol, electric charging, hydrogen, liquefied natural gas, and propane station locations.

Traffic flow data is then drawn from official site of U.S. Department of Transportation. The database is updated monthly by State highway agencies where they collect traffic volume data through both temporary traffic counting and continuous traffic counting programs and report their continuous counting data to Federal Highway Administration. The Traffic flow data was available at a resolution of a day, for the purpose of this project, the data-points were temporally normalised to show data at the resolution per month. For this data, traffic is measured at various points called Control Points along the highways. We observed missing zip codes in this data for the control points and they were handled by imputing the values obtained using nearest neighbours approach.

The EV power usage data is estimated using the EV sales information, highway traffic data and number of EV stations present at that control point. The EV sales data was obtained from Atlas EV hub dashboard, the data is separated by state and is grouped to depict the number of EVs for a particular zip code. The data also comprises of the composition of different EV models in the state, which can be used to precisely compute the power usage for a particular area.

4.2 Data Analysis

Exploratory data analysis was performed on the data-sets. In the traffic flow data-set we have approximately 75 million data points for each year in consideration containing information on control points which is uniquely identified by 3 description columns, date and time-stamp on each day of the year and traffic flow at each control point on each particular day.

In the charging station location data-set, we have $\sim$ 56000 data points containing information on ZIP code, station ID, various charger types in each station, location coordinates of the station, etc. EV charging stations from a total of 5834 cities are spanned and a total of $\sim$ 15000 ZIP codes are covered.

The EV charging stations data has a field with latitude and longitude which is used to pin the station on a map, with several additional fields describing the type of connector used, level of charging provided, etc. Existing EV stations locations in various cities are as shown in Fig 1.

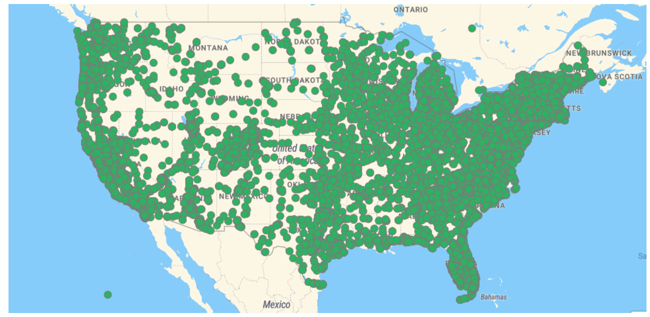


Figure 1: EV station markers for USA

Fig 2 shows the growth of EV stations over the years which is obtained by exploring the EV charging stations data-set sourced from the U.S. Department of Energy.

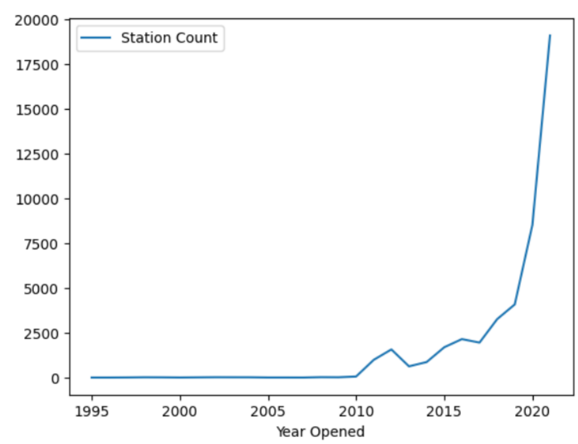


Figure 2: No. of EV charging stations with time

4.3 Optimization

The first step in location optimization is to define a objective function that penalizes for every additional charging station setup. It's objective is to minimize the new charging capacity along a highway by making sure that the net demand along a highway, after the introduction of new charging stations, is greater than or equal to the current demand. We formulate an optimization problem to determine the capacity and also pinpoint location for new EV charging stations.

We created node points along the highways which can be potential locations for new EVs. Charging demand along a highway is estimated by considering the proportion of EV traffic flow along the highway and multiplying it with the estimated power usage for that grid. Charging demand for grid k can be depicted as follows:

$$D_k = T_k \times (\frac{E_k}{V_k}) \times P_K$$

where:

T_k: Traffic flow in grid k
E_k: EV sales estimated for that grid
V_k: Total number of vehicle sales in that area
P_k: Estimated power usage for covering the distance along the road

The existing capacity of each charging station is calculated using the data about different types of chargers available in that station and combining it with the charging capacity for each type of charger. It can be depicted as follows:

$$C_k = \sum_{i=1}^{n} CT_i * n_i$$

where:

CT_i: Charging capacity of a charger type k
n_i: number of chargers of a particular type

From the above data, we can estimate the additional charging capacity required along each road. From this estimate of the additional demand, we proceeded to formulate the optimization problem. In the first approach we have assumed a constant charging capacity for all the roads under consideration. The optimization problem is as follows (We used Gurobi solver and PuLP package in Python to solve our optimization problems):

$$\min \sum_{i=1}^{n} c^* x_i$$

$$r_i : \sum_{i=1}^{n} c^* x_i \geq D_i - C_i$$

where

n: Number of new charging stations
c^*: Constant charging capacity for each charging station
r_i: Road 'i'
C_i: Capacity along a road as calculated in previous step
x_i: Demand along a road as calculated in previous step

In the above equation, number of new nodes along a given road are calculated by dividing the length of the road by a fixed distance along which new stations will be placed (we considered 25 Km distance)

There are a few shortcomings in the above approach where the net demand required $(D_i - C_i)$ may not be satisfied by the assumed constant capacity for all the stations. To overcome this shortcoming in the next approach we have considered a variable charging station capacity for each road. This is done by creating a list of energy values for each road under consideration by dividing the net demand required $(D_i - C_i)$ by the maximum number of new nodes which can be placed on a given road (as calculated above)

The list formulated above would be of the form:

$$L_i = \left[\frac{1}{n} * (D_i - C_i), \frac{2}{n} * (D_i - C_i), ..., \frac{n}{n} * (D_i - C_i)\right]$$

The modified optimization equation formulation for the above problem is as below:

$$\min \sum_{i=1}^{n} c_i$$

$$r_i : \sum_{i=1}^{n} c_i \geq D_i - C_i$$

where

n: Number of new charging stations
c_i: New charging capacity for each charging station from the list L_i
r_i: Road 'i'
C_i: Capacity along a road as calculated above
x_i: Demand along a road as calculated above

By solving the above problem, we could come up with new charging station capacity for new nodes along each road. These nodes along with their charging capacity were then used to plot the visualization of new EV stations alongside existing EV stations

4.4 User Interface

The programming for the interface was done on Python Dash and the server was hosted on a local machine. The user interface consists of a GeoJSON projection of the United States showing the network of roads across the country. The data is mapped to latitude and longitude to allow synchronization with other data such as charging station locations, traffic flow and EV sales data. The interface has sufficiently high levels of resolution containing data for roads upto the county level.

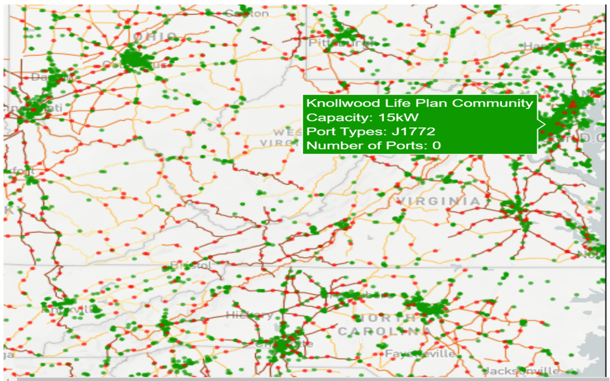


Figure 3: Zoomed Interface

The roads are color coded by traffic volume, going from light yellow to dark red to allow easy interpretation of data and analysis of new hotspots. The existing charging stations are overlaid on the network and details such as charging station capacity and number of available chargers are also displayed.

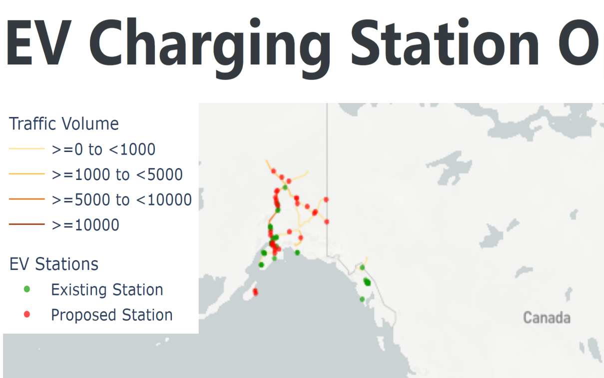


Figure 4: Road Colouring

The interface also comes with a tooltip displaying important details of a particular marker on hover and more detailed description on clicking a point of interest. In addition there is an option to filter roads by type (Interstate,Highway,local) to allow for more in-depth analysis of the data. Various Statistics are also visualized in graphs alongside the map display.

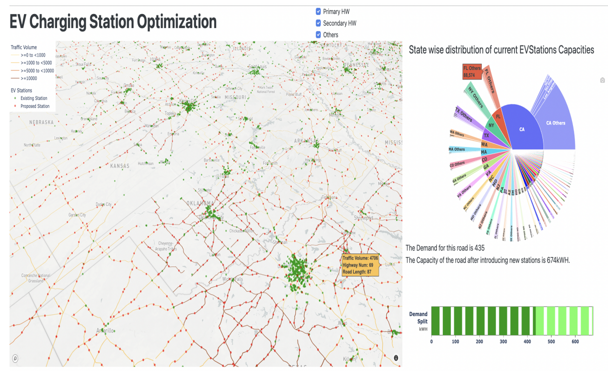


Figure 5: Display with Proposed Additional Capacity

4.5 Innovation Summary

In our project, we have implemented a scalable solution encompassing the entire country of United States which is not explored by previous research in this field. Moreover, our solution proposes to cover a wide area around the USA national highways that can be further utilized to explore possibilities for new EV charging stations along the highways, which is not a central focus in the current EV charging station market. This will help in tackling range anxiety, which is a key limitation for users of electric vehicles looking to travel long distances.

In the optimization part of the problem, we have combined a modified clustering based approach with a traditional optimization method like MILP to include both spatial and parametric information to find the optimal location for the charging station.

Existing visualizations in this field are limited in providing the users with the locations of charging stations but in this approach we are trying to assist users by providing an interactive visualization which will help them better prepare their journey

5 EXPERIMENTS

5.1 Visualization Questions

(1) What patterns can we get from the visualization? How do they correlate to EV placement in reality?
(2) Are there noticeable changes in the visualization over different regions?
(3) Are we able to identify areas of improvement based on the visualization?

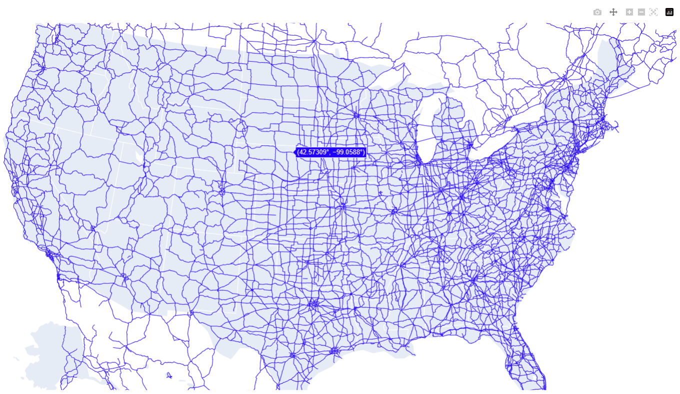
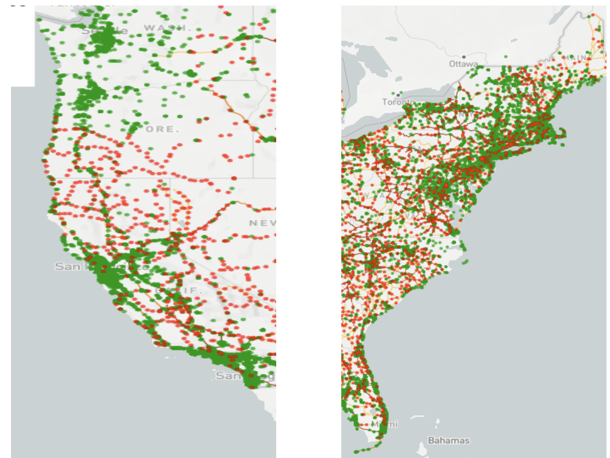


Figure 6: Road Network across US



(a) West Coast **(b) East Coast**

Figure 7: Comparison between West Coast and East Coast

On observing the country wide data we can see very clear patterns on the distribution of charging infrastructure. Most of the charging stations are concentrated around urban centers. In particular the network is more densely populated around cities along the east and west coast. The densities between cities along the East and West Coast are visibly higher than those in the Mid-West and Western regions of the country. The distribution of charging stations also varies significantly from region to region. The infrastructure coverage along the East Coast is dense enough that it becomes difficult to identify major highways and roads just by looking at the charging station locations. On the other hand for the West Coast and Midwest there are clear patterns and roads can be clearly identified.

On observing the data at a smaller resolution we find that for smaller population centers the stations are generally placed along the entry and exit routes through these cities. Most of the infrastructure placed along such population centers appears to be prioritizing travellers over the actual residents of the town.

We have created a cleaned database of traffic flows and interactive visualization of road networks with traffic data overlay and augment it with existing EV charging station data. Our model enables users to identify new regions that could benefit from the additional charging infrastructure. From the Visualization it quite clear that there exists a significant demand gap in the Southern Mid-West regions of the US. The coverage for the West Coast appears to follow the market trends, but is missing out on certain lesser utilized roadways.

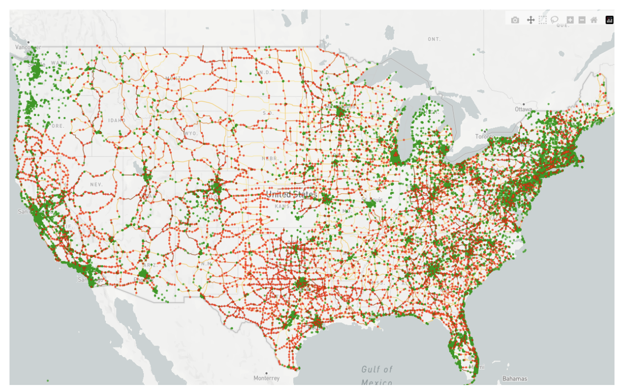


Figure 8: High Demand in Southern Mid West

We can clearly observe high density in residential and urban centers, with lower density along interstate roads. To test the model's predictions we have removed specific high usage stations from the existing database and see how close the model predicts the location of a new charging station to the removed station.

5.2 GUI Questions

(1) Does the GUI have sufficient resolution to view county-level networks?
(2) How does loading different amounts of data contribute to user experience?
(3) Are there other methods to improve the user experience and shorten load times?

The visualization created spans the entire United States and has sufficient resolution that when we zoom in we can clearly see all the nodes along the roads. Loading the entire data-set, which included the hourly traffic flow along all the roads under consideration, was a big challenge. When loading the data-set we could see a dip in performance as the visualization was taking a long time to load. To counter this, monthly traffic flow data was considered instead of a hourly rate. This led to a performance boost in the visualization and gave a smooth experience when analyzing different nodes along the entire United States and when zooming in and out of the visualization. We plotted our data on a scatter map box which is a GIS plotting for back-end. We have about 84K points for roads and 56K points for stations. We are utilizing GPU resources for rendering the plots using WebGL back-end (an extension for OpenGL). Loading complete data-set by using the GPU resources reduced our loading time from 2 minutes to 10 seconds. The time taken to zooming in and zooming out of the map reduced from 5 seconds to 0.2 seconds. Some alternative approaches to reduce the loading stress could be to use a lazy loading approach. One such method which utilizes this is PapaParse, a leading library for fast in-memory CSV loading.

6 CONCLUSION

We have analyzed the trends of EV charging station Infrastructure across the United States and identified definite areas of improvement. The visualization can be utilized by EV owners, manufacturers as well as government entities and companies investing in EV infrastructure.

So far, all the team members have contributed a similar amount of effort by voluntarily picking up tasks in which our interests and expertise lie.

7 FUTURE WORK

The dataset can be augumented with responses from a predictive model in the future to account for upcoming trends in EV sales and traffic flows. The Optimization model could also be improved with additional constraints by taking into account nearby facilities such as restaurants, hotels and resorts (EV charging takes a while after all!).

The visualization could be improved with additional filters to allow more in-depth analysis of the placement of new charging stations, the package could also be linked with Google Maps to allow for better functionality and open the possibility of combining pre-existing navigation services. Additional options for faster loading should be explored possibly utilizing distributed computing on the cloud.

8 APPENDIX

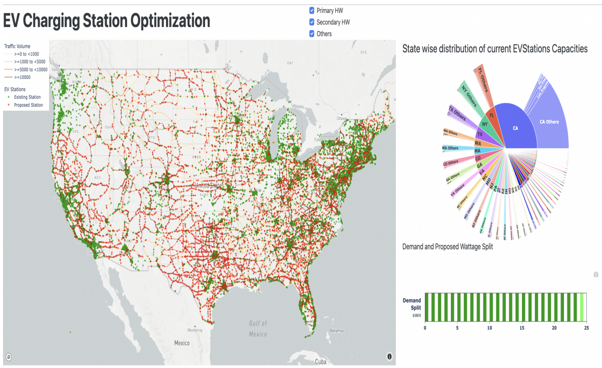


Figure 9: Demand and proposed wattage

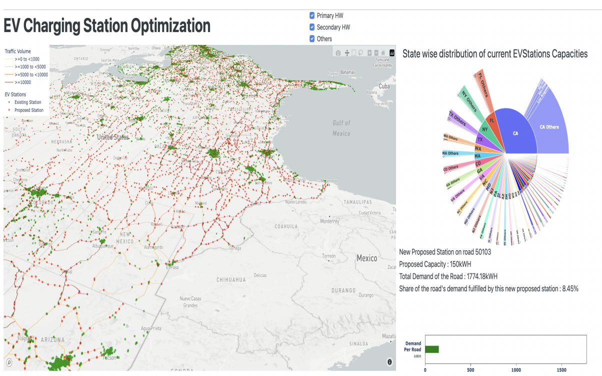


Figure 10: 3D view of visualization

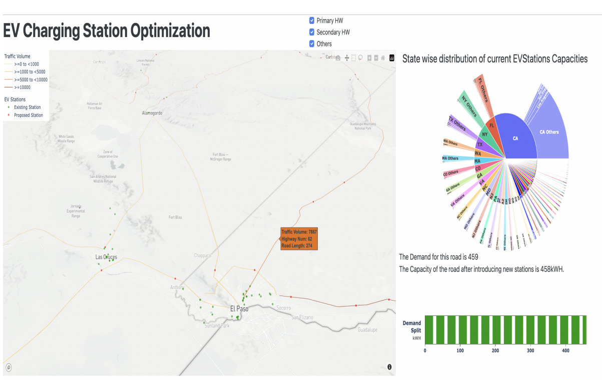


Figure 11: Road demand after new stations

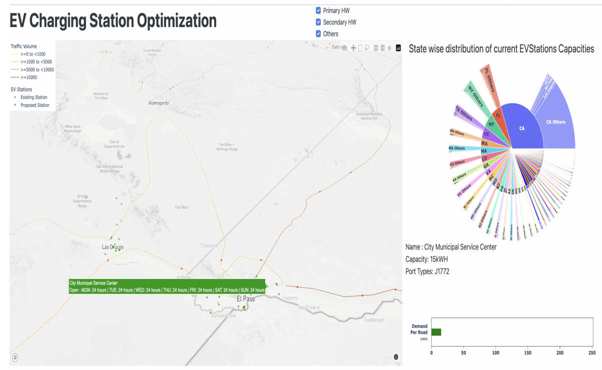


Figure 12: Demand fulfillment for existing road

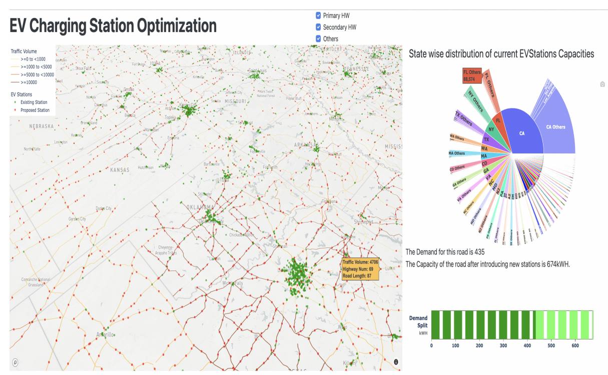


Figure 13: Existing demand vs existing capacity

REFERENCES

[1] Ahmad, Fareed, et al. "Optimal location of electric vehicle charging station and its impact on distribution network: A review." Energy Reports 8 (2022): 2314-2333.

[2] Bae, Sangjun, et al. "A game approach for charging station placement based on user preferences and crowdedness." IEEE Transactions on Intelligent Transportation Systems (2020)

[3] Mazumder, Mondeep, and Sanjoy Debbarma. "EV charging stations with a provision of V2G and voltage support in a distribution network." IEEE Systems Journal 15.1 (2020): 662-671.

[4] Luo X, Qiu R. Electric Vehicle Charging Station Location towards Sustainable Cities. Int J Environ Res Public Health. 2020 Apr 17;17(8):2785. doi: 10.3390/ijerph17082785. PMID: 32316616; PMCID: PMC7215474.

[5] Luo, Chao, Yih-Fang Huang, and Vijay Gupta. "Placement of EV charging stations—Balancing benefits among multiple entities." IEEE Transactions on Smart Grid 8.2 (2015): 759-768.

[6] Brenna, M., Foiadelli, F., Leone, C. et al. Electric Vehicles Charging Technology Review and Optimal Size Estimation. J. Electr. Eng. Technol. 15, 2539–2552 (2020).

[7] Padmanabhan, S., Petratos, A., Ting, A., Zhou, K., Hageman, D., Pisel, J. R., & Pyrcz, M. J. (2021). Us. arXiv. https://doi.org/10.48550/arXiv.2108.07772.

[8] M. C. Catalbas, M. Yildirim, A. Gulten and H. Kurum, "Estimation of optimal locations for electric vehicle charging stations," 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), 2017, pp. 1-4, doi: 10.1109/EEEIC.2017.7977426.

[9] D. Gong, M. Tang, B. Buchmeister and H. Zhang, "Solving Location Problem for Electric Vehicle Charging Stations—A Sharing Charging Model," in IEEE Access, vol. 7, pp. 138391-138402, 2019, doi: 10.1109/ACCESS.2019.2943079.

[10] A. Y. S. Lam, Y. -W. Leung and X. Chu, "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions," in IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846-2856, Nov. 2014, doi: 10.1109/TSG.2014.2344684.

[11] Q. Cui, Y. Weng and C. -W. Tan, "Electric Vehicle Charging Station Placement Method for Urban Areas," in IEEE Transactions on Smart Grid, vol. 10, no. 6, pp. 6552-6565, Nov. 2019, doi: 10.1109/TSG.2019.2907262.

[12] Jordán, Jaume et al. "A Multi-Agent System for the Dynamic Emplacement of Electric Vehicle Charging Stations." Applied Sciences 8 (2018): 313-327.

[13] Y. Yang, Y. Zhang and X. Meng, "A Data-Driven Approach for Optimizing the EV Charging Stations Network," in IEEE Access, vol. 8, pp. 118572-118592, 2020, doi: 10.1109/ACCESS.2020.3004715.

[14] M. Aljaidi, N. Aslam, X. Chen, O. Kaiwartya and Y. Ali Al-Gumaei, "Energy-efficient EV Charging Station Placement for E-Mobility," IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society, 2020, pp. 3672-3678, doi: 10.1109/IECON43393.2020.9255254.

[15] J. Li, X. Sun, Q. Liu, W. Zheng, H. Liu and J. A. Stankovic, "Planning Electric Vehicle Charging Stations Based on User Charging Behavior," 2018 IEEE/ACM Third International Conference on Internet-of-Things Design and Implementation (IoTDI), 2018, pp. 225-236, doi: 10.1109/IoTDI.2018.00030.

[16] Henrik Fredriksson, Mattias Dahl, Johan Holmgren, Optimal placement of Charging Stations for Electric Vehicles in large-scale Transportation Networks, Procedia Computer Science, Volume 160, 2019, Pages 77-84, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2019.09.446.

[17] Rodriguez, E., Ferreira, N. & Poco, J. JamVis: exploration and visualization of traffic jams. Eur. Phys. J. Spec. Top. 231, 1673–1687 (2022). https://doi.org/10.1140/epjs/s11734-021-00424-2.

[18] B. Badri-Koohi, R. Tavakkoli-Moghaddam, and M. Asghari, "Optimizing Number and Locations of Alternative-Fuel Stations Using a Multi-Criteria Approach", Eng. Technol. Appl. Sci. Res., vol. 9, no. 1, pp. 3715–3720, Feb. 2019.

[19] Avila, A.M., Mezić, I. Data-driven analysis and forecasting of highway traffic dynamics. Nat Commun 11, 2090 (2020). https://doi.org/10.1038/s41467-020-15582-5.

[20] Koch, Patrick, et al. "Constrained optimization with a limited number of function evaluations." ProcEEDings 24. Workshop comPutational intElligEncE. 2014.

[21] Bradley, Paul S., Kristin P. Bennett, and Ayhan Demiriz. "Constrained k-means clustering." Microsoft Research, Redmond 20.0 (2000): 0.

ONLINE RESOURCES

A https://www.autolist.com/news-and-analysis/2022-survey-electric-vehicles

B https://www.reuters.com/business/autos-transportation/us-automakers-say-they-aspire-up-50-ev-sales-by-2030-sources-2021-08-04/

C https://www.altenergymag.com/news/2022/09/09/ev-charging-infrastructure-market-size-to-expand-around-usd-21747-billion-by-2030/38036/

D https://www.eonenergy.com/electric-vehicle-charging/costs-and-benefits/battery-capacity-and-lifespan.html: : text=Electric%20car%20battery%20capacity,-Lithium%2Dion%20batterytext=The%20average%20capacity%20is%20around,higher%20the%20kWh%20the%20better.